# THE EFFECT OF PERCEPTUAL NOISE ON THE ERIKSEN FLANKER EFFECT: INSIGHTS FROM BAYESIAN PARAMETER ESTIMATION & MODEL COMPARISON.

By

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# Abstract

Decades of research using the Eriksen Flanker Task have provided valuable insight into the mechanisms of visual attention. However, this body of work has largely overlooked a critical aspect of our visual experience – the dynamic and noisy nature of our visual environments. This thesis aims to address this gap in the literature by exploring how adding noise to the stimuli influences attentional focusing in the flanker task. To reach this aim, we present three novel flanker tasks, two of which explore noise in the motion domain while the final study explores noise in the color domain. Furthermore, by comparing these results to a standard task, we explore differences in flanker suppression across noisy and standard, noise-free conditions. Within this field, there is also debate as to whether increases in attentional selectivity, or the suppression of flankers, proceeds as a gradual or discrete process. To test these differing views, two computational models have been proposed which realize the two viewpoints, namely the Shrinking Spotlight Model (SSP) of White et al. (2011) implementing the former and the Dual-Stage Two-Phase Model of Hübner et al. (2010) implementing the latter. Using the rarely used Bayesian approach, we fit both models to the data, and through a combination of average performance analyses, distributional analyses and model simulation, we can explain how noise influences the flanker effect and how this is accounted for under each theoretical framework. Firstly, we find that noise does indeed influence the flanker effect, in that adding noise to the stimuli impedes flanker suppression. Secondly, by independently manipulating the noise level in targets and flankers, we find solid evidence that the adverse effect of noise stems mainly from adding noise to the target. Finally, and in contrast to previous research using the standard paradigm, we find decisive evidence that a discrete improvement model (DSTP) best accounts for flanker suppression under noisy conditions. Our distributional analyses allow us to ascertain

that the superiority of DSTP can be localized mainly to its ability to better model data patterns indicative of considerably poor flanker suppression, particularly observed in high noise conditions. Combining our data analyses with the predictions of both models, we propose a theory of flanker suppression under noisy conditions, in which the extent of flanker interference is primarily determined by the saliency of the target: the less salient the target, the greater the flanker interference.

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**Jordan Deakin**

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# List of Abbreviations

| | |
|---|---|
| **CAF** | Conditional Accuracy Function |
| **DCDF** | Defective Cumulative Density Function |
| **DDM** | Drift-Diffusion Model |
| **DF** | Delta Function |
| **DSTP** | Dual-Stage Two-Phase Model |
| **EAP** | Expected a-posteriori (estimates) |
| **ELI** | Error Location Index |
| **ER -** | Error Rate |
| **KDE** | Kernel Density Estimator |
| **RT** | Response Time |
| **SSP** | Shrinking Spotlight Model |

# Chapter 1

# General Introduction

## An Introduction to Attention

Each time we open our eyes, the visual system is presented with an overwhelmingly complex and noisy stream of information, which far exceeds the finite processing capacity of the human brain. This input, estimated at around 108 bits per second at the optic nerve (Itti & Koch, 2000), arises from the presence of a multitude of features and objects, some of which may require a behavioral response. There is general consensus that visual selective attention deals with this complexity by selecting behaviorally relevant objects for further processing while filtering out irrelevant ones. Since our actions depend on what we attend to, this mechanism is crucial for successfully navigating the environment and much research has been dedicated to uncovering how attention manages this feat. This research has highlighted the intricate and versatile nature of selection attention, demonstrating its ability to function both overly and covertly across objects, features and locations, while being influenced by stimulus driven, bottom-up factors as well as the goals of the observer in a top-down fashion (Bisley, 2011; Carrasco, 2011; Cavanagh et al., 2023; Cave, 2013; Eriksen & St. James, 1986; Maunsell & Treue, 2006; Posner et al., 1980).

### Attentional Selection

The aim of attention is to select only a subset of input for further processing and therefore is often described as a filter (e.g. Broadbent, 1958). This suggests two stages of perceptual processing, an initial or 'preattentive' (Neisser, 1967) stage and a later stage devoted only to task relevant items that have been selected by the attentional filter. Early debates surrounding attention concerned the location of this filter in perceptual processing, namely whether attentional selection occurs early or late. By presenting subjects with both task relevant and task irrelevant information, researchers could explore the fate of task irrelevant stimuli to inform their theories of when attentional selection occurs. On one hand, *early selection* theorists argued that all inputs first undergo a shallow stage of processing, in which only their rudimentary ‘physical’ features are registered. Next, attention filters out relevant information to undergo deeper processing in a second stage (Broadbent, 1958; Kahneman & Henik. 1981; Treisman & Geffen, 1967; Yantis & Johnston, 1990). Importantly, this places the attentional filter early in the processing pipeline since the extraction of complex attributes like semantics or identity are reserved only for attended stimuli. Thus, the early selection view also argues that the semantics of unattended stimuli should not affect performance, since these stimuli are filtered out prior to extraction of these characteristics. Broadbent’s (1958) filter theory of attention is one such early selection view, which assumes that attention distinguishes relevant and irrelevant input ‘channels’ on the basis of early physical characteristics. This view is supported by findings from both auditory and visual attention research, which show that efficient selection occurs when task-relevant and irrelevant items possess distinct physical features. For example, in ‘shadowing’ tasks, participants are played two spoken messages through each ear and asked to shadow (repeat aloud) only one message. These tasks showed that for shadowing to be effective, a clear physical difference between both inputs is required (e.g., different pitches) and that when such differences are present, listeners can recall physical characteristics of the to-be-ignored message, yet very little of its content (Cherry 1953; Moray, 1959). In agreement with early selection views, effective shadowing was determined only by differences in the physical characteristics of the inputs, while the poor recall of the to-be-ignored input supported the idea that it was filtered out early before any semantic information could be extracted from it.

Similarly, explorations of visual attention show that when briefly presented with an array of items, participants can recall only very few. However, when cued to report only part of the display, for example, the top row only, recall accuracy greatly increases (Sperling, 1960). Again, in line with the early selection view, this suggests that all stimuli were processed in parallel and held in a rapidly decaying sensory store (which Neisser (1967) called iconic memory). The physical characteristic of location, provided by the cue, was sufficient to allow attention to successfully select only the relevant row. Similarly, partial reports have been shown to be more accurate when relevant items are distinguished by color or size from irrelevant items, and that these physical distinctions facilitate recall more so than distinctions based on semantic properties, like whether an item is a letter or a digit (von Wright, 1968).

This phenomenon is also evident in visual search paradigms, where participants are tasked with judging whether a given target item is present or absent in an array of items. By manipulating the number of distractors (set size) and their features, researchers could infer how the presence of these distracting items hinders the search for the behaviorally relevant target. Typically, these inferences are made from computing search slopes, where the search time is plotted as a function of set size (Wolfe, 2020). Early work showed that when the target is defined by a unique feature (e.g. a *feature* search for a red circle among green circles) reaction time is independent of set size and the search slope is flat. In contrast, more difficult searches produce steeper search slopes, where reaction time increases linearly with the number of items in the array (e.g. a *spatial configuration* search for a ‘T’ among ‘L’s, Bergen & Julesz, 1983). In their Feature Integration Theory of attention and object recognition, Treisman & Gelade (1980) argued that these two distinct types of search slopes are products of two distinct modes of attention, namely a parallel and serial stage. The early parallel stage extracts information automatically and in parallel across the entire array, producing a ‘master map’ of locations which registers the location of certain physical features (color, orientation etc.), but not the objects which they belong. Next, attention is directed to these locations in a serial manner and combines the features into recognizable objects. In other words, the focused, ‘serial’ mode of attention operates as a ‘glue’ that binds individual features into recognizable objects. To account for the different patterns of search slopes, Treisman & Gelade (1980) argued that in feature searches, the unique physical property of the target renders unique activity on the master map of locations and is turn, highly salient. An item’s salience refers to its ability to stand out in a visual scene and is computed by local feature contrasts between items (Bruce & Tsotsos, 2009). Thus, with a salient target, the information from the parallel stage is sufficient to detect the target and in turn, the target effortless draws attention since it appears to ‘pops out’ from the array. Importantly, since processing in the parallel stage of attention operates across all items in the array simultaneously, search for a ‘pop out’ target is equally effortless, regardless of how many items there are in the array. The result is a flat search slope, where reaction time is independent of set size.

In searches where the target is not defined by a unique basic feature, however, the master map of locations contains multiple areas of activation. This basic featural information is insufficient to determine whether the target is present and instead, the serial mode of attention is required. Under the original FIT formulation, Treisman & Gelade (1980) proposed that in this case, attention randomly visits items serially and identifies them until the target is found. Naturally, the more items in an array, the longer it takes to search through these items individually, leading to a linearly increasing search slope as set size increases. This leads to a ratio of ~2:1 between target absent and target present trials, since observers must on average search through half of the items in a target present trial to eventually find the target. Together, these findings suggest that early physical features allow attention to isolate relevant inputs, whereas the extraction of semantics and identity can only be achieved once an item is selected, in line with early selection accounts. Also consistent with this view, while mere detection of a unique target does not require focused attention, feature searches that require *identification* of a unique target often show a dependency on set size under certain circumstances (Bravo & Nakayama, 1992).

Alternatively, some theorists argued in favor of late selection (e.g. Deutsch & Deutsch, 1983), which assumes substantial (both featural and semantic) processing of all input before the attentional filter selects inputs based on these characteristics to be stored in short term memory. This was prompted by findings that the semantic identity of to-be-ignored stimuli had a more substantial influence than would be predicted by early selection accounts. To account for the poor recall of unattended inputs, late selectionists argue that that while the semantics of unattended input are extracted, they are quickly forgotten (Norman, 1968). For example, although individuals can selectively listen to a conversation in a noisy environment ('cocktail party problem', Cherry 1953), hearing one's name in another conversation often draws attention (Moray, 1959). Similarly, indirect measures of recall have shown that unattended stimuli produce covert responses, even if a subject cannot overtly recall said stimulus. For example, Corteen & Dunn (1974) showed that subjects showed an increased galvanic skin response to words presented in the unattended ear, when these words had previously been paired with an electric shock. Other research has also shown that unattended messages that have similar content to attended messages interfere more compared to when the content is different (Peters, 1954) and that syllables/words presented in both ears can be grouped to form a meaningful sentence, even if subjects are instructed to attend to one input stream (Gray & Wedderburn, 1960). Consequently, proponents of early selection (e.g. Treisman, 1964) accounted for these results by assuming that attention does not completely filter unattended items but attenuates them, where semantic interference from unattended items represents a failure of early selection.

Research in the visual modality has also demonstrated semantic processing of unattended items, more consistent with the late selection view. For example, partial report paradigms described earlier supported early selection, since participants could effectively recall a subset of items based on a physical (but not semantic) cue (Sperling 1960; von Wright, 1968). In contrast to this view however, categorical selection of items, for example based on letters or digits, has been shown to be possible under certain conditions (Merikle, 1980). Similarly, work using visual search paradigms has shown that the semantic identity of distractor items often influences search for a known target. For example, Moores et al. (2003) briefly presented participants with an array of items and asked them to report whether a given target object (e.g., motorbike) was present or absent in the array, while varying whether the distractor items were semantically related to the target. Although this manipulation had no effect in target-present trials, in target-absent trials, they observed a decline in performance when a semantically related distractor item was present (for example, a motorbike helmet). This suggested that knowledge of the target had led to the activation of semantically related items, which had then competed for attentional selection, with these items being more likely to be selected by attention than items not related to the target. Similarly, even if a distractor item is not semantically related to a target, but shares the same name (i.e., homophonic distractor, the presence of a baseball bat in a search for an animal bat), it is more likely to be selected than item without this association (Meyer et al. 2007). Again, this processing of the names and semantics of unattended stimuli prior to attentional selection supports an argument for late rather than early selection.

Given the support for each theory, the idea of both early and late selection seems plausible and other approaches have attempted to reconcile the two viewpoints. For example, in visual search, Treisman & Gelade’s (1980) Feature Integration Theory discussed earlier was one of the leading theories to account for different search slopes for ‘parallel’ and ‘serial’ searches and aligns more with the early selection view. Despite being a highly influential theory however, FIT is not without its issues. Importantly, the idea of a strict dichotomy between parallel and serial search is no longer accepted and were spurred by findings that some searches, which would be assumed to be conducted serially, produced notably shallower search slopes than would be predicted by FIT (Wolfe, 1989). In response, Wolfe et al. (1989) introduced the Guided Search Model, which assumes that the ‘parallel’ and ‘serial’ stages of attention do not operate distinctly, but rather information in the parallel stage is used to *guide* attention in the serial stage. Thus, a key distinction between FIT and Guided Search is that serial searches do not proceed randomly, but rather are guided by the information provided by the parallel stage. Thus, searches are not strictly serial or parallel, and this departure from the parallel/serial dichotomy allows Guided Search to account for the continuum of search slopes observed in search tasks, where the gradient of the slope is determined by the usefulness of the information provided by the parallel stage (Wolfe et al. 1989). Since 1989, the Guided Search model has been continually revised, with the latest revision being Guided Search 6.0. Guided Search 6.0 contains aspects of both early and late selection, including a non-selective pathway which registers more complex attributes (such as scene gist) prior to the attentional filter (akin to late selection), whereas Guided Search’s selective pathway assumes rudimentary processing prior to the attentional filter (akin to early selection).

## The Flanker Task

Although search paradigms provide useful information regarding how distracting items influence performance, the use of these paradigms introduces a confounding factor, in that the influence of task-irrelevant items is confounded by the search process itself (Eriksen & Eriksen, 1974). Therefore, to allow for a cleaner investigation of the effects of distracting items on target identification, Eriksen & Eriksen (1974) introduced the highly influential flanker paradigm, in which the location of the target is kept constant. Along with other so-called ‘conflict’ tasks, such as the Stroop (Stroop, 1935) and Simon (Simon & Wolf, 1963) tasks, great insight into selective attention, including whether it occurs early or late, has stemmed from various implementations of the flanker paradigm and it is this task which is the focus of this thesis.

In this task, participants are presented with an array of items and asked to identify the central target. For example, in the following array (← ← ← ← ←), participants must decide whether the central arrow is leftwards or rightwards facing while ignoring the ‘flanking’ arrows. There are two main trial types; response-congruent (i.e., ← ← ← ← ←) in which the flanking arrows are linked to the same response as the target, and response-incongruent (i.e., ← ← → ← ←), where the target and flankers are linked to opposite responses. The main finding from this task, an effect known as the flanker congruency effect, shows that responses in incongruent trials are on average slower and less accurate than in congruent trials. Despite its impressive capabilities, the flanker effect demonstrates the limits of visual selective attention: despite observers knowing what or where to attend to, the influence of distracting items cannot simply be ignored. Regardless of their irrelevance to the task, attention appears to ‘spill over’ to the flankers, their identity is processed and subsequently hinders the response to the target.

Like visual search paradigms, the flanker task has been pivotal in informing theories of visual selective attention and has also been used to inform the early/late selection debate. For example, the flanker congruency effect demonstrates that the associated response (an attribute more complex than a physical characteristic) is extracted from the flankers prior to selection and is therefore cited as strong evidence for late selection. On the other hand, distinguishing the target from the flankers, for example, by increasing the physical spacing between items (Eriksen & Eriksen, 1974; Miller, 1991; Servant & Evans, 2020) or uniquely coloring the target (Baylis & Driver, 1992; Harms & Bundesen, 1983) has shown to reduce the effect, with these aspects of the task supporting the idea of early selection, where the response congruency effect reflects a mere failure of early selection. Early selection accounts have also argued that the congruency effect occurs because the flankers are task relevant: since they represent the alternative response to the target, flankers are therefore primed and attended. In an attempt to control for priming based on response congruency, Miller (1987) implemented a flanker task in which the flankers were not linked to a response (neutral flankers) yet formed associations between target and flankers by pairing certain targets and flankers more often than others. In other words, the identity of the flankers could predict the identity of the target (valid trials), whereas in other trials this was not so (invalid trials). Miller (1987) observed that in a high correlation block, where 92% of the trials were valid, responses were notably faster in valid compared to invalid trials, whereas no difference was observed in a low correlation block where only around half of trials were valid. Inconsistent with the early selection account, this suggests that, even when priming was controlled for, participants were able to pick up on the semantic association between targets and flankers. However, Paquet & Lortie (1990) argued that Miller's (999) findings do not discount early selection views entirely. For example, they noted that in one experiment (in which the flanker validity effect was smaller), Miller (1987) had used a fixation cross, whereas in another (where the effect was larger), no fixation cross was used. In turn, the reduced flanker validity effect could stem from the physical cue of the fixation cross allowing subjects to better select the target, in line with early selection accounts. Paquet & Lortie (1990) further argued that, despite using neutral flankers, Miller (1987) may not have eliminated the priming of flankers. They argued that his use of letter flankers could have still led to priming, since the activation of one letter (the target), may subsequently lead to priming of other letters. Accordingly, Paquet & Lortie (1990) explored the flanker validity effect using a factorial combination of experiments where two factors were manipulated, namely whether a fixation cross was present and whether the flankers were letters (like the target) or digits. Firstly, in the absence of a fixation cross, there was a substantial validity effect, which was twice as large for letter flankers than for digit flankers. However, when a fixation cross was used, the validity effect for letter flankers was halved and was no longer substantially different to the effect obtained using digit flankers. Consequently, Paquet & Lortie (1990) argued that when early selection is possible (by means of a fixation cross), flanker stimuli undergo little semantic processing.

Just as evidence for both early and late selection in search paradigms has led more recent theories to acknowledge both types of attention, the same is true when accounting for data from the flanker task. For example, Lavie (1995), attempted to provide an end to the early/late selection debate with her Perceptual Load Theory, which assumes that the extent of distractor processing depends on the amount of information presented in a task. If the task is sufficiently demanding so that ‘perceptual’ resources are exhausted, few resources are left over for processing of unattended stimuli. On the other hand, if the task does not exhaust perceptual capacity, then attention spreads to and processes irrelevant items. This theory retains aspects of both early (the idea of limited perception) and late selection (that perception is automatic) and assumes that flanker effects occur because the typical displays used (two or four flankers) are simple enough that perceptual capacity is not exhausted. To support this notion, Lavie (1990) conducted a series of experiments in which she increased perceptual load in flanker displays. The first experiment increased load by simply adding more flanker items to the display. She found that incongruent flankers introduced more interference than neutral flankers in a low load condition (small set size), but not in a high load condition (larger set size). In a second task, she manipulated perceptual load by increasing the processing demands of the task, without changing the appearance of the display. This manipulation was inspired by Treisman & Gelade's (1980) Feature Integration Theory discussed earlier, which suggests that attention selects targets when they possess a unique physical feature. If a target is defined by a conjunction of features however, then attention is unable to select the target and items are serially identified. This implies that processing a conjunction of features is more perceptually demanding than the processing of one feature. Consequently, Lavie devised a flanker experiment combined with aspects of a go, no-go task (Donders, 1969), in which a shape was presented next to the target. This shape could be a blue or red circle or square and determined the response to the target. In the low load condition, if the shape was blue, participants were to respond to the target, yet withhold a response if the shape was red. Since response to the target is determined only by the color of the adjacent shape, the requirements of the task are low, and the condition is therefore low load. In the high load condition, both the color (red or blue) *and* the form (square or circle) of the shape determined the response to the target and therefore, participants had to process a conjunction of features to respond. Again, Lavie (1995) observed significant interference effects from incongruent distractors *only* in the low load condition. Other theories of processing in the flanker task have also acknowledged both early and late selection assumptions, for example, assuming that early and late selection are both possible, with late selection recovering performance should early selection fail (e.g. Hübner et al. 2010).

The flanker task is clearly a useful paradigm for uncovering how attention operates. Not only has this task been useful in informing the early/late selection debate but has also informed another concurrent debate regarding how attentional selection occurs, namely whether it proceeds as a gradual (e.g., zoom-lens model, Eriksen & St James., 1986), or discrete (Gratton et al., 1992) process. The current thesis aims to address this latter question by implementing a series of novel flanker paradigms. We fit two computational models of attention (a discrete and gradual improvement model) to the data using Bayesian inference, an approach which allows for more stringent reasoning about empirical evidence. In the following sections, we review seminal evidence from the flanker task and how these findings have been used to infer whether attentional selectivity improves gradually or discretely.

## The Flanker Effect & Response Competition

Since its inception in 1974, the flanker effect has been repeatedly replicated, and is robust across a myriad of configurations and stimuli, including letters, digits, arrows and faces to name a few (Baylis & Driver, 1992; Declerck et al., 2019; Driver & Baylis, 1989; Eriksen & St. James, 1986; Eriksen & Yeh, 1985; Harms & Bundesen, 1983; Hübner et al., 2010; Hübner & Többel, 2012; Moore et al., 2021; Mullane et al., 2009; Purmann et al., 2011; Schmitz et al., 2014; Servant et al., 2014, 2015; Stins et al., 2008; White et al., 2011; Willemssen et al., 2004). Rather than being a low-level perceptual effect, multiple lines of research have localized the interfering effect of flankers to the response stage, showing that the processing of flankers is sufficiently deep that their associated response is activated. While in congruent trials, all items provide evidence for the same response, incongruent trials provide evidence for two opposing responses. In order to respond correctly, attention is tasked with first suppressing the influence of incongruent flankers. This suppression takes time and is thought to reflect the longer response time (RT) latencies observed in incongruent trials, with a combination of behavioral, physiological, and neurological research supporting this conjecture. Firstly, beyond the simple 1-1 mapping of stimuli to responses used in the more common arrow flanker task, others have used more complex mappings, in which two or more stimuli are linked to the same response. The original flanker task of Eriksen & Eriksen (1974) employed this mapping using letters, where participants were tasked with identifying a central target letter as either an ‘S’,’H’,’K’, or ‘C’, with ‘S’ and ‘H’ being mapped to one response and ‘K’ and ‘C’ mapped to another. This manipulation allowed for the testing of whether the flanker effect is in fact response based or whether the effect stems from incongruent flankers simply being ‘different’ to the target. For example, if the perceptual form of the flankers, and not the linked response, is the critical factor, then there should be discernable differences between trials where the flankers are identical to the target (e.g., H H H H H) and trials where the flanking letters are different yet still linked to the same response (e.g., S S H S S). Indeed, Eriksen & Eriksen (1974) found no differences between the previous trial types. Only when flankers were linked to the opposite response to that of the target did they cause notable interference. Support for this notion has also stemmed from the analysis of ‘neutral’ trials, in which the flankers are assigned no response. Overall, neutral flankers tend to result in intermediate levels of interference, introducing more interference than congruent trials but less interference than incongruent trials (Eriksen & Eriksen, 1974; Eriksen & Schultz, 1979; Taylor, 1977). Critically, only when neutral flankers share perceptual similarity to items from the incongruent response set are considerable interference effects observed, demonstrating that the physical characteristics of the flankers only impact performance when these characteristics influence the associated response (Eriksen & Eriksen, 1974; Eriksen & St. James, 1986; Yeh & Eriksen, 1984).

A further line of evidence supporting the response-based nature of the flanker effect comes from electroencephalogram (EEG) studies, which have revealed the presence of a negative-going potential in the motor cortex known as the lateralized readiness potential (LRP, Kornhuber & Deecke, 1965; see Smulders et al. 2012 for a review). This potential appears around 200-800ms before the response in the hemisphere contralateral to the responding hand, showing an increase in activity which peaks just before the response is overtly executed. Thus, the LRP can be used as an index for the preparation of a motor response and because of its lateralization, can also be used to determine to which degree the flanker response is activated, even if no response is given (Coles, 1989; Gratton et al., 1988). For example, Gratton et al. (1988) showed that even prior to stimulus presentation, clear lateralization of the LRP could be observed and the direction of this lateralization could predict the accuracy of very fast ‘guess’ responses after stimulus onset: if lateralized in the direction of the target response, the given response tended to be accurate, whereas if lateralized in the direction of the flanker response, an error response was given. Furthermore, analysis of the relationship between RT and accuracy showed that, shortly after stimulus onset, incongruent trials produced considerably poorer accuracy than congruent trials, suggesting that the early response process is dominated by the incongruent flankers. Accordingly, the LRP shows a ‘dip’ in the direction of the incorrect flanker response during the period in which the incorrect response is more likely to be given, before lateralizing in the direction of the correct response as response time (RT) latency increases. This demonstrates that flankers are thoroughly processed, resulting in preparation of their associated response before a correction is made and the correct response is finally executed. Previous research has also shown that the stimulus onset asynchrony

(SOA) between presentation of the flankers and target can influence the magnitude of the flanker effect. Namely, if the flankers are presented before the target, flanker effects are increased, yet this effect diminishes if the SOA is sufficiently long. To explore this further, Mattler (2003) examined the behavior of the LRP across three levels of SOA. Consistent with behavioral findings, Mattler (2003) found that: 1) the onset of the LRP associated with the correct response was delayed in incongruent compared to neutral or congruent trials, consistent with the idea that incongruent flankers interfere with the target response; and 2) this onset latency decreased with increasing SOA. In other words, the longer the SOA between flanker and target onset, the earlier the onset of the LRP related to the correct response and the faster the response to the target.

While the LRP can be used to infer how responses are prepared *before* their execution, a final line of evidence comes from studies using electromyography (EMG), in which the analysis of muscle activity is used to infer the strength of response activation *after* the response is executed. Thus, this combination allows researchers to track the interfering effect of flankers from early processing levels, right down to the motor response. These studies have revealed the presence of so-called ‘partial errors’ in incongruent trials, which show execution of the flanker response, before the target response is given. For example, Coles et al. (1985) conducted a task in which participants responded by squeezing a dynamometer with either the left or right hand. By recording EMG activity in each, they could observe the extent to which a given response was activated covertly, even if this was not the final response given. Moreover, beyond the simple button press responses typically used in flanker tasks, the use of a dynamometer allowed the authors to examine subthreshold ‘squeeze activity’ in cases where the incorrect response was activated, executed yet aborted before the level of force reached the threshold required for the final response. Firstly, the authors found that in some trials, both arms showed EMG activity, with this occurring more often in incongruent compared to congruent trials. Secondly, they found that the degree to which the incorrect response was activated (measured through the squeeze response) was directly related to the latency at which the correct response was eventually given. In other words, the larger the magnitude of the incorrect response activation, the slower the eventual correct response to the target and these findings have been repeatedly replicated elsewhere (Burle et al., 2014; Eriksen et al., 1985; Fournier et al., 1994; Gratton et al., 1988; Servant et al., 2015; Smid, 1993). Together, these findings provide a solid basis for the argument that the flanker effect is predominantly response based.

## Distributional Measures

Typically, the flanker effect is quantified by taking the average difference in performance between incongruent and congruent trials. However, more recent distributional analyses have provided greater insight into how attention operates, both within and beyond the flanker task. Given the endogenous noise in the brain, humans do not produce the same exact response across trials, instead producing a range, or distribution, of RTs to the same stimulus. RT distributions are asymmetric and positively skewed, with a bulk of responses centered around a given value and a smaller proportion of slower responses constituting the tail (Rousselet & Wilcox, 2020). Measures of central tendency such as the mean and median provide poor representations of asymmetric distributions like those observed with RT. Specifically, these measures tend to be pulled towards the tail end of the distribution, away from the leading edge where most responses are concentrated. Although the median is more robust to this effect, taking a measure of central tendency involves compressing the distribution into a single value, at the expense of the rich information provided by the entire RT distribution (Miller, 1988; Rousselet & Wilcox, 2020) and by analyzing distributional data, researchers have uncovered further properties of the flanker effect, namely its time course, which cannot not be revealed by analyses of average performance alone.

Critically, such distributional analyses of flanker tasks have revealed a key finding, in that the interfering effect of flankers is not constant over the course of a trial, but rather is strongest at stimulus onset before being suppressed over time, consistent with the LRP and EMG studies discussed earlier (Burle et al., 2014; Gratton et al., 1988, 1992; Hübner & Töbel, 2012; Pratte et al., 2010; Pratte, 2021; Ridderinkhof et al., 2005; Stins et al., 2008; Wylie et al., 2009). Seminal work by Gratton et al. (1992) demonstrated this by analyzing the relationship between accuracy and RT, binning RT into quantiles, and comparing accuracy at different RTs for congruent and incongruent trials separately. These functions, known as conditional accuracy functions (CAFs), show that while accuracy in congruent trials is consistently high across all RTs (represented by a flat CAF), accuracy in incongruent trials is relatively poor for the fastest RTs, before reaching the level of congruent trials as RT increases. In other words, the fastest responses are susceptible to interference because they occur before the flankers are suppressed. Conversely, slower responses occurring after flanker suppression exhibit minimal interference. Thus, the difference between the congruent and incongruent CAF at the earliest quantiles can be used to gauge the strength of initial interference, while the slope of the incongruent CAF across RT latencies can be used to infer how quickly these flankers are suppressed. Indeed, the CAF has been used to demonstrate larger early interference effects in tasks with a short SOA between flanker and target (Hübner & Töbel, 2019), in line with the results of Mattler (2003) discussed previously, as well as in tasks where speed is stressed over accuracy (Wylie et al., 2009).

Similarly, if the cumulative density functions (CDFs) for congruent and incongruent trials are plotted, the difference between the two at each quantile can be used to quantify the flanker effect over time. This difference can be plotted against average RT across the two conditions to comprise the so-called ‘delta function’ (DF, De Jong et al., 1994). Typically, in the flanker task, this function is positive going, reflecting the fact that the impact of a manipulation (i.e., the congruency manipulation) typically grows with RT (Luce, 1968). If little or no suppression is applied, then the function monotonically increases, since no top-down mechanism is deployed to counter the effect of the manipulation. On the other hand, when strong suppression is applied, the DF levels off (or even turns negative) for the slowest RTs, since suppression takes time to build up and consequently, the observed benefit would be largest for the slowest responses (Ridderinkhof, 2002). Accordingly, steeper DFs have been observed in children with attention deficit hyperactivity disorder (ADHD) compared to matched controls, a disorder partly characterized by deficits in inhibitory mechanisms (Ridderinkhof et al, 2005; Scheres et al, 2003) as well as in tasks where the strength of interference is increased, either by means of a short flanker-target SOA (Hübner & Töbel, 2019) or by increasing the perceptual strength of the flankers (de Bruin & Sala, 2018). Thus, along with the CAF, the DF can be used as an index into the efficacy, strength, and time course of flanker suppression.

The critical point of these findings is that they suggest that attentional selectivity changes over time, where fast errors in incongruent trials stem from a state of attention that is diffuse and vulnerable to interference, whereas later, more accurate responses result from a state in which attention is focused only on the relevant stimulus or location (Benso et al., 1998; Broadbent, 1958; Castiello & Umiltà, 1990; Deutsch & Deutsch, 1963; Eriksen & St. James, 1986; Eriksen & Yeh, 1985; Jonides, 1983; Shiffrin & Schneider, 1977; Ullman & Koch, 1988). In other words, there is a consensus that attention transitions from some kind of diffuse to some kind of focused state. However, as we will show, debate remains regarding the nature of this transition. While some viewpoints posit two, consecutive stages with a discrete transition, others interpret this as evidence that the increase in attention selectivity, or the suppression of flankers, proceeds as a single process, with the shift from diffuse to focused attention occurring gradually.

## Two Theories of the Dynamics of the Flanker Effect

While these two viewpoints attempt to explain the dynamics of attention in the flanker task, both originate from two more general theories of how attention operates, namely the zoom-lens theory (Eriksen & St. James, 1986; Eriksen & Yeh, 1985) and the dual-process theory (De Jong et al., 1994; Gratton et al., 1992; Johnston & Heinz, 1978; Kornblum et al., 1990). The zoom-lens theory posits that visual attention operates like a zoom-lens covering a contiguous region of space. Only stimuli falling within the attentional zoom-lens are further processed, while stimuli on the fringes or outside the zoom-lens receive shallower processing or are ignored. The width of the zoom-lens is variable, and its width is inversely related to its processing capabilities: observers can attend to a wide area with low resolution or a narrower area with higher resolution (Brefczynski & DeYoe, 1999; Müller et al., 2003). Under the zoom-lens theory, early flanker interference is modeled by assuming that the zoom-lens is diffuse at stimulus onset, covering both target and flankers, before zooming in on the target during a single process. Since only stimuli falling within the zoom-lens determine the response, the flankers are *gradually* suppressed over time and attentional selectivity increases by means of a narrower spotlight.

In contrast to the zoom-lens model, the ‘dual-stage’ theory proposes that the automatic processing of all stimuli and subsequent attentional focusing occur as two distinct, consecutive phases, in line with more classic theories in which selective attention is characterized as a discrete filter (e.g., Broadbent, 1958). All stimuli in the visual environment undergo superficial processing during the ‘diffuse’ stage before selective attention filters relevant information to undergo deeper processing during the ‘focused’ stage. In the flanker task, early flanker interference is modelled through the first, diffuse phase in which attention is distributed across both targets and flankers. At some point, selective attention filters out the flankers in one discrete step, at which point attention enters the second, 'focused' phase, in which attention is directed only to the target. While both states are capable of driving responses, the temporal property of the flanker effect is accounted for by positing that fast, error prone responses are the product of the automatic (or early) processing stage, while the late selection stage drives later, more accurate responses. Thus, while under the zoom-lens theory, attentional selectivity can improve at any point during the decision process, the dual-stage theory posits an all or nothing processing of the flankers, with selectivity improving only once the target is selected (or the flankers are fully suppressed). Despite their clear differences, both theories can explain existing evidence although some lines of evidence provide more support for one theory over the other. In the following we will illustrate this point by discussing seminal behavioral evidence from flanker tasks and how each theory accounts for these findings.

## Target Flanker Spacing

Studies manipulating target-flanker spacing are typically seen as strong support for the zoom-lens model, with flankers closer to the target being repeatedly shown to introduce more interference than flankers further from the target (Eriksen & Eriksen, 1974; Eriksen & Hoffman, 1973; Eriksen & St. James, 1986; Fournier & Eriksen, 1990; Fox, 1998; Hommel, 1995; Kobayashi et al., 2022; Miller, 1991; Murphy & Eriksen, 1987; Servant & Evans, 2020). Although Eriksen & Eriksen (1974) posited that the scope of the zoom-lens spans around 1º of visual angle, interference effects have been observed at greater seperations, namely 3º (Fournier & Eriksen, 1990) and 5º of visual angle (Miller, 1991). In the framework of the zoom-lens model, far flankers interfere less, since they fall outside the scope of the zoom-lens earlier as attention gradually zooms in on the target. This notion is heavily supported by studies designed to provide ‘snapshots’ of the zoom-lens as it shrinks over time, the results of which support the idea that the focusing of attention is a gradual process. For example, the seminal study of Eriksen & St. James (1986) showed that a target cue presented prior to stimulus onset can reduce the flanker effect, whereby the longer the stimulus-onset asynchrony (SOA) between cue and stimulus presentation, the smaller the flanker effect. Importantly, this relationship is modulated by the spacing between target and flankers, where at short SOAs, interference from both near and distant flankers is observed. As SOA increases however, interference from distant flankers diminishes, while interference from near flankers persists. The authors interpreted this as evidence that attention utilizes the cue and subsequently begins to narrow the focus of attention, being narrow enough to suppress distant flankers, yet still wide enough to process flankers closer to the target and similar findings have been replicated elsewhere (Eriksen & Hoffman, 1973; Murphy & Eriksen, 1987; Shulman et al., 1979). Together, these effects support a gradual narrowing of attention over time, consistent with the zoom-lens theory.

However, the dual-process model can also accommodate these findings by suggesting that early selection mechanisms possess some kind of spatial filtering, the disruption of which leads to increased interference when flankers are closer to the target. In fact, Eriksen & Eriksen’s (1974) original interpretation of the effects of spacing are somewhat consistent with this view, who suggested that “[target] selection is more rapid if the spatial discrimination is easy” (Eriksen & Eriksen, 1974, p. 144). In other words, the further the flankers are from the target, the easier the spatial discrimination required to ‘select’ the target from the flankers and the earlier the switch to a more focused mode of attention, the result of which is a reduction in the flanker effect. Similarly, the relationship between cue-stimulus SOA and the flanker effect could also be accommodated under the dual-process theory by assuming that the time at which attention switches from the diffuse to the focused mode is variable. In other words, the SOA effect could be explained by assuming that the earlier the cue, the more likely it is that attention enters the focused mode before the presentation of the array. Noteworthy however is that the interaction between SOA and distance provides a challenge for the dual-process model (Eriksen & St. James, 1986).

## Perceptual Grouping

Given that the zoom-lens theory is a theory of spatial attention. target-flanker spacing manipulations provide an ideal setting for providing support for this theory. However, it is well known that attention not only operates across contiguous regions of space but also across objects or perceptual units, with studies exploring these phenomena providing a challenge for the zoom-lens theory. Just as the effects of spatial attention have been demonstrated in the flanker task, a wealth of evidence has demonstrated that this so-called ‘object-based’ attention is also at play. For example, there is consensus that selective attention has a tendency to form perceptual units, where this formation is governed by a number of Gestalt laws, such as similarity, proximity and good continuation to name a few (Wertheimer, 1938). That is, items that are similar, close together, or appear to be continuations of one another (i.e., stimuli arranged on a line), are grouped, and attended to as one unit. This preattentive  grouping is thought to disrupt the spatial discrimination required to segment and select items as individual objects and subsequently prolongs interference (Banks & Prinzmetal, 1976; Kahneman & Henik, 1981; Prinzmetal & Banks, 1977), in line with Eriksen & Eriksen’s (1974) interpretation discussed earlier. While Eriksen & Eriksen (1974) discussed this in the context of proximity between items, the same effects have been demonstrated with other Gestalt principles and in some cases, can even override the effects of spacing. For example, in an influential study by Driver & Baylis (1989), the authors compared two conditions in which the outer flankers were designed to either group with or away from the target through the principle of common fate, a principle which suggests that items moving at the same speed and in the same direction will be grouped together by attention. In their paradigm, the outer flankers moved with the target while the inner flankers remained stationary. Contrary to the assumptions of the zoom-lens model, the distant flankers which were grouped with the target introduced more interference than the inner flankers not grouped with the target, demonstrating that attention was directed to the target and the outer flankers, despite these items occupying a noncontiguous region of space. A possible argument against this account is that here, information about location received less priority, given that in moving displays, positional information is subject to change. In other words, the effects found by Driver & Baylis (1989) could be specific to moving stimuli. To refute this, Baylis & Driver (1992) conducted a follow up study, where they explored the effects of grouping by similarity in the color domain with static stimuli. Furthermore, they used a more elegant ‘X’ shaped design, where the central target was presented with two sets of flankers on each diagonal, each of which could be designed to group with or away from the target. This configuration allowed the authors to explore the effects of grouping while keeping spatial separation constant. Firstly, they found that incongruent flankers sharing the same color as the target introduced more interference than flankers that were colored differently from the target (despite both sets of flankers being equidistant from the target). Secondly, using the linear display of Driver and Baylis (1989), they replicated the same effects using color, that is, far flankers sharing the same color as the target introduced more interference than near flankers colored differently from the target. Finally, they showed that the same effects could arise when using the principle of good continuation to group items instead of grouping by similarity, demonstrating that the effects uncovered by Baylis & Driver (1989) were not motion-specific but were indeed the result of the more general effects of perceptual grouping. Not only are the effects of grouping clear in the flanker task, but there is also evidence that this operates on a continuum: the more likely flankers are to be grouped with the target, the larger the flanker effect. In turn, this notion implies that by perceptually segregating the target from the flankers, spatial selectivity can be enhanced, and the flanker effect reduced. Using a similar paradigm to that of Baylis & Driver (1992), Harms & Bundesen (1983) demonstrated this using a three-item flanker task in which three 'levels of segregation' were used; 1) where all items were the same color, 2) where one flanker was colored differently and 3) where the target was uniquely colored. If the above notion is true, then responses should be faster and more accurate from levels 1 to 3, and this is indeed what the authors found. Similarly, Kramer & Jacobson (1992) implemented a task in which the target and flankers could be embedded in the same or different perceptual objects. Consistent with the 'graded grouping' account of Harms & Bundesen (1983), Kramer & Jacobson (1992) found the largest effects when target and flankers were embedded in the same object, smaller effects in a control condition where no object-based manipulation was made and the smallest effect when target and flankers were embedded in different objects. In essence, spatial selectivity is challenged when target and flankers are perceived as a unified entity, making it difficult to focus attention exclusively on the task. In turn, the flanker effect increases.

At first glance, these findings cause a considerable problem for the zoom-lens theory, a theory which at its core suggests that attention cannot be directed to noncontiguous regions of space. However, the zoom-lens theory can account for these effects if some additional assumptions are made. For example, if one assumes that the rate at which the zoom-lens shrinks is influenced by perceptual factors, for example, the extent to which representations of target and flankers overlap (Logan, 1996; Yu et al., 2009), then it could be argued that target-flanker similarity slows the shrinking of the zoom-lens, leaving more time for flankers to interfere and subsequently increasing the flanker effect. On the other hand, similar to how the dual-process theory accounts for the effects of target-flanker spacing by assuming that early filtering mechanisms are disrupted in conditions of narrow spacing, a more general assumption can be made that any factor that increases the similarity between target and flankers, whether that be similar location or similar features, will disrupt early filtering. Thus, the dual-process theory easily accounts for the results of object-based manipulations by assuming grouping disrupts early spatial filtering mechanisms, prolonging the onset of the focused mode of attention and subsequently increasing the flanker effect.

## Sequential Dependency & Proportion Manipulations

A particularly interesting line of research has revealed the presence of sequential dependency effects in the flanker task, whereby the flanker effect in the current trial is modulated by the congruency of the previous trial. This was first demonstrated by Gratton et al.'s (1992) seminal work and is often seen as strong support for the dual-process model. Specifically, this so-called ‘Gratton effect’ shows that, following incongruent (congruent) trials, the flanker effect decreases (increases). Similarly, if the overall proportion of congruent to incongruent arrays is manipulated, the flanker effect increases if most trials are congruent, yet decreases if most trials are incongruent. The authors interpreted this as evidence that participants were able to make strategic adjustments in cognitive control, opting to respond on the basis of either a diffuse or focused mode of attention depending on the requirements of the task. Under this view, the Gratton effect can be explained as follows: in congruent trials, a diffuse mode of attention is sufficient to respond, and this is adopted for the next trial. If the following trial is congruent, then responses are faster, however this mode of attention proves detrimental if the following trial is incongruent and the flanker effect increases. In contrast, incongruent trials necessitate a greater reliance on the focused mode of attention and flanker effects in the following trial are subsequently reduced. Similarly, if congruent (incongruent) arrays constitute the majority of trials, then a diffuse (focused) mode of attention is more likely to be adopted overall and the flanker effect increases (decreases) as a result. In accordance with the dual-process theory, these strategic choices support the notion of two, distinct attentional states that are adopted based on their perceived utility. However, under the zoom-lens theory, there is also evidence that the focus of the zoom-lens is under voluntary control, for example, as demonstrated by the cue size effect, where the width of the spotlight can be determined by task demands or expectations (Castiello & Umiltà, 1992; Eriksen & St. James, 1986; Henderson, 1991; LaBerge, 1983; Theeuwes, 1991). The finding that participants can choose which attentional mode to use does necessitate the existence of two, distinct stages: if attentional focusing proceeds gradually, participants could strategically choose to respond earlier in the decision process (before the zoom-lens has sufficiently narrowed, akin to a more ‘diffuse’ stage), or later on when attention is fully focused on the relevant stimulus (akin to the more ‘focused’ stage). Given that responses are variable from one trial to the next, it is not trivial to isolate a discrete switch from diffuse to focused attention and these findings could just as easily be accounted for under the zoom-lens theory.

To sum up, while the theories propose conceptually different accounts regarding the dynamics of attentional focusing, both theories can explain a range of phenomena observed both within and beyond the flanker task. While the existence of a transition from diffuse to focused attention is relatively easy to demonstrate, pinpointing *how* this switch occurs is more difficult.

## Computational Models

Within the field of selective attention, there is a long history of developing computational models to allow for more stringent reasoning about empirical evidence (Abadi et al., 2019; Heinke & Humphreys, 2003, 2005; Zhang & Lin, 2013). By implementing theories as formal, verifiable models, researchers can explore how and why a given theory provides a better account of the evidence and this line of research has been adopted in the flanker task also. Specifically, to explore whether a gradual or discrete improvement in selectivity better describes the dynamics of attention in the flanker task, two computational models have been proposed which realize the two theories, namely the Shrinking Spotlight Model of White et al. (SSP, 2011) which implements the zoom-lens theory and the Dual-Stage Two-Phase Model of Hübner et al. (DSTP, 2010) which implements the dual-process theory. Both models share the underlying framework of the Ratcliff drift-diffusion model (DDM, Ratcliff, 1978), a model which conceptualizes two choice decisions as a noisy accumulation of sensory evidence over time for each alternative. Once a criterial amount of evidence is reached for a given response, that response is executed. This model, and computational models in general, provide two major benefits. Firstly, computational models allow for a simultaneous treatment of RT and accuracy, two variables known to be intrinsically linked yet are often treated separately in traditional analyses of average performance. Secondly, the models allow for a decomposition of RT and accuracy into dissociable cognitive processes through analysis of their parameters. That is, the parameters of these models are not purely descriptive, but reliably reflect distinct cognitive processes (Matzke & Wagenmakers, 2009). By analyzing changes in parameter estimates across experimental manipulations, researchers can confidently deduce changes in the underlying cognitive processes the parameters represent. Before discussing the two models (SSP and

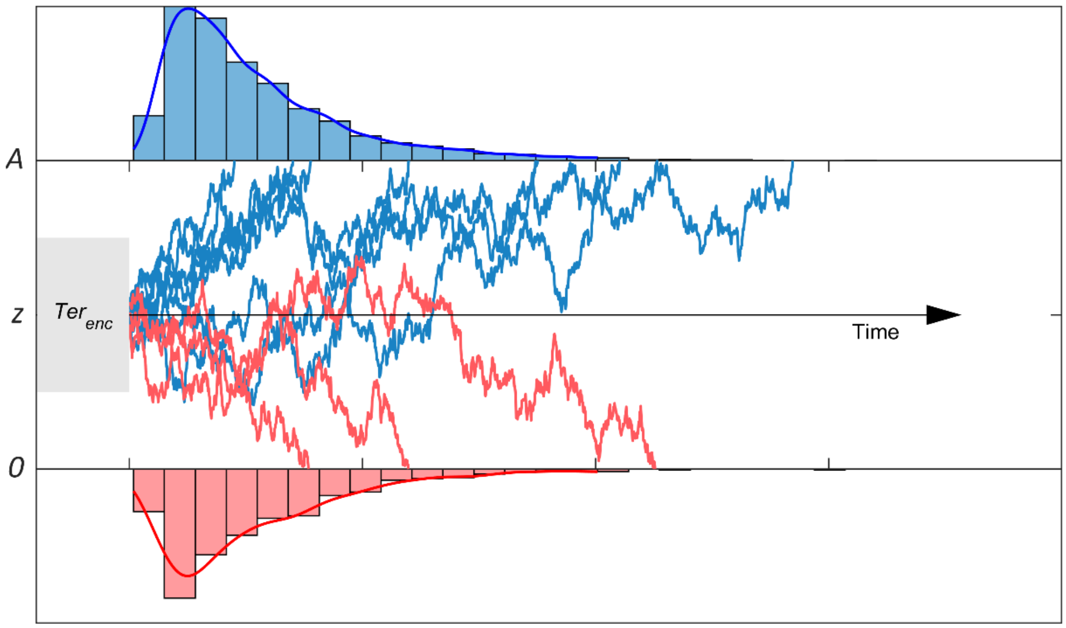
DSTP), we first introduce the underlying diffusion model framework in more detail and the necessary adjustments required to fit flanker task data.

## Drift Diffusion Models

The Ratcliff diffusion model (Ratcliff, 1978) has been shown to explain data from a variety of tasks including visual search (Lin et al., 2015), random-dot motion discrimination (Palmer et al., 2005), lexical decision tasks (Ratcliff et al., 2004) and recognition memory tasks (Arnold et al., 2015) (see Ratcliff et al., 2016 for a review). The model assumes that perceptual decisions are made by sequentially sampling information (or evidence) from a stimulus over time and integrating this evidence toward a response. To model variability in the RTs, noise is added to the process, and evidence accumulation proceeds as a random walk (see Figure 1 for a schematic illustration), which produces the positively skewed distributions typically found in RT experiments. In its simplest form, the DDM has four parameters: response boundary (***A***), starting point (***z***), non-decision time (***Ter***), and drift rate (***v***). The response boundary (***A)*** represents the criterial amount of evidence needed before a response is made and can therefore be interpreted as a form of response caution (Forstmann et al., 2016; Myers et al., 2022; Wagenmakers, 2009). If the upper boundary is hit, the correct response is executed, whereas if the lower boundary is hit (0), an error is made. Through the response boundary, the DDM can model the speed accuracy-

**Figure 1**

A schematic diagram of the drift-diffusion model.




Blue (red) traces represent evidence accumulation for correct (incorrect) responses, while blue (red) distributions represent the resulting RT distributions. $Ter_{enc}$ refers to the time necessary for stimulus encoding prior to the onset of evidence accumulation.

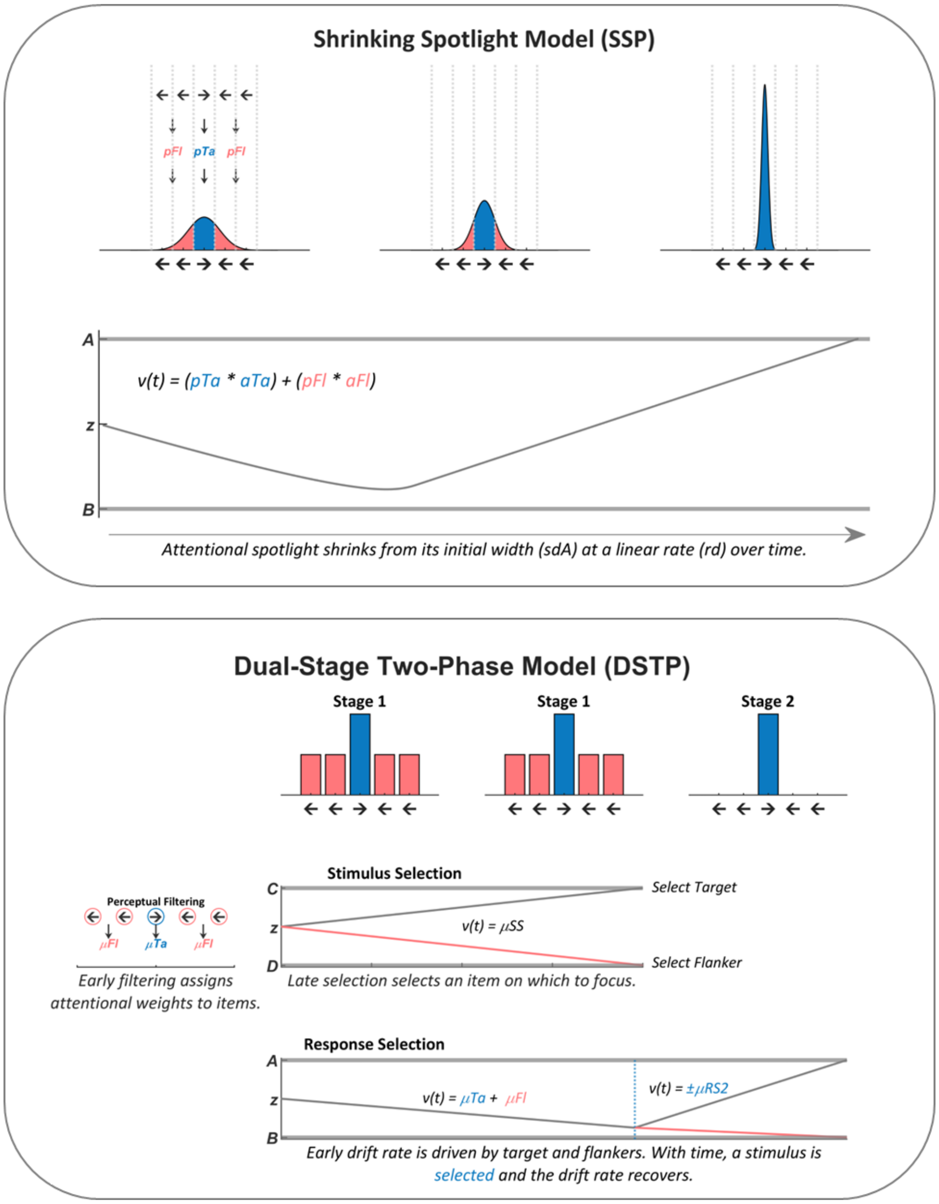
trade-off where a lower response boundary leads to fast, less accurate responses while a larger response boundary leads to the reverse (Voss et al., 2004; Wagenmakers et al., 2008). Thus, it is through this parameter that the DDM provides a simultaneous treatment of RT and accuracy. The starting point (*z*) of the diffusion process can vary although equidistance between the two response boundaries is often assumed and $\boldsymbol{z} = \boldsymbol{A}/2$. Conceptually, this reflects no bias towards either response. If participants are biased towards one response however, for example by means of a cue, the DDM can model this by moving the start point closer to the cued response boundary (Mulder et al., 2012). The drift rate parameter (***v***) reflects the rate of evidence accumulation and is interpreted as the quality of the sampled evidence, with higher drift rates leading to faster and more accurate responses (Palmer et al., 2005; Ratcliff, 1978; Ratcliff & McKoon, 2008). Finally, the non-decision time parameter (***Ter***) encompasses everything outside the decision process, including stimulus encoding before evidence accumulation and motor response execution after. Hence, the total RT is composed of decision time (the time taken for the diffusion process to hit a boundary) plus the non-decision time.

Although error and correct responses typically differ in latency, for example, errors are slower than correct responses when accuracy is stressed and faster when speed is stressed (e.g., Luce, 1986), this 'simple' DDM predicts that correct and error responses have the same RT when equidistance between the response boundaries is assumed (Ratcliff & Tuerlinckx, 2002). To model different RT latencies for correct and error responses, the DDM can be extended into the 'full' diffusion framework, which includes between-trial variability in start point (***sz*)**, non-decision time (***ster***) and drift rate (***sv***). Specifically, while between-trial variability in start point produces faster errors (Laming, 1968), between trial variability in drift rate produces the reverse and a combination of the two can produce 'crossover patterns', where the relationship between correct and error RT latencies is dependent on accuracy, with these additions typically improving quality of fit (Ratcliff, 1978; Ratcliff et al., 1999; Ratcliff & Rouder, 1998). Furthermore, Ratcliff & Tuerlinckx (2002) showed that between-trial variability in non-decision time is required to fit data in which the leading edge of the RT distribution shows clear variability across manipulations, although the extent to which this parameter influences model behavior is positively correlated with the value of the drift rate.

Despite its success however, the DDM cannot model the pattern of data observed in the flanker task, specifically the finding of faster errors in incongruent trials only (Ratcliff & Tuerlinckx, 2002). Although between-trial variability in start point can produce faster errors, this leads to faster errors in both conditions, contrary to the pattern found in flanker tasks. Instead, the two models (SSP and DSTP) account for this typical error pattern by assuming the drift rate varies over time: early in the decision process, drift rate and subsequent evidence accumulation are negatively influenced by the presence of incongruent flankers before recovering over time as these flankers are suppressed. In the following sections we provide a more detailed, mathematical description of the models within their DDM framework and how their time-varying drift rate assumption accounts for existing empirical evidence.

**Figure 2**

Schematic illustrations of SSP and DSTP.




SSP (upper panel): *aTa* and *aFl* are determined by the proportion of the attentional spotlight allocated to target and flankers respectively. DSTP (lower panel): Grey lines represent evidence accumulation in a trial in which the target was correctly selected, whereas red lines represent a failure of the stimulus selection mechanism in which the flanker is incorrectly selected. Note that to illustrate the progression of evidence accumulation more clearly, the within trial noise has been removed from the evidence traces in these diagrams.

**The Shrinking Spotlight Model (SSP)**

The top panel of Figure 2 shows a schematic diagram of SSP and how the zoom-lens theory is implemented to produce a gradual increase in selectivity over time. The zoom-lens is modelled as a normal distribution, where the standard deviation represents its width at a given time point *t*, and the mean represents the location of the target (which here is 0 but is arbitrary). At stimulus onset, the width of the zoom-lens is given by parameter ***sdA***, which represents the initial amount of activation triggered by the array. Over time, the zoom-lens shrinks at a linear rate ***rd*** to a minimum value of .001. Thus, at any time, *t*, the width of the zoom-lens ($sd_t$) is given by:

$$sd_t = sdA - (rd * t)$$

Target and flankers are assumed to be one perceptual unit wide with a perceptual strength equal to the parameter ***p***, which can be decomposed into ***pTarget*** and ***pFlanker*** respectively**.** Since all items are assumed to have the same perceptual strength, ***pFlanker = ±pTarget***, where ***pFlanker*** is negative in incongruent trials and positive in congruent trials. The rate of evidence accumulation ***v***, or drift rate, is given by the weighted sum of the perceptual strengths, where the weights are given by the proportion of the attentional spotlight allocated to each item at time *t* (*aFlanker/aTarget*). To ensure the area under the spotlight sums to 1, any portion of the spotlight not allocated to the target is allocated to the flankers. Hence, for a three-item display, the drift rate at each time step is calculated by:

$$aTarget = \int_{-.5}^{.5} N(0, sd_t)$$

$$aFlanker = 1 - aTarget$$

$$v_t = (aTarget * pTarget) + (aFlanker * pFlanker)$$

Figure 2 illustrates how these equations combine to produce the time-varying drift rate leading to a gradual increase in selectivity. As the zoom-lens is wide and diffuse at stimulus onset, both flankers and target contribute to the drift rate. In incongruent trials, the negative value of ***pFlanker*** causes evidence to initially accumulate towards the incorrect response boundary shortly after stimulus onset. As the spotlight shrinks, ***pTarget*** exerts a progressively stronger influence on the drift rate, until evidence accumulation is driven solely by the target. Subsequently, the drift rate recovers, and evidence begins to accumulate towards the correct response boundary. In congruent trials, the drift rate remains constant (equal to ***+p***), reflecting no interference. In this thesis, we implement the models in the ‘full’ diffusion framework, meaning our implementation of SSP had eight free parameters: the five SSP parameters, response boundary ***A***, non-decision time ***Ter***, perceptual strength ***p***, the initial width of the spotlight ***sdA*** and the shrink rate ***rd*** as well as the three between-trial variability parameters (***sz, sv, ster***). Given that the spotlight parameters ***sdA*** and ***rd*** can trade off (the same output can be obtained by a wide spotlight that shrinks quickly or a narrow spotlight that shrinks slowly), we also calculate an additional measure, the interference ratio (***sdA/rd***), post-hoc to account for this (White et al., 2018). This ratio corresponds to the point at which the spotlight reaches its minimum width (.001) and can be used to quantify the duration of interference. For all experiments in this thesis, we report this ratio also.

Due to its underlying diffusion framework, SSP has been shown to model a range of phenomena observed in two-choice decision tasks, including bias manipulations and speed accuracy trade-offs (White et al. 2011). More importantly however, its additional zoom-lens assumption means that SSP can account for key findings observed in the flanker task (Evans & Servant., 2020; Grange & Rydon-Grange, 2020; White et al., 2011). For instance, the well-established effect of target-flanker spacing (flankers closer to the target introduce more interference), can be accounted for under SSP. Although SSP does not contain an explicit mechanism to incorporate the effects of spacing, if the rate at which the spotlight shrinks is linked to the spacing between items (for example, based on the degree of overlap discussed earlier, Logan, 1996; White et al., 2011; Yu et al., 2009), then SSP can model the effect by assuming that the zoom-lens shrinks slower when flankers are closer to the target (see Servant & Evans, 2020; but see author discussion). A similar explanation can also account for the effects of perceptual grouping in the flanker task, however to our knowledge, no formal tests of SSP in studies of perceptual grouping have been conducted to date. Finally, SSP's single-process assumption can also account for the strategic adjustments in cognitive control evoked by task expectations described earlier (Gratton et al., 1992). For example, when manipulating the proportion of congruent relative to incongruent trials, White et al. (2011) replicated the finding that flanker effects were larger when the majority of trials were congruent. When fitting SSP to the data, the authors showed that this in turn led to a wider attentional spotlight at stimulus onset (a larger value of ***sdA***). Consistent with Gratton et al.'s (1992) interpretation, this reflects a greater reliance on a more diffuse mode of attention when most trials are congruent and a more focused mode of attention (a smaller value of ***sdA***) when most trials are incongruent.

**The Dual-Stage Two-Phase Model (DSTP)**

While SSP was developed to account for the flanker task specifically, DSTP was developed by Hübner et al. (2010) as a more general DDM-based implementation of the dual-process theory. A schematic of DSTP is shown in the lower panel of Figure 2. In accordance with the dual-process theory, DSTP posits two phases of response selection: *RS1* and *RS2*. *RS1* represents the diffuse mode of attention vulnerable to interference, while *RS2* represents the later focused mode of attention where response evidence is driven only by the selected item. At stimulus onset, *RS1* accumulates early evidence towards the response boundaries $\boldsymbol{A}$ or $\boldsymbol{B}$, based on evidence sampled from both target and flankers. DSTP presumes some initial amount of attentional selectivity in *RS1* through a stage of early perceptual filtering prior to evidence accumulation. Therefore, the drift-rate for *RS1* ($v_{RS1}$) is an additive combination of the parameters $\boldsymbol{\mu Ta}$ and $\boldsymbol{\mu Fl}$ , which represent the target and flankers respectively:

$$v_{RS1} = \mu Ta \pm \mu Fl$$

In incongruent trials, $\boldsymbol{\mu Fl}$ is subtracted from $\boldsymbol{\mu Ta}$, while in the congruent condition the parameters are summed. Consequently, early interference effects in *RS1* are captured by a lower initial drift rate for incongruent compared to congruent trials. These parameters are thought to represent a combination of perceptual strength and attentional weight, where the weights are determined by the effectiveness of early filtering (Hübner et al., 2010). Hübner et al. (2010) showed that, despite target and flankers sharing the same perceptual strength, certain experimental manipulations, which we will discuss later, can result in changes in $\boldsymbol{\mu Ta}$ and $\boldsymbol{\mu Fl}$.

Hence, the parameters can reflect not only changes in perceptual strength but also the attentional weight assigned to target and flanker during perceptual filtering respectively.

Outside of the response selection process, a late selection mechanism (*SS*) also modelled as a diffusion process runs in parallel to *RS1*, the drift rate of which ($v_{SS}$) is given by the parameter $\boldsymbol{\mu SS}$. The termination of this process determines the discrete time point at which attention switches from the diffuse phase (*RS1*) to the focused phase (*RS2*).

$$v_{SS} = \mu SS$$

This process (*SS*) accumulates towards one of two boundaries ($\boldsymbol{C}$ or $\boldsymbol{D}$) where the boundaries represent candidate items for selection: if boundary $\boldsymbol{C}$ is hit, the target is selected whereas if boundary $\boldsymbol{D}$ is hit, the flanker is selected. Once an item is selected, the response selection process enters the focused attention phase *RS2*, and the drift rate abruptly changes to ***μRS2***.

$$v_{RS2} = \pm\mu RS2$$

If the target is selected, ***μRS2*** is positive, whereas if the flanker is selected, ***μRS2*** is negative. To model the increase in attentional selectivity, ***μRS2*** is usually assumed to be a significantly higher value than the *RS1* parameters (***μTa*** and ***μFl***) (Hübner, 2014). Thus, unlike SSP which assumes that observers always successfully narrow attention in on the target, DSTP assumes that the focused mode of attention can be erroneous, with the drift rate abruptly increasing if the target is selected or decreasing if the flanker is selected.

Compared to SSP, DSTP is clearly the more complex model, with our implementation containing 10 free parameters. Since we assumed equidistance between the response and stimulus selection boundaries, we have one free boundary parameter for each process, the response boundary (***A***) and selection boundary (***C***), in addition to non-decision time (***Ter***), early drift rate for target (***μTa***), early drift rate for flanker (***μFl***), the drift rate for the stimulus selection process (***μSS***), the drift rate for *RS2* (***μRS2***) and the three between-trial variability parameters (***sz, ster, sv***).

Like SSP, DSTP has been shown to account for the same key patterns observed in flanker tasks (Grange & Rydon-Grange, 2022; Hübner et al., 2010; Hübner & Töbel, 2012, 2019; Servant et al., 2014). Importantly, these studies show that fitting DSTP to standard flanker tasks leads to behavior consistent with assumptions of the dual-process theory. For instance, Hübner et al. (2010) showed that when fitted to data from an experiment varying target-flanker spacing, DSTP can account for the spacing effect with an increase in the ***μFl*** parameter under narrow compared to wide spacing conditions. This in turn leads to an increase in the number of errors produced by *RS1*. Hence, DSTP suggests that poorer performance under narrow target-flanker spacing conditions results from poorer early filtering, possibly due to grouping by proximity discussed earlier. This same study also supports the interpretation that changes in the ***μFl*** parameter can be interpreted as changes in the attentional weight allocated to the flanker during early filtering, since its value changes in the expected direction, despite its perceptual strength remaining the same across spacing conditions. Again, a similar account could explain the effects of perceptual grouping although, like SSP, DSTP has not been fit to studies of perceptual grouping in the flanker task to our knowledge.

Similarly, DSTP can also model the strategic changes in attentional focusing evoked by task demands through the relative involvement of each of the attentional phases. Again, in line with the dual-process theory, Hübner et al. (2010) showed that DSTP could model the greater reliance on a diffuse mode of attention when congruent trials occurred more frequently and the opposite when incongruent trials were more frequent. In particular, when the majority of trials were incongruent, DSTP exhibited a higher tendency to produce responses in the early response phase *RS1*, consistent with the idea of a stronger reliance on the diffuse mode of attention. Importantly, since this strategy is detrimental in incongruent trials, DSTP also predicted a higher proportion of fast errors in response to incongruent stimuli in *RS1*. In contrast, when incongruent trials were more likely, the fits of DSTP showed a strengthening of both early and late selection (lower values of $\boldsymbol{\mu Fl}$ and higher values of $\boldsymbol{\mu SS}$ and $\boldsymbol{\mu RS2}$), with more trials ending in responses generated from the late phase of response selection (*RS2*) (even in congruent trials, where late selection may not be necessary). Again, Hübner et al. (2010) interpreted this as the modelling of strategic choices in cognitive control based on the expectation of the task: participants can choose to rely on the early or late phase depending on the perceived utility of each.

## Model Comparison

Despite a simulation study by White et al. (2019) showing that both models make quantitatively different predictions, that is, each model fits its own simulated data better than the other, comparisons between the two have yielded mixed results (Evans & Servant, 2020; Grange & Rydon-Grange, 2022; Hübner et al., 2010; Hübner & Töbel, 2012; Servant et al., 2014; Weichart et al., 2020; White et al., 2011). Since both models can account for the same effects despite their differences, it is not surprising that research has provided evidence in favor of SSP (White et al. 2010; Evans & Servant, 2020 for one dataset; Grange & Rydon-Grange, Experiments 1 & 2), in favor of DSTP (Hübner et al. 2010; Hübner & Többel, 2012, 2019; Servant et al, 2014; Grange & Rydon-Grange, Experiment 3) or in favor of both (Evans & Servant, 2020; Weichart et al. 2020). As well as being able to model the same data, each model can take on the key assumptions of the other under certain parameterizations. Namely, SSP's gradual transition can resemble a discrete switch if the spotlight shrinks quickly enough relative to its width at stimulus onset, while DSTP's discrete transition can resemble SSP's gradual transition, if the time of the transition is assumed to vary across trials. Thus, despite having qualitatively different mechanisms, the output of the models can indeed be very similar. For example, Evans & Servant (2020) conducted what is arguably the most recent and comprehensive comparison of the models, showing that both can provide high-quality fits to the same data. They compared the fits of SSP and DSTP (as well as the Diffusion Model for Conflict Tasks (DMC), Ulrich et al., 2015) to three datasets, namely that of White et al. (2011) (five arrows as stimuli), Servant et al. (2015) (5 letters, S and H) and Ulrich et al. (2015) (three letters, H and S). The results were largely mixed for the latter two datasets, with some participants showing evidence in favor of SSP and others for DSTP while the data from White et al. (2011) showed strong evidence in favor of SSP.

To understand these mixed results, researchers like Evans & Servant (2020) have compared the predictions of the models to the distributional measures discussed earlier, which show how the flanker effect changes across time. Indeed, some studies have found clear characteristics in the temporal relationship between RT and accuracy (as measured by conditional accuracy functions, CAFs) that can determine the superiority of one model over the other (Hübner & Többel, 2012; Servant et al., 2014). For example, Hübner & Többel (2012) conducted two flanker experiments with left and right-facing arrows and manipulated the response-stimulus interval (RSI) between the two studies. For the longer RSI (2000ms), the authors found a greater proportion of fast errors in incongruent trials relative to a shorter RSI (350ms). Although the fits of both models were very similar for correct trials, this was not the case when the error distributions were examined. In the former condition, SSP underestimated accuracy for the fastest responses and predicted that attentional selectivity improved too quickly leading to a win for DSTP, while for the latter condition, SSP was found to be superior. A similar pattern was found by Servant et al. (2014), who implemented a color flanker task in which the perceptual strength of the target was manipulated through color saturation and found a clear preference for DSTP, particularly when the perceptual strength of the target was low. Apart from a relatively slow increase in accuracy in the incongruent condition, they also found the unusual pattern that accuracy in the incongruent condition never reached the high level of accuracy observed in the congruent condition, even for the longest RTs (i.e., nonconvergence of the CAFs). Like Hübner & Töbel (2012), the authors found that SSP predicted an increase in selectivity that occurred too quickly, yet also failed to match the lack of convergence in the CAFs, since SSP's zooming always ends in correct focusing on the target. In contrast, DSTP could model these effects by preserving the diffuse state of attention through less frequent engagement of the late selection stage and thus could produce interference effects that persisted even into the longest RTs. The parameter estimates across saturations conditions supported this notion, where the drift rate for the late selection process was generally lower for low saturation conditions, resulting in a reduced probability that the focused staged of attention would be initiated and the diffuse mode would be preserved. It is worth noting that SSP can reproduce this unusual nonconvergent pattern for long RTs by assuming that the spotlight shrinks very slowly, yet this would likely result in a considerably high proportion of fast errors in the incongruent condition, possibly mismatching the data at hand. These findings particularly highlight the importance of using a combination of distributional measures to explore which aspects of data are best explained by a model, since the only discernable difference between the two models was revealed by the CAF. Hence, given the success of these distributional analyses, we will employ them here to understand the outcome of our model comparisons in this thesis.

## The Present Thesis

Despite decades long research using a range of stimuli and judgements (e.g., letters, digits and arrows; Declerck et al., 2019; Mullane et al., 2009; Purmann et al., 2011; Schmitz et al., 2014; Stins et al., 2008; Willemssen et al., 2004), research into the flanker effect has often overlooked the noisy nature of our visual environments, yet, in everyday situations, very often must we make decisions where the quality of the input is obscured by noise. To address this gap in current research, the current thesis aims to explore how perceptual noise in the stimuli influences the flanker congruency effect. To reach this aim, we conducted three novel flanker tasks in which we vary the level of perceptual noise present in the stimuli. Two of these studies employ a stimulus borrowed from the field of perceptual-decision making, namely the random dot kinematogram (RDK, Britten et al., 1992; de Bruin & Sala, 2018; Lange-Malecki & Treue, 2012) to explore noise in the motion domain, while the final study uses a novel type of noise, which we term ‘color noise’, to explore noise in the color domain. This ‘color noise’ study uses colored fields of static dots (random-dot patterns, RDPS) inspired by RDKs, allowing us to not only explore the influence of noise on the flanker effect, but also how this differs depending on the featural domain used.

RDKs consist of fields of randomly moving dots, a proportion of which move coherently in one direction while the rest move randomly. By manipulating the percentage of coherently moving dots (motion coherence), the perception of smooth motion within the RDK is achieved.

Importantly, varying motion coherence allows the perceptual noise present in the RDK to be quantitatively increased/decreased. These stimuli are frequently used in perceptual decision-making experiments, where observers are tasked with judging the direction of coherent motion within a single RDK (Palmer et al., 2005). Particularly interesting for the current thesis, neurons in the lateral interparietal area (LIP), an area proposed to be the ‘home’ of decision making in the brain (Shadlen & Kiani, 2013), show activity consistent with the assumptions of the DDM during these tasks. Specifically, when viewing an RDK, neurons in the LIP display increased firing rates when the input favors a response to a target in the neuron’s receptive field, whereas a decrease in firing rate is observed when the input favors the opposite response. The rate at which this increase/decrease occurs is directly related to the stimulus strength (motion coherence), akin to the role of drift rate in the DDM. Furthermore, just before response execution. these firing rates reach a common level, or threshold, regardless of motion coherence, akin to the role of the response boundary (Hanks & Summerfield, 2017; Roitman & Shadlen, 2002). We chose these stimuli as they not only because they allow for a quantitative manipulation of perceptual noise, but also because they mimic our noisy dynamic environment in a lab setting. Therefore, the RDK is an ideal stimulus to explore how selective attention deals with such perceptual noise in the context of the flanker task. RDK flanker tasks have been implemented previously by Lange-Malecki & Treue (2012), Pratte (2021) and de Bruin & Sala (2018), who showed that RDKs can produce flanker effects of a similar magnitude to those observed with static stimuli. However, while the former two investigations did not manipulate the noise present in the stimuli, the latter manipulated only the noise present in the flankers. In this thesis, we manipulate the noise in targets *and* flankers, both simultaneously in Study 2 and independently in Study 3. Furthermore, the ‘noisiest’ condition employed by de Bruin & Sala (2018) was one in which the motion coherence of the flankers was

40%, whereas here we include both a 20% and 30% motion coherence condition to explore the flanker effect under appreciably noisier conditions.

In this thesis, we present four studies. Firstly, we conducted a baseline study (Study 1) using standard letter stimuli (‘S’ and ‘H’), but matched all other aspects, such as stimuli size and target-flanker spacing to the RDK/RDP configuration, which allowed us to explore how flanker suppression differs across noisy and standard, noise-free conditions. We then conducted two studies in which participants identified the direction of coherent motion within a target RDK flanked by flanker RDKs. In addition to manipulating response congruency, the noise present in the items was manipulated (though motion coherence) as a random factor across four levels, creating a range of low to high noise trials (noise level = 10%, 40%, 70% and 80%). In Study 2, we manipulated the noise present in target and flankers simultaneously, while in Study 3, we manipulated target-flanker noise independently, allowing us to test whether the effects of noise stem mostly from noise in the target or noise in the flanker. In our final ‘color noise’ study (Study 4), the same procedure was used but with static fields of colored dots, a proportion of which could be colored either cyan or red, while the remaining dots were given a random hue. Participants were tasked with identifying whether the central target was ‘more red’ or ‘more cyan’. These stimuli were designed to be somewhat comparable to the RDK stimuli, allowing us to manipulate the percentage of noise dots (10%, 40%, 70% or 80%) across the same levels and compare differences in flanker suppression across the two featural domains.

In each of these studies, we fit SSP and DSTP to the data, to explore whether a gradual or discrete improvement in selectivity best explains our findings. To our knowledge, neither SSP nor DSTP have been fitted to a flanker task in which the level of perceptual noise is manipulated. Thus, by deviating from the typical standard paradigm (which uses noise-free stimuli), we aim to uncover more decisive evidence for which model provides a better account of the dynamics of attention in the flanker task. In addition to using standard methods, such as Analysis of variance (ANOVA)-tests and t-tests to analyze average performance, we also analyze standard distributional measures, namely the defective cumulative distribution functions (DCDFs), delta functions (DFs, De Jong et al., 1994), conditional accuracy functions (CAFs, Gratton et al. 1992) and the error location index (ELI, Servant et al., 2018) where possible. As discussed earlier, these measures build on average performance measures by allowing for an examination of how flanker interference changes across time. Not only can these distributional measures be used to explore changes in flanker suppression across different levels of noise but also as an index of quality of fit, allowing us to explore which aspects of the data are best explained by each model. Indeed, as discussed earlier, these measures can be crucial for determining why a given model is superior.

We fitted the two models, SSP and DSTP, to each noise level and participant independently, thereby decomposing RT and accuracy into the underlying processes through the model parameters. Doing so allowed us to explore how and why perceptual noise influences flanker suppression under the assumptions of each model, for example, whether noise influences the speed of SSP's zooming (***rd***) or how the involvement the late and early selection in DSTP differs depending on perceptual noise (e.g., the relative contribution of *RS1/RS2* to responses). For model fitting, it is common to use a maximum likelihood approach (e.g., White et al. 2011; Hübner et al. 2010). Here, we employed the rarely used Bayesian method (see Evans & Servant, 2020; Weichart et al., 2020; for exceptions), which allowed us not only to integrate quantitative knowledge from previous findings into the fitting process through the prior distributions but also to quantify our uncertainty in the parameter estimates through the posterior distributions. We also employed a Bayesian framework for model comparison by approximating the marginal likelihood (evidence) for each model and taking the ratio to compute Bayes Factor. The use of Bayes Factors allows us to ascertain which of the two models is better at explaining the data, by simultaneously assessing the quality of the fit, parsimoniousness (i.e., Occam's razor) and the functional form of the models (Myung & Pitt, 1997). Note that this method differs from other model comparison measures such as the Bayesian Information Criterion (BIC, Schwarz, 1978) or the Akaike Information Criterion (AIC, Akaike, 1974), which measure the complexity of the models through simple parameter counting methods and are commonly used in comparisons between DSTP and SSP (see Evans & Servant, 2020 for an exception). In the following we will briefly discuss our predictions for each study.

Firstly, we expected our baseline letter task to replicate the typical data patterns found in standard flanker tasks. Specifically, we expected typical flanker effects in both RT and ER, as well as the expected time course of the flanker effect in our distributional measures. That is, the congruency effect in RT would increase with increasing latency (as illustrated by the DF, e.g., Hübner & Töbel, 2019), whereas in ER, the congruency effect would decrease with RT, owed to by an increase in accuracy in incongruent trials across time (as illustrated by the CAF, e.g., Gratton, et al., 1988; Stins et al., 2008). These distributional patterns, along with the parameter estimates of the models could then be used to characterize the time course of interference under standard flanker conditions forming a basis for understanding our RDK results.

In Study 2, target-flanker noise was manipulated randomly across trials over four levels (10%, 40%, 70% and 80%). Given that high noise, incongruent flankers provide less evidence for their response, we expected smaller flanker effects in high noise conditions. As noise decreased however, we expected the effect to increase. Specifically, in the lowest noise condition (10% noise) we predicted that the effects would resemble those observed in the noise-free letter task, since this condition is most comparable to a standard flanker task. Consequently, this should result in a progressive decrease in the flanker effect from low to high noise conditions. This effect should also be evident across all distributional measures as noise increases, for example, the DFs should become shallower and the CAFs should show smaller early interference effects, representing better flanker suppression in high noise conditions. We also expected the critical parameters of the models to align with these predictions. Firstly, we expected SSP's spotlight parameters ***rd*** and ***sdA*** to show evidence of better attentional focusing under higher noise conditions, namely a narrower spotlight at stimulus onset (smaller values of ***sdA*** owed to by smaller levels of initial activation) which shrinks at a faster rate (higher values of ***rd***). For DSTP's early filtering parameters $\boldsymbol{\mu Ta}$ and $\boldsymbol{\mu Fl}$, we expected that they would decrease with increasing noise as they reflect the perceptual strength of the stimuli. However, since they also reflect attentional weighting, we expected differential effects of noise on $\boldsymbol{\mu Ta}$ and $\boldsymbol{\mu Fl}$. Specifically, given that we predict low noise flankers cause more interference, we expect the effect of increasing noise to be stronger for $\boldsymbol{\mu Fl}$ than for $\boldsymbol{\mu Ta}$, showing reduced attentional weight to the flankers as noise increases. Regarding the involvement of late selection, Hübner et al. (2010) found that under conditions of difficult early selection (e.g., narrow spacing conditions), the late selection stage was more frequently engaged to recover performance from large early interference to an acceptable level. Accordingly, we expect the late stimulus selection mechanism to be increasingly engaged as noise decreases, to counter the large early interference effects that we assume low noise flankers will introduce.

Hence, overall, we expected that adding noise to the stimuli would reduce the flanker effect since this manipulation reduces the perceptual strength and subsequent response evidence given by incongruent flankers. Accordingly, attention would be more readily capable of dealing with interference in such high noise conditions. In SSP, this would be reflected as smaller levels of initial activation (a narrower attentional spotlight at stimulus onset) and more effective suppression (faster zooming). Under DSTP, this would be reflected as more selective early filtering in high noise conditions and less reliance on the late selection stage. Seeing that attentional control systems have been shown to operate similarly across static and moving stimuli (Lange-Malecki & Treue, 2012), we expected that the effects would be comparable across the color and motion domains and these predictions therefore apply to the color noise task (Study 4) also. In anticipation of our results, we do indeed find evidence that noise influences the flanker effect, however not in the direction we expected. Since we manipulated target-flanker noise simultaneously in Study 2, we could not test whether this stemmed from noise in the target or noise in the flankers. Thus, Study 3 allowed us to test this assumption by manipulating target-flanker noise independently. Given previous research that low-noise flanker RDKs can increase the flanker effect (de Bruin & Sala, 2018) and that flankers dominate the response early in the decision process, we expected noise in the flankers to be the critical factor determining how noise influences the flanker effect. We therefore predicted that, regardless of the noise level in the target in Study 3, the flanker effect would increase as the noise present in the items decreased.

Finally, as to the question of whether a discrete or gradual improvement model provides a better explanation, we did not expect a clear-cut outcome as to which model was superior when using standard letter stimuli, given the previous mixed results with standard flanker tasks discussed previously (e.g., Evan & Servant, 2020). However, for the RDK and color noise studies, we expected more decisive evidence in favor of one model over the other. The inclusion of high noise trials offers a more stringent test of the models, since these conditions are likely to yield higher ERs than those observed in standard tasks. Given the previous demonstrations that error distributions can be crucial for determining the superiority of a model, we expected to find more clear-cut evidence in favor of one model for the noise studies and this is indeed what we find: a discrete improvement model (DSTP), provides a better account of attentional focusing under noisy conditions.

# Chapter 2

# A Letter Flanker Task

## General Method

Before we delve into the letter flanker task, we first describe the experimental and modelling methods used for all studies in this thesis.

### Model Fitting Procedure

#### Bayesian Parameter Estimation and a-posteriori estimates (EAP)

The Bayesian parameter estimation was achieved using the Differential Evolution Markov Chain Monte Carlo (DE-MCMC) method. MCMC methods use an iterative process to estimate a target density function, which here is the posterior parameter distribution of each model. At each step, a new proposal is generated based on the previous estimate, constituting a chain that ‘walks’ through parameter space and it is these proposals which make up the estimates for the posterior distribution. Within traditional MCMC methods such as the Metropolis-Hasting algorithm, a candidate proposal is sampled from a kernel distribution conditioned on the previous proposal. In other words, new proposals are generated by adding noise to the previous proposal. However, deciding which tuning parameters to use for this distribution can be cumbersome, and the chosen tuning parameter can have a large impact on the effectiveness of the algorithm. For example, as demonstrated by Turner et al. (2013), if the tuning parameter is too small, the chain moves too slowly and does not accurately explore the entire space, whereas if it is too large, the chain can jump around erratically, often becoming ‘stuck’ in areas of parameter space. Unlike traditional

MCMC methods, DE-MCMC uses multiple interacting chains for sampling a model's parameter space (Ter Braak, 2006), the advantage being that the interactions between chains reduces the burden of choosing an appropriate tuning parameter. In addition, the usage of multiple chains

**Table 1**

Prior parameter distributions used in this thesis.

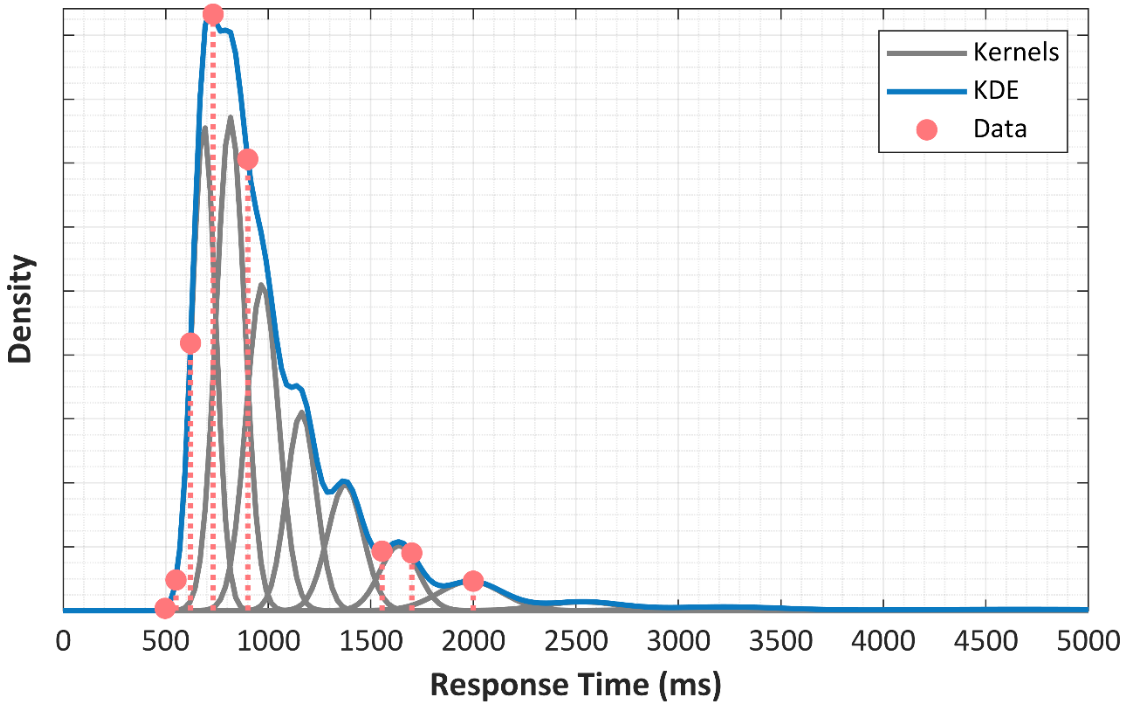
| **SSP** | **DSTP** |
|---|---|
| $A \sim TN(0.2, 0.2, 0, \infty)$ | $A \sim TN(0.2, 0.2, 0, \infty)$ |
| $ter \sim TN(0.3, 0.3, 0, \infty)$ | $C \sim TN(0.2, 0.2, 0, \infty)$ |
| $pTarget \sim TN(0.5, 0.5, 0, \infty)$ | $\mu Tar \sim TN(0.4, 0.4, 0, \infty)$ |
| $rd \sim TN(70, 30, 0, \infty)$ | $\mu Fl \sim TN(0.3, 0.3, 0, \infty)$ |
| $sdA \sim TN(4, 4, 0, \infty)$ | $\mu SS \sim TN(0.5, 0.5, 0, \infty)$ |
| $pFlanker \sim TN(0.4, 0.4, 0, \infty)$ | $\mu RS2 \sim TN(1.2, 1.2, 0, \infty)$ |
| | $ter \sim TN(0.3, 0.3, 0, \infty)$ |
| $\mathbf{Between - Trial\ Variability}$ | |
| $sz \sim TN(0.1, 0.1, 0, \infty)$<br>$ster \sim TN(0.1, 0.1, 0, \infty)$ | $sv \sim TN(0.2, 0.2, 0, \infty)$ |

Note: TN represents the probability density function for a truncated normal distribution in the form $TN$(μ, σ, lower truncation, upper truncation).

allows the sampling process to better deal with correlations between parameters common in DDM-based models (e.g., between drift-rate and response boundary) (Turner et al., 2013) and since the behavior of each chain is partly determined by the other chain, this method allows for a more efficient exploration of the parameter space. The sampling process in DE can take on different aims by the way new samples (proposals) are generated. Broadly speaking, these transition rules can either aim to find the best fitting parameters or they can determine posterior distributions (see Storn, 2008 and Qiang, 2014 for examples). Here we followed Turner et al.'s (2013) suggestion and employed two steps based on two different transition rules. The first transition rule, the current-to-best algorithm, aims to find the best fitting parameters, whose final samples form starting values for the second step, where the DE-MCMC transition rule generates posterior distributions (see Turner & Sederberg, 2012 for both transition rules). For the first step, we used 1000 iterations (generations) and 30 chains while for the second step, we used 30 chains and 10,000 iterations, 500 of which were considered part of the burn-in period and therefore discarded. This meant, for each parameter, we obtained 285,000 posterior samples. The prior distributions for posterior parameter estimation were taken from Evans & Servant’s (2020) work and were truncated normal distributions (see Table 1). Since relatively few studies have fit the models using a Bayesian approach, it was difficult to find suitable prior distributions. We therefore used Evans & Servant’s (2020) priors, since these were based on a mixture of priors used in previous applications of the simple diffusion model (Evans & Brown, 2017; Evans et al., 2018) as well as parameter values found in previous comparisons of SSP and DSTP (White et al., 2018). These priors were particularly attractive as they were made to be less informative to account for the lack of prior research into their values, yet still informative enough to constrain the estimates to suitable areas of parameter space.

**Figure 3**

Example Kernel Density Estimate (KDE) constructed from simulated data.




The blue distribution shows the estimate of a model density function produced by oKDE. The grey distributions are the Gaussian kernels used to construct this estimate under which the data points (pink dots) can be evaluated to compute likelihood values.

Because the time-varying drift rates render the likelihood functions computationally intractable (Ratcliff, 1980), we followed Turner & Sederberg's (2014) method and utilized a kernel density estimator (KDE) to determine likelihood values for a given parameter setting. As in Narbutas et al. (2017), we utilize a KDE method termed on-line KDE (oKDE, Kristan et al., 2011), a probability density approximation method which estimates the shape of a density function using a combination of Gaussian 'kernel' distributions (see Figure 3). Compared to the traditional KDE proposed by Silverman (1986), the oKDE method is more flexible, since it optimizes the number of kernels and their widths. Hence, oKDE leads to a more efficient and more adaptable KDE than the standard KDE method (Kristan et al., 2011; Narbutas et al., 2017 for detailed discussion). This allowed us to efficiently estimate the density functions of each model, under which the data could be evaluated to compute likelihood values. In this thesis, we created the KDE from 300 simulated trials of a model. Both models were simulated in seconds using Euler's method, with a diffusion coefficient of .1 and an integration constant of 1ms in accordance with previous research (Hübner et al., 2010; Servant & Evans, 2020; White et al., 2011, 2018). Since the estimation of likelihoods via simulation can be highly variable, we also added a "purification step" with 30% probability into the DE-MCMC algorithm (Holmes, 2015). This step ensured that the chains did not get 'stuck' in areas of artificially high likelihood, leading to better mixing amongst the chains. To assess convergence, we calculated split $\hat{R}$ (Gelman et al. 2013), a diagnostic statistic which evaluates convergence by comparing within-chain variance to between-chain variance, with $\hat{R} < 1.1$ being optimal. For all results presented in this thesis, $\hat{R}$ was below the criterial value of 1.1.

The posterior distributions were estimated for each participant and each noise level (if in the experimental design) separately. Since limited research exists on the fitting of these models in a Bayesian framework, we decided to start simple with a non-hierarchical approach. However, our use of a non-hierarchical approach also allowed us to explore individual differences across participants (see Evans et al., (2018) for a discussion on large variations in Bayes Factor across participants). To summarize the posterior distributions, we calculated the expected a-posteriori (EAP) estimates, taking the mean of each marginal posterior for each participant and averaging the results. Furthermore, we fitted a kernel distribution to each marginal posterior to calculate the 89% highest density credible interval and averaged the width of this interval across all participants. This allowed us to further make use of the benefits of the Bayesian approach by incorporating the uncertainty in the EAP estimates into our analyses. The 89% credible interval was chosen as it is thought to provide a more stable estimate than say the typical 95% interval (Kruschke, 2014). To examine whether noise had a meaningful influence on the EAP estimates in the noise tasks, we also conducted ANOVAs on each parameter. For DSTP, additional measures can be obtained through simulation (Hübner et al., 2010), which we calculated by taking the EAP estimates for each participant and simulating 20,000 trials from DSTP before averaging the measures across all participants. Firstly, we calculate the proportion of trials in which the late selection process terminates before the response process (***p(Selection)***), or in other words, the proportion of trials in which attention enters the focused mode. We also determined the selectivity of early and late selection by calculating the proportion of error responses produced by *RS1* (***$p(RS1_0)$***) and *RS2* (***$p(RS2_0)$***) as well as the proportion of trials in which the late selection mechanism incorrectly selected the flanker (***$p(Select_{Flanker})$***), allowing us to assess the accuracy of these processes. These measures are normalized to account for all responses produced by *RS1* and *RS2* respectively. Finally, we also compute a '***suppression ratio***', which indexes the point at which a stimulus was selected relative to overall decision time (*t(Selection)/decision time)*). This measure can tell us how early/late a stimulus was selected while controlling for overall decision time and therefore is useful for determining the speed of the selection process.

**Bayesian model comparison**

The model comparison in this thesis is based on the ratio between the marginal likelihoods (evidence) of the two models, or Bayes Factor (Kass & Raftery, 1995). The calculation of the integral version of the marginal likelihood is computationally expensive as it requires the solving of a multi-dimensional integral across the whole parameter space (albeit limited by the priors). In this thesis, we utilize recent progress in numerically approximating the integral termed Thermodynamic Integration for DE-MCMC (TIDE; Evans & Annis, 2019). For our purpose, this method is convenient as it requires only a simple extension of DE-MCMC. We used 10,000 generations with 30 chains (temperatures) and omitted the first 1500 samples as a burn-in period when estimating the marginal likelihood. Finally, to assess the strength of the evidence for the two models we used the interpretation proposed by Jeffreys (1998) (Table 2).

**Table 2**

Interpretation of the direction and strength of Bayes Factor given by Jeffreys (1998)

| **Bayes Factor ($\frac{M_1}{M_2}$)** | **Interpretation** |
|---|---|
| >100 | Decisive evidence for $M_1$ |
| 30 – 100 | Very strong evidence for $M_1$ |
| 10 – 30 | Strong evidence for $M_1$ |
| 3 – 10 | Substantial evidence for $M_1$ |
| 1 – 3 | Anecdotal evidence for $M_1$ |
| 1 | No Evidence |
| 1/3 – 1 | Anecdotal evidence for $M_2$ |
| 1/10 – 1/3 | Substantial evidence for $M_2$ |
| 1/30 – 1/10 | Strong evidence for $M_2$ |
| 1/100 – 1/30 | Very strong evidence for $M_2$ |
| < 1/100 | Decisive evidence for $M_2$ |

## Experimental Method

### Task Procedure and Stimuli

Due to the COVID-19 pandemic, all experiments were hosted online using Gorilla Experiment Builder (Anwyl-Irvine et al., 2020) and coded in JavaScript using the jsPsych 6.0.1 library for creation of psychological experiments (de Leeuw, 2015). At the beginning of the experiments, all participants completed the Virtual Chinrest Task (Li et al., 2020) to ensure a viewing distance of approximatly 60cm. This, along with the dimensions of the participant's screen were used to scale the stimuli and target-flanker spacing accordingly. In all tasks, three-item displays were presented on a black background and the distance between the target and flankers was set to 1º of visual angle. For the letter task (Study 1), these stimuli were square images of the letters 'S' and 'H' presented in white font, with a height and width subtending 3º of visual angle. For the RDK tasks (Studies 2 and 3), circular random-dot kinematograms were used (with diameters also subtending 3º of visual angle), the presentation of which used the jsPsych-RDK plugin (Rajananda et al., 2018). Each RDK contained 50 white dots with a diameter of 2-pixels and a lifetime of 30 frames. Each dot moved at a speed of 1.5 pixels per frame and if a dot travelled outside of the aperture, it was regenerated on the opposite side and the circular aperture edge was invisible. For the color noise task, we used static fields of colored dots, which we term RDPs (random dot patterns). Since the creation of these stimuli was slightly more complex, we leave the specific details to the method section of the color noise study in Chapter 4. For now, it is important to note only that these stimuli were designed to be similar to RDKs.

Each trial began with the presentation of a white fixation cross for 500ms before the stimuli were presented and participants were instructed to identify the central stimulus as quickly and as accurately as possible using the keyboard. The stimuli remained on screen until a response was made. For the letter task, all participants responded using the ‘S’ key for ‘S’ responses and the ‘H’ key for ‘H’ responses. For the RDK tasks, the ‘Z’ and ‘M’ keys were used for left and right responses respectively. Given that this provides an intuitive mapping of a leftwards response to the left hand and a rightwards response to the right hand, we decided not to counterbalance these keys across participants and the same is true for the letter task. For the color noise task, the ‘Z’ and ‘M’ keys were used for ‘red’ and ‘cyan’ responses but were counterbalanced across participants. Each block began with 16 practice trials with feedback, in which the words ‘Correct’ or ‘Incorrect’ appeared for 500ms after the response, followed by 64 experimental trials with no feedback. Every 32 trials, participants took a minimum 60 second break before being prompted to continue when ready. The experiments were split over two days, with participants completing both blocks of the letter task on the first day (a total of 64 practice trials and 128 experimental trials), followed by half (four) of the blocks in Study 2 (64 practice trials and 256 experimental trials). On the second day, participants completed the remaining four blocks of Study 2, to give a total of 128 practice trials and 512 experimental trials). Thus, by the end of the experiment, each participant had completed 64 experimental trials per condition (per response congruency level in the letter task and for each combination of noise level and response congruency). While Studies 1 & 2 shared participants (N = 49), a new set of participants completed Study 3 (N = 45) and the color noise task in Study 4 (N = 36). Again, Studies 3 and 4 were split over two days and by the end of the experiment, participants had completed 64 trials per condition.

**Data analysis**

Before any analysis, the data was cleansed. We removed participants whose accuracy was below chance (see individual study sections for details) and any RTs faster than 150ms or slower than 3000ms which led to the removal of 0.49%, 1.1%, 3.3% and 0.18% of the data for Study 1, Study 2, Study 3, and Study 4 respectively. To analyze average performance, we took the median RTs and mean arcsine transformed ERs for each participant and analyzed them using inferential statistics such as ANOVA and t-tests. We also present the results from distributional measures, namely the defective cumulative density functions (DCDFs), delta functions (DFs), conditional accuracy functions (CAFs) and the error location index (ELI) where possible. To apply the distributional measures to the models, we generated 20,000 trials per condition for each participant using their EAPs and averaged them to calculate vincentized group measures.

DCDFs illustrate the cumulative density functions of RTs by plotting the average RTs of each RT quantile on the x-axis and the corresponding quantile on the y-axis. To simultaneously assess fits to RT and ER, the quantiles are weighted by the proportion of correct responses (or incorrect responses for error DCDFs). Here we used 17 quantiles ranging from 10% to 90% in equal increments of 5%. The delta functions (DFs) subtract the average RTs in the incongruent condition from the congruent condition for each corresponding quantile (De Jong et al., 1994). The y-axis of the DF shows the congruency effect at each quantile, and the x-axis shows the average RT quantiles across both conditions. Conditional accuracy functions (CAFs) plot accuracy for a given RT quantile against the average RT quantiles of both incorrect and correct responses for congruent and incongruent trials separately. The quantiles chosen for the CAF were from 10% to 90% in equal increments of 20%. We chose coarser quantiles for the CAF compared the RT measures (DCDFs and DFs) to account for the fact that some conditions showed relatively small ERs.

Finally, Servant et al. (2018) proposed the error location index, which offers a slightly different approach to analyzing the congruency effect in accuracy across time, providing more information than can be obtained from the CAF alone. The ELI can help distinguish between fast errors that are the result of response capture and slow errors that are the result of some other process, for example, perceptual errors, with an ELI of 1 representing very strong response capture (where all errors are faster than correct responses) and an ELI of 0 indicating that all errors are slower than correct responses (i.e., perceptual errors). The ELI should be particularly useful for examining the noisy flanker tasks, in which some conditions contained high levels of noise. Since these conditions should produce more errors, either due to perceptual noise or response conflict, ELI would help tease apart these two error sources. Since the error location functions and subsequent indices rely on the empirical error CDF, the ELI is only useful if there are sufficient errors for this function to be meaningful**.** To confirm this was the case and following the method of Servant et al., (2018), a bootstrapping procedure was performed for conditions in which we wished to calculate this index.

## Introduction

In this study, participants decided whether the central target in a three-item array was a ‘H’ or an ‘S’, similar to a standard flanker task. The aim of this study was threefold: 1) to fit the models to data from a typical flanker task as a baseline for the noise studies; 2) as a sanity check to ensure our fitting procedure produced reasonably high quality fits; and 3) to check that we were still able to replicate earlier findings with static, noise-free stimuli as discussed in the introduction, despite our stimuli being slightly larger than those typically used (e.g., Evans &

Servant, 2020; Grange & Rydon-Grange, 2022; Hübner et al., 2010; Hübner & Többel, 2012, 2019; White et al., 2011). Specifically, we expected flanker effects in both average RT and ER, as well as the typical distributional patterns (positively sloped DFs and converging CAFs). Since both models have previously demonstrated their ability to account for standard flanker tasks, we expected participants to be evenly distributed regarding which model they showed evidence in favor of, with most participants showing anecdotal evidence supporting either model or a general split in the number of participants showing evidence for each (e.g., Evans & Servant, 2020). If one model were to win however, we predicted that this would be SSP, mainly due to its previous success in modelling tasks with a short RSI (Hübner & Többel, 2012). As our studies employed a relatively short RSI of 500ms, we believed this could potentially tip the balance in favor of SSP.

# Method

## Participants

A total of 51 participants from the University of Birmingham took part in exchange for course credit. 2 participants were removed from the sample as their accuracy was below chance level. This left 49 participants in the final sample (43 females and 6 males, mean age = 19.39 years).

## Stimuli

The stimuli were square images of the letters 'S' and 'H' subtending 3º of visual angle (matching the size of the RDKs/RDPs in our later studies) and presented at a viewing distance of 60cm. The letters were presented in white font on a black background with the target appearing in the center of the screen. The distance between the edges of target and flanker letters was set 1º of visual angle.

## Procedure & Design

The task followed a 2 x 2 repeated measures design with factors Target Letter (S or H) and Congruency (Congruent or Incongruent), both of which were randomized across trials. Participants were instructed to identify the central letter in the array using the ‘S’ (for S) and ‘H’ (for H) keys on the keyboard. The procedure follows that outlined in the General Method section. By the end of the task, each participant had completed 64 trials per level of Response Congruency.

# Results

## Behavioural Analysis

### Average Performance Analysis

RTs slower than 3000ms or faster than 150ms were excluded from analysis, accounting for 0.5% of the data. A paired samples t-test revealed a typical congruency effect in that responses in incongruent trials were on average 20.8ms slower than in congruent trials ($t(48) = 8.682$, $p < .001$, *Cohen’s d* = 1.240). We performed the same analysis on the arcsine transformed ERs ($t(48) = 5.332$ , $p < .001$, *Cohen’s d* = .762)  and again found a significant congruency

**Table 3**

Study 1: Average RT and accuracy across all 49 participants in the letter task.

| Measure | RT (ms) | | Accuracy (%) | |
|---|---|---|---|---|
| Condition | Congruent | Incongruent | Congruent | Incongruent |
| | 449.06 (52.58) | 470.85 (51.05) | 96.83 (2.91) | 93.60 (5.56) |

Note: standard deviations are shown in parentheses.

effect: incongruent trials produced ERs around 3.2% higher than congruent trials. These results can be found in Table 3.

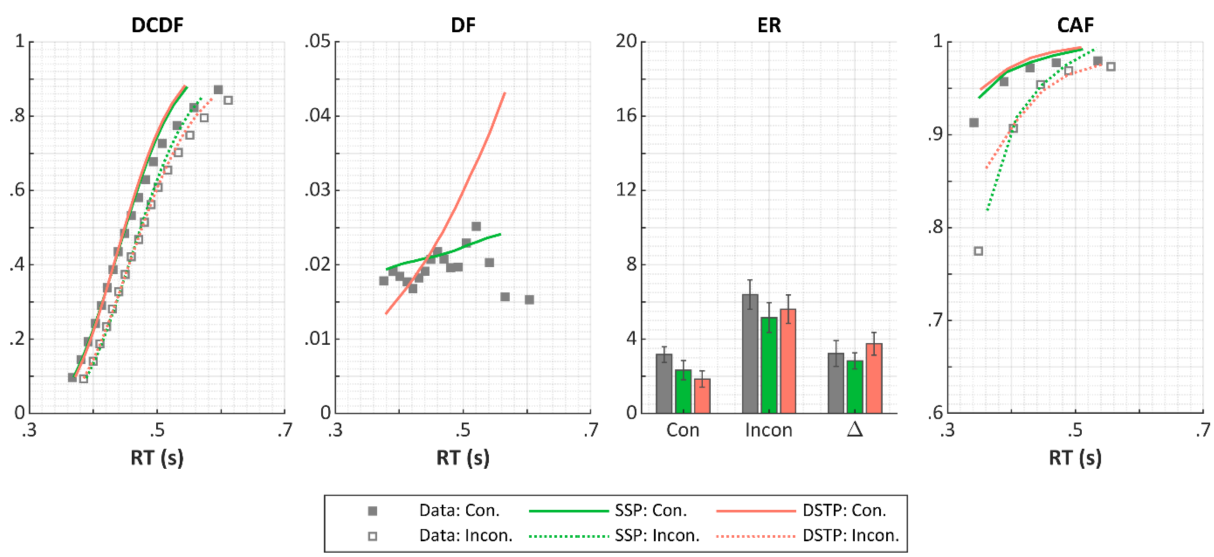
**Distributional Analysis**

Figure 4 shows the averaged distributional measures which overall, showed the typical effects observed in flanker tasks discussed previously. The DCDFs show that incongruent trials produced slower RTs across all RT quantiles, as also illustrated by an overall positive DF. Overall, however, the DF appeared to be positive going for short RTs before decreasing for longer RTs, indicative of strong suppression (Burle et al., 2014; Ridderinkhof et al., 2004).

In addition to the significant flanker effect in average ER, accuracy in congruent trials was higher than in incongruent trials across all RT quantiles and the difference between the two conditions decreased with increasing RT as expected. Specifically, for the fastest responses, the

**Figure 4**

Study 1: Averaged distributional measures across all 49 participants in the letter task.




DCDF: Defective cumulative density function. DF: Delta function. ER: Error rate (%). CAF: Conditional accuracy function.

congruency effect in accuracy was around 13.8%, before the CAFs converged at the longest RTs. Somewhat surprisingly, accuracy in the congruent condition also increased with RT, whereas the typical finding is that accuracy in this condition is independent of RT. While this effect has been found before, that is, a congruent CAF that increases with RT, the relatively steep congruent CAF found by Gratton et al., (1988) was for latencies much shorter than those observed here, consistent with fast guesses. While our CAF does increase, accuracy is consistently above 90%, suggesting this increase in the congruent CAF is not due to guessing but perhaps a speed-accuracy trade off.

## Model Fitting

### Bayes Factor

Table 4 shows the number of participants who fall into each evidence category based on the strength and direction of evidence specified by Jeffreys (1998). Half of participants (24/49) showed anecdotal evidence for either model in line with our original expectation that the results would be rather mixed. Overall, however, we found that a large majority of participants (35/49) showed evidence in favor of DSTP, yet for most of these participants, the strength of the evidence was weak. In contrast, only 14 participants showed evidence in favor of SSP. Contrary to expectation, these findings are inconsistent with some previous studies discussed in the introduction to this thesis (e.g., Evans & Servant, 2020 with the exception of one dataset) where no clear support for either model was found. As noted earlier, we originally predicted that if one model were to win, then this model would be SSP, mainly due to its previous success in modelling data from tasks with a short RSI (350ms) (see discussions in General Introduction based on Hübner & Többel (2012)). Thus, the win for DSTP was surprising. However, as we will show, we find similar issues with SSP, despite our relatively short RSI.

**Table 4**

Study 1: Number of participants falling into each Bayes Factor category for the letter task.

| | Study 1 |
|---|---|
| Extreme (SSP) | 0 |
| Very Strong (SSP) | 0 |
| Strong (SSP) | 2 |
| Moderate (SSP) | 1 |
| Anecdotal (SSP) | 11 |
| Anecdotal (DSTP) | 13 |
| Moderate (DSTP) | 11 |
| Strong (DSTP) | 5 |
| Very Strong (DSTP) | 3 |
| Extreme (DSTP) | 3 |
| | Letter |

Note: Since we fit all both models to each participant separately, the number of participants in each category sums to the total number of participants (N = 49).

## Quality of Fit

To understand the Bayes Factor results, we applied the distributional analyses to simulated data from the models and compared them to the data, which are also shown in Figure 4. Overall, both models fitted the data well. For both trial types, fits to the early and intermediate quantiles were very good, however, both models underpredicted RTs in the tail end of the DCDFs. For congruent trials, the predictions of the models were almost indistinguishable from one another, whereas for incongruent trials, DSTP's predictions were a better fit. This failure to match the tail is further illustrated by the DF, where both models fail to predict the later, negative going portions of the DF, although neither model is set up to account for such a pattern (but see Hübner & Töbel, 2019). Despite this, SSP's predicted DF was a better match than DSTP's, with DSTP underestimating the intercept and overestimating the slope, whereas SSP's predicted DF was suitably shallower and better matched the intercept. Noteworthy however, is the reason SSP's predicted DF is suitably shallow is because it underpredicts RTs in the incongruent condition, not because the fit to the data DCDF better overall. In other words, despite DSTP capturing the DCDFs better in terms of overall RT, it did not match the congruency effect across RTs as well as SSP.

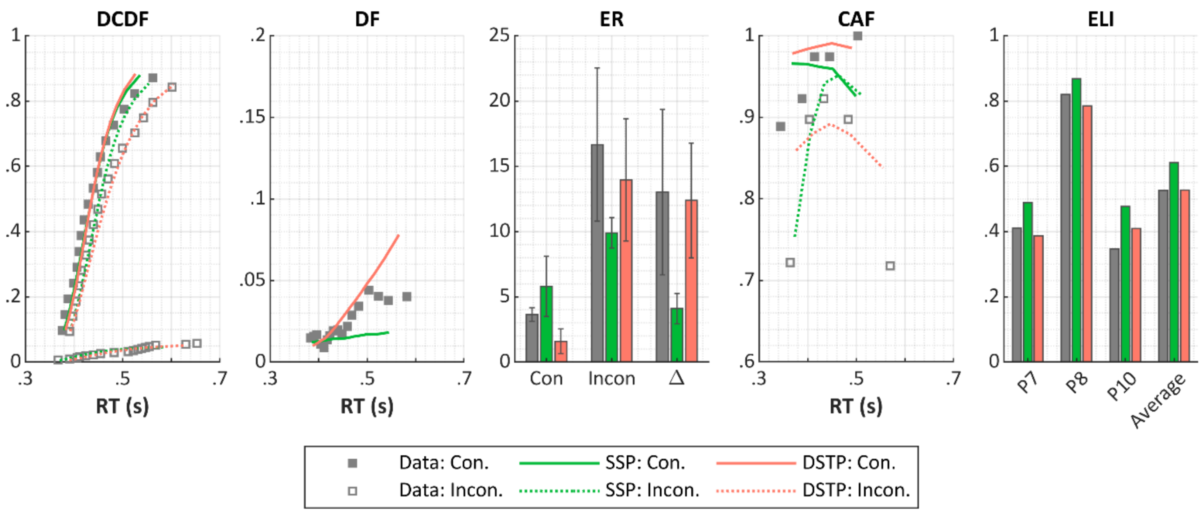
For average ER, we observed some mismatches between the model predictions and the data, yet SSP's predictions were closer overall (with the exception of the incongruent condition). However, given that the overall ER in the letter task was quite small, these mismatches are negligible, and more information can be obtained from the CAFs. Firstly, the model predictions were very similar for congruent trials yet, as was the case for RT, diverged in incongruent trials. While DSTP overestimated accuracy at the earliest quantile, SSP's match was clearly better. In fact, in terms of the congruency effect at the earliest quantile, SSP's prediction of 13.1% almost perfectly matched that of the data (13.9%) compared to the 8.5% predicted by DSTP. We highlighted earlier that SSP's prediction of a steep incongruent CAF has previously been noted as a potential flaw of the model (Hübner & Töbel, 2012), yet here, this prediction allowed SSP to better match the congruency effect in the earliest portions of the CAF. In contrast however, the later quantiles of the incongruent CAF were better matched by DSTP, with SSP's steep CAF leading to a slight overprediction of accuracy at the latest quantiles. Thus, it appeared the CAFs were overall better modelled by DSTP and, in line with Hübner & Töbel (2012), we find that despite our short RSI, SSP's prediction of steep CAF can indeed lead to mismatches to the data.

Given these distributional analyses, it is still somewhat surprising that most participants showed evidence in favor of DSTP, since it seemed that the results were rather mixed, with SSP providing a better fit to some aspects of the data and DSTP providing a better fit to others. Specifically, SSP better predicted some aspects of the congruency effect across time (the early portion of the CAF and slope of the DF), whereas DSTP provided better fits to the absolute values (the incongruent DCDF, ER, and incongruent CAF). To understand this further, we took the three participants who showed extreme evidence for DSTP and calculated the same distributional measures, with the expectation that DSTP would show significantly higher quality fits and highlight any specific failures of SSP which led to these participants favoring DSTP. Firstly, before examining the distributional data from these three participants (Figure 5), we note that two of these participants showed the largest congruency effects in ER of all participants, hinting that the superiority of DSTP may be attributed to the error distributions, in line with the findings of Hübner & Töbel, (2012) and Servant et al., (2014).

Indeed, as the figure shows, DSTP provides a considerably better match to the overall ER in incongruent trials and the congruency effect in ER for these participants. Not only this, but DSTP also better predicts the location of these errors relative to correct trials, which are illustrated by the ELI and the CAF. Since the three 'extreme' DSTP participants showed high ERs in incongruent trials, we were able to calculate incongruent ELI for these participants and for each model.

**Figure 5**

Study 1: Averaged distributional measures for the 3 participants showing extreme evidence for DSTP in the letter task.




DCDF: Defective cumulative density function. DF: Delta function. ER: Error rate (%). CAF: Conditional accuracy function, ELI: Error location index.

Firstly, DSTP's estimate of the ELI was closer to the data, with the average estimate (.53) across the three participants (.53) being near enough perfect. In contrast, SSP overestimated the ELI, predicting a larger proportion of fast errors than observed in the data, which is also evident in the CAFs. For congruent trials, accuracy is rather high across all RTs yet increases with RT. While neither model matches the function perfectly, DSTP's predicted pattern is clearly better. In fact, SSP predicts the opposite effect, namely a congruent CAF that decreases with increasing RT. For incongruent trials, the CAF shows a curvilinear pattern, first increasing and then decreasing. While SSP matches the steep increase very well, it fails to adequately match the later decrease. Most crucially, this decrease means that the CAFs from the data do not converge. While SSP incorrectly predicts that the functions converge, DSTP does not. As noted earlier, DSTP can match this pattern through less frequent involvement/failure of the late selection stage, predicting slow errors in the incongruent condition, while retaining the high accuracy for congruent trials. Interestingly however, it appeared SSP had attempted to model this effect by predicting slow errors, albeit for both congruent and incongruent conditions and when we examined the EAP estimates for these participants, we realized this was due to the between-trial variability in drift rate (Ratcliff & Rouder, 1998). Specifically, these participants showed the highest values for variability in drift rate under SSP, yet also the highest probability of the late selection mechanism incorrectly selecting the flanker under DSTP. This demonstrated that while DSTP's architecture allowed it to model the slow errors in the incongruent condition, SSP had attempted to do so by increasing variability in drift rate, which influenced both conditions and led to further mismatches to the CAF, most notably, a congruent CAF that decreased with RT. Note that while SSP *could* produce slow errors in incongruent trials only by assuming the spotlight shrinks extremely slowly, this would likely result in a very large proportion of errors, particularly for the fastest responses. As it happens, we see this in Figure 5, where SSP's predicted congruency effect in the first quantile of the CAF (21.3%) is almost double that of the data (11.9%). Hence, slower zooming would have predicted more fast errors, leading to further mismatches to the data. Note that we will present a more detailed examination of this effect in Study 2. Overall, DSTP clearly provided a better to fit to error responses for these participants.

As well as better matching error responses, we found that DSTP better modelled correct responses also. Examining the DCDFs, the predictions of the models in congruent trials are very similar and match the DCDFs well. In incongruent trials however, we again see clear differences. While SSP matches the early quantiles well, it greatly underpredicts RT in the later quantiles, whereas DSTP models these quantiles almost perfectly. This is further reflected in the DF, where

DSTP better predicts the steeper slope, while SSP greatly underestimates it. In other words, and in agreement with the predictions of the CAF, SSP assumes attentional selectivity improves too quickly and underpredicts the duration of interference.

**Table 5**

Study 1: Average EAP estimates across all 49 participants from the letter task. Standard deviations are shown in brackets.

| **SSP** | ***A*** | ***ter*** | ***p*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** | ***IR*** |
|---|---|---|---|---|---|---|---|---|---|
| **EAP** | .12 | .34 | 1.16 | 85.56 | 2.01 | .13 | .13 | .19 | .02 |
| | (.08) | (.06) | (.24) | (2.92) | (.93) | (.06) | (.07) | (.07) | (.01) |

| **DSTP** | ***A*** | ***C*** | ***µTar*** | ***µFl*** | ***µSS*** | ***µRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **EAP** | .19 | .16 | .53 | .21 | .88 | 2.27 | .30 | .12 | .12 | .18 |
| | (.11) | (.09) | (.18) | (.09) | (.22) | (.35) | (.07) | (.04) | (.06) | (.08) |

| **DSTP Simulated Measures** | **Condition** | |
|---|---|---|
| | **Congruent** | **Incongruent** |
| ***p(selection)*** | .634 | .683 |
| ***Suppression Ratio*** | .275 | .280 |
| ***P(targetSelected)*** | .976 | .976 |
| ***P(flankerSelected)*** | .024 | .025 |
| ***P(RS1_0)*** | .023 | .086 |
| ***P(RS2_0)*** | .000 | .025 |

### EAP Estimates

Table 5 shows the averaged EAP estimates across all 49 participants. For now, these estimates offer little value alone for our research question but will be useful later when comparing the letter task to the noisy RDK task of Study 2. For SSP, the perceptual strength of the items ***p*** is high, while non-decision time ***ter*** and the response boundary ***A*** are rather low. The initial width of the spotlight ***sdA*** is narrow, yet still wide enough to encompass both flankers and target. Combined with the shrink rate, this leads to a rather short duration of flanker interference, where the spotlight reaches its minimum width at around 23.4ms into the decision (interference ratio). For DSTP, early filtering appears to operate well, where the partial rate for the target ***μTa*** is higher than that of the flanker. Regarding late selection, a stimulus was selected in the majority of trials (***p(Selection)***), and this selection occurred slightly earlier in congruent compared to incongruent trials (***suppression ratio***). Regarding *which* stimulus was selected, the target was correctly selected in most trials, however, the probability of incorrectly selecting the flanker was marginally higher in incongruent trials and consequently, so was the probability of *RS2* producing an error ($\boldsymbol{p(RS2_0)}$). Likewise, in *RS1*, the probability of making an error ($\boldsymbol{p(RS1_0)}$) was higher in incongruent compared to congruent trials yet small overall.

## Discussion

In the letter task, we found significant congruency effects in both average RT and ER. Our distributional analyses showed the expected time course of flanker interference, with responses in incongruent trials being consistently slower than in congruent trials across all RT quantiles. Furthermore, the CAFs showed that incongruent trials produced more errors, primarily for the fastest RTs. However, over time, the interference was suppressed and accuracy for both trial types became comparable. This trend was further supported by the positive DF: the time cost of flanker suppression was illustrated by the positive DF for correct trials and the effective suppression was illustrated by the later, negative slope.

Regarding model comparison, half of participants showed anecdotal evidence for either model, yet overall, DSTP was found to be superior, with some participants showing high strength evidence for DSTP. To illustrate why these participants preferred DSTP, we took the participants who showed extreme evidence for DSTP, and by analyzing the distributional analyses, we could localize this win to DSTP's ability to better model the pattern of interference over time, particularly in cases where the data showed interference effects that persisted into the longest RTs and CAFs that did not converge. While DSTP could model this effect through failure of the stimulus selection process, SSP could not, predicting that attentional selectivity increased too quickly and subsequently predicting CAFs which converged and a DF that was too shallow. Since SSP has no mechanism to produce such slow errors while retaining a high-quality fit, analysis of the parameter estimates revealed SSP had attempted to model these slow errors in the only way it could: through between-trial variability in drift rate which was insufficient to match the data. In summary, DSTP's win stemmed from some participants who showed less typical patterns of data, indicative of poor flanker suppression, most notably nonconverging CAFs and steeper DFs.

Overall, the results of Study 1 satisfied our aims, in that we were able to replicate key distributional trends observed in flanker tasks and the fits were of reasonably high quality. Given this, we felt the results were generally representative of flanker interference and suppression under noise-free conditions and would act as a suitable baseline for comparison with the noisy RDK task of Study 2. In the next chapter, we present the results of Study 2, before comparing the results to those presented here.

# Chapter 3

# Simultaneous Manipulation of-Target Flanker Noise

## Introduction

The aim of this task was to explore how perceptual noise influences the flanker effect. We used RDKs to manipulate the noise present in the stimuli through motion coherence on a continuum from low to high noise. Since the flanker effect is predominantly response based and noisier stimuli provide less evidence for their associated response, we predicted that the degree of response capture and subsequent flanker effect would be inversely related to the noise present in the flankers. Since low noise RDKs are most like standard stimuli, we expected low noise conditions to yield flanker effects comparable to those found in the letter task before the effect would diminish with increasing noise. We also expected this to be evident in the distributional measures and that both models would show evidence of poorer flanker suppression for low noise conditions. In SSP, this would be reflected as a wider attentional spotlight at stimulus onset (***sdA***), whereas in DSTP, this would be reflected as poorer early perceptual filtering (high ***uFl***) and greater reliance on the late selection mechanism (high ***p(Selection)***). To foreshadow our results, our results do not align with our original predictions but instead show the opposite: the addition of perceptual noise leads to a larger flanker effect.

## Method

### Participants

The same 49 participants who participated in Study 1 also completed Study 2.

### Stimuli

The specifications of the RDKs are given in the General Method section. The Noise Level factor determined the proportion of randomly moving noise dots in each RDK. The proportion could be either 10%, 40%, 70% or 80% and was the same for both the target and the flankers (target and flankers shared the same noise level within a trial). The direction of the coherently moving dots was either leftwards or rightwards, while the noise dots moved in random directions.

### Procedure & Design

The task followed a 2 x 2 x 4 repeated measures design with factors Target Direction (leftwards or rightwards), Response Congruency (Congruent or Incongruent) and Noise Level (10%, 40%, 70% or 80%). All factors were randomized across trials and participants were tasked with judging the direction of coherent motion in the central, target RDK. The task was run in 8 blocks, each starting with 16 practice trials with feedback (one practice trial for each combination of Congruency, Target Direction and Noise Level). The procedure followed that outlined in the General Method section. By the end of the task, participants had completed 64 trials per condition (per combination of Response Congruency and Noise Level).

## Results & Discussion

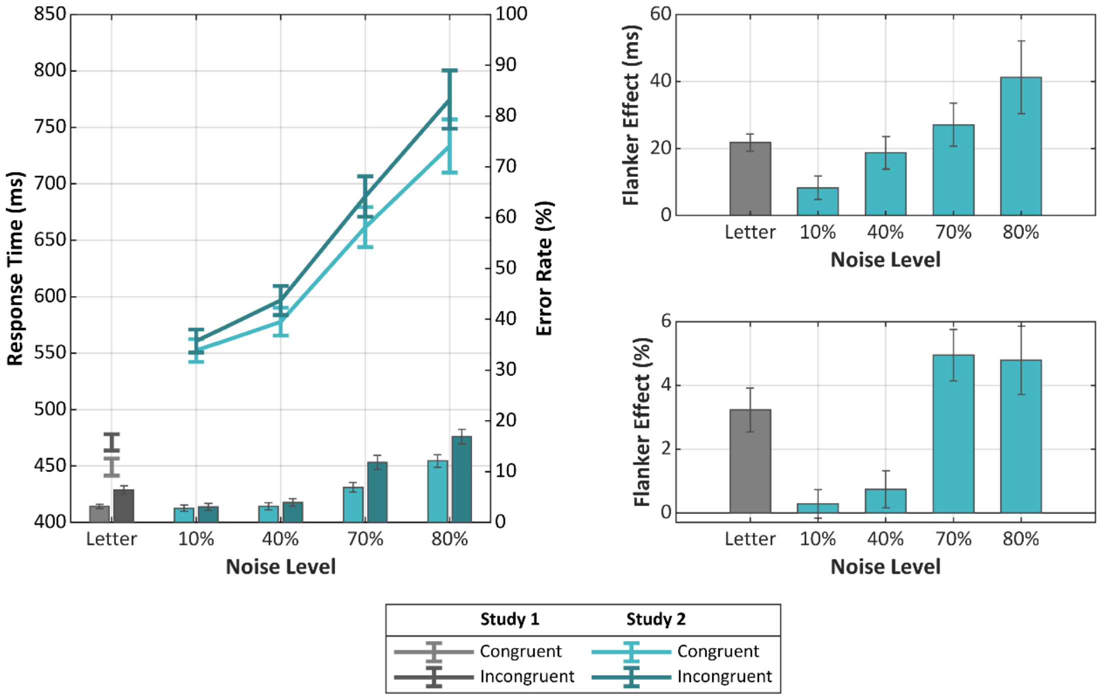
### Behavioral Analysis

#### Average Performance Analysis

RTs faster than 150ms and slower than 3000ms were excluded from analysis, which accounted for 1.1% of the data. The average RTs were subject to a 2 x 4 repeated measures ANOVA with factors Congruency (Congruent or Incongruent) and Noise Level (10%, 40%, 70% or 80%). These results are shown in Figure 6, along with those from Study 1. The results showed

**Figure 6**

Study 2: Average RT and error rate across all 49 participants in Studies 1 and 2.




The left panel shows the average RT and error rate for congruent and incongruent conditions for each condition. The top right panel shows the average congruency effect in RT, while the lower right panel shows the average congruency effect in error rate. Error bars represent the standard error of the mean.

the typical congruency effect ($F(1,48) = 34.264$, $p$ <.001, $\eta_p^2 = .417$), with RTs in the incongruent condition being on average 23.9ms slower than the congruent condition. The main effect of Noise Level was also significant ($F(3,144) = 106.520$, $p$ <.001, $\eta_p^2 = .689$), overall RT increased with increasing noise (10%: 556.5ms; 40%: 587.3ms; 70%: 675.1ms; 80%: 754.1ms). Most critically for our research question, the interaction between Congruency and Noise Level was also significant ($F(3,144) = 4.537$, $p = .005$, $\eta_p^2 = .086$). With 10% noise, the smallest congruency effect of 8.3ms ($p = .023$) was found, before gradually increasing with noise (40%: 18.8ms, $p < .001$; 70%: 27.1ms, $p < .001$; 80%: 41.3ms , $p$ = <.001).

We performed the same analysis on the arcsine transformed ERs. The results again showed the typical congruency effect, ($F(1,48) = 41.869$, $p < .001$, $\eta_p^2 = .466$), with ERs in the incongruent condition being on average 2.7% higher than the congruent condition and the main effect of Noise Level was also significant ($F(3,144) = 133.113$, $p < .001$, $\eta_p^2 = .735$). Overall ER increased with noise (10%: 2.9%; 40%: 3.6%; 70%: 9.4% 80%: 14.5%). Finally, the interaction between Congruency and Noise Level was again significant ($F(3,144) = 8.582$, $p < .001$, $\eta_p^2 = .152$). For 10% and 40% noise, the smallest congruency effects were found (0.3%, $p = .824$ and 0.7%, $p = .075$ respectively), before increasing for higher levels of Noise (70%: 4.9%, $p < .001$; 80%: 4.8%, $p < .001$). Overall, these findings contrasted our initial hypothesis that the flanker effect should decrease with increasing noise, instead showing the opposite. In other words, the noisier the stimuli, the larger the flanker effect.

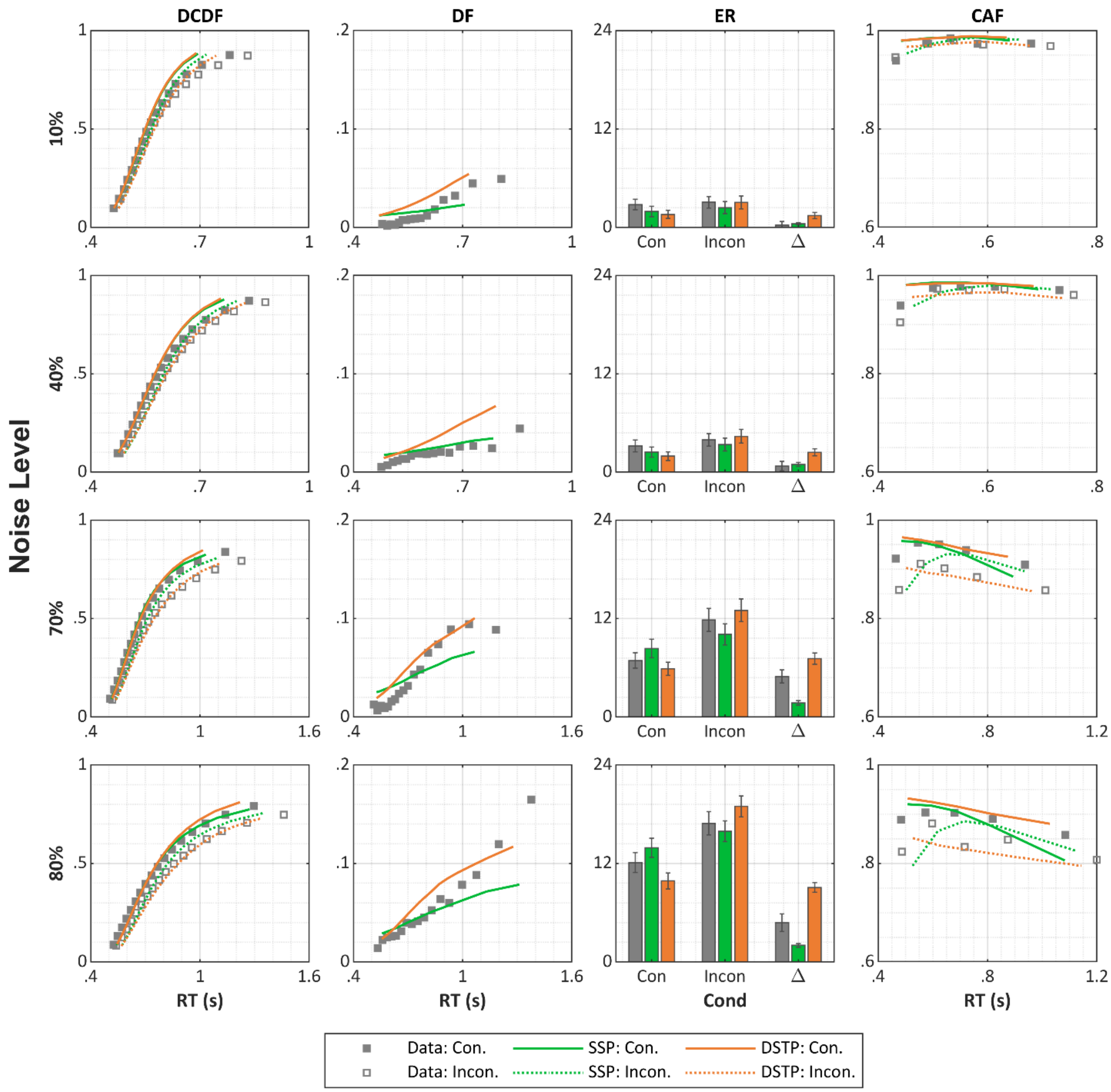
**Distributional Analysis**

The distributional measures are shown in Figure 7, where each row represents a different noise level. In agreement with the average performance analysis, the distributional measures suggested that flanker suppression was poorer in high noise conditions. The DCDFs and positive values of the DF indicated a congruency effect across all quantiles, and this was true for all noise levels. Most interestingly, the slope of the DF generally increased with increasing noise (with the exception of the lowest noise condition), indicative of less effective flanker suppression in noisier conditions.

The congruency effect in ER increased with increasing noise and analysis of the CAFs allowed us to determine at which RT latencies were these errors most likely. For the lowest noise condition, the earliest quantiles of the CAFs showed no early interference effect. In fact,

**Figure 7**

Study 2: Distributional measures averaged across all 49 participants in Study 2.




Note: DCDF: Defective cumulative density function. DF: Delta function. ER: Error rate (%). CAF: Conditional accuracy function, ELI: Error location index.

incongruent trials produced accuracy levels marginally higher than congruent trials for the fastest responses. However, as noise increased, we observed a greater proportion of fast errors in incongruent compared to congruent trials, which would suggest that the larger congruency effects in high noise conditions are the result of increased response capture. As well as differences in early interference across noise conditions, we also observed differences in how the interference was suppressed over time. While in low noise conditions, the CAFs converged, in high noise conditions this was not so, and the congruency effect in accuracy remained for the longest RTs. Consistent with the DFs, this suggests a failure of fully suppressing the flankers in noisy conditions, with interference persisting into the longest responses. Noteworthy is that we also observed that the proportion of slow errors increased with noise, where in low noise conditions, accuracy for longer RTs remained consistently high, whereas in high noise conditions, both the congruent and incongruent CAF began to decrease for longer RTs. Note that that the presence of slow errors (the decline of accuracy for longer RTs with increasing noise) does not affect our interpretation of the lack of convergence in the CAFs in high noise conditions. In general, slow errors are often observed when decision making is difficult (Ratcliff et al., 2016) and therefore are expected in the noisiest conditions. Since response capture should only influence the proportion of fast errors in incongruent trials and not the proportion of slow errors (see Servant et al., 2018 for a discussion), this does not affect our interpretation of the congruency effect across noise conditions since the decline in accuracy across RTs were observable and comparable for both trial types.

In summary, the distributional analyses were inconsistent with our original hypothesis but in agreement with our analysis of average performance: high noise conditions showed patterns of poorer suppression across all measures, reflected in the steeper DFs, larger congruency effects in overall ER, a larger proportion of fast errors in incongruent compared to congruent trials for the fastest responses and a lack of convergence of the CAFs for the slowest responses.

## Model Fitting

### Bayes Factor

Given the behavioral analysis, we expected that DSTP would be the superior model, particularly for the high noise conditions. Recall our findings from the letter task in which we found a subset of participants who showed unusual patterns of data consistent with poor flanker suppression, namely nonconverging CAFs and steep DFs, with these participants showing extreme evidence in favor of DSTP. Whereas in the letter task, these patterns were an exception, in the noisier RDK conditions, they appear to be the norm, with steeper DFs and the average CAFs showing a lack of convergence. As a result, we expected strong evidence in favor of DSTP for high noise conditions and this is indeed what we find. The results are shown in Table 6.

**Table 6**

Study 2: Number of participants falling into each Bayes Factor category.

| | Study 1 | Study 2 | | | |
|---|---|---|---|---|---|
| | Letter | 10% | 40% | 70% | 80% |
| Extreme (SSP) | 0 | 1 | 0 | 0 | 0 |
| Very Strong (SSP) | 0 | 0 | 0 | 1 | 1 |
| Strong (SSP) | 2 | 1 | 1 | 2 | 5 |
| Moderate (SSP) | 1 | 1 | 4 | 3 | 5 |
| Anecdotal (SSP) | 11 | 17 | 14 | 11 | 7 |
| Anecdotal (DSTP) | 13 | 15 | 12 | 10 | 8 |
| Moderate (DSTP) | 11 | 8 | 5 | 10 | 8 |
| Strong (DSTP) | 5 | 1 | 4 | 4 | 4 |
| Very Strong (DSTP) | 3 | 3 | 3 | 3 | 6 |
| Extreme (DSTP) | 3 | 2 | 6 | 5 | 5 |

Note: Since we fit all both models to each participant and condition separately, the number of participants in each category sums to the total number of participants (N = 49).

Firstly, both models were better able to account for the data in low noise conditions, with overall evidence decreasing as noise increased (see Appendix B). Since low noise conditions showed patterns of data more typical to standard flanker tasks (e.g., converging CAFs), it is not surprising that both models better accounted for these conditions. In fact, for the low noise conditions, both models accounted for the data equally well, with most participants (32/49) falling within the ‘anecdotal’ evidence categories. As noise increased however, the number of participants falling into these anecdotal categories began to decrease. In other words, we were able to find more decisive evidence for one model in noisier conditions, with most of these participants showing evidence for DSTP, in line with our expectation. Specifically, in the highest noise condition (80% noise), 23 participants showed at least moderate evidence in favor of

DSTP, compared to only 11 participants for SSP. As Table 6 shows, not only did more participants show evidence in favor of DSTP in this condition, but this evidence was of greater strength.

**Quality of Fit**

The simulated distributional measures for both models are shown along with the data in Figure 7. Both models fit the overall shape of the DCDFs well, albeit for a slight underprediction of the tail in low noise conditions. In line with the Bayes Factor results, the predictions of both models, particularly for congruent trials, are very similar for low noise conditions, although the predictions differ slightly for incongruent trials. Specifically, SSP underpredicts incongruent RTs more so than DSTP, yet the differences are small overall. Similarly, DSTP appears to better model the DF for the 10% noise condition, whereas SSP better models the 40% noise condition, again consistent with the overall mixed Bayes Factor results we find for low noise conditions. For high noise conditions (70% and 80%) however, the models show much clearer differences. Although SSP provides a slightly better match to the tail of the DCDF in congruent trials, it notably underpredicts RT in incongruent trials, subsequently underestimating the congruency effect, whereas DSTP's matches are notably better. The failure of SSP to predict a sufficiently large congruency effect in these conditions is highlighted further by the DF, where SSP's predicted DFs are too shallow, while DSTP's are fittingly steep. Thus overall, RTs for correct responses were better modelled by DSTP, particularly in high noise conditions.

For average ER, the predictions of the models are similar in low noise trials. Like the RT results, ER in incongruent trials is better modelled by DSTP although for congruent trials the reverse is true. However, given that overall ER in low noise conditions was rather small, these differences are negligible and yet again, the models show much clearer differences in high noise conditions. At the highest noise level (80%), overall ER and the congruency effect are slightly better modelled by SSP. However, while SSP underestimated the congruency effect and DSTP provided an overestimation at 80% noise, DSTP offers a clearly superior fit to both overall ER and the congruency effect at 70% noise. In other words, DSTP better models average ER in noisy conditions. This observation is particularly supported by the CAF which is arguably more important than average ER when assessing the predictions for error responses. Whereas for low noise conditions, the predicted CAFs for both models are similar, for high noise conditions, SSP underestimates the duration of flanker interference, predicting that congruent and incongruent CAFs converge with increasing RT, a pattern that is not present in our data. In line with our findings from Study 1 and research discussed previously (Servant et al., 2014), DSTP models this relationship better, correctly predicting that the two functions do not converge. Noteworthy however is that, like in the letter task, SSP's prediction of a steep slope allows it to match the earliest quantiles of the CAF well, however, this leads to clear overpredictions for the later quantiles and convergence of the CAFs.

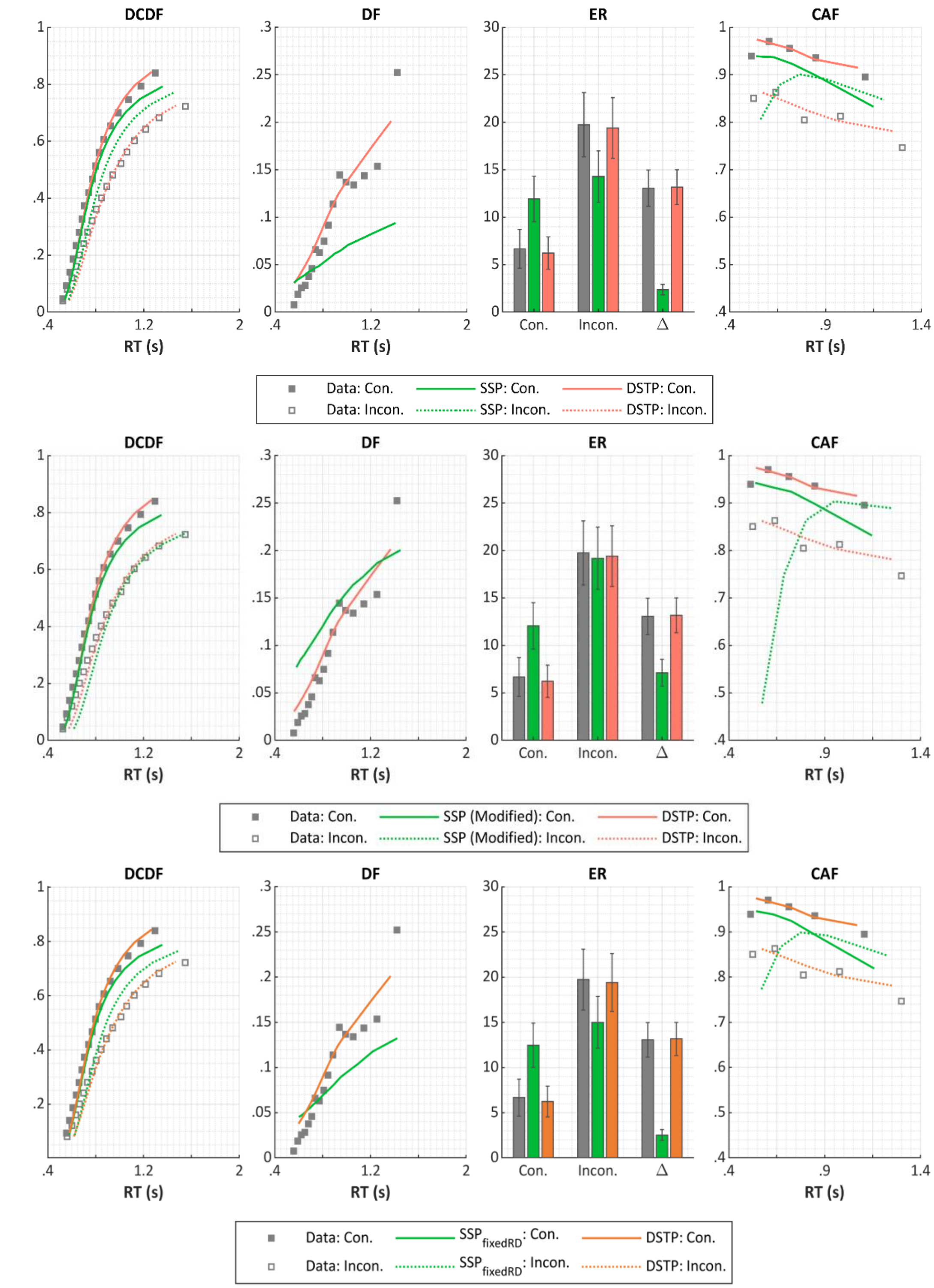
**Failures of SSP**

Overall, the distributional analyses provided three main observations regarding the ability of DSTP and the limitations of SSP to match key aspects of the data in noisy conditions. First, SSP underestimated the slope of the DFs. Second, it predicted an incongruent CAF that was too steep and thirdly, it failed to capture the lack of convergence in the CAFs. In contrast, DSTP modelled these effects well. Our analyses of both the current task and the letter task suggest that the ability of DSTP to model these effects justifies its increased complexity and sways Bayes Factor in DSTP's favor. To demonstrate this further, we took a similar approach as in the letter task, taking participants who showed very clear evidence in favor of DSTP and calculating the same distributional measures for these participants only. The rationale behind this analysis was that these participants would particularly highlight the above listed failures of SSP, that is, they would show steep DFs and CAFs that do not converge, patterns which SSP would fail to match. This would allow us to further confirm that DSTP's ability to model these specific effects was the reason it was superior in the Bayes Factor comparison for the high noise conditions.

The distributional measures for the 11 participants who showed at least very strong evidence in favor of DSTP in the 80% noise condition are shown in the upper panel of Figure 8 and are consistent with our predictions. As the figure shows, these participants show an average congruency effect in RT (74.7ms) that is almost double that of the overall participant average. While SSP predicts an average congruency effect of 56.1ms, DSTPs estimate of 90.9ms is slightly better. Likewise, in ER, these participants show a larger congruency effect of 13.1%. While SSP predicts a congruency effect of 2.8%, DSTPs estimate of 13.0% is markedly closer.

**Figure 8**

Study 2: Averaged distributional measures for the 11 participants showing at least very strong evidence in favor of DSTP in Study 2.




Note: Defective cumulative density functions (DCDF), delta functions (DF), error rate (ER), conditional accuracy functions (CAF).

Regarding the three failures of SSP listed earlier, we also see that; 1) SSP provides a clear underestimation of the DF, which is considerably steeper (slope = .26) for these participants compared to the overall average DF (slope = .16); 2) the CAFs show no increase in accuracy in incongruent trials from fast to intermediate RTs, whereas SSP predicts a steep increase; and 3) SSP predicts that the congruent and incongruent CAFs converge when this is not the case. For each distributional measure, DSTP provides a clearly superior fit than SSP for these participants, consistent with the Bayes Factor results.

SSP's striking failure to predict the key distributional patterns in noisy conditions warrants an investigation into the reasons for this shortcoming. To explore this further, we examined the EAP estimates used to simulate SSP, which clearly underpredict the time course of flanker interference. To recap, the three critical parameters for predicting the congruency effect under SSP are the initial width of the spotlight ***sdA***, the shrink rate parameter ***rd*** and the perceptual strength parameter ***p***. For ***sdA***, the value is proportional to size of the congruency effect, with a higher value (a wider spotlight) resulting in higher levels of interference, since more attentional weight is given to flankers at stimulus onset. The shrink rate parameter ***rd*** controls for the suppression of flanker interference, with higher values resulting in faster shrinkage of the spotlight and earlier increases in attentional selectivity. Finally, the size of the congruency effect is also proportional to the perceptual strength parameter ***p***, as ***p*** modulates the depth of the 'dip' in evidence accumulation for the incongruent condition (see introduction to SSP in this paper and White et al., 2011). Consequently, with larger values of ***p***, the initial interference is larger (if other parameters are assumed to be constant). This parameter is also critical for predicting the overall shape of the CDF, where the less skewed the distribution, the smaller the value of ***p***. Hence, given the decrease in skewness with increasing noise, the value of

***p*** should be lower in order to match the drawn-out shape of the distribution in high noise conditions (indeed, as we will show in the section on the EAP estimates, ***p*** decreases with increasing noise). Now this raises the question why DE-MCMC did not find solutions with lower ***rd*** or higher ***sdA*** to allow SSP to prolong the duration of flanker interference to better match the data.

To answer this question, we focus on ***rd***. SSPs main failures relate to the pattern of the congruency effect across time, and as indexed by the CAFs and DFs, SSP predicts attentional selectivity improves too quickly or in other words, the spotlight shrinks too quickly. We therefore postulated that forcing the spotlight to shrink slower by manually lowering the value of ***rd***, would prolong the duration of flanker interference, allowing SSP to better match the DF in high noise conditions. However, given that the EAP estimates for ***rd*** do indeed underpredict flanker interference, we predicted doing so would reduce the quality of fit to other aspects of the data. Hence, the final EAP estimates were a compromise between balancing quality of fit for all aspects of the data, with this compromise leading to an overall underprediction of the duration of flanker interference for SSP. To do this, we again use the participants who show at least very strong evidence in favor of DSTP in the 80% noise condition, since these participants particularly highlight the shortcomings of SSP. We reran the simulations for these participants, yet for each, we gradually reduced ***rd*** until ***rd*** was 40% of its original value (the point at which the slope of SSP's DF somewhat matched that of the data). These results are shown in the middle panel of Figure 8. As expected, SSP's predicted congruency effect increased and the predicted DF was steeper, better matching that of the data (at least in the tail end of the distribution). However, this led to greater mismatches to other aspects of the data. Firstly, reducing ***rd*** lead to notable changes in the leading edge of the incongruent DCDF, with SSP predicting too large a congruency effect in these early quantiles and consequently overpredicting the early parts of the DF. Secondly, this reduction also led to large differences in the CAF, with SSP predicting a congruency effect in accuracy of 34.8% in the first RT bin, whereas for the data, this was much smaller (8.8%). In fact, with this setting, accuracy for the fastest responses in incongruent trials was around chance level. Thirdly, although lowering ***rd*** led to later convergence of the CAFs, they still indeed converge. In other words, for our data, it appears SSP is incapable of producing CAFs that do not converge without this leading to significant mismatches to other aspects of the data. Despite this, we postulated that this may not be the most ideal way of assessing whether, given a slow shrink rate, SSP can produce longer durations of interference, especially that, given such a low value of ***rd***, DE-MCMC would likely find different values for the other parameters. To support this further, we reran the fitting process for these participants while keeping ***rd*** fixed to 40% of its original value for each participant yet allowed all other parameters to vary. The results are shown in the lower panel of Figure 8. Like the averaged results, SSP again underestimated the duration of flanker interference and by examining the average EAP estimates for these participants only, we could see that SSP had counteracted the large interference effect (introduced by the low value of ***rd***) by making the value of ***sdA*** lower. Whereas in the original results, the average value for ***sdA*** for these participants was around 4.4, the new estimate with a fixed value of ***rd*** was lowered to around 2.7, while all other parameters showed little change across the two fits. In other words, SSP had attempted to improve quality of fit by again underestimating the congruency effect, yet this time, by further narrowing the width of the spotlight at stimulus onset.

Another reason behind SSP's failures is possibly related to the fact that the perceptual strength parameter ***p*** is lower in high noise conditions. We previously mentioned that the ***p*** parameter not only influences the spread of the RT distribution but also the congruency effect, with smaller values of ***p*** leading to smaller congruency effects if all other parameters remain constant. Since high noise conditions produced longer, drawn-out RT distributions, the best fitting parameters for these conditions were ones in which the perceptual strength parameter ***p*** was low. In turn, this led to a general underprediction of the congruency effect, since SSP models both target and flanker perceptual strength with a common parameter. Although this is a sensible assumption given that target and flankers shared the same noise level within a trial, it also means that, in the conditions with the largest flanker effects (high noise trials), SSP assumes that the low strength flankers cause less interference. Indeed, when examining the 89% highest density intervals of the posteriors, we found that as noise increased, the width of the interval became smaller for ***p***, whereas it increased for ***rd*** and ***sdA***. This would imply that SSP was more ‘certain’ that ***p*** should be low for high noise condition to match the shape of the distribution. In turn however, this leads to less interference and greater uncertainty in the estimates for the spotlight parameters, since their effect would be reduced, the less interference there is to suppress. In contrast, DSTP has separate parameters for target and flankers and therefore the congruency effect is less constrained by the physical properties of the stimuli. From this, we postulated that we may be able to improve the fit of SSP by allowing SSP to model the perceptual strength of target and flankers independently. To explore whether this was the case, we reran the fits for all 49 participants with a version of SSP that contained separate perceptual strength parameters for target and flankers (***pTarget*** and ***pFlanker*** respectively). We henceforth refer to this version as $SSP_{pFl}$ to reflect the addition of the extra parameter. It is worth noting that this adjustment changes the behavior of the model slightly. While in SSP, the drift rate in congruent trials remains constant, in $SSP_{pFl}$, the drift rate for congruent trials varies over time, depending on whether ***pTarget*** < ***pFlanker***. When ***pTarget*** < ***pFlanker***, the drift rate for congruent trials decreases over time, converging to the value of ***pTarget*** when the flankers are fully suppressed. In contrast, if ***pTarget*** > ***pFlanker***, the opposite is true, where the drift rate for congruent trials increases over time towards the value of ***pTarget***.

To check whether $SSP_{pFl}$ was superior to SSP, we calculated the marginal likelihood for $SSP_{pFl}$ and compared it to SSP. The results of this comparison are shown in the middle panel of Table 7 and as expected, $SSP_{pFl}$ was found to be superior, yet most participants fell into the anecdotal evidence category. Surprisingly, the addition of the ***pFlanker*** parameter was most beneficial for the low noise conditions, with a larger number of participants showing evidence for $SSP_{pFl}$ in these conditions. Given that $SSP_{pFl}$ was not largely superior to SSP, we expected

**Table 7**

Study 2: Number for participants falling within each Bayes Factor category for each model comparison.

| | 10% | 40% | 70% | 80% |
|---|---|---|---|---|
| Extreme (SSP) | 1 | 0 | 0 | 0 |
| Very Strong (SSP) | 0 | 0 | 1 | 1 |
| Strong (SSP) | 1 | 1 | 2 | 5 |
| Moderate (SSP) | 1 | 4 | 3 | 5 |
| Anecdotal (SSP) | 17 | 14 | 11 | 7 |
| Anecdotal (DSTP) | 15 | 12 | 10 | 8 |
| Moderate (DSTP) | 8 | 5 | 10 | 8 |
| Strong (DSTP) | 1 | 4 | 4 | 4 |
| Very Strong (DSTP) | 3 | 3 | 3 | 6 |
| Extreme (DSTP) | 2 | 6 | 5 | 5 |

| | 10% | 40% | 70% | 80% |
|---|---|---|---|---|
| SSP | 0 | 0 | 0 | 0 |
| SSP | 0 | 0 | 0 | 0 |
| SSP | 0 | 0 | 0 | 0 |
| SSP | 0 | 1 | 0 | 0 |
| SSP | 3 | 4 | 9 | 13 |
| $SSP_{pFl}$ | 41 | 40 | 40 | 35 |
| $SSP_{pFl}$ | 5 | 3 | 0 | 1 |
| $SSP_{pFl}$ | 0 | 0 | 0 | 0 |
| $SSP_{pFl}$ | 0 | 1 | 0 | 0 |
| $SSP_{pFl}$ | 0 | 0 | 0 | 0 |

| | 10% | 40% | 70% | 80% |
|---|---|---|---|---|
| $SSP_{pFl}$ | 1 | 0 | 0 | 0 |
| $SSP_{pFl}$ | 1 | 1 | 2 | 0 |
| $SSP_{pFl}$ | 0 | 1 | 1 | 4 |
| $SSP_{pFl}$ | 10 | 11 | 9 | 6 |
| $SSP_{pFl}$ | 20 | 15 | 12 | 8 |
| DSTP | 7 | 7 | 5 | 12 |
| DSTP | 5 | 4 | 9 | 4 |
| DSTP | 3 | 2 | 3 | 4 |
| DSTP | 1 | 4 | 3 | 8 |
| DSTP | 1 | 4 | 5 | 3 |

Note: Since we fit all both models to each participant separately, the number of participants in each category sums to the total number of participants (N = 49).

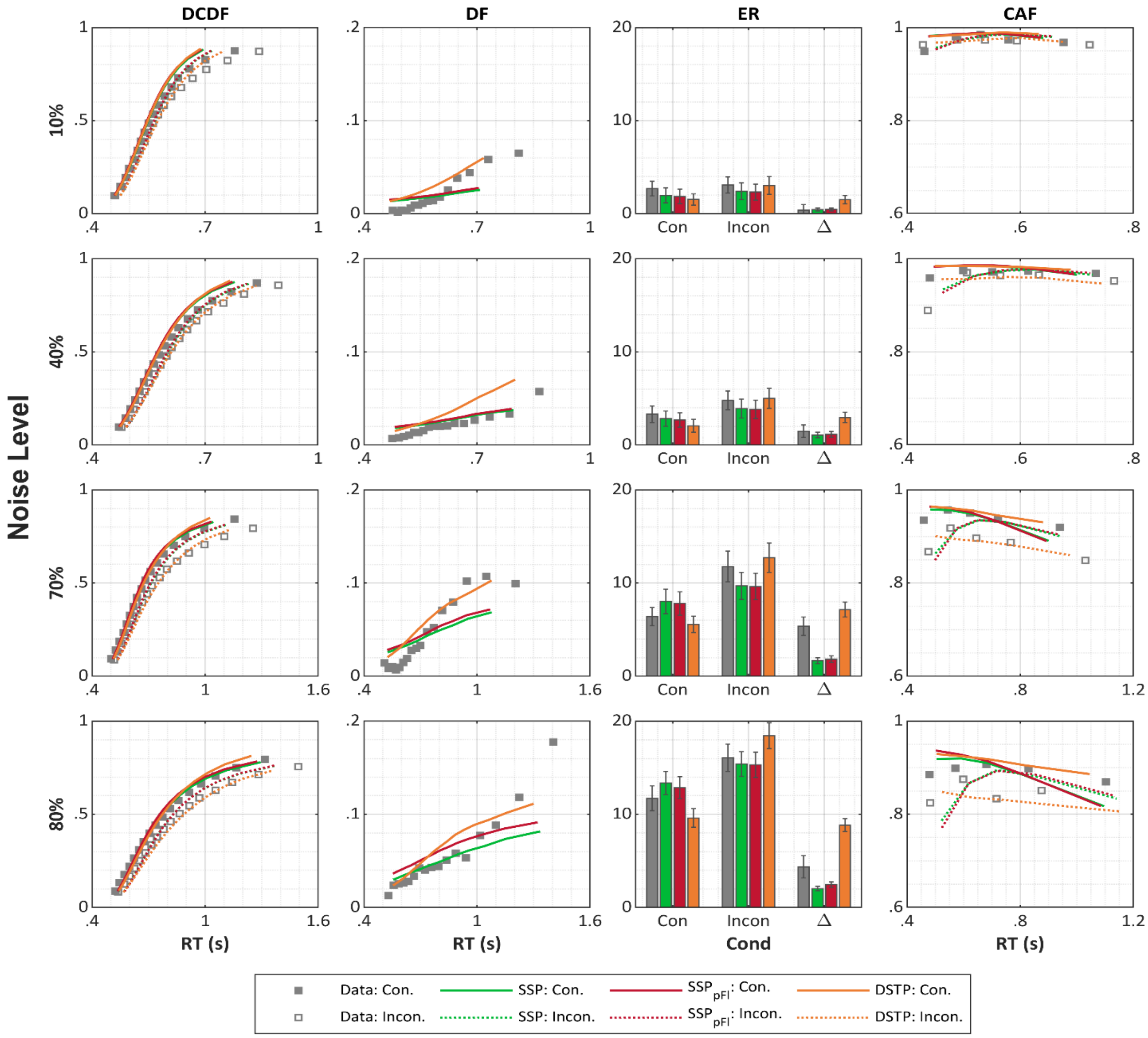
that $SSP_{pFl}$ would still be inferior to DSTP in high noise conditions, and this was indeed the case. The results of the comparison between $SSP_{pFl}$ and DSTP are shown in the right panel of Table 7.

There are two key things to note about these results. Firstly, SSP is now superior for the lowest noise condition. Secondly, DSTP is still superior for the high noise conditions although to a slightly lesser extent. Overall, 32/49 participants show evidence in favor of $SSP_{pFl}$ in the 10% noise condition, 28/49 in the 40% condition, 24/49 in the 70% condition and 18/49 in the 80% noise condition. Focusing only on the participants who show at least moderate evidence, 12 participants show at least moderate evidence for $SSP_{pFl}$, compared to the 10 for DSTP in the 10% noise condition. At 40% noise, the results are more mixed, with 13 participants preferring $SSP_{pFl}$ compared to the 14 for DSTP. However, for the two highest noise conditions (70% and 80%), the evidence is still clearly in DSTP's favor with 20 participants (compared to the 12 for SSP) showing at least moderate evidence for DSTP in the 70% noise condition and 19 participants (compared to the 10 for SSP) in the 80% noise condition.

The simulated distributional measures for all three models (SSP, $SSP_{pFl}$, DSTP) are shown in Figure 9 and the predictions of $SSP_{pFl}$ are almost indistinguishable from SSP at the average level, even for congruent trials, where the calculation of the drift rate differs between the two models. The fact that $SSP_{pFl}$ is now superior for the lowest noise conditions particularly highlights the mixed nature of the original comparison between SSP and DSTP for low noise conditions. That is, despite $SSP_{pFL}$ being only marginally superior to SSP, this swayed the Bayes Factor comparison in $SSP_{pFl}$ favor when compared to DSTP. We also noted that, despite DSTP still remaining superior for high noise conditions, the addition of the ***pFlanker*** parameter had indeed allowed $SSP_{pFl}$ to predict more interference in these conditions and this is visible in the averaged distributional measures. As the figure shows, in the highest noise condition, the predicted DF by $SSP_{pFl}$ (slope = .082) is very slightly steeper than that predicted by SSP (slope = .071), however, $SSP_{pFl}$ predicts more interference in the earlier portions in the DF and subsequently overestimates the intercept, similar to what we found with our investigation of SSP

**Figure 9**

Study 2: Averaged distributional measures for all 49 participants in Study 2 with the addition of $SSP_{pFl}$.



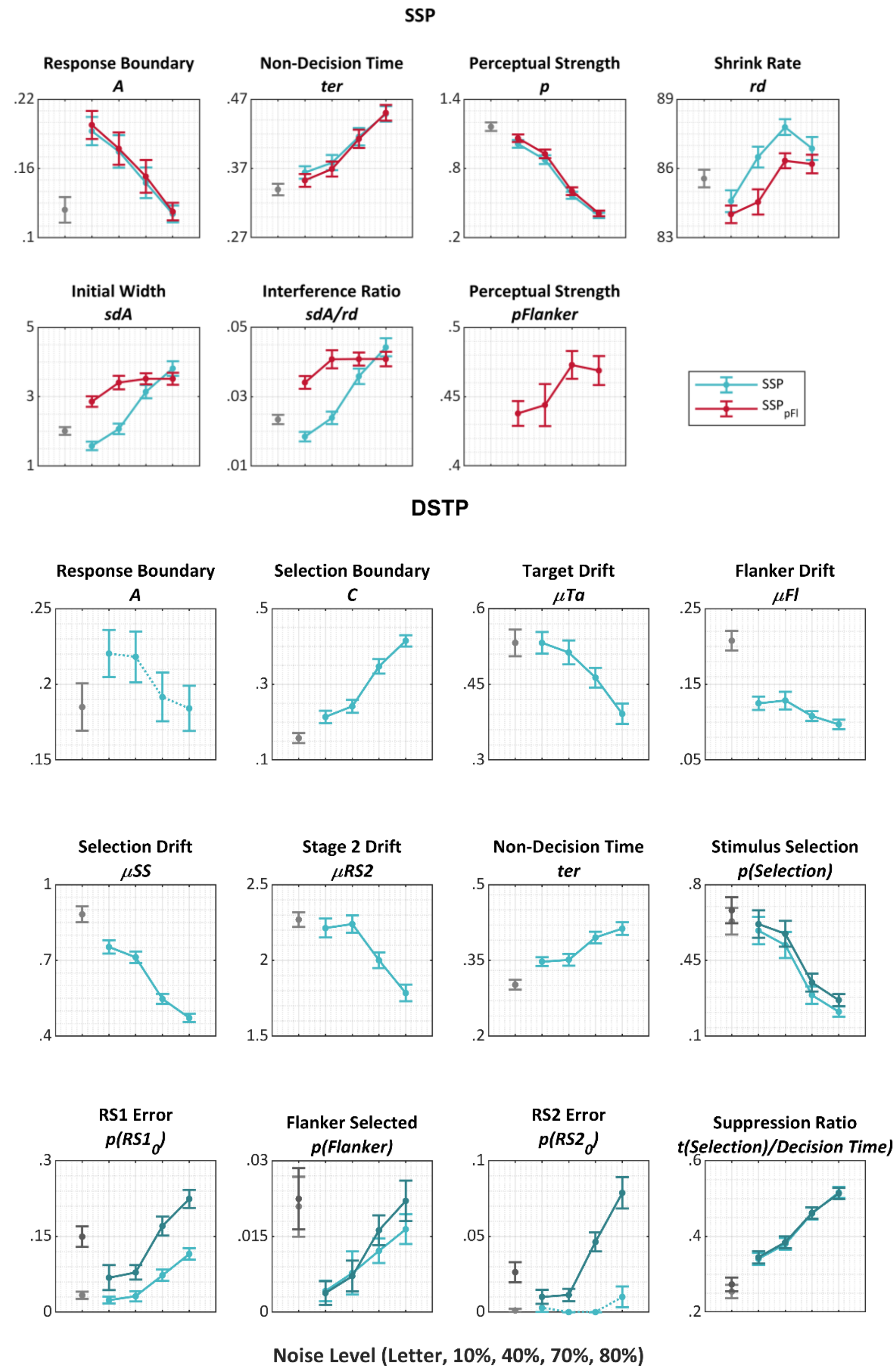

Note: Defective cumulative density functions (DCDF), delta functions (DF), error rate (ER), conditional accuracy functions (CAF) earlier, in which we lowered the value of ***rd***. This possibly explains why the win for $SSP_{pFl}$ (when compared to SSP) was less strong in the highest noise condition, with some participants still showing a preference for SSP. Importantly, despite $SSP_{pFl}$ being numerically superior to SSP, this did not solve the problems associated with SSP we found earlier. Namely, the DF is still too shallow, the predicted incongruent CAF is too steep and the predicted CAFs of $SSP_{pFl}$ still converge. Thus, it seems while the addition of ***pFlanker*** may have slightly improved SSP, its main problem appears to be the inevitable zooming in on the target which underestimates the duration of interference and causes the CAFs to converge, a problem that is not solved by the addition of the ***pFlanker*** parameter.

### EAP Estimates

Despite SSP's (and $SSP_{pFl}$'s) failure to match key aspects of the data in noisy conditions, all models modeled the average increase in the congruency effect with increasing noise. By examining the EAP estimates and how these change across noise levels, we could uncover how the key mechanisms in each model account for this effect. The averaged EAP estimates across all 49 participants are presented in Figure 10 and we also include the simulation-based measures for DSTP discussed in the General Method section. To ensure noise had an effect, we conducted a one-way ANOVA on each parameter/measure to explore how they changed across noise conditions. For brevity, we discuss these results qualitatively although the significance results are illustrated in Figure 10, with solid lines representing significant effects of noise and dotted lines representing non-significant effects.

**Figure 10**

Study 2: Average EAP estimates for all models across all 49 participants in Study 2.




Note: For DSTP, the simulated measures (*p(Selection)*, *p(RS1$_0$)*, *p(Flanker)*, *p(RS2$_0$)* and *suppression ratio*) can be calculated for incongruent and congruent trials separately. In these cases, darker (lighter) lines represent incongruent (congruent) trials.

**SSP**

For SSP, we found significant effects for all parameters. Non-decision time ***ter*** increased with increasing noise which we attribute to longer perceptual encoding times for high noise/low perceptual strength stimuli, as opposed to differences in motor response execution (Miller et al., 1999). The perceptual strength parameter ***p*** decreased with increasing noise as expected, since noisier RDKs have weaker perceptual strength. Somewhat counterintuitively however, we also found a decrease in the response boundary parameter ***A*** with increasing noise, indicative of more cautious responses in less noisy conditions. Since these low noise conditions are easier overall (Palmer et al., 2005), we expected the opposite effect. One possibility, however, relates to the idea that, in high noise conditions, participants terminated the response early due to a sense of urgency. Some researchers have added an additional assumption to the DDM which suggests that, instead of being fixed over time, the response boundary collapses later in the decision due to this sense of urgency (see Hawkins et al., 2015 for a review). In other words, if observers spend too long on a given trial without success, the criterial amount of evidence needed to respond is reduced so that observers can move on to the next trial. Given that identifying a noisy target is more difficult than a low noise target and flanker interference appears to be stronger in these conditions, such a sense of urgency is more likely to occur in high noise trials (Palestro et al., 2018). This assumption could also explain the nonconvergence of the CAFs and the increased proportion of slow errors we observe in high noise conditions. These slow errors occur naturally under a DDM with collapsing boundaries and tend to truncate the rightmost portion of the RT distribution. The CAFs suggests that flanker interference persisted into the longest RTs, or to put it another way, participants terminated the decision before interference was fully suppressed. If we assume that, without this sense of urgency, participants would have delayed their response and the CAFs would have converged, then the CAFs we see are possibly truncated due to participants terminating the decision prematurely because of this urgency signal. We will return to this point in the general discussion, although the response boundary effect is still largely unexpected.

For the parameters most relevant for the research question (the spotlight parameters ***sdA*** and ***rd***), we found that the initial width of the spotlight ***sdA*** became increasingly wider as noise increased. However, while the effect of noise on ***sdA*** is in the expected direction (but contrary to our initial hypothesis), the shrink rate parameter ***rd***, shows the opposite effect, namely an increase in shrink rate with increasing noise. Given that these two parameters can trade off as discussed in our introduction to SSP, we calculated the interference ratio (***sdA***/***rd***) which quantifies the duration of flanker interference. Despite the counterintuitive pattern of ***rd*** (a faster shrinking spotlight with increasing noise), the overall duration of flanker interference is longer in high noise conditions, owed to by the wider spotlight (larger ***sdA***). Hence, the faster shrinkage in high noise conditions does not fully compensate for the increased width of the spotlight and ***sdA*** remains the critical parameter explaining the interaction: the more noise, the wider the attentional spotlight at stimulus onset and the longer the duration of interference.

### $\mathbf{SSP_{pFl}}$

For $SSP_{pFl}$, the estimates for response boundary, non-decision time and perceptual strength are almost identical to SSP, although note that for $SSP_{pFl}$, the ***p*** parameter represents the perceptual strength of the target only. Interestingly, now that ***pFlanker*** is allowed to vary freely, $SSP_{pFl}$ predicts that the perceptual strength of the flankers *decreases* with decreasing noise, despite this being objectively not the case. In other words, $SSP_{pFl}$ had attempted to model the larger congruency effect in high noise conditions by predicting the counterintuitive pattern that the flankers have greater perceptual strength, the noisier they are.

Compared to SSP, the estimated shrink rate ***rd*** is smaller, whereas the initial spotlight width ***sdA*** is wider. Nonetheless, both models predict the same noise effect, at least in terms of its direction. However, the magnitude of the noise effect on ***sdA*** differs between the two models. Although ***sdA*** significantly increases with noise in both models, the effect is substantially reduced for $SSP_{pFl}$ and in turn, so is the effect of noise on the interference ratio. This discrepancy stems from the contrasting predictions of the two models regarding the perceptual strength of the flanker. Under SSP, the strength of both target and flankers increases with decreasing noise. Thus, to model the smaller congruency effects in low noise conditions, SSP must counter the large interference introduced by high strength flankers. To do so, SSP predicted a very narrow spotlight in low noise conditions. In contrast, since $SSP_{pFl}$ predicts that the perceptual strength of the flanker is lower for the low noise conditions, this adjustment is not necessary, and the spotlight is wider for $SSP_{pFl}$ as a result. Despite these discrepancies, the overall assumptions are the same for both models: noise leads to a wider spotlight at stimulus onset and flanker interference persists longer in high noise conditions.

### DSTP

For DSTP, we found significant effects of noise for all parameters except response boundary ***A***, which stands in contrast to SSP's prediction that the response boundary significantly decreases with increasing noise. Like SSP however, non-decision time ***ter*** significantly increased with increasing noise, which we again interpret as slower perceptual encoding of high noise stimuli. For both parameters governing the early response stage (***μTa*** and ***μFl***) we found decreases as noise increased, consistent with the idea that these parameters capture changes in perceptual strength. Moreover, the value of ***µTa*** is overall larger than ***µFl*** and the effect of increasing noise is clearly stronger for ***µTa*** than ***µFl***. Hence, DSTP predicts that less attentional weight is allocated to the target as noise increases. Together, this results in a lower drift rate for *RS1* for both congruent and incongruent trials, and an overall increase in the probability of *RS1* producing an error ($\boldsymbol{p(RS1_0)}$ in Figure 9) as noise increases. Across all noise conditions, the probability of *RS1* producing an error is higher for incongruent compared to congruent trials as expected, yet the difference between the two trial types grows with increasing noise. Simply put, these findings suggest that early perceptual filtering is less selective in high compared to low noise conditions.

In addition to poorer early filtering in high noise conditions, we also found effects of noise on the late selection mechanism. Namely, the selection boundary ***C*** increased with noise, while the drift rate ***µSS*** decreased, together resulting in less frequent engagement of the late selection mechanism with increasing noise (***p(Selection)*** in Fig. 9). In fact, in high noise conditions, the majority of responses were produced by *RS1* (***p(Selection)*** < 0.5) whereas for low noise conditions (***p(Selection)*** *> 0.5*), the majority of responses were produced by *RS2*. Regarding *which* stimulus was selected, while most trials ended in correct selection of the target, some trials did end in incorrect selection of the flanker, with this occurring more often in high noise conditions. As a result, the probability of *RS2* producing an error response ($\boldsymbol{p(RS2_0)}$) in incongruent trials also steeply increased with noise, since incorrectly selecting the flanker most often leads to an error response when flankers are incongruent. Finally, we looked at the time point at which a stimulus was selected, relative to overall decision time (***suppression ratio***) to assess the speed of the late selection mechanism. In the lowest noise conditions (10% and 40%), a stimulus was selected in the first half of the decision (***ratio*** < .5). Although a stimulus was selected in the minority of high noise trials, when stimulus selection *did* occur, it occurred considerably later than in lower noise conditions. Specifically, at the highest noise level (80%), the ***suppression ratio*** was 0.51, with the selection mechanism terminating around midway through the decision process. In other words, flankers were suppressed later in the decision as noise increased, leaving more time for interference. Thus, DSTP explained our results by assuming that adding noise to the stimuli disrupted the selectivity of early perceptual filtering. However, we also found an influence of noise on the late stimulus selection mechanism responsible for flanker suppression, in that this mechanism was less likely to be engaged in noisy conditions. When this mechanism was engaged in noisy conditions however, it was prone to errors.

## Comparison of Noisy and Noise-Free Stimuli

The next section focuses on comparing both the data and model predictions for each task to determine differences in conflict resolution under noisy (Study 2) compared to no-noise (Study 1) conditions. Since the letter stimuli of Study 1 contain no added noise, we originally assumed the results should be most similar to the lowest noise condition (10% noise) of the RDK task of Study 2. From our behavioral analysis of the letter task however, we already see that this is not the case, since the flanker effect in both RT and ER was larger notably larger than the 10% noise condition.

### Behavioral analysis

To compare the two tasks, we took each noise condition of Study 2 and compared it with the letter task from Study 1 by means of a 2 x 2 repeated measures ANOVA, with factors Congruency (Congruent and Incongruent) and Task (Letter and Motion). The aim of this analysis was to examine at which noise level of the RDK task was the magnitude of the flanker effect most similar to the letter task. As is clear from Figure 6, responses in the letter task were much faster than in the RDK task, meaning all main effects of Task were significant. We therefore do not report this effect and focus only on the Task x Congruency interaction.

For 10% noise, the interaction was significant ($F(1,47) = 8.058$, $p = .007$, $\eta_p^2 = .146$). For the letter task, the congruency effect of 20.8ms was almost double that of the 10% noise condition (8.4ms). For 40% noise however, the interaction was not significant ($F(1,47) = .081$, $p = .777$, $\eta_p^2 = .002$), as was the case for the 70% ($F(1,47) = .878$, $p = .353$, $\eta_p^2 = .018$) and 80% noise conditions ($F(1,47) = 3.761$, $p = .058$, $\eta_p^2 = .074$). For the 80% noise condition, although the interaction did not reach significance, the congruency effect in the 80% noise condition (41.7ms) was double that found in the letter task (20.8ms). These results contrast with our original hypothesis that the letter task would be most like the lowest noise condition of Study 2. Instead, the congruency effect in the letter task (20.8ms) was most similar to intermediate levels of noise in the RDK task, namely the 40% noise condition (19.2ms).

For the arcsine transformed ERs, the interactions for 10% ($F(1,47) = 16.100$, $p < .001$, $\eta_p^2 = .251$) and 40% noise ($F(1,47) = 6.953$, $p = .001$, $\eta_p^2 = .127$) were significant, where the congruency effect in the letter task of 3.2% was considerably larger than in the 40% (0.7%) and 10% noise (0.3%) conditions. In contrast, for 70% ($F(1,47) = .190$, $p = .665$, $\eta_p^2 = .004$) and 80% ($F(1,47) = .034$, $p = .854$, $\eta_p^2 = .001$) noise, the interactions were not significant, although the congruency effect in the letter task was smaller than both the 70% (4.9%) and the 80% (4.8%) noise conditions.

Overall, the average congruency effects in the letter task were most similar to midrange levels of noise in the RDK task. Specifically, the congruency effect (in both RT and ER) was larger than the 40% noise condition yet smaller than the 70% noise condition. Note that although the comparisons of the congruency effect in the letter task and those in high noise conditions (80% and 70%) were not significant, we assume this is due to the higher variance in noisier conditions. Thus overall, it seems that interference in the letter task lay somewhere in between high and low noise conditions.

## Distributional Analysis

The discussion of the DCDFs is not meaningful, as overall RT was much faster in the letter task, so we begin with a comparison of the letter and motion DFs. In agreement with our ANOVA analyses, the slope of the DF for the letter task (.03 in for the positive portion) is more similar to the 40% noise condition (slope = .08) than any other, yet this is not the case for the CAF. In fact, the CAF from the letter task differs from all RDK conditions overall but appears to share aspects of the CAFs from both high and low noise conditions. Specifically, the congruency effect in the first quantile for the letter task (13.8%) is most like that observed in the highest noise condition (6.5%) yet still twice as large in comparison. Unlike the high noise conditions however, the CAFs do indeed converge as is the case for the low noise conditions. This mixture of aspects of the CAFs from the RDK task would suggest that early interference in the letter task is similar to high noise conditions, while flanker suppression is more similar to low noise conditions. Hence and consistent with the behavioral analysis, performance in the letter task appears to contain aspects comparable to both high and low noise conditions which combine to give an intermediate level of performance.

Given our predictions presented earlier, we originally expected that the noise-free letter stimuli would yield patterns of data most similar to the 10% noise condition if low noise stimuli result in less interference, yet the finding that the letter task falls somewhat between high and low noise conditions challenges this assumption. However, assuming that the magnitude of the flanker effect is directly determined by noise as suggested by our Study 2 results, one possibility is that, despite containing no added noise, the letter stimuli were perceived as having lower perceptual strength than the low noise RDKs, as motion is known to be a salient feature, capable of strong attentional guidance (Wolfe & Horowitz, 2017). In the next section, we compare the EAP estimates of both models across the two tasks, paying particular attention to the parameters governing perceptual strength, since these parameters would give some insight into whether the letter stimuli were indeed perceived as having lower perceptual strength than the low noise RDKs.

## EAP Estimates

The EAP estimates for the models, as well as the additional measures calculated for DSTP are shown in Figure 10.

Although $SSP_{pFl}$ was marginally superior to SSP in Study 2, we decided to use the estimates of SSP for comparison to the letter task for three reasons. Firstly, we fit SSP (and not $SSP_{pFl}$) to the letter task. Secondly, $SSP_{pFl}$'s prediction that ***pFlanker*** increases with increasing noise makes little sense and finally, $SSP_{pFl}$ predicts that interference in the letter task is considerably lower than all RDK conditions, when our analyses suggest this is not the case. On the other hand, SSP predicts that interference in the letter task is comparable to intermediate levels of noise, in line with our analyses. Thus overall, the predictions of SSP seemed to be more representative of our data.

Apart from the response boundary ***A*** and the spotlight parameters, we found the EAP estimates for the letter task were closest to the 10% noise condition in line with our original expectation. Importantly, the estimate of the perceptual strength parameter ***p*** was similar to, yet higher than the 10% noise condition and the same was found for non-decision time. This is important as it suggests that our noisy RDK stimuli did indeed have lower perceptual strength than the noise-free letter stimuli. If, as suggested by Study 2, the magnitude of the congruency effect is determined by noise, then this implies that the intermediate level of performance observed in the letter task cannot be attributed to the letter stimuli being perceived as having lower perceptual strength than the low noise RDKs. Consistent with the behavioral results, the shrink rate parameter ***rd***, the initial spotlight width ***sdA*** and the corresponding interference ratio for the letter task all lie between 40% and 10% noise, suggesting that the duration of flanker interference is most similar to lower noise conditions of the RDK task. In fact, the only parameter in the letter task clearly unlike the lower noise RDK conditions was the response boundary ***A***, where the estimate was closest to the 80% noise condition. That is to say, the mixture of less cautious responses (most similar to high noise conditions) and strong suppression (most similar to low noise conditions) combined to allow SSP to produce a level of interference in the letter task comparable to intermediate levels of noise in the RDK task.

DSTP shows a similar pattern to SSP, in that most parameters for the letter task are comparable to the lowest noise condition of the RDK task. DSTP makes the same predictions about the response boundary ***A*** as SSP: participants respond less cautiously in the letter task, most similar to the level of caution executed in the highest noise condition. Regarding the parameters that make up the drift rate for the early response stage *(RS1)*, namely ***μTa*** and ***μFl***, we see an interesting pattern. While the value of ***μTa*** is closest to the 10% noise condition (again suggesting that letter targets do not have lower perceived perceptual strength than low noise RDKs), ***μFl*** is not. In fact, the value of ***μFl*** is considerably higher than in the 10% noise condition suggesting that more attentional weight is given to the flanker in the letter task compared to the 10% noise condition. Consequently, we see that the probability of the early response selection process producing an error ($\boldsymbol{p(RS1_0)}$) in the letter task is also considerably higher than the 10% noise condition, consistent with this notion. For the late stimulus selection parameters, all are once again most similar to the low noise motion conditions, suggesting that flanker suppression in the letter task is akin to these conditions. Despite this however, the simulation results show that the probability of the late selection mechanism incorrectly selecting the flanker is considerably higher in the letter task compared to the 10% noise condition, although this probability is rather small overall. In summary, DSTP suggested that the main differences between the letter task and low noise conditions of the RDK task were a lower response boundary and an increased early attentional weight to flankers in the former.

## Discussion

Using RDKs in Study 2, we manipulated response congruency and the noise present in the items (10%, 40%, 70% and 80% noise) randomly across trials and found that adding noise to the stimuli resulted in larger average flanker effects, contrary to expectation. The distributional analyses showed steeper DFs, larger early interference effects in the CAFs and a lack of convergence of the two functions in high noise conditions, suggesting that the ability to suppress flankers was impaired and the duration of interference was longer under conditions of high noise.

Since DSTP better modelled these effects in Study 1 and the nonconverging CAFs in Servant et al. (2014), we expected DSTP to be superior for high noise conditions and this was indeed the case. Bayes Factor comparisons in high noise conditions were largely in DSTP's favor and the distributional measures showed that while DSTP modelled high noise conditions well, SSP underpredicted the duration of flanker interference, predicting CAFs that converged and a DF that was too shallow for longer RTs. We postulated that the reason SSP underestimated interference in high noise conditions was related to its assumption that the magnitude of the congruency effect is constrained by the perceptual strength of the stimuli, where low strength (high noise) stimuli lead to smaller congruency effects. Furthermore, since SSP predicted an incongruent CAF that was too steep (and CAFs that converged in high noise conditions), we assumed SSP's failures could also be related to its assumption that participants always correctly narrow attention in on the target. In contrast, DSTP's strengths lay in its ability to predict slow, congruency-dependent errors through a lack of engagement/failure of the late selection mechanism which allowed interference to persist into the slowest responses, thus allowing for steeper DFs and CAFs that did not converge. This was further highlighted by taking only participants who showed high strength evidence in favor of DSTP in the highest noise condition and demonstrating that these participants showed particularly extreme instances of these patterns: even steeper DFs, larger flanker effects and nonconverging CAFs, all of which, SSP failed to adequately match. By forcing SSP's spotlight to shrink more slowly, we could show that this indeed led to larger predicted congruency effects in high noise conditions, yet at the expense of quality of fit to other aspects of the data. Thus, it appeared SSP could not model the long duration of interference in high noise conditions, without this leading to a poorer quality of fit.

To test whether SSP was limited by its assumption that the congruency effect is determined by the perceptual strength of the stimuli, we refit the data with a version of SSP ($SSP_{pFl}$) that allowed the perceptual strength of target and flankers to vary freely. Although numerically, this version was slightly superior to SSP, the parameter estimates made less sense, most notably the assumption that the perceptual strength of the flankers increases with decreasing noise and $SSP_{pFl}$ was still inferior to DSTP for the high noise conditions. Like SSP,

$SSP_{pFl}$ predicted incongruent CAFs that were too steep and CAFs that converged in these conditions. This suggested that the perceptual strength assumption was not the main determinant of the failure of SSP, but rather its assumption that participants always successfully, and rather quickly, narrow attention in on the target.

Despite DSTP being the superior model, all models captured the increase in the flanker effect with increasing noise. While SSP suggested that the width of the spotlight is dependent on noise, with more noise leading to a wider spotlight , DSTP modelled these effects by assuming noise disrupts early filtering, although we also observed effects of noise on the late selection mechanism. Specifically, the late selection mechanism was less engaged and more error-prone in high noise conditions. It is worth noting that Hübner et al. (2010) observed greater involvement of the late selection mechanism in cases where early interference was high (Exp 1 and 2), interpreting this as evidence that the late selection stage "compensates" for early interference to produce levels of performance matching the data. However, their third experiment showed that a reduced flanker effect can stem from a combination of both better early filtering and a higher engagement of late selection. These findings are in line with those here, where we found more involvement of the late selection stage in conditions where early interference was low (low noise conditions). In other words, the improvement in early selectivity alone (from high to low noise conditions) was insufficient to match the data and as such, we see a strengthening of both early and late selection as noise decreases.

We then compared the letter and RDK task to explore differences in flanker suppression under noisy and noise-free conditions. Our average performance and distributional analyses indicated that performance in the letter task was most similar to intermediate levels of noise (40% noise) in the RDK task and this was supported by the distributional measures also, where the slope of the letter DF was most similar to that observed in the 40% noise condition. However, we observed clear differences between the letter and RDK tasks when examining the CAFs, where the CAF for the letter task appeared to share aspects of both high and low noise conditions. Particularly, the large early interference effects in the letter CAFs were most similar to high noise conditions, whereas the later portions converged, most similar to low noise conditions. This suggested that a mixture of larger early interference (most similar to high noise conditions) and efficient flanker suppression (most similar to low noise conditions), combined to give the intermediate level of performance we observed in the letter task.

The EAP estimates of both models supported this notion, in that while most letter parameters were similar to the low noise conditions, some were more similar to high noise conditions. A common prediction across both models pertained to the response boundary $\boldsymbol{A}$, which was notably lower in the letter task compared to the RDK task. As discussed previously, low response boundaries are typically interpreted as reflecting less cautious responses. This begs the question, why are participants less cautious in the letter task? Our interpretation of this finding relates to the randomization of noise levels in the RDK task and how this influences participant's expectations of interference from one trial to the next. Specifically, in the RDK task, different levels of noise yield very different patterns of performance. Due to this unpredictability, participants may choose to respond more cautiously overall. In contrast, the letter task provides only two trial types to be expected: congruent and incongruent and the discrimination between 'S' and 'H' is rather easy, leading to a less cautious approach and explaining the reduced response boundary. Not only was the response boundary lower in the letter task, but DSTP also predicted a higher value of $\boldsymbol{\mu Fl}$ compared to the RDK task. Typically, increases in $\boldsymbol{\mu Fl}$ are attributed to the imprecision/disruption of the early perceptual filter. For example, increases in $\boldsymbol{\mu Fl}$ have been observed when flankers are closer to the target or when the spatial location of the target is uncertain (Hübner et al, 2010). Given that the letter stimuli are noise-free and occupy the same (constant) space as the RDKs, we find it unlikely that the letter stimuli somehow disrupt early perceptual filtering more so than noisy RDKs. As noted earlier, Hübner et al.'s (2010) investigation of DSTP also revealed that the precision of the early filter is not only determined by stimulus properties but can also be influenced by task expectations. The authors found that increasing the proportion of congruent relative to incongruent led to observers adopting a more diffuse mode of attention, subsequently increasing the partial rate of the flankers ($\boldsymbol{\mu Fl}$). Following this, one explanation as to why $\boldsymbol{\mu Fl}$ is substantially increased for the letter task also relates to the participant's expectations. If we are correct in assuming that participants are less cautious in the letter task due to there being only being two trial types (congruent or incongruent), then it could be said that this expectation also influences the state of attention at stimulus onset. In the letter task, the adoption of a diffuse mode of attention would suffice in 50% of trials, whereas in the RDK task, the lack of predictability regarding the upcoming trial may result in participants attempting to better focus their attention prior to stimulus onset. Therefore, if subjects adopt a diffuse mode of attention in the former, a higher attentional weight will be assigned to the flankers at stimulus onset, as suggested by DSTP.

Not only are the EAP estimates consistent with this argument but so are the simulation-based measures and together they can explain key aspects of the distributional data observed in the letter task. Recall that, in the letter task, we found a substantial congruency effect in the earliest quantile of the CAF, indicative of strong early flanker interference, or in terms of DSTP, greater attentional weight to flankers for the earliest responses. Not only that, the probability of *RS1* producing an error ($\boldsymbol{p(RS1_0)}$) was considerably higher for the letter task compared to low noise RDK conditions: a low response boundary coupled with greater attentional weight assigned to flankers results in a higher susceptibility to early interference and in turn, a higher probability of early fast errors. While early ERs in congruent trials (***$p(RS1_0)$***) are similar across 10% noise and the letter task, incongruent letter trials produce more errors in the latter. In line with the idea that participants respond less cautiously in the letter task and also adopt a more diffuse mode of attention, this strategy works well in congruent but not in incongruent trials, reflecting the large interference effect observed in the CAF, the reduction in the response boundary, the higher attentional weight assigned to flankers and subsequent higher probability of *RS1* producing an error as predicted by DSTP. One surprising aspect of the comparison, however, pertains to the late selection mechanism. We see that while the probability of *RS2* producing an error is rather small (for both RDK and letter stimuli), the probability of incorrectly selecting the letter flanker is higher and more similar to the high noise RDK conditions. One explanation for this is that the tendency to respond less cautiously in the letter task also applies to the late selection mechanism, although we believe this is not under voluntary control. For example, for the letter task, the selection boundary ***C*** is considerably lower than all motion conditions. This in turn would lead to a higher probability of the late selection mechanism incorrectly selecting the flanker. However, given that the late selection mechanism on the whole operates rather well, this has a negligible impact on performance.

It is important to note that this interpretation is hard to reconcile with the effects of response boundary we found for Study 2. Recall that we interpreted the counterintuitive decrease in the response boundary with increasing noise as reflecting premature termination of the decision process due to a sense of urgency, since high noise targets are more difficult to identify. However, the finding that the letter task yields an even lower response boundary, despite the discrimination being easier and the CAFs converging challenges this interpretation for Study 2, although noteworthy is that the winning model DSTP predicts a weaker and nonsignificant effect of noise on the response boundary for Study 2. To answer our main question however, it seems the main difference between highly noisy and noise-free conditions is poorer flanker suppression in the former, whereas the difference between low-noise and noise-free conditions can potentially be explained by less cautious responses in the latter.

To summarize, the EAP estimates of SSP and DSTP both support the idea that the main differences between the letter and 10% noise condition (which we originally assumed would be very similar) reflect differences in strategy across the two tasks. Namely, we assume that in the letter task, participants adopt a less stringent attentional strategy, 1) because the letter discrimination is rather easy in comparison to the motion discrimination and 2) because participants can better predict the level of focus needed for an upcoming trial. While this 'laissez-faire' approach can suffice in 50% of trials (congruent), it is clearly detrimental in incongruent trials, particularly when coupled with a lower response boundary. Thus, in the data we see large congruency effects in ER for the fastest responses and in DSTP, we see a higher probability of error responses from *RS1*. However, since the suppression mechanisms (in both SSP and DSTP) are most similar to, if not more efficient than in low noise RDK conditions, flanker suppression operates very well most of the time if participants do not respond too hastily. This point is particularly illustrated by the DF and CAFs. Despite the large initial interference, accuracy in the letter task steeply increases with RT for both trial types and, consistent with the idea of strong flanker suppression, the DF turns negative for the latest responses. Together, this mixture of large early interference and strong flanker suppression results in a level of performance that is midway between high and low noise RDK conditions.

Both models gave insight into *how* noise increases the flanker effect, with SSP predicting that the noisier the items, the wider the attentional spotlight and DSTP predicting that noise disrupts early filtering and delays the onset of the focused mode of attention. However, the question as to *why* this occurs and the theoretical basis for these results is still somewhat unclear. As we have noted, the results stood in stark contrast to our original predictions, which were based on the idea that noise weakens the evidence for a given response and therefore, weak flankers in high noise conditions should result in smaller levels of interference. This assumption was based on the fact that flankers dominate the decision process early on, and that previous research using RDKs has shown that high strength (low noise) flankers introduce higher levels of interference (de Bruin & Sala, 2018), although the authors did not manipulate the noise level of the target. Given that the target is at fixation, increasing its perceptual strength by reducing the noise level is likely somewhat beneficial, despite the fact that the strength of the flankers also increases. Indeed, all models shared a common assumption that the effect of noise was greater for the target than for the flankers. Specifically, DSTP's $\boldsymbol{\mu Ta}$ parameter showed a steeper decrease with increasing noise than $\boldsymbol{\mu Fl}$ and, when allowing SSP to model target and flankers separately, the effects of noise on the perceptual strength of the target remained largely unchanged compared to when both target and flankers were modelled with a common parameter. In other words, the effects of noise on SSP's perceptual strength parameter were mostly determined by the target. Thus, the decrease in the congruency effect with decreasing noise could be attributed to a beneficial effect of decreasing the noise level of the target. However, this notion would require an explanation as to why standard flanker tasks using noise-free stimuli show robust congruency effects, or why our letter task showed a congruency effect that was larger than those obtained with low noise RDKs, despite containing less noise. Although we postulated an explanation for this discrepancy, our explanation was based on participant's expectations of the task rather than the strength of the target.

The fact that our results directly contrast our 'response-based' predictions, hints to the idea that the effect of noise may stem from something other than the response, namely a perceptual effect. In the introduction of this thesis, we reported clear evidence for the consensus that the flanker effect is response-based, yet also evidence that perceptual effects, such as those induced by perceptual grouping, can influence its magnitude. We also briefly touched upon perceptual load theory, which argues that the extent of flanker processing depends on the load requirements of the task (Lavie, 1995). Lavie (1995) showed that when a task involved higher perceptual load (e.g., responding to a target based on a conjunction of features rather than just one), flankers introduced minimal interference. Here, it could be argued that our noise manipulation also influences perceptual load. If we assume that perceptual load is higher in high noise conditions (since discriminating the motion direction is more demanding), then load theory would predict only shallow processing of flankers, since discriminating the motion direction of high noise targets leaves little remaining capacity for deeper flanker processing. However, our results also stand in direct contrast to this prediction, since high noise conditions yielded the largest interference effects.

In the following chapter, we test an alternative explanation for our results, which posits that the larger flanker effects in high noise RDK conditions are the product of perceptual grouping. To test this assumption, Study 3 manipulated the noise in the target and noise in the flankers independently. This allowed us to test the predictions of our grouping hypothesis, which we will discuss in detail in the next chapter, but also to further explore the differential effects of noise on target and flankers suggested by both models. We also fit DSTP and SSP to the data to see whether their predictions align with this hypothesis, how their predictions change depending on whether noise in the target or noise in the flanker changes and whether a discrete improvement model (DSTP) still provides the best account of our findings.

# Chapter 4

# Independent Manipulation of Target-Flanker Noise

## Introduction

In Study 2, adding noise to the stimuli increased flanker interference. Both SSP and DSTP suggested that noise hinders attentional focusing, leading to a longer duration of interference and a larger congruency effect. As to whether a discrete or gradual improvement model provides the best account of our data, the results so far have provided strong support for the discrete improvement model, DSTP, mainly for its ability to model longer durations of interference observed particularly in high noise conditions.

Study 3 aims to gain further insight into *why* noise disrupts flanker suppression and to provide a more theoretical basis for these results. Since Study 2 showed that weaker stimuli lead to larger congruency effects, the results stand in contrast with an explanation based purely on the strength of the response evidence. This led us to believe that the results may stem from a perceptual effect which in turn modulates attentional focusing. Here we postulate an explanation based on target-flanker similarity, with Study 3 allowing us to test the predictions of this account. This explanation is based on numerous findings presented in the introduction to this thesis, which show that the higher the similarity between target and flankers, the larger the flanker effect (Baylis & Driver, 1992; Harms & Bundesen, 1983; Moore et al., 2021). These effects are typically attributed to the tendency to group items into perceptual units, the formation of which is governed by various Gestalt principles, one of which is similarity (Wertheimer, 1938). That is, items that are similar are more likely to be grouped and attended to as one unit, with this preattentive (Neisser, 1967) grouping adversely impacting the spatial selectivity required to perceive target and flankers as individual objects (Banks & Prinzmetal, 1976; Kahneman & Henik, 1981; Prinzmetal & Banks, 1977). As a result, target selection is hindered, and the flanker effect increases. Similar effects have been demonstrated with the other Gestalt principles, including the principle of good continuation (Baylis & Driver, 1992) as well as the principle of common fate, where items that move in the same speed and direction are grouped as one unit (Driver & Baylis, 1989).

We hypothesize that in Study 2, noise increases the flanker effect because the noisier the items, the more similar they appear. In high noise conditions, target and flankers are similar in their shared lack of a clear motion signal and are therefore grouped, whereas the strong opposing motion signals in incongruent, low noise trials disrupt this grouping. Since target selection occurs later when items are grouped, the duration of interference is longer, and the flanker effect increases with noise. This hypothesis can explain not only the average performance and distributional effects, but the model predictions also. For example, SSP's predicts that the attentional spotlight is wider, and interference persists longer in high noise trials. Similarly, attending to target and flankers as one unit will disrupt early spatial filtering and prolong the switch to the focused mode of attention, as suggested by DSTP.

To help test whether the larger flanker effects in high noise conditions are due to perceptual grouping by similarity, the next study manipulated target and flanker noise levels independently. Specifically, we use two levels of target noise, one in which the target is high noise (80% noise) and one in which the target is low noise (10% noise). We then manipulate flanker noise across the same four levels as Study 2 (10%, 40%, 70% and 90%). For the high noise target condition, the target-flanker similarity hypothesis would predict an increase in interference with increasing flanker noise since target and flankers becomes more similar as flanker noise increases. In terms of the EAP estimates, this would be reflected in less effective suppression under SSP as flanker noise increases (smaller values of ***rd*** and/or larger values of ***sdA***), whereas for DSTP, we should see poorer earlier selectivity (lower ***μTa***, higher ***μFl***) and a later onset of the late selection mechanism. Additionally, although grouping is detrimental in incongruent trials, it could be beneficial in congruent trials. Therefore, the increase in the flanker effect with increasing noise should be driven by both poorer performance with increasing flanker noise for incongruent trials and the opposite for congruent trials.

The low noise target condition should produce smaller flanker effects overall, since the target is always somewhat 'different' to the flankers yet possibly for different reasons depending on the level of flanker noise. With low noise, incongruent flankers, target and flankers differ based on their opposing motion signals, whereas with high noise flankers, the items differ based on their noise level. Given that high noise flankers are weaker, the congruency effect could be strongest when the level of flanker noise is at its minimum (10%). However, in Study 2, this condition showed no significant flanker effects (8.4ms in RT, 0.7% in ER). If we assume that target and flankers are most different in this condition, and this is why the congruency effect for the 10% noise condition was not significant in Study 2, then we predict the flanker effect for the low noise target condition should also increase with increasing flanker noise. Again, these effects should be captured by both models, showing evidence of poorer suppression as flanker noise increases, yet better overall suppression in the low compared to the high noise target condition.

To summarize, if the effects of Study 2 are due to grouping by similarity in high noise conditions, then flanker effects in the high noise target condition should be overall larger than in the low noise target condition. Secondly, the flanker effect should increase with increasing flanker noise for both target noise levels since in both cases, target and flankers become more similar as flanker noise increases.

# Method

## Participants

A total of 50 participants (43 females and 7 males, mean age = 19.44 years) from the University of Birmingham took part in the task in exchange for course credit. 5 participants had to be removed from the sample due to accuracy levels below chance or unusually long average RTs (~1800ms). These RTs mostly stemmed from the high noise target condition. This left 45 participants in the final sample (39 females and 6 males), with a mean age of 19.44 years.

## Stimuli

The RDKs were identical to those used in Study 2.

## Procedure & Design

The task followed a 2 x 2 x 4 design, with factors Congruency (Congruent or Incongruent), Target Noise (80% or 10%) and Flanker Noise (80%, 70%, 40% or 10%). All factors were randomized across trials. The task was run in eight blocks of 128 trials, each of which began with 16 practice trials and shared the same trial-by-trial procedure as the previous tasks, which was presented in the General Method section. By the end of the task, participants had completed a total of 1152 trials (128 practice trials and 1024 experimental trials), with 64 trials per condition for each combination of Congruency, Target Noise and Flanker Noise.

# Results

## Behavioral Analysis

### Average Performance Analysis

The average performance measures are shown in Figure 11. For both RT and ER, we performed a 2 x 4 x 2 repeated measures ANOVA, with factors Target Noise (High (80%) and Low (10%)), Flanker Noise (10%, 40%, 70% and 80%) and Congruency (Congruent and Incongruent). For both analyses, all effects were significant, most notably the three-way interaction between all factors. To explore this further, we performed a simple effects analysis, splitting the data by Target Noise and performing a 2 x 4 repeated measures ANOVA on each condition, with factors Flanker Noise and Congruency. For brevity, we report only this simple effects analysis, although the results of the 2 x 4 x 2 ANOVA for RT and ER are available in Appendix C.

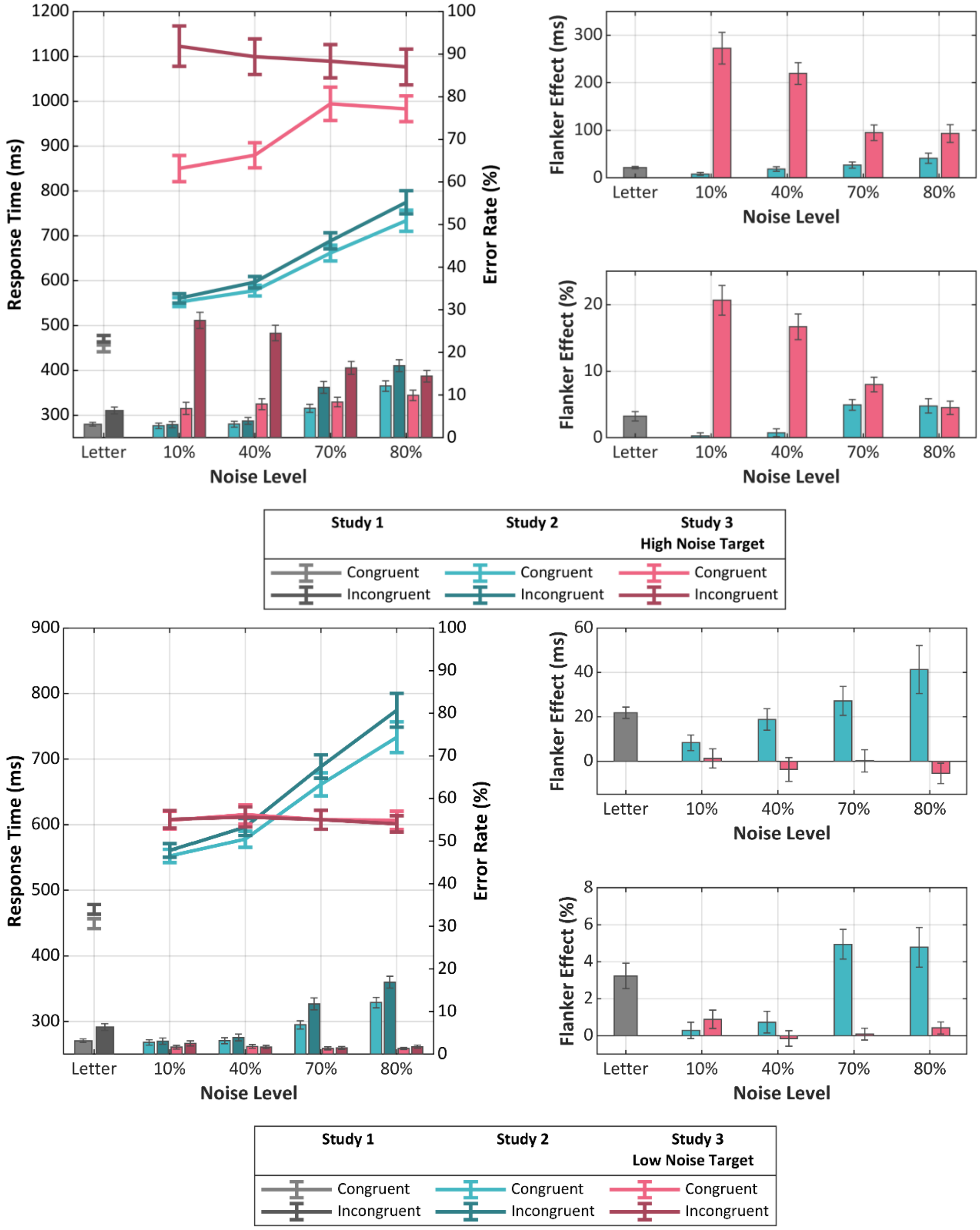
High Noise Target

The 2 x 4 ANOVA for the high noise target condition revealed all effects to be significant for RT. The effect of Congruency ($F(1,44) = 108.477$, $p < .001$, $\eta_p^2 = .711$), showed incongruent trials yielded RTs that were on average 170.1ms slower than congruent trials. The main effect of Flanker Noise ($F(3,132) = 7.590$, $p < .001$, $\eta_p^2 = .147$) showed that RT decreased with increasing Flanker Noise (20%: 1029.6ms; 30%: 1041.6ms; 70%: 989.2ms; 90%: 986.2ms). Importantly, the Congruency x Flanker Noise interaction was significant ($F(3,132) = 20.872$, $p < .001$, $\eta_p^2 = .322$). For the high noise target, the flanker effect decreased with increasing Flanker Noise (10%: 272.8ms; 40% 219.6ms; 70%: 95.0ms; 80%: 93.1ms), the opposite of what is predicted by the target-flanker similarity hypothesis. The target-flanker similarity hypothesis would also predict that grouping is beneficial in congruent but not incongruent trials, therefore RT should decrease with increasing Flanker Noise for congruent trials yet increase for incongruent trials. The results showed the opposite effect: for congruent trials, responses were slower with higher levels of Flanker Noise (10%: 849.9ms; 40%: 879.4ms; 70%: 994.1ms; 80%: 983.1ms, $p < .001$) whereas for incongruent trials, responses were generally faster, although these differences were less pronounced and not significant (10%: 1122.6ms; 40%: 1099.0ms; 70%: 1089.0ms; 80%: 1076.2ms, $p = .278$).

Like the RT analyses, the 2 x 4 ANOVA on ER revealed all effects to be significant for the high noise target condition. The congruency effect ($F(1,44) = 130.715$, $p < .001$, $\eta_p^2 = .748$) showed incongruent trials produced ERs on average 12.4% higher than congruent trials. The main effect of Flanker Noise ($F(3,132) = 9.443$, $p < .001$, $\eta_p^2 = .177$), showed that ER decreased with increasing Flanker Noise (10%: 17.3%; 40%: 16.2%; 70%: 12.4%; 80%: 12.2%). Finally, the significant interaction ($F(3,132) = 35.857$, $p < .001$, $\eta_p^2 = .449$), showed that the flanker effect also decreased with increasing Flanker Noise (10%: 20.6%; 40%: 16.7%; 70%: 7.9%; 80%: 4.5%). Contrary to the predictions of the target-flanker similarity hypothesis, analysis of the effect of Flanker Noise on each congruency level again revealed a detrimental effect of increasing Flanker Noise on congruent trials, (10%: 7.0%; 40%: 7.9%; 70%: 8.4%; 80%: 10.0% , $p < .001$), whereas for incongruent trials, increasing Flanker Noise had a significant, beneficial effect (10%: 27.6%; 40%: 24.6%; 70%: 16.3%; 80%: 14.4%; , $p < .001$).

**Figure 11**

Study 3: Average RT and error rate for all 45 participants in Study 3.




The left panels show the average RT and error rate for congruent and incongruent conditions for each condition. The top right panels show the average congruency effect in RT, while the lower right panels show the average congruency effect in error rate. Error bars represent the standard error of the mean.

Low Noise Target

For the low noise target condition, we found no congruency effects for RT and only the effect of Flanker Noise to be significant ($F(3,132) = 3.036$, $p = .031$, $\eta_p^2 = .065$). RT decreased slightly with increasing Flanker Noise (10%: 607.4ms; 40%: 613.6ms; 70%: 607.6ms; 80% : 603.9ms). Similarly, no effects were significant for ER. Like the RT analysis, it appeared most interactions in the higher level 2 x 4 x 2 ANOVA were driven by the presence of significant effects in the high noise target condition and a lack of these effects in the low noise target condition.

In summary, while we found the main effect of Target Noise predicted by the target-similarity hypothesis, that is, that high noise target conditions would yield larger flanker effects, the effects of Flanker Noise are in the opposite direction: only when the target is noisy do low noise flankers lead to larger congruency effects. When the target is not noisy, flanker effects are smaller overall and are independent of the level of noise in the flankers.

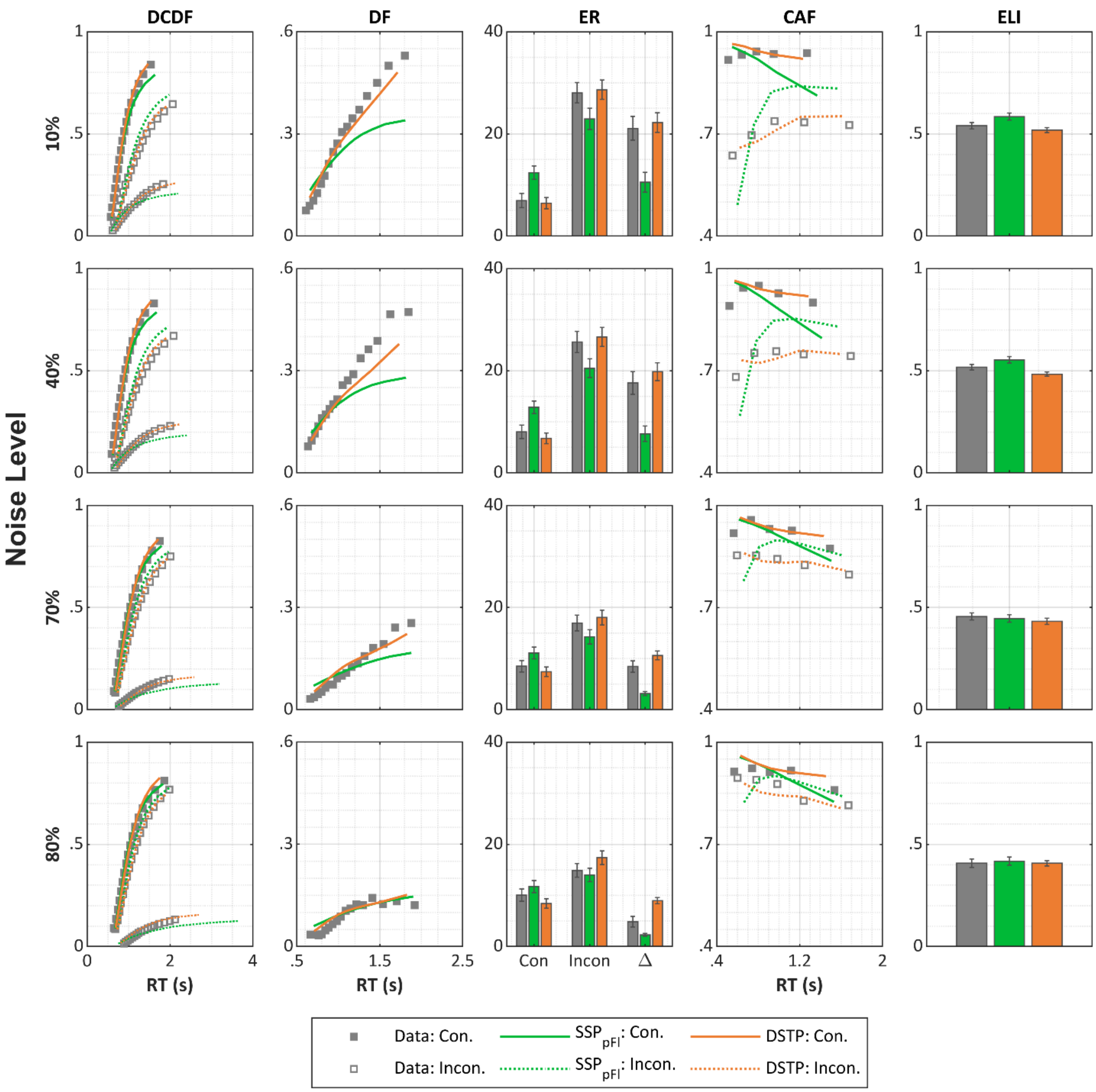
**Distributional Analyses**

High Noise Target

The distributional measures for the high noise target condition are shown in Figure 12. Note that given the high ER, we could reliably compute error location indices (ELI) and error DCDFs for incongruent trials which are also included.

**Figure 12**

Study 3: Averaged distributional measures for the high noise target condition of Study 3 across all 45 participants.




Note: DCDF: Defective cumulative density function. DF: Delta function. ER: Error rate (%). CAF: Conditional accuracy function, ELI: Error location index.

Firstly, the correct DCDFs show incongruent trials produced slower RTs across all quantiles, reflected in the overall positive values of the DFs and this is the case for all levels of flanker noise. Furthermore, the DF is positive going across all levels yet becomes increasingly shallower as flanker noise increases (10% slope: 0.42; 40% slope: 0.36; 70% slope: 0.20; 80% slope: 0.10; $F(3,60) = 118.650$, $p < .001$, $\eta_p^2 = .856$), indicative of more effective flanker suppression with high noise flankers. For incorrect trials, the earliest quantiles of the incongruent error DCDF are shifted rightwards as flanker noise increases. In other words, we see a higher proportion of faster errors in the lower flanker noise conditions indicative of higher response capture. Higher response capture in low noise flanker conditions is signified by the CAF also. Specifically, at the lowest level of flanker noise, the congruency effect in the earliest quantile of the CAF is considerably large (28.1%), before decreasing gradually as flanker noise increases (40%: 20.9%; 70%: 6.6%; 80%: 1.7%). Not only do low noise flankers lead to larger early interference effects, but we also see that this interference persists into the longest responses, with the CAFs for congruent and incongruent conditions being almost parallel. In fact, with the exception of the 80% flanker noise condition, accuracy in incongruent trials never comes close to that of congruent trials and the CAFs do not converge[1].

This lack of convergence in the CAFs is also captured by the ELI. The fifth column shows the average ELI across subjects for incongruent trials and the model predictions. Contrary to what is usually observed in flanker tasks (ELI > .5), the ELI is relatively low across all levels of flanker noise. As flanker noise decreases, the ELI passes the .5 mark, since we see a higher

[1] The 80% noise condition of Study 2 is identical to the 80% flanker noise condition here. However, in the former, we found an early congruency effect in the CAF, yet here, we do not, despite the average flanker effect being considerably larger. Although Studies 2 and 3 used different observers, this suggests that in Study 2, the larger flanker effect in the 80% noise condition was not purely due to larger initial response capture but rather poorer flanker suppression and the longer duration of interference compared to low noise trials.

proportion of fast errors in this condition. However, in agreement with the CAFs which show nonconvergence, the ELIs suggest that error RTs are more or less equally distributed among slow and fast responses**,** or that the duration of flanker interference is longer, the lower the noise in the flankers. Noteworthy however is that such midrange ELIs can be difficult to interpret (Servant et al. 2018), although when combined the other measures, our results suggest that flanker suppression for the high noise target becomes increasingly poorer, the stronger the flankers are (the less noise they contain).

Overall, the distributional analyses for the high noise target condition were consistent with the average performance analysis and stand in contrast to the predictions of the target-flanker similarity hypothesis. Specifically, despite target and flankers being more dissimilar in low noise flanker conditions, we found evidence of increasingly poorer suppression as flanker noise decreased.

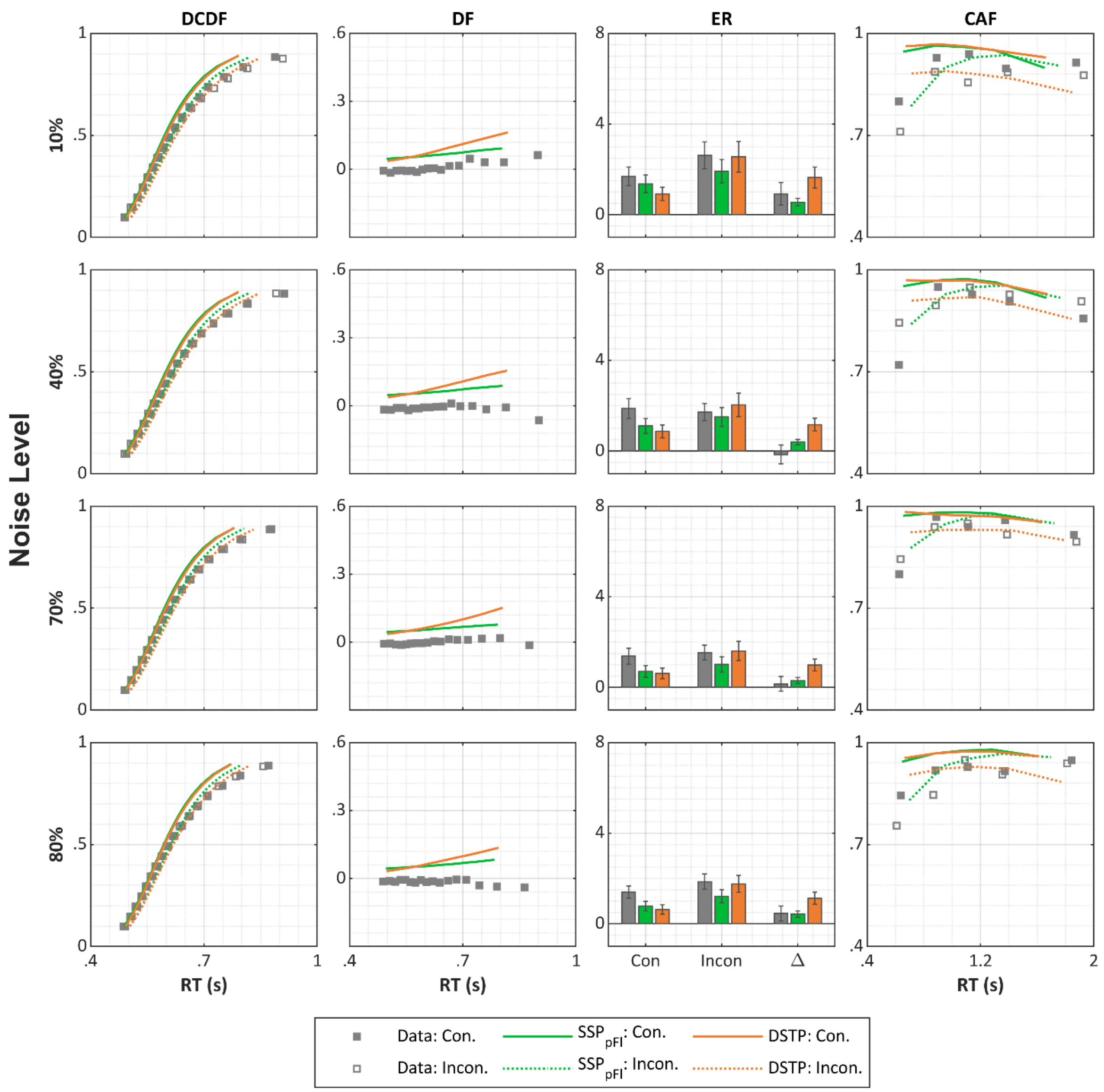
Low Noise Target

The distributional measures for the low noise target condition are presented in Figure 13. Consistent with the average performance analysis, the DCDFs show little variation across different levels of flanker noise, and the DFs for all conditions are almost flat, with their values fluctuating around zero. The only systematic difference observable is in the later portions of the DFs, which appear to be slightly steeper for lower levels of flanker noise. In fact, for the lowest level of flanker noise, the values for the later portion of the DF are positive, whereas for the highest level of flanker noise, the values are negative. This would suggest that, like the high noise target condition, flanker suppression operates more efficiently when the flankers are noisy. However, these differences are of a very small magnitude and flanker suppression with a low noise target is highly effective overall.

As discussed, analysis of the ER for the low noise target condition showed no significant effects and this is evident in the CAFs also. The congruency effect in the earliest quantile of the CAF fluctuates across different levels of flanker noise: in some conditions (10% and 80% flanker

**Figure 13**

Study 3: Averaged distributional measures for the low noise target condition of Study 3 across all 45 participants.




Note: DCDF: Defective cumulative density function. DF: Delta function. ER: Error rate (%). CAF: Conditional accuracy function, ELI: Error location index.

noise), accuracy in congruent trials is higher than incongruent trials as expected, yet in others (40% and 70%), the reverse is true. Similarly, the difference between the congruent and incongruent CAF fluctuates across RT latencies, particularly for the higher levels of flanker noise. Only in the lowest flanker noise condition do incongruent trials produce lower levels of accuracy than congruent trials across all RTs, yet these differences are small. Again, despite the lack of a significant interaction in the average performance analysis, the distributional analysis would suggest that flanker suppression is efficient overall for the low noise target condition, but possibly even more so when the flankers contain high levels of noise.

## Model Fitting

Since we manipulated target and flanker noise independently, we fit $SSP_{pFl}$ instead of SSP to the data from Study 3. As noted in the previous chapter, this changes the behavior of the model in that the drift rate for congruent trials now varies over time. Although we do not fit SSP to the results from Study 3, we believe this is important to reiterate for two reasons. Firstly, when fitting $SSP_{pFl}$ to the results of Study 2, ***pTarget*** was consistently larger than ***pFlanker*** and therefore, the drift rate in congruent trials *increased* over time. However, given that in the high noise target condition of Study 3, the target is weaker than the flankers in all but one condition, the estimates for ***pTarget*** will likely be lower than those for ***pFlanker*** and as a result, the drift rate in congruent trials will *decrease* over time. Secondly, since the difference between the two parameters will likely be larger for Study 3 compared to Study 2, the effects of this time-varying drift rate will be more evident than in Study 2, where we found little differences between SSP and $SSP_{pFl.}$

**Bayes Factor**

The results of the Bayes Factor comparison are shown in Table 8, where the most striking finding is that the winning model changes depending on the noise level of the target. For the high noise target, the comparison is largely in favor of DSTP, whereas for the low noise target, the results are in favor of $SSP_{pFl}$. A common theme throughout this thesis has been that DSTP is better able to capture effects consistent with poorer flanker suppression, most notably, CAFs that do not converge. The Bayes Factor analysis for Study 3 further supports this point. Aspects of the data that DSTP has previously modelled well (steep DFs, nonconverging CAFs and large congruency effects in ER) became increasingly more evident in the data as flanker noise decreased for the high noise target. Accordingly, most participants showed evidence in favor of DSTP overall, yet this proportion increased with decreasing flanker noise (80%: 72%; 70%: 85%; 40%: 83%; 10%: 96%). Likewise, a subset of participants showed extreme evidence in favor of DSTP, and this too gradually increased with decreasing flanker noise. We therefore assume that this increase in evidence strength for DSTP reflects its superior ability to model these effects specifically. As we will show in the next section, DSTP better fits these aspects of the data in Study 3 also.

For the low noise target condition, most participants showed evidence in favor of $SSP_{pFl}$. Note that although the percentage of participants preferring SSP did decrease with decreasing flanker noise, the differences were very small (80%: 76%; 70%; 76%; 40%: 74%; 10%: 72%). Given that flanker noise had little effect in this condition, it is not surprising that the Bayes Factor results show little changes across flanker noise conditions.

**Table 8**

Study 3: Number of participants falling into each Bayes Factor category for Study 3.

| | High Noise Target | | | | Low Noise Target | | | |
|---|---|---|---|---|---|---|---|---|
| | 10% | 40% | 70% | 80% | 10% | 40% | 70% | 80% |
| Extreme ($SSP_{pFl}$) | 0 | 0 | 0 | 0 | 1 | 0 | 1 | 0 |
| Very Strong ($SSP_{pFl}$) | 0 | 0 | 0 | 1 | 0 | 0 | 0 | 0 |
| Strong ($SSP_{pFl}$) | 1 | 0 | 0 | 5 | 1 | 4 | 1 | 1 |
| Moderate ($SSP_{pFl}$) | 0 | 2 | 1 | 3 | 19 | 16 | 18 | 18 |
| Anecdotal ($SSP_{pFl}$) | 1 | 6 | 6 | 4 | 12 | 14 | 15 | 16 |
| Anecdotal (DSTP) | 4 | 6 | 8 | 8 | 4 | 4 | 3 | 2 |
| Moderate (DSTP) | 5 | 5 | 10 | 10 | 2 | 1 | 2 | 2 |
| Strong (DSTP) | 4 | 3 | 4 | 9 | 1 | 2 | 4 | 3 |
| Very Strong (DSTP) | 6 | 3 | 3 | 2 | 1 | 0 | 1 | 2 |
| Extreme (DSTP) | 24 | 20 | 13 | 3 | 4 | 4 | 0 | 1 |

Note: Since we fit all both models to each participant and condition separately, the number of participants in each category sums to the total number of participants (N = 45).

## Quality of Fit

High Noise Target

The distributional analyses for the high noise target conditions and the model predictions are shown along with the data in Figure 12. In line with the Bayes Factor comparison, DSTP provides a better fit to every measure, particularly in low noise flanker conditions. Firstly, the fits of both models to the correct DCDFs are very good. Across all levels of flanker noise, the predictions of DSTP almost perfectly match the data. For $SSP_{pFl}$, the fits to the 80% flanker noise condition are of remarkably high quality considering its previous failure to match high noise conditions of Study 2. However, we have found a persistent issue with SSP in that it predicts that selectivity in incongruent trials increases too quickly, and we see this once again in Study 3: as flanker noise decreases, $SSP_{pFl}$ predicts incongruent RTs that are too fast and underestimates the congruency effect, particularly in the later quantiles. This underprediction is further illustrated by the DF. While both models model the function well in the 80% flanker noise condition, $SSP_{pFl}$ increasingly underpredicts the slope of the later portion as flanker noise decreases, predicting that the DF levels off when this is not the case. In other words, $SSP_{pFl}$ again predicts that attentional selectivity improves too quickly.

For ER, the predictions of both models are more similar for the 80% flanker noise condition, however, for all other levels of flanker noise, DSTP clearly provides a better match to the data. A particularly interesting aspect of the results pertains to the differential effect of flanker noise we found on congruent and incongruent trials for the high noise target condition. Contrary to the predictions of the target-flanker similarity hypothesis, we found that RTs and ERs for the congruent condition increased with increasing flanker noise, whereas the opposite was true for incongruent trials. While DSTP correctly predicts this effect, that is an increase in ER with increasing flanker noise for congruent trials, $SSP_{pFl}$ predicts the opposite. For incongruent trials however, both models correctly predict that ER increases, yet DSTP's predictions are much closer to the data.

Examining the CAFs, it is clear why $SSP_{pFl}$ underestimates the ER in incongruent conditions. We again see the familiar pattern of $SSP_{pFl}$ predicting an incongruent CAF that is too steep and predicting that the two CAFs converge, with this mismatch becoming increasingly more evident as flanker noise decreases. Since the architecture of $SSP_{pFl}$ leads to a decreasing drift rate in congruent trials (when ***pTarget*** < ***pFlanker***), $SSP_{pFl}$ also mismatches the congruent

CAF, predicting that it steeply decreases with increasing RT for all levels of flanker noise. On the other hand, DSTP's fit to both the congruent and incongruent CAF are notably better and DSTP correctly predicts that the functions do not converge. Thus, while DSTP matched both CAFs very well, $SSP_{pFl}$'s fit to both functions was poor, with the model predicting an incongruent CAF that was too steep, a congruent CAF that decreased with increasing RT and convergence of the two functions.

Finally, like the other measures, the incongruent ELIs for both models are similar for the 80% flanker noise condition yet diverge as flanker noise decreases. Consistent with the CAF, $SSP_{pFl}$'s estimate of the ELI is too high, since it overpredicts the number of errors concentrated among the fastest responses, whereas DSTP's estimate is closer.

Low Noise Target

The fits of both models to the low noise target conditions are shown in Figure 13, with $SSP_{pFl}$ providing a better fit to most aspects of the data. Firstly, the RT data showed no consistent flanker effect across time, as illustrated by the DFs which fluctuate around zero for all levels of flanker noise. Despite this, the fits of both models to the DCDFs were good overall, particularly for earlier RT quantiles. Although both models still predicted small congruency effects, $SSP_{pFl}$'s predictions were smaller, and its shallower DFs were a better fit than those predicted by DSTP.

ER in low noise target conditions was also better modelled by $SSP_{pFl}$ yet was low overall. Although DSTP better captured ER in incongruent trials, $SSP_{pFl}$ better matched congruent trials and the average flanker effect in ER, while DSTP underestimated the former and overestimated the latter. The models also differed in their predictions of the CAF. Given that the direction of the congruency effect varies unpredictably across RT, DSTP predicts CAFS that are parallel, while $SSP_{pFl}$ predicts its hallmark convergence. In the previous studies, DSTP's ability to produce such nonconverging CAFs was one of the main reasons for its superiority, yet here, we see a case where this prediction is not the correct one. DSTP's prediction of parallel CAFs means that it fails to capture the early increase in the incongruent CAF and the later convergence, while $SSP_{pFl}$'s typical error pattern allows it to better model both.

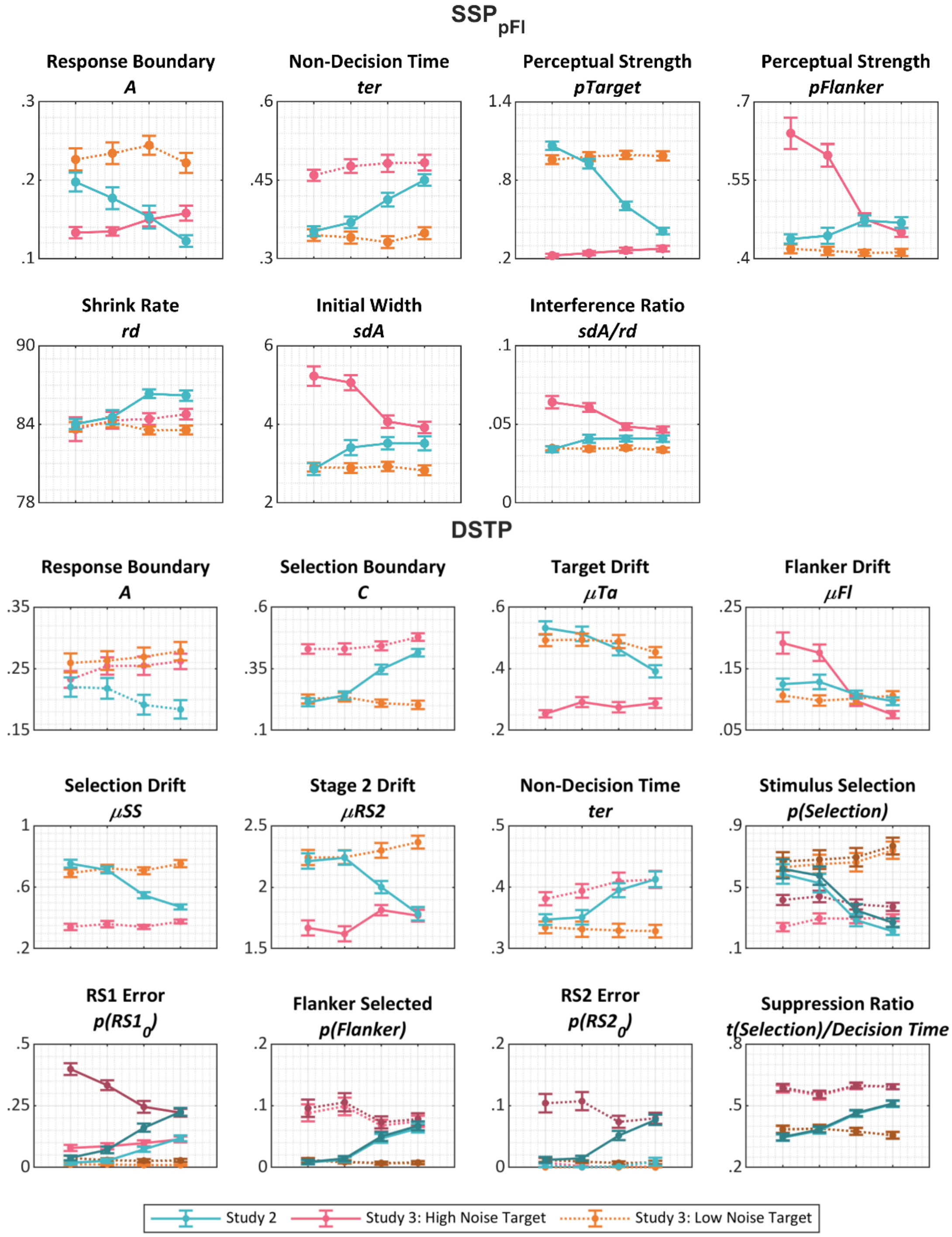
Overall, the distributional analysis of the low noise target condition was consistent with the Bayes Factor results. Not only is $SSP_{pFl}$ the more parsimonious model, but it also better matched most aspects of the data in the low noise target condition, both in RT and in ER.

**EAP Estimates**

Figure 14 shows the EAP estimates for Study 3 along with those of Study 2. Note that for Study 2, we use the EAP estimates of $SSP_{pFl}$ (not SSP), for a more direct comparison to the results of Study 3. We also performed a 2 x 4 ANOVA on the EAP estimates from Study 3, with factors Target Noise and Flanker Noise. The significant effects of flanker noise are illustrated in Figure 14, where solid lines represent significant effects of flanker noise while dotted lines represent no effect. Our behavioral analysis of Study 3 was partly in line with the target-flanker similarity hypothesis, in that overall interference effects were larger with a high compared to low noise target. However, they clearly contrasted the predictions regarding the effects of increasing flanker noise, and this is evident in the EAP estimates also. Instead, both the behavioral analysis and the EAP estimates imply a more 'target-centric' explanation that does not depend on relationships between target and flanker as suggested by the target-flanker similarity hypothesis, but rather are determined predominantly by the noisiness of the target. Specifically, the extent to which flankers will interfere is modulated by the noise level of the target. If the target is noisy, interference from flankers increases as their noise level decreases. If the target is not noisy, attention more readily deals with interference, the flanker effect is smaller, and the noise level of the flankers has little influence.

**Figure 14**

Average EAP estimates for Studies 2 and 3.




Note: For DSTP, the simulated measures (*p(Selection)*, *p(RS1$_0$)*, *p(Flanker)*, *p(RS2$_0$)* and *suppression ratio*) can be calculated for incongruent and congruent trials separately. In these cases, darker (lighter) lines represent incongruent (congruent) trials.

**SSP**$_{pFl}$

Before we discuss each parameter, a cursory glance at the EAP estimates reveals an interesting pattern consistent with the above interpretation. Specifically, many parameters of $SSP_{pFl}$ show a consistent pattern, in that the estimates for Study 2 lie in between the two target noise conditions of Study 3, transitioning from being most similar to the low noise target conditions in conditions of low target-flanker noise, before becoming more similar to the high noise target condition in conditions of high target-flanker noise. This would suggest that the critical factor determining the effects of noise we found in Study 2 was the level of noise in the target.

For response boundary ***A***, the estimates are high for low noise target conditions, low for high noise target conditions and the estimates for Study 2 lie in between. In Study 2, we mentioned that the direction of these effects is unexpected, in that participants respond less cautiously in conditions that are more difficult and the same is true for Study 3, where the low noise target condition shows the highest response boundary. The direction of this effect could be explained using the same interpretation discussed in Study 2, that more difficult conditions lead to participants terminating the decision process prematurely due to a sense of urgency, and therefore the average response boundary is lower in these conditions. However, this explanation seems unsatisfactory, especially given that the response boundary significantly increases with increasing flanker noise in the high noise target condition of Study 3. We will return to this point in the general discussion.

The same patterns are evident for non-decision time and the perceptual strength of the target also, in that the estimates for Study 2 lie diagonally in between those of Study 3. These estimates suggest that high noise stimuli are encoded slower than low noise stimuli and again that the effect of noise on non-decision time in Study 2 was due to a change in target noise. That is, faster encoding with low noise stimuli occurs only if the target contains low noise and this notion is further supported by the fact that the non-decision time parameter is not modulated by flanker noise in either condition of Study 3.

For ***pTarget***, $SSP_{pFl}$ correctly predicts the perceptual strength of the target (***pTarget***) is inversely related to the level of noise, where the estimate is low for the high noise target condition and high for the low noise target condition. For Study 2, the estimates again lie diagonally between the two target noise conditions of Study 3. Interestingly, despite the noise level in the target remaining constant across levels of flanker noise, ***pTarget*** increases with increasing flanker noise for the high noise target condition yet remains constant for the low noise target condition. If we assume ***pTarget*** reflects the perceived (and not objective) perceptual strength of the target and combine this with our behavioral findings from the high noise target condition of Study 3, then it could be said that attentional modulates the perceived perceptual strength of the items. To be more specific, in Study 3, we found that the large interference effects with a high noise target were modulated by the noise level of the flankers, where low noise flankers produced more interference. Given that attention serves to enhance the processing of attended stimuli and is a limited capacity resource, attending more to flankers in low noise flanker conditions would lead to less attention being directed to the target. As a result, fewer resources are allocated to target processing and the target is perceived as weaker. Indeed, studies using RDKs have shown that attending to an RDK can increase neural firing rates in area V5/MT and boost the perceived level of motion coherence, even if the objective motion coherence remains the same (Cook & Maunsell, 2002; Liu et al., 2006).

Not only are the estimates for ***pTarget*** consistent with this notion, but so are the estimates for ***pFlanker*** and the initial spotlight width ***sdA***. The perceptual strength of the flankers is overall higher for the high noise target condition and decreases with increasing flanker noise, whereas for the low noise target condition, ***pFlanker*** is low and remains constant across levels of flanker noise. In other words, despite the flankers sharing the same noise levels in both the low and high noise target conditions, their perceived perceptual strength appears to be modulated by attention, where the state of attention is in turn modulated by the level of noise in the target. If the target is high noise, more attention is allocated to the flankers overall, whereby the lower the noise in the flankers, the more attention they receive and the higher their perceived perceptual strength. In contrast, when the target is low noise, less attention is allocated to flankers and the flankers are perceived as weaker as a result.

For the spotlight parameters, ***rd*** shows an unusual effect, in that the shrink rate does not change across the two target-noise levels of Study 3 and is not modulated by flanker noise. Furthermore, the shrink rate is overall lower for both conditions of Study 3 compared to Study 2. The effects found for ***rd*** so far have been difficult to interpret and from Study 2, it appeared ***sdA*** was the critical factor determining the effects of noise. Like in Study 2, the effects of ***sdA*** for Study 3 are much more consistent than those for ***rd*** and are mirrored by the interference ratio. Firstly, the estimates for the high noise target condition are higher than those for Study 2 and the estimates for the low noise target condition are lower than those for Study 2. In other words, the spotlight is wider, and the duration of interference is longer when the target is noisy compared to when it is less noisy. Secondly, for the high noise target, the estimates increase with decreasing flanker noise, consistent with the notion that more attention is allocated to flankers when the target is noisy, and that the attentional weight assigned to flankers is greater, the less noise they contain. In contrast, for the low noise target, there is no effect of flanker noise on ***sdA*** or the interference ratio, suggesting that observers can better constrain their attention when the target contains little noise and as a result, noise in the flankers has little influence. Finally, the estimates for Study 2 again lie in between the estimates for Study 3. That is, the increase in interference with increasing noise that we observed for Study 2 appears to be the result of a change in target noise, where noisier targets lead to a wider attentional spotlight and a longer duration of interference.

**DSTP**

The consistent pattern observed in the parameters of $SSP_{pFl}$, that is, that the Study 2 estimates lie diagonally between the Study 3 estimates, becomes increasingly more evident when examining the estimates of DSTP, where almost all parameters follow this pattern. Again, this would suggest that the effects of noise we found in Study 2 were primarily the result of differences in target noise.

For non-decision time, DSTP makes identical assumptions to SSP, in that low noise targets lead to faster perceptual encoding. For the target drift rate, $\boldsymbol{\mu Ta}$ is high for the low noise target condition and low for the high noise target condition as expected. The estimates for Study 2 are most similar to the low noise target condition for low levels of target-flanker noise and decrease in the direction of the high noise target condition as flanker noise increases. However, the estimate for the highest noise condition of Study 2 is notably higher than the identical condition in Study 3. Despite the conditions being identical, the flanker effect for this condition in Study 3 is considerably larger than that found in Study 2 and may explain this discrepancy. Finally, DSTP makes the same assumptions as $SSP_{pFl}$ regarding the effects of flanker noise on the high noise target conditions, in that $\boldsymbol{\mu Ta}$ increases as flanker noise increases, whereas $\boldsymbol{\mu Ta}$ is independent of flanker noise when the target is less noisy. Since DSTP makes the explicit assumption that $\boldsymbol{\mu Ta}$ represents a combination of perceptual strength and attentional weighting, this is consistent with the idea that less attention is allocated to the high noise target in conditions of low flanker noise, or in the framework of DSTP, early perceptual filtering is poorer as flanker noise decreases, leading to less attentional weight being assigned to the high noise target.

For $\boldsymbol{\mu Fl}$, we see also see similar pattern to $SSP_{pFl}$, where the effects suggest that the attentional weight assigned to flankers is modulated by the noise level of the target. Firstly, $\boldsymbol{\mu Fl}$ is higher overall for the high noise target condition yet decreases steeply as flanker noise increases. Secondly, $\boldsymbol{\mu Fl}$ is low and constant for the low noise target condition. Finally, the estimates for Study 2 show a similar pattern to those for the high noise target condition, however, the estimates are lower overall, and the effect of noise is not as pronounced. This would suggest that decreasing the level of noise in the target in Study 2 counteracted the effect of lower noise flankers, which would have been assigned a much greater attentional weight had the target remained noisy. Given that across all conditions, the noise in the flankers is the same (or the only difference between conditions is the noise level of the target), this again suggests that the attentional weight assigned to flankers is predominantly determined by the noise level of the target, or in the framework of DSTP, the selectivity of early perceptual filtering is determined by the noisiness of the target: low noise flankers overwhelm noisy targets, while low noise targets are robust to these effects.

Combining these parameters to look at performance in *RS1*, early selective filtering works very well for the low noise target condition, with the probability of *RS1* producing an error ($\boldsymbol{p(RS1_0)}$) being very small across all levels of flanker noise. For Study 2, we found that this probability increased with increasing flanker noise, was overall higher for incongruent trials and the difference between the two trial types increased with increasing noise. In other words, early selective filtering was poorer with increasing noise, which by now we can attribute to the increase in noise of the target. The most interesting aspect of these results, however, pertains to the high noise target condition. Recall that in the analysis of average performance, we found a beneficial effect of increasing flanker noise on incongruent trials and the opposite for congruent trials, contrary to the predictions of the target-flanker similarity hypothesis. When comparing the fits of the models to the average ER, we found that DSTP could model these effects, and analysis of $\boldsymbol{p(RS1_0)}$ shows how DSTP accounted for these differences. DSTP suggests that the differential effect of increasing flanker noise on incongruent and congruent trials can be localized to *RS1*, the efficacy of which is determined by perceptual filtering. As $\boldsymbol{\mu Fl}$ shows, more attentional weight is assigned to flankers overall when the target is noisy and the noisier the flankers, the less weight they receive. In congruent trials, attending to flankers is likely beneficial given that they share the same response as the target and the extent of this benefit would be directly determined by the level of noise they contain, where low noise flankers would provide a greater benefit. However, the opposite is true for incongruent trials, where attending to flankers is costly. As the flankers become noisier, the benefit for congruent trials is lost, and $\boldsymbol{p(RS1_0)}$ increases with flanker noise. In contrast, the reverse is true for incongruent trials: as the flankers become noisier, $\boldsymbol{p(RS1_0)}$ sharply decreases. Across the three studies, $\boldsymbol{p(RS1_0)}$ demonstrates a continuum of the selectivity of early filtering depending on the noise level of the target, where if the target is less noisy, selectivity is high and if the target is noisy, selectivity is poor and becomes increasingly poorer as the noise level in the flankers decreases.

The behavior of the late selection mechanism is governed by the selection boundary $\boldsymbol{C}$ and the drift rate of this process $\boldsymbol{\mu SS}$. These parameters show similar effects, in that the estimates for Study 2 lie diagonally between the estimates for Study 3. In turn, the probability of late selection being engaged mirrors this pattern. Specifically, in Study 2, the probability of selection ***p(Selection)*** decreased with increasing target-flanker noise. For Study 3 however, ***p(Selection)*** is independent of flanker noise for both the low and high noise target conditions, where ***p(Selection)*** is consistently low for the high noise target condition and consistently high for the low noise target condition. These effects are mirrored in the other measures related to late selection. Firstly, the probability of incorrectly selecting the flanker (and the probability of making an error in *RS2*, $\boldsymbol{p(RS2_0)}$ is low in the low noise target condition, high in the high noise target condition and the estimates for Study 2 lie in between. Likewise, as illustrated by the ***suppression ratio***, selection occurs early in the low noise target condition, later in the high noise target condition and the estimates for Study 2 again lie in between. The critical point of these results is that DSTP also suggests that the effects we find in Study 2 are primarily the result of changes in the noise level of the target: if the target is noisy, early and late filtering show poorer selectivity, yet if the target is less noisy, we see clear benefits in both.

## Discussion

To summarize, the aim of Study 3 was to test the predictions of the target-flanker similarity hypothesis, which suggests that the more similar the items are, the larger the flanker effect. We postulated that the reason that the flanker effect increased with noise in Study 2 was because target and flankers become more similar and are grouped in high noise conditions and this in turn hindered the transition to a more focused mode of attention. Study 3 tested this assumption by manipulating target-flanker noise independently. In one condition, the target was high noise (80%), whereas in the other, the target contained little noise (10%). We then manipulated flanker noise across the same four levels used in Study 2. The target-flanker similarity hypothesis would predict that, for the high noise target, the flanker effect should increase with increasing flanker noise, since the items become more similar as flanker noise increases. Similarly, although the low noise target is always somewhat ‘different’ to the flankers, we predicted that the flanker effect would also increase with increasing flanker noise. The reason for this was the lack of a significant flanker effect in the low noise conditions of Study 2, which, if the target-flanker similarity hypothesis is correct, suggests that target and incongruent flankers are most dissimilar when they both contain little noise. Thus, as flanker noise increased, we expected the effect to increase. In line with the target-flanker similarity hypothesis, we found that the high noise target condition showed larger flanker effects overall, however, in direct contrast to this hypothesis, we found that the flanker effect decreased with increasing noise for the high noise target, whereas for the low noise target, no effects of flanker noise were found. In other words, this suggests that high noise targets are overwhelmed by flankers and the detrimental effect of incongruent flankers is inversely related to the noise they contain: the ‘stronger’ the flankers are, the more likely they are to overwhelm the high noise target. In contrast, the low noise target seems robust to flanker effects. Regardless of the level of flanker noise, we observed no significant flanker effect.

These findings were supported by the distributional analysis also. For the high noise target, we found evidence of increasingly poorer flanker suppression as the noise level of the flankers decreased and this was mirrored in the EAP estimates of both models. Specifically, SSP suggested that the attentional spotlight is wider, and the duration of interference is overall longer for the high noise target and becomes increasingly longer as the noise level in the flankers decreases, whereas for the low noise target, the duration of interference is shorter overall and is not modulated by flanker noise. DSTP predicted a similar result, in that early perceptual filtering is poorer if the target is noisy and becomes increasingly poorer as the noise level in the flankers decreases. While this poorer filtering is beneficial for congruent trials, it is detrimental in incongruent trials. Furthermore, DSTP suggested that the onset and efficacy of the late selection mechanism is determined purely by the level of noise in the target, where noisy targets lead to less frequent involvement of the late selection stage. Indeed, only parameters related to early filtering showed effects of flanker noise, whereas the late selection parameters showed only an effect of target noise. Specifically, across all levels of flanker noise, the probability of entering the focused mode of attention was consistently low when the target was high noise and consistently high when the target was low noise. Not only is the late selection stage engaged less frequently with high noise targets, when it is engaged, it is engaged later (consistent with SSP's prediction that interference persists longer with high noise targets) and is prone to errors. In summary, SSP predicted that high noise targets lead to a longer duration of interference, where the duration of this interference increases as the level of noise in the flankers decreases. Similarly, DSTP suggested that the switch to the focused mode of attention occurs later with high noise targets and that early perceptual filtering is poorer compared to when the target contains little noise. The critical aspect of these results overall is that they suggest: 1) the Study 2 results were driven by a change in target noise, where stronger (lower noise) targets are less vulnerable to flanker interference; and 2) that the effect of flanker noise on the target is dependent on the target itself, whereby high noise targets are vulnerable to flanker interference and this vulnerability increases as the flankers become stronger. These results stand in contrast to the predictions of the target-flanker similarity hypothesis and in contrast to an explanation based on the response evidence provided by the flankers. Therefore, an alternative account is required.

Instead, we propose an argument based on saliency, where the saliency of the target is the main factor determining the switch to a focused mode of attention. This formulation stems from the fact that both models suggested that the attentional weight assigned to the same stimulus varies depending on the noise level of the flankers. For example, SSP suggests the initial width of the spotlight and the perceived perceptual strength of a high noise target ***pTarget*** changes depending on flanker noise, while DSTP suggests that the attentional weight to the high noise target ***μTa*** changes depending on flanker noise. Since DSTP was the superior model, we base our explanations mostly on the effects predicted by DSTP, although the same idea is supported by SSP. The fact that attentional weight to the same target changes depending on its context, suggests that the representation of the target during early filtering also changes across conditions. We assume that these differences reflect the saliency of the target across different conditions. The saliency of a stimulus describes the extent to which an item stands out in a visual scene and is determined by the relationship between an item and its surroundings. Models of saliency assume that the visual scene is represented as a topographically organized saliency map, where saliency is computed by bottom-up stimulus driven factors before being modulated in a top-down manner by the goals of the observer (Bruce & Tsotsos, 2009; Itti & Koch, 2000; Koch & Ullman, 1985; Zhang et al., 2008). Attention is then directed to items in order of decreasing saliency.

Firstly, we argue that high noise targets are less salient than low noise targets partly because their intensity is lower in relation to the surrounding elements. As flanker noise decreases, high noise targets become even less salient as the higher intensity flankers overwhelm the percept of the target, accounting for the decrease in ***μTa*** (and the increase in ***μFl***) as flanker noise decreases. In other words, early representations of the target achieved through early filtering become increasingly poorer as the noise level in the flankers decreases. We assume that this early filtering provides input to the late selection mechanism responsible for target selection.

Although DSTP does not assume a dependency between early and late selection, Hübner et al. (2010) recognized this assumption as a plausible one. Specifically, we assume that the challenge of target selection faced by late selection is greater when the incoming representation from early filtering is poorer. Indeed, our modelling results show that the drift rate of the late selection mechanism ***μSS*** is also dependent on the level of noise in the target, where low noise targets lead to a lower drift rate. In turn, the time taken to select the target is longer and the flanker effect increases. This is further supported by the ***μRS2*** parameter which increases with increasing flanker noise for high noise target. Recall that this parameter determines the drift rate for *RS2* once a stimulus is selected. Assuming that the quality/strength of the selected item will determine with drift rate, this demonstrates that the representation of a selected high noise target is poorer when it is presented with low compared to high noise flankers. For a low noise target, we assume the same is true. That is, lower noise flankers can degrade the percept of the target. However, given that the target location is known, observers can modulate the saliency of the target in a top-down manner to improve its representation. Simply put, the target location receives higher priority. When the target is low noise, this modulation, combined with the higher intensity of the target is sufficient to allow the target to be perceived as more salient than the flankers and target selection is easier as a result. In contrast, for a high noise target, this top-down modulation is insufficient to counteract the effect of the highly salient flankers and the representation of the target remains poorer.

Although our results do not align with the grouping by similarity hypothesis, Moore et al. (2021) put forward a slightly different account of why increased target-flanker similarity leads to increased flanker effects and this hypothesis is similar to the saliency hypothesis presented here. Specifically, Moore et al. (2021) suggested that the effects of target-flanker similarity do not reflect grouping but rather differences in the quality of visual input. Under their ‘image-segmentation’ hypothesis, they proposed that when targets and flankers are similar, there are no feature discontinuities that support the segmentation of target and flankers into individual objects. This in turn leads to poorer visual input and prolongs the switch to a more focused mode of attention. Conversely, when target and flankers are dissimilar, the presence of these feature discontinuities improves the visual input and subsequently reduces the flanker effect. The study of Driver & Baylis (1989) noted in the General Introduction is useful for distinguishing between these two viewpoints. Recall that Driver & Baylis (1989) found that distant flankers grouped with the target by common motion caused more interference than near flankers not grouped with the target. Their results are consistent with the grouping and not the image segmentation account since all displays were the same in terms of the presence of feature discontinuities. As such, the image segmentation hypothesis would predict that the common fate manipulation would have no effect, when this was not the case. However, later studies failed to replicate the results of Driver & Baylis (1989) (Berry & Klein, 1994; Kramer et al. 1991) and in a series of experiments manipulating target-flanker similarity, Moore et al. (2021) demonstrated that their results were inconsistent with the grouping argument but consistent with the image segmentation hypothesis. Essentially, the image-segmentation hypothesis assumes that the speed of the selection process is dependent on the quality of the input, whereby the lower the discriminability between targets and flankers, the poorer the visual input and the longer it takes to ‘select’ the target from the flankers. If we assume that the reduced saliency of the target leads to a poorer visual input (at least in terms of the representation of the target), then the image-segmentation hypothesis could potentially explain our findings here.

Given that the results were unexpected, we postulated whether these effects are specific to motion stimuli or whether they can be generalized to other featural domains, namely that of color. To test this, we conducted a flanker task using static fields of colored dots, a proportion of which could be colored either red or cyan, while the noise dots were assigned a random hue. Like in Study 2, we manipulated the percentage of noise dots across the same four levels (10%, 40%, 70% and 80%) and expected to find the same effects as in Study 2. Specifically, we expected that the flanker effect would again increase with increasing noise and that the parameter estimates of both models would yield similar patterns as in Study 2. This would allow us to confirm that the noise level in the target, and how this influences saliency, is the critical factor determining interference and that the effect is not specific to RDKs. In the next chapter, we present the results of this ‘color noise’ task as well as the fits and predictions of both SSP and DSTP.

# Chapter 5

# Color Noise

## Introduction

The surprising results of Studies 2 and 3, led us to wonder if these effects are specific to RDKs or the motion domain. We formulated a hypothesis for these results which suggests the saliency of the target determines the extent to which flankers will interfere, however we wished to explore whether this saliency hypothesis could apply to static color stimuli also. To test this assumption, we created a task in the color domain which could be somewhat comparable to the first RDK task in which we manipulated target-flanker noise simultaneously. For this ‘color noise’ task, we created static dot patterns, which we refer to as random-dot patterns (RDPs), in which a given percentage of the dots were colored a given target color (either red or cyan), while the color of the noise dots was chosen pseudo-randomly (see Stimuli section for details). Given the results of the RDK tasks, we expected to find a similar relationship between noise and congruency, in that the congruency effect would decrease as noise decreased. Such a finding would suggest that the attentional mechanisms controlling the change in the congruency effect across noise conditions operate similarly regardless of the feature used. In other words, the increase in the congruency effect with noise found in the motion task is not just specific to the RDKs, but rather a general effect of perceptual noise observable across different featural domains which is driven by saliency. In anticipation of our results, we did not find this effect. Instead, in contrast to Study 2, perceptual noise had a considerably weaker influence on the flanker effect for color stimuli. Importantly, despite this discrepancy, the results still align with our saliency hypothesis.

# Method

## Participants

Participants were recruited through the University of Birmingham's Research Participation Scheme in exchange for course credit. Although 39 participants took part, 3 were removed (2 participants were removed due to unusually low accuracy (83.62% and 59.55%), and a further participant was removed because of unusually slow average RT (633.63ms). This left 36 participants in the final sample, (33 females, 2 males and 1 non-binary person) with a mean age of 19.42 years.

## Procedure & Design

Participants were instructed to identify the 'coherent color' in the central RDP and response using keypresses. As in the motion task, we varied the percentage of randomly colored (noise) dots across four levels: 10%, 40%, 70% and 80%. The procedure was identical to the motion task and followed the same procedure outlined in the General Method section. By the end of the experiment, each participant had completed 64 trials per combination of noise level and congruency.

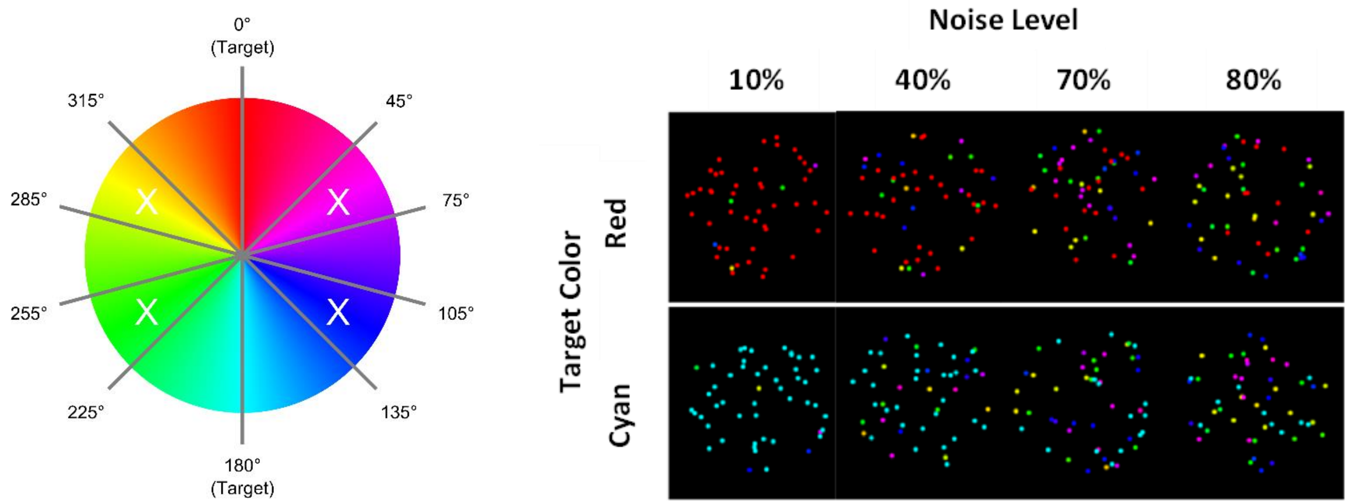
## Stimuli

To create the color RDP patterns, we modified the jspsych-RDK (Rajananda, Lau & Odegaard, 2017) plugin used to create the RDKs in Study 2. We added an extra input of dot color and set the speed of the dots to 0 to make them static. The specifications of the RDPs (dot size, aperture size, target-flanker spacing etc.) were identical to the motion task of Study 2.

Again, due to the COVID-19 pandemic, the task had to be run online. As such, controlling for differences in color properties such as isoluminance across participants was challenging. For the stimulus colors, we used HSL space, where all dots had the same saturation (100) and luminance (50) value and differed only in their hue. Target colors were defined as true red (0 degrees in HSL space) and true cyan (180 degrees in HSL space). While in the RDK task, the random direction of noise dots could be sampled from all 360 directions, we found that doing this in the color domain distorted the effect of noise. For example, since the RDPs contained only 50 dots, often noise dots could be sampled too closely to the target color. Likewise, in HSL space, green and blue hues represent a disproportionate amount of the color space compared to other hues. Thus, to ensure our noise manipulation had the desired effect, we chose to restrict the area of color space from which noise dot hues were sampled. Firstly, to address the problem of noise dots being sampled too closely to the target colors, we added a restricted, ‘padding’ area of 45º either side of each target color, from which noise dot hues could not be sampled. Then, to address the disproportionate representation of different hues, we removed two further areas from the color wheel, namely hues between 75º and 105º and hues between 255º and 285º. This meant that noise dots could be sampled from one of four areas: 45-75º, 105-135º, 225-255º and 285-315º. The left panel of Figure 15 shows the HSL color space (hues only) with the non-restricted (sampled) noise hue areas marked with ‘X’. Within each of these four non-restricted areas, we selected 90 uniformly spaced hues to create a total of 360 noise hues from which noise dots could be sampled. The right panel of Figure 15 shows examples of the resulting RDPs for each noise level.

**Figure 15**

Study 4: Adjusted HSL color space and resulting RDP stimuli for Study 4.




Left panel: Noise dots could only be sampled from areas marked 'X', while targets dots were either true red or true cyan.

Right panel: Resulting RDPs by target color and noise level.

# Results

## Behavioral Analysis

### Average Performance Analysis

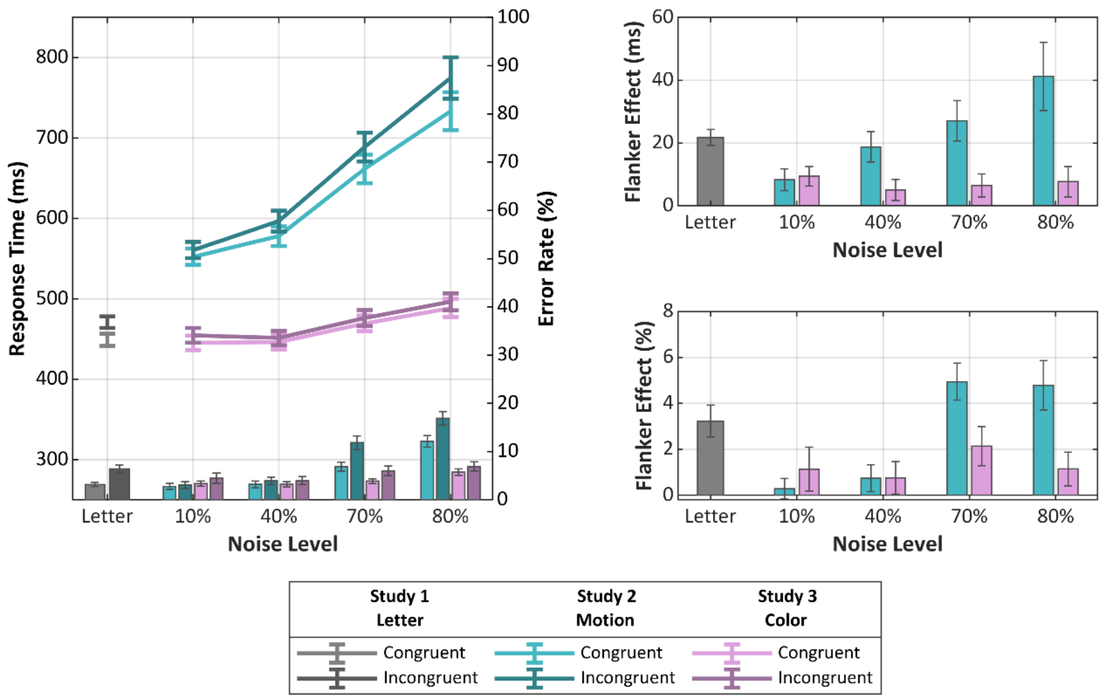
RTs faster than 150ms and slower than 3000ms were removed from analysis which accounted for 0.18% of the data. Median RTs for each condition were then subject to a 2 x 4 repeated measures ANOVA with factors Congruency (Congruent and Incongruent) and Noise Level (10%, 40%, 70% and 80%). These results are shown in Figure 16, along with the results from the letter task (Study 1) and the first RDK study (Study 2).

The results showed the typical congruency effect, $F(1,35) = 13.578$, $p$ = <.001, $\eta_p^2$= .280), with the RTs in the incongruent condition being on average 7.1ms slower than the congruent condition. The main effect of Noise Level was also significant ($F(3,105) = 76.007$, $p$ = <.001, $\eta_p^2$= .685). As expected, overall RT increased as Noise increased (10%: 449.9ms; 40%: 448.7ms;

70%: 472.8ms; 80%: 492.4ms). Critically and unlike the motion task, the interaction between Congruency and Noise Level was not significant ($F(3,105) = .239$, $p = .869$, $\eta_p^2 = .007$).

**Figure 16**

Study 4: Average RT and error rate for across all 36 participants in the color noise task. The results from Study 2 are included for comparison.




The left panel shows the average RT and error rate for congruent and incongruent conditions for each condition. The top right panel shows the average congruency effect in RT, while the lower right panel shows the average congruency effect in error rate. Error bars represent the standard error of the mean.

We performed the same analysis on the arcsine transformed ERs. Although slightly more errors were made in incongruent compared to congruent trials, with the average congruency effect being 1.3%, the effect of Congruency was not significant ($F(1,35) = 3.467$, $p = .071$, $\eta_p^2 = .090$). The effect of Noise Level was significant ($F(3,105) = 12.465$, $p < .001$, $\eta_p^2 = .263$), with

ER increasing as Noise Level increased (10%: 3.9%;  40%: 3.6%; 70% 4.9%; 80%: 6.3%) Finally, the interaction between the two factors was again not significant ($F$(3,105) = .651, $p$ = .584, $\eta_p^2$= .018).

Next, we explored how these results compared to the motion task in Study 2 by means of a 2 x 4 x 2 mixed ANOVA, with factors Feature (Motion and Color) as a between-subjects factor and Noise Level (10%, 40%, 70% and 80%) and Congruency (Congruent and Incongruent) as within-subject factors. Since the aim of this analysis is to reveal differences between the two featural domains, we focus only on effects that include the Feature factor.

For RT, the interaction between Feature and Congruency was significant ($F$(1,83) = 10.991, $p$ = .001, $\eta_p^2$= .117), which showed that the congruency effect in the motion task (23.9ms) was more than three times as large as the congruency effect in color (7.1ms). There was also a significant interaction between Feature and Noise Level ($F$(3,249) = 44.604, $p$ = <.001, $\eta_p^2$= .350), which showed that, while RT increased with increasing noise in both tasks, the effect was much stronger for Motion than for Color. Finally, the three-way interaction between all factors was significant also ($F$(3,249) = 3.036, $p$ = .030, $\eta_p^2$= .035). While the flanker effect in Motion increased with increasing Noise Level, the flanker effect in Color was not modulated by Noise Level.

We performed the same analysis on the arcsine transformed ERs. Again, the interaction between Feature and Congruency was significant ($F$(1,83) = 4.744, $p$ = .032, $\eta_p^2$= .054), where the flanker effect in Motion (2.7%) was twice as large as the effect in Color (1.3%). Secondly, the interaction between Feature and Noise Level was again significant ($F$(3,249) = 32.349, $p$ = <.001, $\eta_p^2$= .280). While ER increased with increasing Noise Level for both tasks, the effect was much stronger for Motion than for Color. Finally, the three-way interaction between all factors did not reach significance ($F$(3,249) = 1.997, $p$ = .115, $\eta_p^2$= .023).

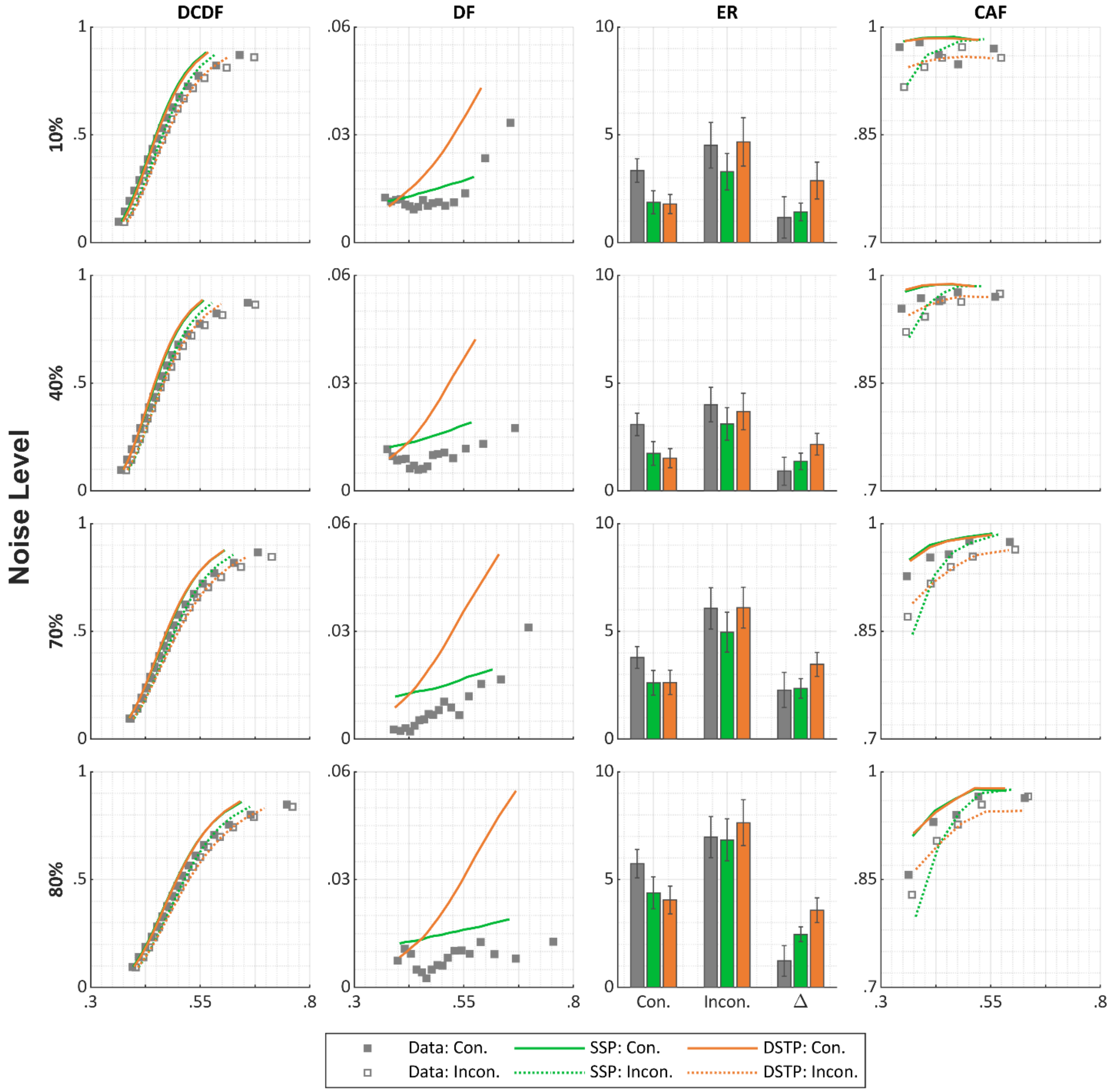
**Distributional Analysis**

We calculated the distributional measures for the color noise task which are shown in grey in Figure 17. Consistent with the average RT results, incongruent trials produced slower RTs across all quantiles, yet this was particularly the case for longer RTs, as expected. The difference (illustrated by the DF) showed no consistent effects across different levels of noise. For example, the DF for the 10% noise condition showed a steep increase for longer RTs. At 40% noise, this effect diminished, reappeared again at 70% noise before diminishing again at 80% noise. At all noise levels, the functions were however rather shallow overall, especially when compared to those found in the motion task.

As reported previously, we found a significant effect of Noise Level on ER for the color noise task, where ER significantly increased with increasing noise for both congruent and incongruent trials. Looking at the CAFs, we see that most of these errors occur for the fastest RTs as noise increases, in other words, the CAFs for both trials show an increase in accuracy from fast to intermediate range RTs and this is particularly the case in higher noise conditions. Regarding the early interference effect, as measured by the difference between the congruent and incongruent CAFs at the first quantile, there were again no consistent differences across noise levels. Instead, the effect was small and fluctuated across noise levels (10%: 5.6%; 40%: 3.2%, 70%: 5.6%; 80: 2.8%). This is consistent with the average performance analysis which suggested that the flanker effect is not dependent on noise in the color task but does depend on noise in the motion task.

**Figure 17**

Study 4: Averaged distributional measures across all 36 participants in the Color Noise task of Study 4.




Note: DCDF: Defective cumulative density function. DF: Delta function. ER: Error rate (%). CAF: Conditional accuracy function.

## Model Fitting

### Bayes Factor

For the color noise task, we found a similar pattern to the motion task, in that the results became more mixed as noise decreased, although there was an overall preference for DSTP. These results are shown in Table 9, along with those from the motion task. At 10% noise, exactly half of participants showed evidence for DSTP, while the other half showed evidence for SSP. However, while the strength of evidence for all participants in favor of SSP was anecdotal, for DSTP, this evidence was of a higher strength. As noise increased, the percentage of participants showing evidence in favor of DSTP generally increased (10%: 50%; 40%: 47.2%; 70%: 72.2%; 80%: 64%), however unlike in the motion task, these differences were less consistent.

**Table 9**

Study 4: Number of participants who fall into each Bayes Factor category for Studies 2 and 4.

| | Study 2 (Motion) | | | | Study 4 (Color) | | | |
|---|---|---|---|---|---|---|---|---|
| | 10% | 40% | 70% | 80% | 10% | 40% | 70% | 80% |
| Extreme (SSP) | 1 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
| Very Strong (SSP) | 0 | 0 | 1 | 1 | 0 | 0 | 0 | 0 |
| Strong (SSP) | 1 | 1 | 2 | 5 | 0 | 1 | 0 | 0 |
| Moderate (SSP) | 1 | 4 | 3 | 5 | 0 | 1 | 2 | 2 |
| Anecdotal (SSP) | 17 | 14 | 11 | 7 | 18 | 17 | 8 | 11 |
| Anecdotal (DSTP) | 15 | 12 | 10 | 8 | 7 | 10 | 10 | 9 |
| Moderate (DSTP) | 8 | 5 | 10 | 8 | 7 | 3 | 6 | 7 |
| Strong (DSTP) | 1 | 4 | 4 | 4 | 1 | 1 | 3 | 6 |
| Very Strong (DSTP) | 3 | 3 | 3 | 6 | 1 | 3 | 3 | 1 |
| Extreme (DSTP) | 2 | 6 | 5 | 5 | 2 | 0 | 4 | 0 |

Note: Since we fit all both models to each participant and condition separately, the number of participants in each category sums to the total number of participants (N = 49 and N = 36).

**Quality of Fit**

The simulated distributional measures are shown along with the data in Figure 17. Both models captured the early quantiles well across all noise levels, yet mismatched the tails of the distributions, predicting RTs that were too fast. As was the case in our previous studies (including the motion task of Study 2), the predictions for congruent trials were very similar for both models yet differ for incongruent trials, particularly in the later quantiles. Namely, SSP again predicted incongruent RTs that were too fast, whereas DSTP's fit to the incongruent DCDFs were slightly better.

Despite this, the DF suggests that SSP is better at modelling the congruency effect over time. However, like in the motion task, this was not because SSP fitted the data better overall, but rather because it underpredicted RTs in the incongruent condition. In other words, DSTP appeared to better match the absolute values of the incongruent DCDF yet overestimated the congruency effect. Furthermore, in the 10% and 70% noise conditions, DSTP's steep predicted DF better matches the later portions of the DF, at least in terms of its slope. However, because DSTP overestimates the congruency effect in the earlier portions of the DF, there is a clear mismatch. In other words, had DSTP predicted a smaller congruency effect for the earlier RTs, the match to the DF would have been clearly better than SSP. Indeed, for 10% and 70% noise, SSP's predicted DF does not show the steeper increase in the late portions of the DF that we observe in the data.

For ER, the predictions of both models are again very similar for congruent trials yet diverge in incongruent trials. Specifically, both models slightly underpredict ER in congruent trials, although SSP's estimates are marginally closer. For the first three noise levels, DSTP's match to the incongruent ER is almost perfect, whereas SSP underestimates the ER in these conditions. In contrast, for the highest noise condition, DSTP slightly overpredicts ER in incongruent trials, while SSP's estimate is closer. Together, this leads to both models overestimating the congruency effect in ER, with this overestimation being larger for DSTP than for SSP. However, considering the results as a whole, ER appears to be better modelled by DSTP.

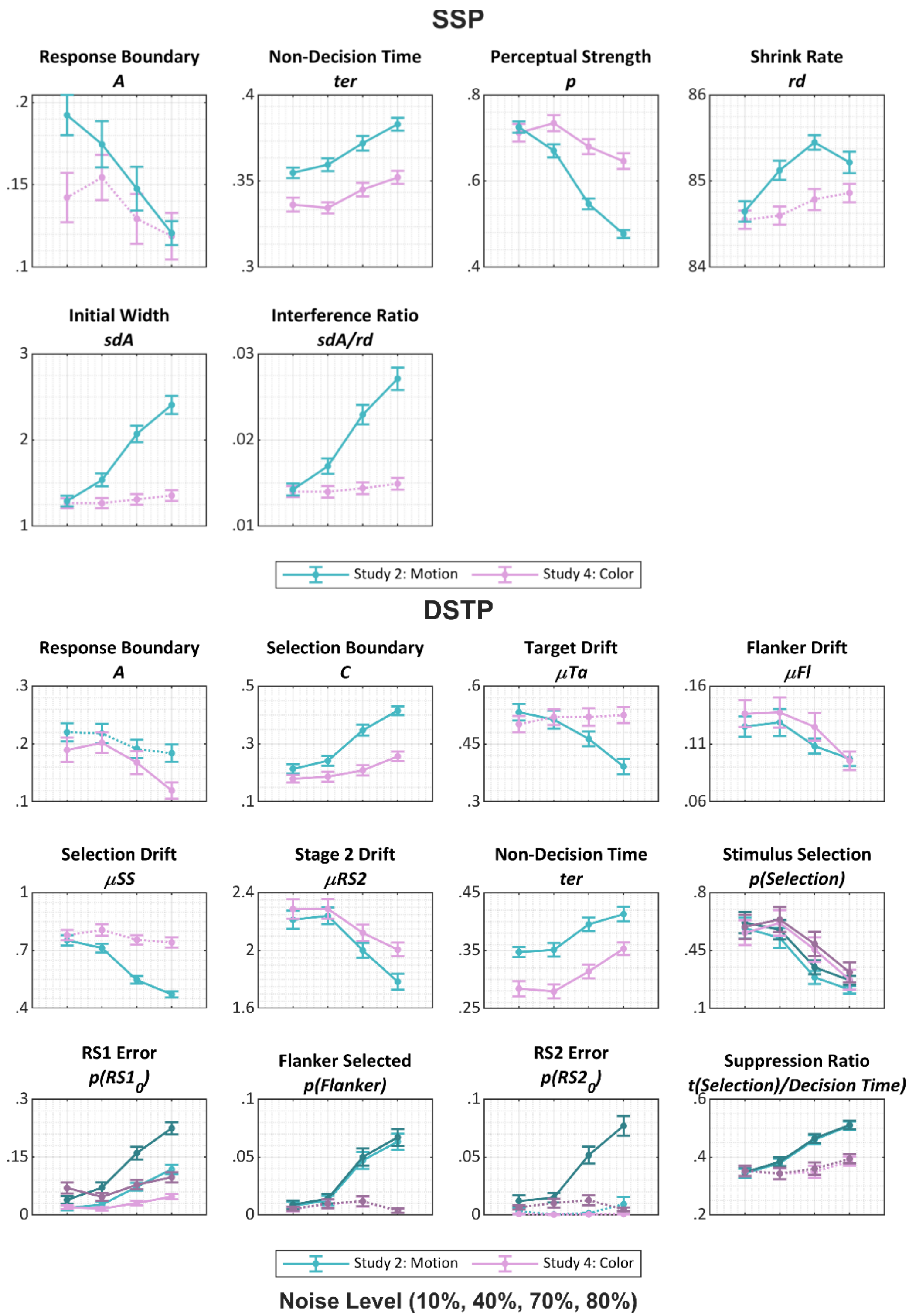
The CAFs for both models are again similar for congruent yet differ in incongruent trials. Firstly, for lower noise conditions, the CAFs are unusual in that they show a crossover effect, although this is likely due to noise in the data and neither model captures this effect. Despite this, the predictions for both models are rather good, although SSP is slightly better since the predicted steep incongruent CAF allows it to better match the early quantiles. However, like in the motion task, the model predictions diverge as noise increases. Specifically, DSTP provides a better match to the incongruent CAF, particularly for the intermediate quantiles. Again, like the motion task, SSP's steep incongruent CAF allows it to better match the earliest quantile in high noise conditions, yet this steepness leads to an overprediction of accuracy at the latest quantiles. Furthermore, SSP underpredicts the latency of these later responses and the latest quantile of the CAF is at a latency slightly shorter than that observed in the data. In contrast, DSTP's estimate is clearly closer, despite the slight underprediction of accuracy in the later quantiles.

### EAP Estimates

The average EAP estimates for the color noise and RDK task are shown in Figure 18, where solid lines represent significant effects of noise while dotted lines represent nonsignificant effects. In the following sections, our main focus is how the parameters differ across the color and motion tasks.

**Figure 18**

*Average EAP estimates for averaged across participants in each task of Studies 2 and 4.*




Note: For DSTP, the simulated measures (*p(Selection)*, *p(RS1₀)*, *p(Flanker)*, *p(RS2₀)* and *suppression ratio*) can be calculated for incongruent and congruent trials separately. In these cases, darker (lighter) lines represent incongruent (congruent) trials.

**SSP**

We have already established clear differences between the color and motion task, the main difference being that the flanker effect appears to be influenced by noise more so in the motion task and this is evident in the EAP estimates also, where the effect of noise is weaker for color than for motion. This implies that, despite the noise level in the RDPs/RDKs being the same, the color RDPs span a narrower range of noise levels than the moving RDKs.

Firstly, the response boundary parameter for the color noise task shows a similar effect as for the motion task in that it decreases with increasing noise. However, while the effect is significant for the motion task, this is not the case for the color task. Furthermore, the boundary is overall lower for color than motion. Considering that the color task appears to be easier overall (RTs are faster and ERs are smaller), this could be interpreted as participants responding less cautiously in the color task, simply because it is easier. However, this stands in contrast to our interpretation of this parameter for motion, where we found the highest response boundaries in low noise conditions, conditions where RTs were faster, and ERs were smaller. We postulated that, in the motion task, this effect may arise due to participants terminating the decision process early in difficult (high noise) trials due to a sense of urgency. Given this, it could be said that the same applies to the color noise task and that the sense of urgency is more pronounced with color since RTs are faster overall, however, given that flanker suppression appears to operate well in the color noise task, if this sense of urgency is present, then it has a minimal effect.

The non-decision time parameter shows similar effects across the two tasks, albeit that non-decision time is clearly faster in the color than in the motion task. Again, we assume that our manipulations do not influence motor response execution time and therefore interpret this effect as faster perceptual encoding of color stimuli. Indeed, previous research has suggested that there is an asynchrony between the perception of color and motion, with motion being perceived between 50-118ms slower than color (Livingstone & Hubel, 1987; Moutoussis & Zeki, 1997; Viviani & Aymoz, 2001). Furthermore, although the effect of noise is significant in both tasks, the increase with increasing noise is slightly shallower for color than for motion.

For the perceptual strength parameter, we see an interesting pattern which suggests that the color stimuli were perceived as less noisy than the RDK stimuli. Firstly, although in the 10% noise condition, the estimates for color and motion are identical, this is not the case for higher levels of noise. Instead, the 'high noise' color stimuli appear to have levels of perceptual strength comparable to low noise RDKs. Secondly, although the estimates for color do decrease with increasing noise, this effect is less pronounced than in motion. Despite the object noise level in the two tasks being the same, this would again suggest that the range of noise in each task was different. Namely, the color RDPs appear to span a lower and narrower range of noise levels than the RDKs.

For the shrink rate parameter ***rd***, the estimates are again identical for the lowest noise level yet are smaller for color than for motion as noise increases. Furthermore, while ***rd*** is strongly influenced by noise in the motion task, this effect is not significant for the color task and the same is true for the initial width of the spotlight ***sdA***. Instead, while the estimates for the 10% noise condition are again identical, the width of the spotlight is consistently low for the color task, whereas it steeply increases for the motion task and the same effects are mirrored in the interference ratio. In other words, the duration of interference is consistently short for the color task, most comparable to low noise conditions in the RDK task.

**DSTP**

Like SSP, DSTP predicts that non-decision time increases with increasing noise and is longer for motion than for color. Contrary to our original expectation and similar to the predictions of SSP, ***μTa*** remains constant and high across noise levels for the color task, whereas for the motion task, ***μTa*** steadily decreased with increasing noise. This can be interpreted in one of two ways, either that the noise manipulation in color had no effect or that the attentional weight given to the color target is independent of noise. Since we found significant effects of noise on overall performance for the color task, we assume the latter is the most likely explanation. That is, early perceptual filtering operates very well for color regardless of the noise level.

In contrast, for ***μFl***, the estimates decrease with increasing noise as was the case in the motion task. However, despite the estimates for color being slightly higher than for motion, when combined with ***μTa***, early perceptual filtering operates more efficiently in color than in motion. In Figure 18, this is illustrated by the probability of *RS1* producing an error $\boldsymbol{p(RS1_0)}$, which is clearly lower for color than for motion, even at the highest levels of noise. Despite this however, $\boldsymbol{p(RS1_0)}$ is indeed influenced by noise in the color task, where errors in *RS1* are more likely in high noise conditions, however the effect of noise is much weaker than for motion. Given that early filtering operates well in the color task, we attribute this effect to the significant decrease in response boundary ***A*** with increasing noise. Since lower boundaries lead to less accurate responses, this could explain the increase in $\boldsymbol{p(RS1_0)}$ with increasing noise. Note that like in Study 2, there are clear differences in the predictions of each model regarding the response boundary, with SSP predicting that noise significantly influences the response boundary in the motion task but not the color task, while DSTP predicts the reverse.

The late selection parameters show similar effects to the early filtering parameters, in that late selection operates more often in color than in motion and is unaffected by noise, with the estimates for color being most similar to low noise RDK conditions. Specifically, the drift rate for the selection process ***μSS*** is consistently high and in turn, the probability of selecting an item ***p(Selection)*** is higher for color than for motion. Not only is a stimulus selected more often in color, but this process is more efficient: the probability of incorrectly selecting the flanker ***p(Flanker)*** and producing an error in RS2 ***p(RS2$_0$)*** are both consistently low for color. Likewise, the onset of the late selection mechanism (reflected in the ***suppression ratio***), is earlier for color than for motion, leading to an overall shorter duration of interference, regardless of noise.

A common theme across both models is the assumption that color RDPs are perceived as being less noisy than moving RDKs and the drift rate for RS2 (***μRS2***) supports this point also. Firstly, the estimates are higher for color than for motion. Recall that DSTP takes an 'all or nothing' approach to flanker suppression, where once an item is selected, ***μRS2*** is driven exclusively by that item. The higher the perceptual strength of said item (or the lower the level of noise), the higher the drift rate and the higher the estimates for color stimuli. Interestingly, unlike most parameters related to late selection, ***μRS2*** does decrease with increasing noise for the color task. Given that attending to a narrower region allows for more fine-tuned discrimination (Müller et al., 2003), this high concentration of resources to the selected item means that focused attention is likely more sensitive to the effects of noise and therefore noise has an effect in both motion and color. However, in agreement with the idea that the color noise stimuli span a smaller range of noise levels, the effect of noise is weaker for color.

So far, we have neglected the fact that ***p(Selection)*** also decreases with noise for color. In Study 2, we interpreted this effect as late selection being hindered by the presence of noise, yet the effects of ***p(Selection)*** for color would suggest this is not the case, especially given that the color noise task shows lower levels of interference overall. However, in Study 2 we demonstrated that noise did indeed have a detrimental effect on the late selection mechanism, in that its onset was later and its selectivity was poorer. In contrast, although ***p(Selection)*** decreases with noise for the color task, its selectivity is high and its onset is early, regardless of the noise level, suggesting that for color, the decrease in ***p(Selection)*** does not represent a hindering or disruption of this process. Instead, we attribute these effects to the response boundary also. That is, ***p(Selection)*** decreases with increasing noise in the color task, simply because the lower response boundary for high noise conditions increases the probability that the response process will terminate before the selection process and ***p(Selection)*** is lower as a result. Likewise, our ***suppression ratio*** controls for the effects of response boundary since it is normalized to account for overall decision time. In other words, the later onset of stimulus selection with increasing noise in the motion task cannot be attributed to response boundary effects and instead suggests a disruption of this mechanism. We therefore interpret the effects of ***p(Selection)*** in the motion task as reflecting this disruption also.

## Discussion

To recap, the purpose of the color noise task was to test whether the effects of noise found in Study 2 could be generalized to the color domain or were specific to motion or the RDKs. Since previous research has proposed a unified attention system spanning both static and dynamic stimuli in the flanker task (Lange-Malecki & Treue, 2012), we expected to find the same effects in both tasks, namely that the flanker effect would increase with increasing noise in the color task also, yet this was not the case. Instead, the flanker effect in the lowest noise conditions was comparable across color and motion, yet as noise increased, the congruency effect in the color task remained consistently small, while the effect in the motion task scaled with increasing noise. The distributional measures for the color task agreed with the average performance analyses, in that there were no consistent differences across levels of noise. Instead, the results suggested that at all levels, flanker suppression was highly efficient, illustrated by shallower DFs and CAFs which showed small early interference effects yet converged for the latest responses. In contrast, for the motion task, the DF became increasingly steeper as noise increased and the CAFs showed a lack of convergence.

Regarding model comparison, we found a clear preference for DSTP for both tasks, although the strength of this evidence was greater for motion than for color. Furthermore, while the number of participants showing evidence for DSTP increased with increasing noise for the motion task, this was less the case for the color noise task, where a clear preference for DSTP was found for all noise levels. By analyzing the simulated data, we could attribute this finding mostly to DSTP's superior ability to model incongruent trials, where the incongruent DCDF, CAF and average ER were all better modelled by DSTP. This was true for both the color and motion tasks, although in the motion task, the greater evidence can be attributed mostly to DSTP's ability to model nonconverging CAFs, an effect that is not present in the color noise data. Most critically however, analysis of the EAP estimates consistently supported the notion that, despite the RDKs and RDPs being matched on their objective noise level, color RDPs were perceived as being less noisy and spanning a narrower range of noise levels than moving RDKs. Specifically, both models suggested that the perceptual strength and attentional weight assigned to color noise stimuli was most similar to the low noise RDK condition across all levels of noise.

The fact that we could not replicate the same effects in the color domain would suggest that our saliency argument does not apply to color stimuli, yet we argue that this is not the case. To recap, our argument was based on the idea that the more salient the target, the easier it is to select the target from the flankers and the smaller the interference. The consistent finding that the color stimuli were perceived as having higher perceptual strength (and possibly higher saliency) means that this argument cannot be ruled out. We propose that, despite us attempting to match the noise level across all color and motion stimuli, the ‘high noise’ color stimuli are just as salient as low noise RDKs. A wealth of research suggests that when a target is highly salient, it effortlessly attracts attention and shows no influence of distractors (e.g. pop out searches, Treisman & Gelade, 1980). Just as observers can easily select the target in low noise RDK conditions, we assume that this selection is equally easy for the color stimuli across all levels of noise. Accordingly, this effortless selection of highly salient color targets leads to no effect of the flankers. In other words, if we assume there is some given threshold which determines whether or not a target is salient enough to be easily selected, then the low noise RDK stimuli and all color stimuli lie above this threshold and our target saliency argument remains valid.

# Chapter 6

# General Discussion

## Recap of Findings

This thesis had two major aims. First, we aimed to explore how selective attention deals with perceptual noise and how this influences the flanker congruency effect. Secondly, we aimed to find more decisive evidence for whether a discrete or gradual improvement in selectivity provides the best account of attentional focusing in the flanker task. To reach the first aim, we conducted three flanker tasks in which the level of perceptual noise in the items was manipulated along a continuum from low to high noise. To reach the second aim, we fitted both a gradual improvement model (the Shrinking Spotlight Model (SSP) of White et al., 2011) and a discrete improvement model Dual-Stage Two-Phase Model (DSTP) of Hübner et al., 2010) to the RT and accuracy distributions from all three tasks using Bayesian model fitting, where the parameter estimates of the models allowed us to explain how attention deals with perceptual noise within both theoretical frameworks.

In our first RDK study (Study 2), we manipulated the noise level in target and flankers simultaneously across trials and found the unexpected effect that adding noise to the stimuli increased flanker interference. These results were also supported by our distributional analyses, which showed evidence of increasingly poor flanker suppression as noise increased, with both models providing converging evidence that high noise conditions lead to a longer duration of interference and a larger flanker effect. Under SSP, this was reflected in a wider attentional spotlight at stimulus onset and a larger interference ratio, whereas under DSTP, this was reflected in poorer early filtering and a hindering of target selection. We first hypothesized that this effect may stem from target and flankers being subject to perceptual grouping by similarity in high noise conditions yet were able to rule out this hypothesis in Study 3, where we manipulated the level of noise in the target and flankers independently. The most striking aspect of the combined results of Studies 2 and 3 was that the average performance analyses, the distributional analyses and the model predictions all provided converging evidence that the magnitude of the flanker effect is primarily determined by the noise level of the target. Specifically, high noise targets are vulnerable to interference, where the cost of attending to incongruent flankers is inversely related to the level of noise they contain. On the other hand, low noise targets are more robust to interference. To account for these results, we proposed a hypothesis based on saliency which we recap later.

In Study 4, we tested whether these effects could be replicated with static stimuli in a different featural domain, namely that of color. Replicating these results using static stimuli would allow us to confirm that the effects observed in Studies 2 and 3 were not specific to motion or RDKs, but rather reflect a more general effect of noise on selective attention. We devised a flanker task that could be compared to the RDK task, which used static fields of colored dots (RDPs) inspired by the RDKs. Target dots were assigned a target color (either red or cyan), while noise dots were assigned a random hue. Using the same noise levels as in Study 2, we manipulated the percentage of noise dots in target and flanker RDPs simultaneously and randomly across trials. However, we did not find the same effects. Instead, flanker suppression was highly effective across all levels of noise and the EAP estimates of both models suggested that, despite color and motion stimuli being matched on their objective noise level, their perceived noise level differed. Specifically, ‘high noise’ color RDPs were perceived as having levels of perceptual strength comparable to low noise RDKs, and the effect of noise on performance was less pronounced. This alluded to the idea that the color RDPs span a narrower and importantly, lower range of noise levels than the RDKs.

## How does attention deal with perceptual noise?

To account for the results from our noisy flanker tasks, we proposed a hypothesis based on saliency, where the saliency of the target is the primary factor determining whether or not flankers will interfere. To recap, this hypothesis suggests a dependency between early and late selection mechanisms, where the product of early filtering mechanisms provides input to a late selection mechanism responsible for target selection. The onset of this late selection mechanism is determined by the quality of the input received from early filtering, where target selection occurs more effortlessly if the incoming representation is of a higher quality. We believe that high noise targets are more poorly represented during early filtering and their representation becomes increasingly poor as the noise level in the flanker decreases. This is supported by the parameter estimates of both models, which indicate that the attentional weight assigned to the same target differs depending on the noise level of the flankers. Specifically, DSTP predicted that less attentional weight is assigned to a high noise target (***μTa***) when it is presented with low noise flankers and SSP predicted the same effect in its ***pTarget*** parameter. This led us to believe that these differences reflect differences in the saliency of the target across conditions. In particular, a high noise target is less salient when presented with lower noise flankers and becomes increasingly less salient as the intensity of the flankers increases (as the noise decreases). In other words, high noise targets are overwhelmed by low noise flankers. We also assume some amount of top-down modulation of the known target location, allowing the saliency of the target to be increased in a top-down manner, yet in high noise target conditions, this modulation is insufficient to counteract the effect of the more salient flankers. Thus, the representation of the high noise target produced from early filtering mechanisms remains poorer and becomes increasingly poor the lower the noise in the flankers. This representation is then passed to the late selection mechanism, whose aim is to ‘select’ the target from the flankers. If this representation is poorer, the task of selecting the target is more challenging and the late selection mechanism becomes less efficient. Although DSTP does not assume dependency between early and late selection mechanisms, Hübner et al. (2010) recognized the possibility that early selection provides input to late selection mechanisms as a plausible assumption. Indeed, we found that the efficacy of the late selection mechanism in DSTP, which is determined by the drift rate parameter $\boldsymbol{\mu SS}$ was lower in high noise target conditions. Further support for this notion comes from the estimates for the $\boldsymbol{\mu RS2}$ parameter, which shows an increase for the high noise target as the noise level in the flankers increases in Study 3. To recap, $\boldsymbol{\mu RS2}$ determines the drift rate for the response selection process once an item has been selected. If we assume that the value of $\boldsymbol{\mu RS2}$ is dependent on the quality/intensity of the selected item, then the drift rate for the high noise target is higher when the noise in the flankers is lower (since the representation of the target is of higher quality in these conditions). In summary, a high noise target is poorly represented during early filtering due to its low intensity but even more so if presented with low noise flankers. This leads to a greater challenge for the late selection mechanism meaning its onset occurs later, leaving more time for flankers to interfere and a larger flanker effect. Noteworthy is that this poorer selectivity in early filtering appears to be beneficial in congruent trials, since attending to congruent flankers gives more evidence for the target response. Hence, in the high noise target condition of Study 3, we found a steep decline in performance as flanker noise increased for congruent trials and the opposite for incongruent trials. In contrast, low noise targets are more salient overall (partly due to their higher intensity) and are therefore more robust to these effects. We also believe the top-down modulation, combined with the higher intensity of a low noise target, allows the low noise target to be perceived as more salient than the flankers. The result is a higher quality representation of the target in low noise target conditions, more effortless target selection and a reduction in the flanker effect. In the color noise task of Study 4, we failed to replicate the same results found in the RDK task in Study 2. However, our results suggested that, despite matching the color RDPs and moving RDKs on their objective noise level, ‘high noise’ color RDPs were perceived as being less noisy than high noise RDKs, with both models predicting that all color RDPs had a perceptual strength comparable to low noise RDKs. In turn, both models suggested that early filtering operates very well in the color task and that target selection occurs consistently early across all levels of color noise. These results are somewhat in line with our target saliency hypothesis. Given that both models suggested color RDPs are comparable to low noise RDKs, we believe the target is better represented across all levels of color noise and target selection occurs early, hence the very small flanker effects found in the color noise task. It could be argued that the finding that flankers have no influence in low noise target conditions of Study 3 and the color noise task of Study 4 suggest that saliency cannot explain our results. However, research has shown that attentional selection of highly salient items often operates independently of distractor items. For example, take the visual search literature described in the introduction of this thesis. In ‘pop out’ searches, when the target is highly salient, search is equally effortless, regardless of how many items there are in the array. Similarly, we propose that the reason flankers have no effect in these conditions is because the target is highly salient and therefore, attentional selection operates independently of the flanker items. In turn, the level of noise in the flankers has minimal effect. In contrast, when the target is not salient, attention cannot readily select the target and flankers are attended. In turn, their interfering effect is proportional to the amount of response evidence they give for the flanker response.

Finally, regarding differences across noisy and noise-free conditions, our comparison of Studies 1 (letter task) and 2 (RDK task) suggested that the main difference is that high noise conditions lead to poorer and slower flanker suppression. Specifically, while we found evidence of poor flanker suppression in high noise conditions (CAFs that did not converge and steeper DFs), in the letter task, the CAFs did converge and the DF was considerably shallower, even turning negative in the later portions. In terms of our saliency argument, the EAP estimates suggest that the representation of a high noise target is considerably poorer than the letter target, accounting for the larger flanker effect. However, one question remains when considering the other end of the noise spectrum: why do letter stimuli induce larger flanker effects than low noise RDKs? In standard tasks, target and flankers are completely free from perceptual noise, yet decades of research have consistently produced flanker effects, even flanker effects of a considerably larger magnitude than we observed in Study 2, where the largest congruency effect (that in the 80% noise) was 44ms. However, as previous research has shown, noise is clearly not the only factor influencing the flanker effect and we found evidence for this in our comparison of the letter study and RDK study also. Both models suggested that observers respond less cautiously in the letter task and DSTP predicted that a higher attentional weight is assigned to flankers in the letter task compared to low noise RDK conditions. From this, we hypothesized that differences in task expectation are the reason for these effects. That is, letter stimuli lead to larger flanker effects because observers respond less cautiously and adopt a more diffuse mode of attention, mostly because the letter task contains two trial types, 50% of which are congruent and introduce no interference. This ‘hands-off’ approach in turn leaves observers vulnerable to early interference effects in incongruent trials. However, if participants do not response too hastily, flanker suppression occurs very well. We predicted this solely based on the comparison of Study 1 and 2, however Studies 3 and 4 provided strong evidence for our saliency hypothesis which asserts that the noise level in the items influences saliency, which in turn influences attention and the flanker effect. Since DSTP assumed that the partial rate for the letter flankers $\boldsymbol{\mu Fl}$ is significantly higher than the low noise RDK condition, this would suggest that early filtering in the letter task is poorer. Under the saliency hypothesis, it could be said that despite the letter stimuli containing no noise, the letter flankers were more salient than the low noise RDK flankers, possibly because letter items are subject to grouping whereas the opposing motion signals in incongruent, low noise RDK conditions (not present in the letter task), allow for a better presentation of the target. However, DSTP suggested that the attentional weight to the target was the same across these conditions, with only the weight to the flanker differing. These discrepancies between low noise RDK conditions and the letter task are difficult to explain and could stem either task expectations, grouping and/or saliency effects or interactions between these factors. For future work, we would suggest intermixing letter trials with RDK trials in attempt to remove any confounding effects of task expectation and we will return to this point later in the discussion. However, to answer our main research question, that is, how does flanker suppression change across noisy and noise-free conditions, our results provide strong evidence for the argument that noise leads to poorer flanker suppression, where this is determined mostly by high levels of noise in the target.

Our saliency hypothesis is somewhat reminiscent of the "image-segmentation" hypothesis of Moore et al. (2021), who offered this hypothesis as an explanation for target-flanker similarity effects. We previously described how these effects are often attributed to perceptual grouping, whereas Moore et al. (2021) argued that they represent poorer visual input when target and flankers are similar. In turn, the challenge faced by spatial selection mechanisms is greater when the input provides "a relatively indistinct representation of the target separate from the flankers" (Moore et al., 2012, p. 660). However, while the image-segmentation hypothesis measures the quality of the input based on the distinctiveness of the target representation compared to the flankers (in terms of similarity), our hypothesis measures quality based on the quality of the target representation. Important to note however is that this is not to say that the quality of the target representation is not influenced by the flankers, since saliency of an item by definition is determined by the surrounding items. Instead, we argue that, even given physical differences between target and flankers, a target can still be less salient than the flankers. To illustrate this difference, consider the high noise target, low noise flanker conditions of Study 3. Like in the target-flanker similarity hypothesis presented in Study 2, it could be argued that in these conditions, the representation of the target is distinct from that of the flankers (in terms of similarity) as the items largely differ on their noise level, which would suggest that the target can be easily segmented from the flankers. Despite this, we found that these conditions yielded the largest flanker effects. Here we argue that, despite this physical difference, the target is still less salient than the flankers because the low noise flankers have higher intensity relative to the target. By replacing the 'distinctiveness' assumption with one based more on the quality of the target representation, the image-segmentation hypothesis could explain the results here by assuming that poorer representations of the target induced by a reduction in saliency lead to poorer visual input and a later onset of the target selection mechanism. Likewise, the saliency hypothesis could account for target-flanker similarity effects explored by Moore et al. (2021), by assuming a uniquely colored target is more salient by virtue of being unique.

A similar argument was provided by Eriksen & Schultz (1989), who applied their 'continuous flow' model of information processing to explain processing in the flanker task. In this model, the percept of the input improves gradually over the course of a trial and directly feeds (or 'flows') into response mechanisms, in which responses for target and flankers are jointly primed. The authors suggested that the extent of this priming is determined by the amount of featural overlap between an item and the target. That is, when target and flankers are similar, it takes longer to discriminate the target from the flankers and the duration of priming to the flanker response is longer. In turn, this implies that by making the target more distinctive, the length of time needed to discriminate features of the target will be shorter, and the flanker effect will be smaller. To test this hypothesis, the authors manipulated the target in three ways across conditions. In one condition, the target was double the size of the flankers, with the expectation that this would reduce the time needed to perceive its critical features and reduce the flanker effect. In another condition, the target was lower contrast relative to the background with the expectation that this would yield the opposite effect and in their final condition, the target was double the size of the flankers but was low contrast. This latter manipulation would likely yield intermediate flanker effects relative to the other condition and this is indeed what they found. Like the image-segmentation hypothesis, the continuous flow conception could explain our results here also assuming that the time needed to resolve features of the target is dependent on its saliency and the saliency hypothesis may explain the results of Eriksen & Schultz (1979), by assuming that the target is more salient in the size manipulation, less salient in the low contrast manipulation and of an intermediate level in the mixed manipulation of size and contrast.

However, it is worth nothing that the continuous flow model deviates from the assumptions of the DDM, since it assumes response mechanisms are continually primed and responses are flexible. In contrast, the DDM assumes an accumulation of evidence and a distinction between this accumulation stage and later response execution. In addition, evidence for the continuous flow hypothesis directly contradicts the assumptions of the DDM. In the introduction to this thesis, we noted that studies using covert measures of response activation have revealed the existence of ‘partial errors’ in incongruent trials, where a response is partially executed before a correction is made (Burle et al., 2014; Coles et al., 1985; Gratton et al., 1988; Servant et al., 2015). This is strong evidence in favor of a continuous flow model yet contradicts the assumption of the DDM that responses are executed only once the response threshold is breached. Furthermore, choice reaching, and mouse tracking studies have revealed ‘change of mind’ responses in the flanker task (Erb et al., 2021; Erb & Marcovitch, 2018; Kinder et al., 2022; Menceloglu et al., 2021). In these tasks, participants respond by reaching for or moving a mouse to a given response area and analysis of these movement trajectories has revealed higher levels of curvature in incongruent trials, where the trajectory first proceeds towards the flanker response area before a correction is made. This has led researchers to propose extensions of the DDM to account for these findings (Resulaj et al., 2009). These models posit two response boundaries for each alternative, the first of which is a ‘change of mind’ boundary, while the other is the typical response boundary. This extension allows for a flexible DDM, which accounts for changes of mind by assuming the initial response is executed once the change of mind boundary is breached after which corrections can be made before evidence reaches the final response threshold. Since SSP and DSTP are implemented in the typical, two bound diffusion framework and our task used keypresses, we could not explore these changes of mind and our assumptions are based on the DDM framework (that evidence accumulation and responses process are distinct). However, we also acknowledge the fact that our results could be explained by a model that does not assume this distinction, like the continuous flow model. Our tasks could be easily employed in a choice reaching paradigm and future work could extend SSP and DSTP to the ‘change of mind’ framework, where the resulting movement trajectories could be used to further explore the effects of noise on the efficacy of flanker suppression.

Aside from the aforementioned theories, an alternative and slightly different explanation for our results is that selection in high noise target conditions is not hindered due to poor target representation but rather is strategically ‘turned’ off. This explanation was inspired by the results of Rouder & King (2003), who conducted a letter flanker task in which the target was a morph of the letters ‘A’ and ‘H’. The authors found that when flanked by ‘H’s, this ambiguous target was more likely to be identified as a ‘A’ and vice versa when flanked by ‘A’s, which implied that the flankers were used to aid in identification of the ambiguous target. The authors interpreted this as evidence that when the visual input renders insufficient evidence for a response, the attentional system “looks elsewhere” for sources of guidance, where in the flanker task, this alternative source is the flankers. Applied to our task, this would suggest that observers are biased towards a more diffuse focus of attention when the target is high noise, explaining SSP’s prediction of a wider spotlight and DSTP’s prediction of less frequent and slower engagement of late selection in high noise target conditions. In congruent trials, this strategy is likely beneficial since congruent flankers provide evidence for the target response, and this could explain the differential effects of increasing flanker noise on congruent and incongruent trials in the high noise target condition of Study 3. However, contrary to what we find here, Rouder & King (2003) found that this strategy of ‘reaching out’ to the flankers was beneficial and led to a negative flanker effect, where congruent trials yielded poorer performance than incongruent trials. In contrast, when the target was a well-formed letter, a typical flanker effect was found. The authors explained these differences by assuming that flankers introduce a contrastive effect at the perceptual level and response interference at the response level, where the perceptual effects overwhelm the response interference when the target is ambiguous. To be more specific, ambiguous targets induce the ‘contrastive mode’ of attention where, by comparing the target to the flankers, observers can deduce that the target is ‘different’ to the flankers and responses are faster in incongruent trials as a result. On the other hand, well-formed targets are recognised quickly and automatically, leading to a typical flanker effect. Applied to our task, if participants are strategically preserving a diffuse mode of attention with the intention that flankers will aid in target identification, then this strategy backfires in incongruent trials. The idea that uncertainty prompts individuals to seek alternative sources of guidance seems plausible and a broad focus of attention is likely advantageous in some contexts, for example, in tasks that are heavily stimulus driven (Chrysikou et al., 2014). Indeed, in Study 3, ‘reaching out’ to flankers in congruent trials was beneficial to performance and studies using centrally presented Gabor patches with intensity levels close to the detection threshold have found that target detection improves when presented with collinear Gabor patches, where it is thought that the flankers help reduce uncertainty regarding the target (Petrov et al., 2006). Although different from the type of uncertainty we employ through noise here, uncertainty in the flanker task can be induced by varying the location of the array unpredictably and this has been shown to greatly impair performance (Goolkasian & Bojko, 2001; Hübner et al., 2010; Miller, 1991). Under DSTP, Hübner et al. (2010) showed that this manipulation can lead to poorer early filtering or in other words, a reduction in selectivity. It is reasonable to assume that in conditions of uncertainty, poorer filtering or a broader focus of attention could be advantageous. For example, by adopting a less selective approach, one could ensure that attention covers all possible locations where the target could appear to ensure that the target is not missed. However, given that this impairs performance in the flanker task, it appears this strategy is detrimental, just as strategically reaching out to the flankers in our task is detrimental in incongruent, if indeed a more diffuse mode of attention is preserved for strategical reasons. However, while we acknowledge this as a possibility, we believe our target saliency hypothesis is the more likely explanation, especially given the finding that the percept of the target changes depending on its context, something that would be difficult to reconcile with this strategic 'reaching out' explanation.

## Discrete or gradual selection?

Across all studies, the Bayesian approach to model fitting and comparison allowed us to find strong evidence that a discrete improvement model of attentional selectivity (DSTP) better accounts for the data. This, combined with the analysis of distributional data and model predictions allowed us to explain *why* DSTP was superior, and we found that this could be attributed to its superior ability to model patterns consistent with poorer flanker suppression consistently observed with high noise targets. Although we found evidence that DSTP better modelled correct trials, its main strengths were its predictions for error responses and how the relationship between errors and their latency changes based on the duration of interference. A common theme throughout this thesis was that DSTP was able to capture CAFs that showed no convergence, whereas SSP always predicted that participants successfully narrow their attention in on the target. In the letter task (Study 1), we found that while half of participants showed anecdotal evidence for either model, a subset of participants showed extreme evidence for DSTP. These 'extreme' participants showed less typical patterns of data consistent with poorer flanker suppression, namely nonconverging CAFs, a steeper average DF and larger than average congruency effects. While DSTP matched their data well, SSP predicted CAFs that converged and a DF which levelled off. In other words, SSP underpredicted the duration of flanker interference, predicting that attentional selectivity improved too quickly. In Study 2, we found that these patterns of data were the norm rather than the exception, with high noise RDK conditions showing nonconverging CAFs, steeper DFs and larger congruency effects. Consequently, we found an even larger win for DSTP in these conditions, since DSTP fit these patterns remarkably well, whereas SSP again predicted that flankers were suppressed too early. In Study 3, these patterns became ever more prevalent in the high noise target condition as flanker noise decreased. Accordingly, DSTP was found to be the superior model and the number of participants showing extreme evidence for DSTP gradually increased with decreasing flanker noise. Finally, although flanker suppression operated very well in the color noise task of Study 4 and these patterns were not present (that is, the CAFs converged and the DFs were shallower), DSTP was still found to be superior, and this could again be localized mainly to its ability to better model the error responses. In summary, we found that DSTP was the superior model and this superiority lay in its ability to model cases in which flanker suppression was poorer and interference persisted into the longest responses, particularly in terms of the relationship between RT and ER, illustrated by lack of convergence in the CAFs. Despite this however, we also found a clear win for DSTP, albeit to a lesser extent, in the color noise task of Study 4, where flanker suppression operated very well and these patterns were not present.

It is worth emphasizing that the support for DSTP is clearly strong, yet not 100% decisive. This variation of support for either model raises the question whether there are individual differences in the style of attentional selection. Indeed, even in high noise target conditions, some participants still showed evidence in favor of SSP, although the evidence strength was notably weaker. Thus, while the results provide clear evidence for DSTP, we still find some variability across participants, consistent with the mixed results found in previous studies (i.e., Evans & Servant, 2020). For example, it is conceivable that individuals may vary in the strength they bias attention towards a more diffuse mode when faced with perceptual noise and that this would likely lead to a win for DSTP. Research using Navon stimuli has supported this point, where reliance on diffuse and focused attentional states is manipulated by requiring participants to attend to a stimulus at either a global or a local level (Navon, 1977). This line of research has revealed individual differences in the 'perceptual profile' (Chamberlain et al., 2017) of participants where the extent to which they are biased to either mode of attention can be influenced by culture (Caparos et al., 2012; Davidoff et al., 2008), neurology (Van der Hallen et al., 2015) and can even vary within individuals depending on affect (Dale & Arnell, 2010; Fredrickson & Branigan, 2005; Gasper & Clore, 2002). Given that we fit the models to each noise condition separately, it is important to note that the preferred model for each participant is not constant across all noise levels, suggesting that individual differences may not be the cause of this variation. To explore this further, the models could be fit to all noise levels simultaneously to see how the strength for each model changes depending on this manipulation.

## Problems with SSP

While previous work has shown that SSP is able to model a range of flanker tasks (Evans & Servant, 2020; Grange & Rydon-Grange, 2022; White et al., 2011), here we found a persistent and previously observed failure: SSP consistently predicted increases in attentional selectivity that occurred too quickly (Hübner & Töbel, 2012; Servant et al., 2014), particularly in conditions in which the target was noisy. One aspect that it consistently failed to model was the CAFs, predicting that they converged when this was not the case. In Study 2, we assumed this could be attributed to the perceptual strength of target and flanker being modelled by a common parameter. However, although allowing SSP to model target and flankers independently slightly improved the quality of fit (at least numerically), it did not solve the problem of SSP assuming flanker suppression occurs too quickly. Furthermore, SSP conflated attentional and perceptual effects, with the parameter estimates for ***pFlanker*** counterintuitively suggesting that the perceptual strength of the items increases with noise. Instead, this points towards a problem with SSP's zooming mechanism.

By changing the deterministic focusing in on the target induced by a spotlight that shrinks too quickly, it seems these problems may be easily rectified. We noted that a similar problem was found by Servant et al. (2014), who found that SSP was unable to model nonconverging CAFs in conditions where the target was weakly saturated. More recently, Weichart et al. (2020) proposed a model inspired by SSP, in which the shrinking of the spotlight is modulated by cognitive control. Importantly, this means that the speed of zooming can vary over the course of a trial. The authors also implemented this SSP within the framework of the leaky-competing accumulator (LCA, Usher & McClelland, 2001). The main difference is that while in a DDM, evidence for each response feeds into one diffusion process, in the LCA framework, there exist two 'racing' diffusers for each response alternative. When fitting this model to the data of Servant et al. (2014), they found that the control-based LCA model provided the best fits compared to a time-based model and even outperformed DSTP. The authors concluded that both the LCA framework and the assumption of control-based zooming dynamics are required to model behavior across conditions in which the perceptual strength of the target varies. However, a much simpler manipulation of SSP has been shown to allow SSP to model nonconverging CAFs specifically. Recall that in the high noise target condition of Study 3, $SSP_{pFl}$ mismatched the CAFs partly because it predicted that the drift rate in congruent trials decreases when ***pTarget*** < ***pFlanker***. However, unlike SSP, $SSP_{pFl}$ did not predict a steep incongruent CAF, and accuracy for the latest responses remained relatively low. This would imply that had $SSP_{pFl}$ not predicted a congruent CAF that decreased with RT latency, or in other words, had $SSP_{pFl}$ retained the original SSP assumption of a constant drift rate in congruent trials, $SSP_{pFl}$ could have modelled this nonconvergence. In fact, White et al. (2011) proposed an alternative version of SSP, in which no zooming occurs in congruent trials and thus, when ***pTarget*** ≠ ***pFlanker***, the drift rate remains constant . This assumption is based on the idea that attentional focusing is effortful and observers operate based on a conservation of effort policy. That is, observers will only narrow their attentional focus if required to. Servant et al. (2014) applied this alternative version of SSP to their color saturation task and, although the fit of this model was poorer when compared to the original version of SSP (mainly because it underestimated accuracy in the congruent condition), the model did indeed capture the nonconverging CAFs in low saturation conditions. Thus, the fact that SSP was consistently inferior to DSTP here does not rule out the idea that attentional focusing occurs as a gradual process. Instead, SSP's implementation of this process may be the issue and the evidence point towards the shrink rate parameter ***rd*** as the culprit. In each study, we calculated the interference ratio (***sdA***/***rd***) to account for the fact that these parameters are highly and that a parameter recovery study by White et al. (2018) showed that the spotlight parameters are poorly recovered. In our studies, the interference ratio was consistently dominated by ***sdA***, while ***rd*** had little effect. Together, this would imply that our DE-MCMC algorithm struggled to find suitable values for ***rd*** and greater weight was assigned to ***sdA***. Furthermore, our probability density approximation (PDA) approach to computing likelihood values likely exacerbated this problem, where approximation errors emanating from the PDA will propagate throughout the estimation process and bias the posterior estimates. These approximation errors are particularly common in 'sloppy' models with correlated parameters like the correlation between ***sdA*** and ***rd*** in SSP. Holmes (2018) defined 'sloppy models' as models in which numerous parameter combinations can lead to the same likelihood value. This results in areas of the likelihood function becoming flat, whereby the estimation process is increasingly influenced by these approximation errors (Evans & Servant, 2020). Thus, the problems with SSP may stem from DE-MCMC failing to find suitable estimates for the shrink rate parameter. However, since previous studies like that of Hübner & Többel (2012) have found similar issues despite not using a PDA approach, we believe that these issues likely do not stem from problems with the fitting process but rather SSP's implementation of the gradual increase in selectivity.

Finally, it is worth noting that our results present a potential hint toward how SSP may be improved in future studies. This hint pertains to the response boundary ***A*** and the fact that the predictions of SSP regarding this parameter were consistently counterintuitive. SSP predicted that participants respond more cautiously in conditions that are easier (low noise conditions where RT, ER and flanker interference are lower), whereas we would expect the opposite. In fact, this expectation is consistent with our finding in Study 1 (letter task). In the letter task, we expect observers to respond less cautiously, since the discrimination between 'S' and 'H' is likely easier than the RDK discrimination and this is indeed what we found (see comparison between Study 1 and Study 2 for more details). Importantly however, the winning model DSTP did not predict the same patterns for ***A*** in Studies 2 and 3. This leads us to believe that SSP had attempted to model aspects of the data through the response boundary, whereas DSTP's assumptions allowed it to model the data through other parameters. However, exactly which aspects of the data this applies to is currently unclear, but we believe this may be related to the nonconvergence of the CAFs and slow errors observed in high noise conditions. In Study 2, we posited an explanation for SSP's predictions of the response boundary, which suggested that these effects may tap into some kind of "urgency" signal (Hawkins et al., 2015). This urgency signal is based on evidence that participants sometimes prematurely terminate the response in order to move onto the next trial. Within the DDM framework, these effects are modelled through response boundaries which decline or 'collapse' over time and applications of these models have shown that the effect of a collapsing boundary is more pronounced, the more difficult the task is (Palestro et al., 2018). Applied to our findings, the boundary effects predicted by SSP may be snapshots of these collapsing boundaries and we assumed that the lower estimates for more difficult conditions may reflect an average of a range of high and low estimates in the posterior distribution. To be more specific, the posterior distribution is an amalgamation of 'good estimates', so we expected that the posterior distributions for $\boldsymbol{A}$ in high noise conditions would span a range of high and low response boundaries, if the collapsing boundary argument is likely. In an attempt to support this, we examined the 89% highest density credible intervals for $\boldsymbol{A}$ from Study 2, expecting that this interval would be larger for the high noise conditions, reflecting the greater uncertainty in the estimates. However, we found the opposite, in that the width of the interval decreased as noise increased, suggesting that this is not the case. Nevertheless, given that SSP predicts different and counterintuitive effects compared to DSTP, we still believe that SSP is attempting to model some aspects of the data through the response boundary, whereas DSTP is less reliant on this parameter when fitting the data and this is a potentially interesting direction for future work. Also noteworthy is that since these models have never been fit to data from a noisy flanker task, we allowed all parameters to vary freely. However, manipulations of task difficulty in the simple DDM have been shown to modelled almost exclusively by the drift rate (Ratcliff et al. 2008) and given that we randomized the noise manipulation across trials, it is conceivable that participants could not have adjusted their response boundary from one trial to the next. In turn, it is also conceivable that had we fixed the response boundary, the estimates of SSP may have been different.

Finally, despite the issues with SSP, its predictions still support our target saliency hypothesis. Specifically, SSP predicts that the duration of interference is longer with a low noise target and further increases as the noise level in the flankers decreases. In contrast, low noise targets lead to a shorter duration of interference which is less dependent on the level of noise in the flankers.

## Methodological Highlights

Unlike most previous modelling studies of flanker effects, we implemented both models in their full diffusion framework (models containing between-trial variability parameters) (see Evans & Servant, 2020 for an exception). This gives a more valid account of performance in the flanker task, since the 'full' models are required to meet key data patterns pertaining to differences in the speed of errors relative to correct responses, yet also acknowledge the existence of natural between-trial fluctuations in responses (Ratcliff & Tuerlinckx, 2002). Our use of PDA (using oKDE) to simulate the density functions of the models allowed for more efficient estimates compared to traditional KDE methods (Kristan et al., 2011; Narbutas et al., 2017 for a detailed discussion) as well as offering a more stringent approach to measuring goodness of fit, since the likelihood functions utilizes the entire, continuous response time distribution as opposed to fitting to discrete RT quantiles, a method commonly used in comparisons of SSP and DSTP (Hübner et al., 2010; White et al., 2011).

Our Bayesian approach to parameter estimation also allowed us to incorporate prior knowledge into the fitting process through the prior distributions and quantify uncertainty through the posterior distributions, which was useful when explaining a potential reason why SSP failed to match the data in Study 2 (the link between the width of the credible intervals of $\boldsymbol{p}$ and the spotlight parameters) as well as assessing whether the collapsing boundary argument was likely as discussed above. Furthermore, our use of Bayes Factor allowed us to incorporate model complexity and functional form into the comparison. Bayes Factor also allowed for the grouping of participants based on the strength and direction of evidence for either model. This latter point is particularly useful, since our examination of participants who showed high strength evidence in favor of DSTP meant we could particularly highlight the aspects of the data that DSTP fitted well. Finally, the combination of this Bayesian approach, distributional and average performance analysis and model simulations inspired by Evans & Servant (2020), allowed us to go beyond quantitative model comparison and explain *why* DSTP was the winning model, localizing this mainly to its superior ability to model the relationship between error responses and their latency.

Due to the nature of the RDK stimuli, prolonged viewing can result in discomfort and as such, we were limited with the number of trials per condition we could run. For the participant's sake, we ran the RDK studies over two days and although more trials per cell could be obtained by continuing the study further, we wished to avoid this due to potential high dropout rates. Consequently, in each task, we had a relatively low (64) number of trials per cell. Early diffusion model studies tended to use large numbers of trials (10,000) with few participants (Ratcliff, 2002; Ratcliff & Rouder 1998) however, recent studies have shown that such a large number of trials isn't necessarily required for effective diffusion model analyses (see Lerche, Voss & Nagler, 2017 for a detailed review and discussion). Indeed, despite having only 64 trials per condition, we obtained rather high-quality fits, our parameter estimation algorithm (DE-MCMC) showed suitable convergence (indicated by a value of split $\hat{R}$ < 1.1, Gelman et al. 2013) and the resulting parameter estimates and changes across conditions were sensible and interpretable. On the other hand, our study provides almost double the number of participants per task than previous investigations of models of the flanker task (White et al, 2011; Hübner et al, 2010; Ulrich et al. 2015; Servant et al, 2015).

## Potential Issues

Although there are clear benefits to using a Bayesian approach, the use of Bayes Factor has often been criticized for its dependence on the priors (Gelman et al, 2013). If the data are sufficiently informative to produce a strong likelihood, then the influence of a 'bad' prior can technically be overcome by a strong likelihood, moving the posterior distribution away from the prior. However, even in cases where the posterior is similar, but the priors differ, the marginal likelihood can greatly vary and subsequently could influence model selection, although such sensitivity to the prior is mainly observed when the priors are uninformative (e.g. uniform priors, Lambert, 2018). By all means, the most difficult challenge we faced during this study was deciding on suitable priors. We decided to use the priors proposed by Evans & Servant (2020), since they were based on a range of values previously found in investigations of the models and were attractive as they were made to be less informative to account for the lack of research into their values. Furthermore, we used the same prior distributions for all studies, so the influence of the prior on our model comparison may be somewhat controlled for. However, this decision also raises some issues. Firstly, the priors proposed by Evans & Servant (2020) were based on research using standard flanker tasks, which typically have considerably faster RTs than those we observed in Studies 2 and 3. Secondly, while we believe our decision to use the same priors across all conditions/tasks mitigated the effect of the prior on the estimation of marginal likelihood, it is possible that these priors were more suitable for some conditions than others. Despite this, our model comparison did make sense and we could show why DSTP was the superior model. Our finding that DSTP was consistently superior, even slightly in the letter task, led to the assumption that we may have somehow put SSP at a disadvantage through the chosen priors. However, we still do find participants how show evidence for SSP, SSP turns out to be the superior model for the low noise target condition in Study 3 and analysis of the posterior distributions showed our likelihood was sufficiently strong to move the posterior away from the priors, even for SSP, suggesting this might not be the case. Nevertheless, the choice of priors was a persistent issue, and we hope that our work can help provide a better basis for constructing priors when applying these models to less typical flanker tasks.

## Future Research

Throughout this thesis, we have used the terms 'noisy' and 'weak' interchangeably when referring to the high noise stimuli, however a distinction can be made between the two. For example, we have consistently referred to the study of Servant et al. (2014), who manipulated the perceptual strength of the target while keeping the flankers constant. Since perceptual strength is indeed inversely related to noise, this study is arguably most similar to the high noise target condition of Study 3. Although we manipulated noise in the flankers also, our results suggest that the target is the main factor and therefore we argue these studies are somewhat comparable. Critically however, Servant et al. (2014) found no effect of perceptual strength on the magnitude of the flanker effect. Under our saliency hypothesis, we would argue that this is because all of Servant et al.'s stimuli were above some given threshold that allows the target to be easily selected, although in their lowest saturation condition, they found nonconverging CAFs, which suggests this may not be the case. Another possible explanation pertains to this distinction between the terms ‘noisy’ and ‘weak’. To be more specific, although Servant et al. (2014) reduced the perceptual strength of the target, their targets were not noisy. Specifically, they used red or blue target circles with varying levels of saturation. Yet even at the lowest saturation level, a low saturation ‘red’ is still qualitatively different from a low saturation ‘blue’. Thus, the lack of an interaction between target perceptual strength and congruency and the presence of one here, could be that our stimuli not only have lower perceptual strength, but are indeed noisy. Similarly, while we offered an explanation of why the flanker effect did not depend on noise in the color noise task based on our saliency hypothesis, it could be said that the lack of an interaction stemmed from the color ‘noise’ stimuli simply not being ‘noisy’ at all. Recall that to produce the color noise stimuli, we excluded certain areas of the color wheel because including them distorted the effects of noise. Particularly, we excluded areas around the two target colors, meaning that a noisy ‘red’ target could never contain dots that were cyan and vice versa, whereas in the RDK tasks, the stimuli were indeed noisy and ambiguous, since leftwards moving targets could always contain some proportion of rightwards moving dots. Although we argued that the color noise task supports the saliency hypothesis, it is admittedly difficult to describe how exactly the color noise targets are more salient than color noise flankers, since saliency is determined predominantly by the relationship between an item and its neighbors. However, this difference, that is, that color noise targets contain only one target color, could account for this. Simply put, the combination of the higher perceptual strength of the color stimuli, combined with the fact that color noise targets contained only one of the known target colors, could have allowed color noise targets to perceived as more salient than the flankers. Indeed, current models of attention, including Guided Search (Wolfe, 2021) mentioned earlier, assume that bottom-up saliency can be manipulated in a top-down manner, where knowledge of the target (e.g., its location) can increase the likelihood that this location will be visited by attention. In contrast, the weaker intensity of noisy RDK targets (relative to the flankers), combined with the presence of evidence for both responses within the target RDK, could combine to produce a less salient target. Thus, it could be the case that the interactions we observe between 'noise' and response congruency appear only when evidence for both responses is present in the target. Future work could further explore distinctions between 'weak', 'noisy' and 'ambiguous' targets to explore whether these differences lead to differential effects of 'noise' on the flanker effect.

Furthermore, our results contrast with some previous studies using RDKs in the context of the flanker task. Firstly, Lange-Malecki & Treue (2012) implemented a motion flanker task with 100% coherence (0% noise) target and flankers and compared this to a standard flanker task using triangles. While our 10% noise condition yielded a flanker effect of ~8ms, their 0% noise task yielded a congruency effect of 10x the magnitude (80ms). In addition, when comparing the static task to the RDK task, they found little difference in the magnitude of the flanker effect, whereas we find clear differences between our letter and RDK tasks. However, the stimuli used by Lange-Malecki & Treue (2012), were three times as small as ours (diameters of 1º compared to our 3º) and the authors presented the flankers before the target, whereas we present all items simultaneously. Given that reducing the size of the target (Eriksen & Schultz, 1979) and presenting flankers before targets (Hübner & Töbel, 2019) have both been shown to increase flanker effects, either of these manipulations could possibly explain this discrepancy. Furthermore, in all our tasks, DSTP predicted that $\boldsymbol{\mu Ta} > \boldsymbol{\mu Fl}$, whereas in other tasks, the reverse has been found to be true (Hübner et al., 2010; Evans & Servant, 2020). This would suggest that despite our findings, flanker suppression was more effective in our task than others, explaining our rather small flanker effects. Similarly, De Bruin & Della Sala et al. (2018) conducted a task similar to the low noise target condition of Study 3, in which they manipulated flanker noise independently of the target, while keeping the target noise constant at 0%. While they found similar effects to what we report here, namely increased congruency effects with higher coherence (lower noise) flankers, the fact that the 0% noise target still produced flanker effects stands in contrast to what we find here. Important to note however, is that RDKs are a complex stimulus which can be implemented in a variety of ways and have a range of different parameters, all of which could account for these discrepancies (Pilly & Seitz, 2009). For example, dot lifetime, speed, size, and density of the dot patches could all potentially influence our findings. We certainly found it surprising that our low noise targets seemed robust in the face of interference, especially considering this previous evidence. Therefore, it is certainly possible that these effects are unique to the type of RDKs we use. Further research could explore which factors in RDKs contribute to these differential effects.

Returning to our tasks, the largest flanker effect we found with a low noise target was minute at 8ms. This raises the question of which manipulations could be introduced to force larger interference effects with low noise targets and similarly, which manipulations would extinguish the congruency effects with a high noise target. Although we could most likely achieve this through manipulations of target-flanker spacing, we are more interested in manipulations which influence the congruency effect while keeping spacing constant. For example, the finding that interference can be diminished by locating target and flankers on different objects (but see Richard et al., 2008), or other object-based manipulations could potentially be used to reach these aims. Furthermore, if we are correct in assuming that the saliency hypothesis is the reason for our findings, then formulating a testable computational model based on these assumptions would further aid in determining whether this explanation is likely.

Finally, some of our results point towards evidence for effects based on the expectation of the task. For example, despite the counterintuitive effects we found with response boundary $\boldsymbol{A}$ for SSP, both models suggested that participants respond more cautiously in the letter task which we argued could be attributed to differences in task expectations. Likewise, in the 80% noise target/80% noise flanker condition of Study 3, we found a congruency effect that was double the size of the identical condition in Study 2. This would suggest that the task procedure likely could have had an effect. For example, the randomization of noise across trials likely influences participants expectations of the task and previous work has shown that by blocking manipulations of target-flanker similarity, the congruency effect can be reduced (Frings et al., 2019). In other words, the beneficial effect of target-flanker dissimilarity is more pronounced in blocked compared to randomized conditions. In our task, blocking noise levels may help reduce the congruency effects observed with high noise targets and future research could explore whether blocking noise in the target or blocking noise in the flankers has a greater effect. Overall, however, we believe our results provide strong evidence that perceptual noise influences the flanker effect by increasing the challenge of target selection and therefore adversely affecting flanker suppression. Our combined results of Studies 2 and 3 provide strong evidence that this is primarily determined by the target itself and our results as a whole can be explained under our saliency hypothesis: the less salient the target, the stronger the flanker effect.

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# Appendices

## Appendix A: Study 1

### Expected a-posteriori (EAP) estimates.

**SSP**

| Subject | *A* | *ter* | *p* | *rd* | *sdA* | *sz* | *ster* | *sv* | *ir* |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.10 | 0.35 | 1.39 | 87.95 | 1.71 | 0.24 | 0.21 | 0.17 | 0.02 |
| **2** | 0.06 | 0.33 | 1.47 | 81.18 | 1.12 | 0.13 | 0.12 | 0.18 | 0.01 |
| **3** | 0.06 | 0.38 | 1.15 | 85.52 | 1.85 | 0.10 | 0.16 | 0.20 | 0.02 |
| **4** | 0.17 | 0.30 | 1.55 | 82.99 | 1.18 | 0.10 | 0.15 | 0.14 | 0.01 |
| **5** | 0.18 | 0.43 | 1.58 | 84.34 | 2.07 | 0.08 | 0.42 | 0.17 | 0.02 |
| **6** | 0.04 | 0.34 | 1.22 | 82.64 | 0.90 | 0.07 | 0.07 | 0.23 | 0.01 |
| **7** | 0.05 | 0.34 | 0.69 | 92.61 | 1.76 | 0.05 | 0.06 | 0.42 | 0.02 |
| **8** | 0.06 | 0.36 | 0.90 | 86.47 | 1.97 | 0.10 | 0.07 | 0.22 | 0.02 |
| **9** | 0.12 | 0.37 | 1.09 | 86.77 | 2.20 | 0.15 | 0.15 | 0.19 | 0.03 |
| **10** | 0.05 | 0.42 | 0.69 | 90.39 | 1.53 | 0.05 | 0.12 | 0.47 | 0.02 |
| **11** | 0.22 | 0.26 | 1.21 | 84.32 | 1.85 | 0.11 | 0.06 | 0.20 | 0.02 |
| **12** | 0.31 | 0.26 | 1.13 | 82.60 | 0.90 | 0.13 | 0.13 | 0.15 | 0.01 |
| **13** | 0.19 | 0.27 | 1.42 | 81.38 | 1.08 | 0.10 | 0.10 | 0.12 | 0.01 |
| **14** | 0.08 | 0.36 | 1.29 | 86.83 | 2.95 | 0.13 | 0.13 | 0.18 | 0.03 |
| **15** | 0.08 | 0.41 | 1.35 | 89.04 | 1.99 | 0.14 | 0.03 | 0.17 | 0.02 |
| **16** | 0.15 | 0.32 | 1.29 | 84.74 | 1.84 | 0.10 | 0.08 | 0.15 | 0.02 |
| **17** | 0.12 | 0.30 | 0.69 | 88.77 | 2.43 | 0.18 | 0.08 | 0.14 | 0.03 |
| **18** | 0.26 | 0.22 | 1.29 | 86.30 | 2.52 | 0.11 | 0.10 | 0.16 | 0.03 |
| **19** | 0.12 | 0.36 | 0.82 | 83.71 | 1.20 | 0.11 | 0.11 | 0.19 | 0.01 |
| **20** | 0.04 | 0.46 | 1.17 | 80.62 | 0.80 | 0.06 | 0.14 | 0.24 | 0.01 |
| **21** | 0.10 | 0.31 | 1.02 | 82.15 | 0.90 | 0.21 | 0.10 | 0.15 | 0.01 |
| **22** | 0.09 | 0.36 | 0.94 | 85.29 | 1.18 | 0.19 | 0.12 | 0.21 | 0.01 |
| **23** | 0.09 | 0.38 | 0.58 | 88.51 | 2.20 | 0.10 | 0.10 | 0.36 | 0.02 |
| **24** | 0.26 | 0.23 | 1.29 | 85.09 | 2.55 | 0.11 | 0.11 | 0.12 | 0.03 |
| **25** | 0.04 | 0.34 | 1.32 | 84.47 | 1.42 | 0.09 | 0.07 | 0.21 | 0.02 |
| **26** | 0.09 | 0.37 | 1.47 | 85.39 | 1.15 | 0.21 | 0.14 | 0.17 | 0.01 |
| **27** | 0.06 | 0.41 | 1.45 | 82.49 | 2.53 | 0.05 | 0.15 | 0.20 | 0.03 |
| **28** | 0.06 | 0.36 | 1.41 | 86.50 | 1.87 | 0.10 | 0.10 | 0.19 | 0.02 |
| **29** | 0.07 | 0.32 | 1.07 | 86.85 | 2.30 | 0.13 | 0.12 | 0.21 | 0.03 |
| **30** | 0.36 | 0.26 | 0.91 | 90.11 | 2.51 | 0.14 | 0.10 | 0.30 | 0.03 |
| **31** | 0.08 | 0.36 | 1.04 | 82.60 | 1.30 | 0.18 | 0.19 | 0.18 | 0.02 |
| **32** | 0.09 | 0.42 | 1.37 | 89.61 | 2.67 | 0.15 | 0.18 | 0.18 | 0.03 |
| **33** | 0.06 | 0.35 | 0.99 | 88.46 | 2.55 | 0.09 | 0.18 | 0.25 | 0.03 |
| **34** | 0.08 | 0.38 | 1.22 | 85.29 | 1.64 | 0.16 | 0.18 | 0.20 | 0.02 |
| **35** | 0.08 | 0.38 | 1.32 | 86.55 | 1.95 | 0.14 | 0.14 | 0.17 | 0.02 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **36** | 0.17 | 0.31 | 1.43 | 83.25 | 1.90 | 0.09 | 0.08 | 0.13 | 0.02 |
| **37** | 0.08 | 0.39 | 1.18 | 87.48 | 2.27 | 0.19 | 0.21 | 0.20 | 0.03 |
| **38** | 0.20 | 0.26 | 1.09 | 84.97 | 1.69 | 0.17 | 0.12 | 0.13 | 0.02 |
| **39** | 0.10 | 0.35 | 0.62 | 83.56 | 4.28 | 0.23 | 0.25 | 0.20 | 0.05 |
| **40** | 0.25 | 0.29 | 1.30 | 84.88 | 1.72 | 0.14 | 0.14 | 0.14 | 0.02 |
| **41** | 0.25 | 0.20 | 1.23 | 85.26 | 2.88 | 0.11 | 0.08 | 0.14 | 0.03 |
| **42** | 0.06 | 0.40 | 0.72 | 83.27 | 0.97 | 0.09 | 0.09 | 0.22 | 0.01 |
| **43** | 0.09 | 0.35 | 0.96 | 87.59 | 2.90 | 0.15 | 0.14 | 0.21 | 0.03 |
| **44** | 0.08 | 0.37 | 1.12 | 87.80 | 2.66 | 0.09 | 0.11 | 0.28 | 0.03 |
| **45** | 0.09 | 0.44 | 1.34 | 88.93 | 2.74 | 0.13 | 0.21 | 0.20 | 0.03 |
| **46** | 0.22 | 0.27 | 1.28 | 84.78 | 2.69 | 0.10 | 0.07 | 0.14 | 0.03 |
| **47** | 0.19 | 0.29 | 1.44 | 85.26 | 1.82 | 0.12 | 0.16 | 0.15 | 0.02 |
| **48** | 0.11 | 0.32 | 1.21 | 84.48 | 3.20 | 0.26 | 0.11 | 0.16 | 0.04 |
| **49** | 0.10 | 0.32 | 1.20 | 82.58 | 4.19 | 0.09 | 0.18 | 0.25 | 0.05 |
| **μ** | **0.12** | **0.34** | **1.16** | **85.56** | **2.01** | **0.13** | **0.13** | **0.20** | **0.02** |

**DSTP**

| **Subject** | ***A*** | ***C*** | ***μTa*** | ***μFl*** | ***μSS*** | ***μRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.09 | 0.25 | 0.17 | 0.07 | 1.34 | 2.50 | 0.24 | 0.13 | 0.12 | 0.15 |
| **2** | 0.04 | 0.25 | 0.95 | 0.15 | 0.65 | 1.77 | 0.34 | 0.08 | 0.12 | 0.16 |
| **3** | 0.24 | 0.05 | 0.48 | 0.23 | 0.87 | 2.06 | 0.29 | 0.09 | 0.14 | 0.18 |
| **4** | 0.24 | 0.08 | 0.50 | 0.20 | 1.20 | 2.75 | 0.27 | 0.05 | 0.17 | 0.14 |
| **5** | 0.25 | 0.10 | 0.54 | 0.30 | 1.13 | 2.67 | 0.40 | 0.06 | 0.42 | 0.15 |
| **6** | 0.18 | 0.07 | 0.57 | 0.38 | 0.95 | 2.67 | 0.27 | 0.10 | 0.04 | 0.15 |
| **7** | 0.23 | 0.05 | 0.67 | 0.31 | 0.38 | 2.60 | 0.26 | 0.06 | 0.05 | 0.31 |
| **8** | 0.06 | 0.29 | 0.87 | 0.31 | 0.63 | 1.91 | 0.37 | 0.12 | 0.08 | 0.14 |
| **9** | 0.28 | 0.07 | 0.39 | 0.17 | 0.89 | 2.30 | 0.30 | 0.14 | 0.15 | 0.19 |
| **10** | 0.10 | 0.08 | 0.47 | 0.18 | 0.40 | 2.40 | 0.38 | 0.09 | 0.07 | 0.55 |
| **11** | 0.27 | 0.12 | 0.47 | 0.24 | 0.87 | 2.62 | 0.24 | 0.10 | 0.06 | 0.17 |
| **12** | 0.31 | 0.19 | 0.43 | 0.05 | 0.95 | 2.23 | 0.23 | 0.12 | 0.13 | 0.16 |
| **13** | 0.26 | 0.09 | 0.47 | 0.20 | 1.07 | 2.44 | 0.23 | 0.08 | 0.10 | 0.13 |
| **14** | 0.26 | 0.07 | 0.45 | 0.29 | 1.02 | 2.48 | 0.29 | 0.16 | 0.11 | 0.15 |
| **15** | 0.21 | 0.05 | 0.45 | 0.30 | 0.99 | 3.19 | 0.36 | 0.12 | 0.03 | 0.14 |
| **16** | 0.24 | 0.06 | 0.44 | 0.32 | 0.98 | 2.42 | 0.30 | 0.12 | 0.06 | 0.14 |
| **17** | 0.10 | 0.36 | 0.57 | 0.09 | 0.62 | 1.73 | 0.33 | 0.16 | 0.07 | 0.13 |
| **18** | 0.30 | 0.17 | 0.49 | 0.23 | 1.04 | 2.30 | 0.18 | 0.10 | 0.09 | 0.15 |
| **19** | 0.06 | 0.23 | 0.52 | 0.05 | 0.84 | 1.96 | 0.39 | 0.07 | 0.11 | 0.25 |
| **20** | 0.03 | 0.27 | 0.85 | 0.12 | 0.61 | 1.77 | 0.46 | 0.04 | 0.14 | 0.21 |
| **21** | 0.08 | 0.29 | 0.76 | 0.08 | 0.69 | 1.81 | 0.31 | 0.16 | 0.09 | 0.13 |
| **22** | 0.08 | 0.30 | 0.81 | 0.13 | 0.62 | 1.83 | 0.37 | 0.17 | 0.11 | 0.17 |
| **23** | 0.11 | 0.34 | 0.59 | 0.09 | 0.55 | 1.94 | 0.37 | 0.12 | 0.08 | 0.46 |
| **24** | 0.29 | 0.15 | 0.49 | 0.27 | 1.03 | 2.16 | 0.20 | 0.12 | 0.11 | 0.11 |
| **25** | 0.03 | 0.26 | 0.93 | 0.23 | 0.63 | 1.80 | 0.34 | 0.07 | 0.07 | 0.16 |
| **26** | 0.08 | 0.16 | 0.55 | 0.14 | 1.33 | 2.31 | 0.34 | 0.17 | 0.08 | 0.14 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **27** | 0.06 | 0.08 | 0.42 | 0.40 | 1.06 | 2.32 | 0.39 | 0.04 | 0.14 | 0.19 |
| **28** | 0.24 | 0.04 | 0.44 | 0.26 | 1.07 | 2.66 | 0.29 | 0.09 | 0.09 | 0.16 |
| **29** | 0.28 | 0.06 | 0.41 | 0.23 | 0.87 | 2.41 | 0.23 | 0.16 | 0.09 | 0.16 |
| **30** | 0.50 | 0.23 | 0.38 | 0.11 | 0.64 | 2.98 | 0.21 | 0.12 | 0.10 | 0.30 |
| **31** | 0.06 | 0.25 | 0.72 | 0.10 | 0.66 | 1.80 | 0.36 | 0.13 | 0.19 | 0.16 |
| **32** | 0.31 | 0.07 | 0.46 | 0.23 | 1.01 | 2.26 | 0.31 | 0.15 | 0.15 | 0.16 |
| **33** | 0.27 | 0.06 | 0.45 | 0.24 | 0.80 | 2.38 | 0.26 | 0.16 | 0.14 | 0.22 |
| **34** | 0.05 | 0.25 | 0.81 | 0.17 | 0.73 | 1.95 | 0.39 | 0.10 | 0.18 | 0.17 |
| **35** | 0.28 | 0.06 | 0.45 | 0.23 | 1.04 | 2.38 | 0.29 | 0.13 | 0.12 | 0.15 |
| **36** | 0.23 | 0.10 | 0.51 | 0.28 | 1.08 | 2.33 | 0.27 | 0.07 | 0.07 | 0.12 |
| **37** | 0.08 | 0.14 | 0.18 | 0.14 | 1.14 | 2.42 | 0.34 | 0.13 | 0.15 | 0.25 |
| **38** | 0.31 | 0.09 | 0.40 | 0.21 | 0.86 | 2.59 | 0.25 | 0.20 | 0.10 | 0.12 |
| **39** | 0.12 | 0.24 | 0.18 | 0.11 | 0.83 | 1.80 | 0.25 | 0.22 | 0.16 | 0.25 |
| **40** | 0.29 | 0.14 | 0.45 | 0.20 | 1.05 | 2.47 | 0.26 | 0.10 | 0.15 | 0.15 |
| **41** | 0.30 | 0.17 | 0.47 | 0.24 | 0.98 | 2.26 | 0.15 | 0.10 | 0.08 | 0.13 |
| **42** | 0.06 | 0.25 | 0.60 | 0.04 | 0.69 | 1.78 | 0.40 | 0.08 | 0.09 | 0.24 |
| **43** | 0.30 | 0.08 | 0.38 | 0.19 | 0.77 | 2.51 | 0.26 | 0.19 | 0.09 | 0.18 |
| **44** | 0.06 | 0.21 | 0.75 | 0.20 | 0.81 | 1.99 | 0.38 | 0.09 | 0.10 | 0.25 |
| **45** | 0.12 | 0.14 | 0.31 | 0.28 | 1.10 | 2.53 | 0.38 | 0.12 | 0.17 | 0.20 |
| **46** | 0.28 | 0.16 | 0.49 | 0.26 | 1.06 | 2.21 | 0.21 | 0.07 | 0.07 | 0.13 |
| **47** | 0.26 | 0.10 | 0.52 | 0.31 | 1.05 | 2.56 | 0.25 | 0.09 | 0.16 | 0.14 |
| **48** | 0.09 | 0.27 | 0.90 | 0.25 | 0.79 | 1.99 | 0.33 | 0.22 | 0.13 | 0.12 |
| **49** | 0.10 | 0.14 | 0.51 | 0.37 | 0.86 | 1.98 | 0.30 | 0.11 | 0.12 | 0.18 |
| ***μ*** | **0.19** | **0.16** | **0.53** | **0.21** | **0.88** | **2.27** | **0.30** | **0.12** | **0.12** | **0.18** |

## Log marginal likelihoods and log Bayes Factor (ln(BF))

| Subject | SSP | DSTP | ln(BF) |
|---|---|---|---|
| **1** | -390.29 | -387.96 | 2.33 |
| **2** | -325.69 | -326.51 | -0.82 |
| **3** | -339.37 | -336.29 | 3.08 |
| **4** | -320.71 | -321.11 | -0.41 |
| **5** | -406.09 | -405.60 | 0.49 |
| **6** | -282.95 | -280.41 | 2.54 |
| **7** | -373.09 | -364.68 | 8.41 |
| **8** | -352.93 | -346.84 | 6.09 |
| **9** | -373.99 | -373.59 | 0.41 |
| **10** | -406.16 | -399.38 | 6.78 |
| **11** | -338.62 | -337.78 | 0.84 |
| **12** | -361.47 | -362.37 | -0.90 |
| **13** | -300.44 | -299.87 | 0.57 |
| **14** | -337.41 | -339.52 | -2.10 |
| **15** | -286.86 | -289.42 | -2.56 |
| **16** | -302.25 | -300.56 | 1.69 |
| **17** | -410.51 | -408.17 | 2.35 |
| **18** | -354.51 | -354.25 | 0.26 |
| **19** | -383.46 | -382.35 | 1.11 |
| **20** | -328.24 | -327.51 | 0.72 |
| **21** | -362.62 | -361.49 | 1.13 |
| **22** | -395.65 | -393.95 | 1.70 |
| **23** | -463.74 | -462.81 | 0.93 |
| **24** | -349.10 | -347.98 | 1.13 |
| **25** | -296.96 | -297.82 | -0.86 |
| **26** | -342.79 | -343.10 | -0.31 |
| **27** | -341.78 | -344.18 | -2.40 |
| **28** | -297.74 | -297.31 | 0.44 |
| **29** | -363.76 | -361.50 | 2.27 |
| **30** | -474.98 | -476.06 | -1.08 |
| **31** | -387.23 | -386.64 | 0.59 |
| **32** | -360.76 | -358.33 | 2.43 |
| **33** | -373.75 | -370.12 | 3.62 |
| **34** | -357.72 | -356.76 | 0.96 |
| **35** | -329.93 | -328.33 | 1.60 |
| **36** | -293.91 | -293.28 | 0.63 |
| **37** | -397.40 | -397.91 | -0.51 |
| **38** | -364.77 | -364.91 | -0.14 |
| **39** | -404.72 | -403.74 | 0.97 |
| **40** | -338.20 | -338.47 | -0.26 |
| **41** | -331.57 | -331.73 | -0.16 |

| | | | |
|---|---|---|---|
| **42** | -373.29 | -371.83 | 1.45 |
| **43** | -387.06 | -385.25 | 1.80 |
| **44** | -352.65 | -351.93 | 0.72 |
| **45** | -365.13 | -360.55 | 4.58 |
| **46** | -313.77 | -314.81 | -1.04 |
| **47** | -320.26 | -319.07 | 1.19 |
| **48** | -385.06 | -383.84 | 1.23 |
| **49** | -367.16 | -363.69 | 3.48 |

# Appendix B: Study 2

## Expected a-posteriori (EAP) estimates.

SSP

| **80% Noise**<br>**Subject** | ***A*** | ***ter*** | ***p*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** | ***ir*** |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.02 | 0.42 | 0.85 | 79.75 | 0.52 | 0.04 | 0.16 | 0.31 | 0.01 |
| **2** | 0.12 | 0.40 | 0.17 | 86.38 | 4.70 | 0.13 | 0.13 | 0.05 | 0.05 |
| **3** | 0.12 | 0.43 | 0.27 | 86.30 | 4.89 | 0.12 | 0.15 | 0.21 | 0.06 |
| **4** | 0.09 | 0.61 | 0.44 | 85.91 | 1.84 | 0.09 | 0.24 | 0.39 | 0.02 |
| **5** | 0.15 | 0.47 | 0.42 | 87.10 | 4.60 | 0.10 | 0.16 | 0.36 | 0.05 |
| **6** | 0.14 | 0.51 | 0.19 | 79.48 | 6.22 | 0.14 | 0.19 | 0.40 | 0.08 |
| **7** | 0.09 | 0.33 | 0.33 | 89.57 | 4.62 | 0.13 | 0.09 | 0.25 | 0.05 |
| **8** | 0.16 | 0.55 | 0.40 | 89.71 | 3.21 | 0.12 | 0.15 | 0.34 | 0.04 |
| **9** | 0.20 | 0.40 | 0.37 | 84.84 | 5.13 | 0.13 | 0.16 | 0.23 | 0.06 |
| **10** | 0.08 | 0.41 | 0.37 | 90.23 | 2.22 | 0.07 | 0.08 | 0.37 | 0.02 |
| **11** | 0.24 | 0.39 | 0.41 | 90.06 | 5.25 | 0.15 | 0.14 | 0.26 | 0.06 |
| **12** | 0.22 | 0.49 | 0.47 | 83.72 | 5.82 | 0.14 | 0.15 | 0.28 | 0.07 |
| **13** | 0.13 | 0.48 | 0.47 | 90.48 | 3.56 | 0.13 | 0.16 | 0.44 | 0.04 |
| **14** | 0.18 | 0.29 | 0.50 | 88.50 | 4.20 | 0.14 | 0.15 | 0.30 | 0.05 |
| **15** | 0.10 | 0.41 | 0.35 | 89.48 | 3.58 | 0.08 | 0.12 | 0.34 | 0.04 |
| **16** | 0.09 | 0.44 | 0.46 | 88.28 | 3.58 | 0.13 | 0.14 | 0.34 | 0.04 |
| **17** | 0.07 | 0.57 | 0.26 | 86.06 | 2.14 | 0.08 | 0.15 | 0.23 | 0.02 |
| **18** | 0.17 | 0.35 | 0.39 | 87.43 | 5.15 | 0.13 | 0.14 | 0.22 | 0.06 |
| **19** | 0.15 | 0.37 | 0.49 | 87.61 | 4.84 | 0.11 | 0.13 | 0.32 | 0.06 |
| **20** | 0.11 | 0.52 | 0.10 | 82.59 | 4.98 | 0.14 | 0.15 | 0.05 | 0.06 |
| **21** | 0.08 | 0.39 | 0.41 | 85.28 | 2.57 | 0.09 | 0.16 | 0.35 | 0.03 |
| **22** | 0.08 | 0.45 | 0.41 | 88.72 | 1.93 | 0.15 | 0.10 | 0.40 | 0.02 |
| **23** | 0.15 | 0.44 | 0.54 | 87.54 | 3.08 | 0.12 | 0.16 | 0.33 | 0.04 |
| **24** | 0.12 | 0.54 | 0.26 | 87.39 | 3.51 | 0.10 | 0.15 | 0.12 | 0.04 |
| **25** | 0.08 | 0.47 | 0.41 | 89.90 | 3.65 | 0.10 | 0.19 | 0.38 | 0.04 |
| **26** | 0.12 | 0.38 | 0.13 | 80.77 | 5.73 | 0.16 | 0.17 | 0.11 | 0.07 |
| **27** | 0.12 | 0.40 | 0.10 | 76.95 | 5.59 | 0.13 | 0.19 | 0.23 | 0.07 |
| **28** | 0.12 | 0.36 | 0.23 | 83.60 | 5.00 | 0.11 | 0.16 | 0.20 | 0.06 |
| **29** | 0.29 | 0.48 | 0.65 | 88.30 | 4.28 | 0.15 | 0.16 | 0.40 | 0.05 |
| **30** | 0.10 | 0.39 | 0.40 | 85.74 | 5.23 | 0.12 | 0.21 | 0.43 | 0.06 |
| **31** | 0.07 | 0.46 | 0.49 | 90.20 | 2.31 | 0.13 | 0.10 | 0.47 | 0.03 |
| **32** | 0.06 | 0.60 | 0.39 | 85.33 | 1.18 | 0.06 | 0.28 | 0.35 | 0.01 |
| **33** | 0.10 | 0.40 | 0.36 | 86.27 | 4.28 | 0.08 | 0.19 | 0.21 | 0.05 |
| **34** | 0.09 | 0.45 | 0.19 | 87.46 | 4.84 | 0.08 | 0.12 | 0.34 | 0.06 |
| **35** | 0.07 | 0.43 | 0.58 | 86.18 | 1.40 | 0.07 | 0.09 | 0.43 | 0.02 |
| **36** | 0.09 | 0.46 | 0.37 | 87.28 | 2.90 | 0.10 | 0.16 | 0.31 | 0.03 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **37** | 0.07 | 0.40 | 0.48 | 89.55 | 1.80 | 0.07 | 0.08 | 0.35 | 0.02 |
| **38** | 0.13 | 0.41 | 0.27 | 86.74 | 4.59 | 0.15 | 0.16 | 0.40 | 0.05 |
| **39** | 0.12 | 0.40 | 0.65 | 90.41 | 2.51 | 0.11 | 0.15 | 0.42 | 0.03 |
| **40** | 0.08 | 0.40 | 0.42 | 92.52 | 3.74 | 0.08 | 0.15 | 0.41 | 0.04 |
| **41** | 0.10 | 0.72 | 0.14 | 78.96 | 6.96 | 0.15 | 0.17 | 0.33 | 0.09 |
| **42** | 0.12 | 0.45 | 0.50 | 89.71 | 2.91 | 0.12 | 0.13 | 0.39 | 0.03 |
| **43** | 0.14 | 0.38 | 0.33 | 88.83 | 4.13 | 0.11 | 0.16 | 0.25 | 0.05 |
| **44** | 0.06 | 0.40 | 0.22 | 86.06 | 2.44 | 0.09 | 0.22 | 0.48 | 0.03 |
| **45** | 0.13 | 0.49 | 0.52 | 90.64 | 2.44 | 0.10 | 0.13 | 0.52 | 0.03 |
| **46** | 0.20 | 0.50 | 0.81 | 92.36 | 4.46 | 0.13 | 0.14 | 0.46 | 0.05 |
| **47** | 0.21 | 0.47 | 0.32 | 82.36 | 6.04 | 0.14 | 0.16 | 0.22 | 0.07 |
| **48** | 0.11 | 0.58 | 0.48 | 89.96 | 3.79 | 0.08 | 0.14 | 0.33 | 0.04 |
| **49** | 0.10 | 0.48 | 0.43 | 87.95 | 2.57 | 0.10 | 0.16 | 0.50 | 0.03 |
| **μ** | **0.12** | **0.45** | **0.39** | **86.87** | **3.81** | **0.11** | **0.15** | **0.32** | **0.04** |

| **70% Noise Subject** | ***A*** | ***ter*** | ***p*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** | ***ir*** |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.04 | 0.35 | 0.58 | 84.80 | 0.97 | 0.06 | 0.06 | 0.21 | 0.01 |
| **2** | 0.15 | 0.41 | 0.47 | 88.72 | 3.95 | 0.11 | 0.12 | 0.23 | 0.04 |
| **3** | 0.14 | 0.47 | 0.51 | 90.84 | 3.25 | 0.15 | 0.18 | 0.38 | 0.04 |
| **4** | 0.09 | 0.60 | 0.66 | 88.20 | 1.57 | 0.08 | 0.25 | 0.50 | 0.02 |
| **5** | 0.33 | 0.29 | 0.82 | 88.19 | 4.36 | 0.13 | 0.10 | 0.27 | 0.05 |
| **6** | 0.11 | 0.46 | 0.18 | 83.72 | 5.16 | 0.11 | 0.15 | 0.34 | 0.06 |
| **7** | 0.07 | 0.34 | 0.54 | 88.33 | 2.94 | 0.10 | 0.08 | 0.34 | 0.03 |
| **8** | 0.16 | 0.47 | 0.51 | 89.81 | 3.93 | 0.12 | 0.12 | 0.34 | 0.04 |
| **9** | 0.26 | 0.39 | 0.73 | 87.94 | 4.07 | 0.16 | 0.17 | 0.36 | 0.05 |
| **10** | 0.26 | 0.29 | 1.08 | 84.95 | 1.40 | 0.11 | 0.08 | 0.24 | 0.02 |
| **11** | 0.41 | 0.26 | 0.74 | 89.01 | 3.47 | 0.14 | 0.12 | 0.26 | 0.04 |
| **12** | 0.39 | 0.29 | 0.66 | 87.95 | 3.33 | 0.14 | 0.12 | 0.23 | 0.04 |
| **13** | 0.09 | 0.46 | 0.48 | 86.45 | 3.91 | 0.08 | 0.12 | 0.34 | 0.05 |
| **14** | 0.31 | 0.19 | 0.89 | 90.33 | 2.94 | 0.14 | 0.09 | 0.30 | 0.03 |
| **15** | 0.11 | 0.39 | 0.52 | 90.60 | 2.89 | 0.09 | 0.12 | 0.33 | 0.03 |
| **16** | 0.08 | 0.42 | 0.46 | 88.58 | 3.23 | 0.07 | 0.10 | 0.31 | 0.04 |
| **17** | 0.08 | 0.56 | 0.63 | 88.64 | 1.86 | 0.11 | 0.16 | 0.39 | 0.02 |
| **18** | 0.17 | 0.44 | 0.81 | 93.23 | 2.91 | 0.11 | 0.10 | 0.45 | 0.03 |
| **19** | 0.28 | 0.28 | 0.87 | 84.40 | 1.86 | 0.13 | 0.09 | 0.22 | 0.02 |
| **20** | 0.14 | 0.39 | 0.23 | 85.68 | 5.30 | 0.13 | 0.16 | 0.30 | 0.06 |
| **21** | 0.08 | 0.40 | 0.63 | 88.35 | 2.34 | 0.08 | 0.09 | 0.41 | 0.03 |
| **22** | 0.08 | 0.41 | 0.54 | 87.95 | 1.86 | 0.08 | 0.16 | 0.40 | 0.02 |
| **23** | 0.33 | 0.26 | 0.82 | 84.58 | 2.46 | 0.13 | 0.11 | 0.25 | 0.03 |
| **24** | 0.19 | 0.48 | 0.55 | 88.33 | 1.93 | 0.15 | 0.16 | 0.25 | 0.02 |
| **25** | 0.08 | 0.46 | 0.67 | 88.45 | 2.61 | 0.08 | 0.15 | 0.42 | 0.03 |
| **26** | 0.12 | 0.40 | 0.17 | 82.38 | 5.42 | 0.15 | 0.17 | 0.15 | 0.07 |
| **27** | 0.15 | 0.42 | 0.23 | 83.88 | 5.86 | 0.17 | 0.20 | 0.43 | 0.07 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **28** | 0.12 | 0.35 | 0.37 | 89.64 | 5.18 | 0.12 | 0.13 | 0.30 | 0.06 |
| **29** | 0.28 | 0.45 | 0.67 | 87.84 | 5.08 | 0.14 | 0.14 | 0.30 | 0.06 |
| **30** | 0.08 | 0.43 | 0.40 | 86.29 | 3.32 | 0.12 | 0.18 | 0.33 | 0.04 |
| **31** | 0.07 | 0.44 | 0.43 | 88.14 | 1.45 | 0.11 | 0.13 | 0.28 | 0.02 |
| **32** | 0.06 | 0.56 | 0.42 | 85.36 | 1.63 | 0.10 | 0.29 | 0.20 | 0.02 |
| **33** | 0.14 | 0.37 | 0.73 | 89.17 | 4.45 | 0.10 | 0.10 | 0.38 | 0.05 |
| **34** | 0.10 | 0.45 | 0.39 | 88.31 | 2.44 | 0.08 | 0.13 | 0.45 | 0.03 |
| **35** | 0.06 | 0.43 | 0.53 | 85.50 | 3.06 | 0.08 | 0.11 | 0.30 | 0.04 |
| **36** | 0.07 | 0.47 | 0.58 | 90.20 | 2.04 | 0.06 | 0.11 | 0.39 | 0.02 |
| **37** | 0.08 | 0.38 | 0.64 | 90.49 | 4.10 | 0.08 | 0.09 | 0.45 | 0.05 |
| **38** | 0.12 | 0.38 | 0.29 | 88.42 | 5.54 | 0.15 | 0.15 | 0.36 | 0.06 |
| **39** | 0.10 | 0.40 | 0.64 | 90.06 | 2.43 | 0.09 | 0.08 | 0.32 | 0.03 |
| **40** | 0.07 | 0.41 | 0.65 | 91.27 | 1.93 | 0.08 | 0.10 | 0.57 | 0.02 |
| **41** | 0.10 | 0.63 | 0.29 | 85.42 | 4.22 | 0.10 | 0.18 | 0.33 | 0.05 |
| **42** | 0.12 | 0.46 | 0.71 | 90.81 | 2.22 | 0.12 | 0.10 | 0.41 | 0.02 |
| **43** | 0.12 | 0.42 | 0.37 | 90.73 | 2.08 | 0.10 | 0.13 | 0.22 | 0.02 |
| **44** | 0.06 | 0.43 | 0.28 | 84.57 | 3.88 | 0.09 | 0.26 | 0.37 | 0.05 |
| **45** | 0.12 | 0.40 | 0.48 | 88.73 | 3.19 | 0.11 | 0.13 | 0.22 | 0.04 |
| **46** | 0.28 | 0.40 | 0.98 | 83.09 | 1.04 | 0.13 | 0.09 | 0.20 | 0.01 |
| **47** | 0.19 | 0.43 | 0.45 | 86.30 | 5.49 | 0.13 | 0.15 | 0.27 | 0.06 |
| **48** | 0.12 | 0.60 | 1.02 | 89.04 | 1.27 | 0.11 | 0.18 | 0.47 | 0.01 |
| **49** | 0.09 | 0.48 | 0.46 | 88.20 | 2.17 | 0.10 | 0.11 | 0.34 | 0.02 |
| **μ** | **0.15** | **0.42** | **0.57** | **87.79** | **3.14** | **0.11** | **0.13** | **0.33** | **0.04** |

**40% Noise**

| **Subject** | ***A*** | ***ter*** | ***p*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** | ***ir*** |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.04 | 0.37 | 1.41 | 86.66 | 1.40 | 0.07 | 0.06 | 0.20 | 0.02 |
| **2** | 0.29 | 0.31 | 0.93 | 83.74 | 1.66 | 0.14 | 0.09 | 0.19 | 0.02 |
| **3** | 0.11 | 0.47 | 0.86 | 89.90 | 1.84 | 0.14 | 0.13 | 0.38 | 0.02 |
| **4** | 0.08 | 0.56 | 1.03 | 87.62 | 2.24 | 0.09 | 0.20 | 0.32 | 0.03 |
| **5** | 0.24 | 0.36 | 1.09 | 86.06 | 1.41 | 0.11 | 0.06 | 0.28 | 0.02 |
| **6** | 0.11 | 0.45 | 0.42 | 90.01 | 2.82 | 0.11 | 0.15 | 0.33 | 0.03 |
| **7** | 0.23 | 0.22 | 1.13 | 83.12 | 1.45 | 0.10 | 0.06 | 0.19 | 0.02 |
| **8** | 0.26 | 0.41 | 1.01 | 83.08 | 0.94 | 0.13 | 0.07 | 0.23 | 0.01 |
| **9** | 0.29 | 0.31 | 0.96 | 84.43 | 1.18 | 0.12 | 0.08 | 0.28 | 0.01 |
| **10** | 0.04 | 0.43 | 1.20 | 84.54 | 1.60 | 0.04 | 0.09 | 0.30 | 0.02 |
| **11** | 0.29 | 0.35 | 0.92 | 84.80 | 2.28 | 0.12 | 0.10 | 0.27 | 0.03 |
| **12** | 0.36 | 0.24 | 0.95 | 91.25 | 4.59 | 0.14 | 0.11 | 0.31 | 0.05 |
| **13** | 0.06 | 0.51 | 0.75 | 87.13 | 1.95 | 0.08 | 0.24 | 0.34 | 0.02 |
| **14** | 0.27 | 0.22 | 1.09 | 87.66 | 2.60 | 0.12 | 0.09 | 0.22 | 0.03 |
| **15** | 0.10 | 0.39 | 0.69 | 91.11 | 1.64 | 0.09 | 0.07 | 0.32 | 0.02 |
| **16** | 0.06 | 0.42 | 0.47 | 85.25 | 1.55 | 0.06 | 0.10 | 0.21 | 0.02 |
| **17** | 0.08 | 0.54 | 0.71 | 86.82 | 1.61 | 0.07 | 0.19 | 0.46 | 0.02 |
| **18** | 0.19 | 0.38 | 1.22 | 85.04 | 1.69 | 0.09 | 0.05 | 0.23 | 0.02 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **19** | 0.25 | 0.30 | 1.05 | 83.13 | 1.57 | 0.12 | 0.10 | 0.18 | 0.02 |
| **20** | 0.12 | 0.39 | 0.51 | 88.11 | 1.34 | 0.12 | 0.12 | 0.29 | 0.02 |
| **21** | 0.07 | 0.43 | 0.92 | 86.91 | 1.49 | 0.11 | 0.17 | 0.37 | 0.02 |
| **22** | 0.06 | 0.41 | 0.58 | 89.79 | 1.48 | 0.08 | 0.09 | 0.35 | 0.02 |
| **23** | 0.12 | 0.43 | 0.82 | 89.97 | 1.60 | 0.13 | 0.18 | 0.37 | 0.02 |
| **24** | 0.31 | 0.34 | 0.84 | 85.23 | 1.39 | 0.16 | 0.11 | 0.17 | 0.02 |
| **25** | 0.08 | 0.41 | 0.85 | 88.19 | 2.75 | 0.08 | 0.10 | 0.32 | 0.03 |
| **26** | 0.11 | 0.41 | 0.36 | 86.80 | 4.14 | 0.15 | 0.15 | 0.28 | 0.05 |
| **27** | 0.12 | 0.45 | 0.24 | 78.86 | 6.37 | 0.22 | 0.29 | 0.33 | 0.08 |
| **28** | 0.11 | 0.37 | 0.60 | 90.43 | 2.73 | 0.13 | 0.14 | 0.28 | 0.03 |
| **29** | 0.37 | 0.33 | 0.89 | 89.98 | 2.99 | 0.13 | 0.10 | 0.29 | 0.03 |
| **30** | 0.11 | 0.39 | 0.90 | 90.87 | 3.50 | 0.12 | 0.15 | 0.44 | 0.04 |
| **31** | 0.05 | 0.44 | 0.63 | 87.11 | 1.31 | 0.06 | 0.16 | 0.33 | 0.02 |
| **32** | 0.27 | 0.30 | 1.05 | 82.28 | 1.28 | 0.13 | 0.12 | 0.17 | 0.02 |
| **33** | 0.25 | 0.29 | 1.15 | 87.17 | 3.72 | 0.10 | 0.08 | 0.25 | 0.04 |
| **34** | 0.12 | 0.42 | 0.98 | 93.70 | 2.95 | 0.10 | 0.09 | 0.57 | 0.03 |
| **35** | 0.20 | 0.33 | 1.20 | 83.41 | 1.17 | 0.10 | 0.06 | 0.20 | 0.01 |
| **36** | 0.11 | 0.41 | 0.75 | 90.03 | 1.95 | 0.10 | 0.10 | 0.38 | 0.02 |
| **37** | 0.07 | 0.38 | 0.63 | 88.50 | 1.46 | 0.06 | 0.05 | 0.33 | 0.02 |
| **38** | 0.09 | 0.39 | 0.48 | 88.98 | 2.13 | 0.15 | 0.12 | 0.17 | 0.02 |
| **39** | 0.22 | 0.30 | 1.21 | 82.54 | 1.80 | 0.12 | 0.11 | 0.16 | 0.02 |
| **40** | 0.05 | 0.39 | 0.63 | 83.10 | 0.78 | 0.06 | 0.08 | 0.34 | 0.01 |
| **41** | 0.10 | 0.52 | 0.43 | 87.36 | 2.33 | 0.11 | 0.11 | 0.12 | 0.03 |
| **42** | 0.29 | 0.28 | 0.97 | 83.67 | 2.28 | 0.13 | 0.12 | 0.17 | 0.03 |
| **43** | 0.28 | 0.27 | 1.01 | 87.56 | 3.37 | 0.13 | 0.08 | 0.24 | 0.04 |
| **44** | 0.11 | 0.44 | 1.13 | 88.89 | 1.72 | 0.25 | 0.19 | 0.30 | 0.02 |
| **45** | 0.27 | 0.31 | 1.14 | 81.07 | 0.72 | 0.14 | 0.12 | 0.15 | 0.01 |
| **46** | 0.23 | 0.41 | 1.18 | 83.22 | 1.97 | 0.13 | 0.08 | 0.14 | 0.02 |
| **47** | 0.32 | 0.33 | 0.89 | 81.34 | 0.98 | 0.13 | 0.11 | 0.23 | 0.01 |
| **48** | 0.26 | 0.41 | 1.21 | 85.01 | 1.81 | 0.11 | 0.09 | 0.15 | 0.02 |
| **49** | 0.29 | 0.31 | 0.84 | 86.87 | 2.01 | 0.17 | 0.13 | 0.24 | 0.02 |
| **μ** | **0.17** | **0.38** | **0.88** | **86.50** | **2.07** | **0.12** | **0.12** | **0.27** | **0.02** |

**10% Noise**

| **Subject** | ***A*** | ***ter*** | ***p*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** | |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.03 | 0.36 | 1.07 | 84.20 | 0.61 | 0.04 | 0.04 | 0.25 | 0.01 |
| **2** | 0.23 | 0.37 | 1.23 | 85.30 | 2.75 | 0.11 | 0.07 | 0.17 | 0.03 |
| **3** | 0.11 | 0.44 | 0.82 | 86.46 | 1.37 | 0.11 | 0.13 | 0.36 | 0.02 |
| **4** | 0.24 | 0.41 | 1.25 | 83.81 | 1.89 | 0.12 | 0.11 | 0.14 | 0.02 |
| **5** | 0.26 | 0.32 | 1.08 | 83.45 | 1.32 | 0.13 | 0.09 | 0.16 | 0.02 |
| **6** | 0.11 | 0.48 | 0.74 | 90.77 | 1.71 | 0.09 | 0.21 | 0.50 | 0.02 |
| **7** | 0.20 | 0.24 | 1.18 | 78.66 | 0.74 | 0.11 | 0.08 | 0.16 | 0.01 |
| **8** | 0.23 | 0.41 | 1.04 | 84.80 | 1.21 | 0.13 | 0.06 | 0.23 | 0.01 |
| **9** | 0.29 | 0.32 | 1.04 | 83.60 | 1.00 | 0.12 | 0.08 | 0.29 | 0.01 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **10** | 0.16 | 0.35 | 1.60 | 79.86 | 0.66 | 0.07 | 0.05 | 0.14 | 0.01 |
| **11** | 0.25 | 0.42 | 1.04 | 94.14 | 1.75 | 0.12 | 0.09 | 0.48 | 0.02 |
| **12** | 0.23 | 0.34 | 1.13 | 86.70 | 1.83 | 0.11 | 0.06 | 0.29 | 0.02 |
| **13** | 0.27 | 0.31 | 1.02 | 81.37 | 1.42 | 0.13 | 0.12 | 0.18 | 0.02 |
| **14** | 0.23 | 0.26 | 1.13 | 82.59 | 1.00 | 0.13 | 0.08 | 0.22 | 0.01 |
| **15** | 0.20 | 0.33 | 1.11 | 86.53 | 1.91 | 0.10 | 0.06 | 0.31 | 0.02 |
| **16** | 0.09 | 0.46 | 0.65 | 86.70 | 1.82 | 0.21 | 0.14 | 0.19 | 0.02 |
| **17** | 0.31 | 0.33 | 1.00 | 84.40 | 4.75 | 0.12 | 0.10 | 0.22 | 0.06 |
| **18** | 0.26 | 0.32 | 1.21 | 81.42 | 0.97 | 0.11 | 0.08 | 0.16 | 0.01 |
| **19** | 0.23 | 0.32 | 1.19 | 84.36 | 1.72 | 0.14 | 0.10 | 0.16 | 0.02 |
| **20** | 0.30 | 0.25 | 1.04 | 84.93 | 1.30 | 0.13 | 0.08 | 0.25 | 0.02 |
| **21** | 0.26 | 0.26 | 1.05 | 83.96 | 1.41 | 0.13 | 0.12 | 0.18 | 0.02 |
| **22** | 0.05 | 0.42 | 0.69 | 84.63 | 0.89 | 0.07 | 0.15 | 0.41 | 0.01 |
| **23** | 0.26 | 0.33 | 1.14 | 79.63 | 0.85 | 0.15 | 0.14 | 0.13 | 0.01 |
| **24** | 0.29 | 0.37 | 0.93 | 85.80 | 2.21 | 0.14 | 0.08 | 0.21 | 0.03 |
| **25** | 0.20 | 0.36 | 1.29 | 78.97 | 0.96 | 0.13 | 0.11 | 0.13 | 0.01 |
| **26** | 0.12 | 0.41 | 0.62 | 89.04 | 4.02 | 0.13 | 0.14 | 0.55 | 0.05 |
| **27** | 0.13 | 0.42 | 0.37 | 87.55 | 3.50 | 0.14 | 0.20 | 0.51 | 0.04 |
| **28** | 0.18 | 0.37 | 1.38 | 81.64 | 1.16 | 0.10 | 0.18 | 0.15 | 0.01 |
| **29** | 0.31 | 0.36 | 0.92 | 85.93 | 2.02 | 0.13 | 0.11 | 0.23 | 0.02 |
| **30** | 0.16 | 0.34 | 0.98 | 86.31 | 2.03 | 0.11 | 0.09 | 0.26 | 0.02 |
| **31** | 0.06 | 0.42 | 0.73 | 85.69 | 0.85 | 0.08 | 0.11 | 0.25 | 0.01 |
| **32** | 0.27 | 0.31 | 1.13 | 84.98 | 1.34 | 0.15 | 0.13 | 0.17 | 0.02 |
| **33** | 0.08 | 0.40 | 0.89 | 83.85 | 1.43 | 0.16 | 0.09 | 0.19 | 0.02 |
| **34** | 0.11 | 0.43 | 1.14 | 89.20 | 3.42 | 0.14 | 0.13 | 0.25 | 0.04 |
| **35** | 0.05 | 0.44 | 0.86 | 84.06 | 1.37 | 0.06 | 0.13 | 0.26 | 0.02 |
| **36** | 0.09 | 0.42 | 0.78 | 87.05 | 1.00 | 0.09 | 0.10 | 0.29 | 0.01 |
| **37** | 0.07 | 0.38 | 0.62 | 90.25 | 1.90 | 0.07 | 0.05 | 0.30 | 0.02 |
| **38** | 0.32 | 0.21 | 0.92 | 86.26 | 1.93 | 0.13 | 0.09 | 0.26 | 0.02 |
| **39** | 0.22 | 0.29 | 1.18 | 80.58 | 0.86 | 0.15 | 0.10 | 0.15 | 0.01 |
| **40** | 0.04 | 0.40 | 0.92 | 81.71 | 0.79 | 0.07 | 0.16 | 0.31 | 0.01 |
| **41** | 0.27 | 0.39 | 1.07 | 86.32 | 1.74 | 0.12 | 0.07 | 0.23 | 0.02 |
| **42** | 0.28 | 0.32 | 1.10 | 81.68 | 1.34 | 0.12 | 0.13 | 0.23 | 0.02 |
| **43** | 0.22 | 0.32 | 1.08 | 81.83 | 1.38 | 0.12 | 0.07 | 0.22 | 0.02 |
| **44** | 0.08 | 0.43 | 0.74 | 86.79 | 1.58 | 0.17 | 0.18 | 0.36 | 0.02 |
| **45** | 0.24 | 0.34 | 1.22 | 81.88 | 1.17 | 0.10 | 0.09 | 0.19 | 0.01 |
| **46** | 0.24 | 0.42 | 1.24 | 80.67 | 0.79 | 0.10 | 0.07 | 0.20 | 0.01 |
| **47** | 0.28 | 0.39 | 1.14 | 83.54 | 1.24 | 0.13 | 0.08 | 0.24 | 0.01 |
| **48** | 0.23 | 0.45 | 1.34 | 80.01 | 0.66 | 0.11 | 0.09 | 0.14 | 0.01 |
| **49** | 0.10 | 0.44 | 0.61 | 90.86 | 1.78 | 0.17 | 0.11 | 0.42 | 0.02 |
| **$\mu$** | **0.19** | **0.36** | **1.01** | **84.59** | **1.58** | **0.12** | **0.10** | **0.25** | **0.02** |

DSTP

**80% Noise**

| **Subject** | ***A*** | ***C*** | ***μTa*** | ***μFl*** | ***μSS*** | ***μRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.02 | 0.29 | 0.64 | 0.13 | 0.60 | 1.76 | 0.41 | 0.05 | 0.15 | 0.31 |
| **2** | 0.14 | 0.59 | 0.19 | 0.03 | 0.36 | 1.66 | 0.42 | 0.17 | 0.12 | 0.13 |
| **3** | 0.23 | 0.49 | 0.30 | 0.05 | 0.56 | 1.91 | 0.36 | 0.15 | 0.15 | 0.44 |
| **4** | 0.13 | 0.35 | 0.46 | 0.06 | 0.50 | 1.97 | 0.57 | 0.12 | 0.21 | 0.52 |
| **5** | 0.17 | 0.37 | 0.44 | 0.09 | 0.65 | 0.57 | 0.48 | 0.12 | 0.16 | 0.42 |
| **6** | 0.19 | 0.48 | 0.16 | 0.06 | 0.48 | 1.38 | 0.45 | 0.15 | 0.18 | 0.53 |
| **7** | 0.11 | 0.54 | 0.37 | 0.06 | 0.62 | 1.78 | 0.35 | 0.20 | 0.09 | 0.34 |
| **8** | 0.23 | 0.52 | 0.46 | 0.05 | 0.29 | 1.69 | 0.51 | 0.13 | 0.15 | 0.45 |
| **9** | 0.30 | 0.54 | 0.41 | 0.07 | 0.42 | 1.82 | 0.34 | 0.15 | 0.16 | 0.37 |
| **10** | 0.09 | 0.45 | 0.43 | 0.10 | 0.52 | 1.77 | 0.41 | 0.09 | 0.07 | 0.48 |
| **11** | 0.30 | 0.61 | 0.42 | 0.07 | 0.36 | 1.74 | 0.36 | 0.15 | 0.14 | 0.34 |
| **12** | 0.34 | 0.44 | 0.44 | 0.11 | 0.38 | 1.80 | 0.41 | 0.14 | 0.13 | 0.36 |
| **13** | 0.23 | 0.36 | 0.42 | 0.12 | 0.47 | 2.26 | 0.41 | 0.14 | 0.15 | 0.59 |
| **14** | 0.29 | 0.45 | 0.52 | 0.09 | 0.50 | 1.99 | 0.23 | 0.16 | 0.14 | 0.47 |
| **15** | 0.14 | 0.45 | 0.42 | 0.15 | 0.35 | 1.76 | 0.40 | 0.11 | 0.11 | 0.48 |
| **16** | 0.11 | 0.38 | 0.41 | 0.10 | 0.61 | 1.70 | 0.43 | 0.15 | 0.13 | 0.44 |
| **17** | 0.09 | 0.39 | 0.31 | 0.08 | 0.67 | 1.89 | 0.56 | 0.12 | 0.13 | 0.41 |
| **18** | 0.53 | 0.17 | 0.25 | 0.14 | 0.31 | 2.71 | 0.18 | 0.13 | 0.12 | 0.23 |
| **19** | 0.20 | 0.47 | 0.52 | 0.10 | 0.52 | 1.76 | 0.35 | 0.13 | 0.12 | 0.45 |
| **20** | 0.17 | 0.61 | 0.13 | 0.04 | 0.41 | 1.35 | 0.45 | 0.15 | 0.15 | 0.26 |
| **21** | 0.09 | 0.36 | 0.43 | 0.07 | 0.49 | 1.71 | 0.39 | 0.12 | 0.15 | 0.47 |
| **22** | 0.09 | 0.42 | 0.45 | 0.11 | 0.49 | 1.75 | 0.46 | 0.19 | 0.10 | 0.47 |
| **23** | 0.23 | 0.41 | 0.58 | 0.07 | 0.45 | 1.92 | 0.39 | 0.13 | 0.15 | 0.46 |
| **24** | 0.18 | 0.50 | 0.36 | 0.06 | 0.44 | 1.63 | 0.53 | 0.14 | 0.15 | 0.27 |
| **25** | 0.19 | 0.17 | 0.29 | 0.18 | 0.34 | 2.46 | 0.40 | 0.15 | 0.15 | 0.57 |
| **26** | 0.26 | 0.43 | 0.15 | 0.08 | 0.29 | 1.67 | 0.25 | 0.20 | 0.16 | 0.36 |
| **27** | 0.20 | 0.48 | 0.10 | 0.05 | 0.29 | 1.90 | 0.32 | 0.15 | 0.18 | 0.42 |
| **28** | 0.20 | 0.47 | 0.30 | 0.08 | 0.42 | 1.80 | 0.32 | 0.16 | 0.15 | 0.41 |
| **29** | 0.52 | 0.30 | 0.41 | 0.14 | 0.43 | 2.34 | 0.29 | 0.14 | 0.15 | 0.37 |
| **30** | 0.15 | 0.39 | 0.28 | 0.09 | 0.69 | 1.98 | 0.34 | 0.15 | 0.18 | 0.55 |
| **31** | 0.08 | 0.38 | 0.51 | 0.11 | 0.53 | 1.65 | 0.48 | 0.17 | 0.11 | 0.51 |
| **32** | 0.08 | 0.32 | 0.41 | 0.05 | 0.56 | 1.94 | 0.58 | 0.08 | 0.26 | 0.45 |
| **33** | 0.14 | 0.43 | 0.41 | 0.12 | 0.66 | 1.91 | 0.38 | 0.12 | 0.15 | 0.37 |
| **34** | 0.12 | 0.55 | 0.23 | 0.15 | 0.44 | 1.75 | 0.44 | 0.09 | 0.11 | 0.48 |
| **35** | 0.07 | 0.33 | 0.58 | 0.10 | 0.52 | 1.73 | 0.43 | 0.08 | 0.08 | 0.49 |
| **36** | 0.14 | 0.36 | 0.40 | 0.07 | 0.49 | 1.96 | 0.44 | 0.13 | 0.15 | 0.49 |
| **37** | 0.08 | 0.41 | 0.50 | 0.07 | 0.61 | 1.86 | 0.41 | 0.10 | 0.07 | 0.42 |
| **38** | 0.19 | 0.42 | 0.25 | 0.07 | 0.50 | 1.43 | 0.36 | 0.16 | 0.16 | 0.57 |
| **39** | 0.15 | 0.46 | 0.64 | 0.07 | 0.55 | 1.66 | 0.40 | 0.13 | 0.14 | 0.49 |
| **40** | 0.10 | 0.33 | 0.41 | 0.17 | 0.49 | 2.00 | 0.39 | 0.10 | 0.13 | 0.54 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **41** | 0.14 | 0.51 | 0.12 | 0.11 | 0.43 | 1.80 | 0.66 | 0.13 | 0.15 | 0.55 |
| **42** | 0.16 | 0.46 | 0.56 | 0.10 | 0.45 | 1.58 | 0.44 | 0.15 | 0.12 | 0.52 |
| **43** | 0.24 | 0.48 | 0.42 | 0.10 | 0.36 | 1.90 | 0.34 | 0.16 | 0.15 | 0.43 |
| **44** | 0.06 | 0.38 | 0.23 | 0.11 | 0.42 | 1.64 | 0.41 | 0.10 | 0.23 | 0.55 |
| **45** | 0.14 | 0.26 | 0.58 | 0.07 | 0.74 | 0.24 | 0.50 | 0.11 | 0.14 | 0.51 |
| **46** | 0.21 | 0.40 | 0.71 | 0.22 | 0.44 | 1.92 | 0.50 | 0.17 | 0.13 | 0.40 |
| **47** | 0.33 | 0.55 | 0.38 | 0.09 | 0.32 | 1.69 | 0.40 | 0.16 | 0.16 | 0.35 |
| **48** | 0.33 | 0.14 | 0.43 | 0.26 | 0.33 | 2.32 | 0.45 | 0.12 | 0.10 | 0.38 |
| **49** | 0.15 | 0.32 | 0.40 | 0.09 | 0.37 | 2.03 | 0.45 | 0.11 | 0.15 | 0.62 |
| **µ** | **0.18** | **0.42** | **0.39** | **0.10** | **0.47** | **1.78** | **0.41** | **0.14** | **0.14** | **0.44** |

**70% Noise**

| **Subject** | ***A*** | ***C*** | ***µTa*** | ***µFl*** | ***µSS*** | ***µRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.04 | 0.22 | 0.49 | 0.05 | 0.84 | 1.96 | 0.35 | 0.05 | 0.05 | 0.26 |
| **2** | 0.18 | 0.48 | 0.52 | 0.09 | 0.53 | 1.85 | 0.41 | 0.13 | 0.11 | 0.33 |
| **3** | 0.26 | 0.35 | 0.40 | 0.11 | 0.55 | 2.23 | 0.38 | 0.17 | 0.15 | 0.52 |
| **4** | 0.12 | 0.31 | 0.63 | 0.10 | 0.44 | 1.86 | 0.57 | 0.10 | 0.21 | 0.56 |
| **5** | 0.15 | 0.47 | 0.55 | 0.13 | 0.60 | 1.72 | 0.43 | 0.12 | 0.08 | 0.27 |
| **6** | 0.16 | 0.53 | 0.19 | 0.11 | 0.27 | 1.66 | 0.44 | 0.13 | 0.14 | 0.46 |
| **7** | 0.07 | 0.37 | 0.58 | 0.19 | 0.66 | 1.81 | 0.37 | 0.15 | 0.09 | 0.31 |
| **8** | 0.22 | 0.52 | 0.57 | 0.09 | 0.43 | 1.70 | 0.46 | 0.13 | 0.12 | 0.46 |
| **9** | 0.29 | 0.44 | 0.52 | 0.08 | 0.71 | 1.92 | 0.36 | 0.16 | 0.17 | 0.44 |
| **10** | 0.07 | 0.30 | 0.57 | 0.06 | 0.77 | 1.87 | 0.43 | 0.07 | 0.12 | 0.30 |
| **11** | 0.24 | 0.58 | 0.53 | 0.05 | 0.49 | 1.68 | 0.38 | 0.12 | 0.11 | 0.26 |
| **12** | 0.52 | 0.20 | 0.28 | 0.10 | 0.40 | 2.81 | 0.28 | 0.12 | 0.11 | 0.21 |
| **13** | 0.14 | 0.34 | 0.50 | 0.13 | 0.53 | 2.01 | 0.45 | 0.11 | 0.12 | 0.51 |
| **14** | 0.20 | 0.46 | 0.65 | 0.05 | 0.63 | 1.89 | 0.27 | 0.11 | 0.08 | 0.33 |
| **15** | 0.14 | 0.39 | 0.59 | 0.09 | 0.55 | 1.93 | 0.39 | 0.13 | 0.11 | 0.46 |
| **16** | 0.09 | 0.41 | 0.47 | 0.11 | 0.66 | 1.81 | 0.42 | 0.09 | 0.10 | 0.40 |
| **17** | 0.14 | 0.21 | 0.46 | 0.09 | 0.69 | 2.28 | 0.51 | 0.13 | 0.13 | 0.51 |
| **18** | 0.17 | 0.48 | 0.75 | 0.09 | 0.53 | 1.56 | 0.44 | 0.12 | 0.10 | 0.49 |
| **19** | 0.32 | 0.09 | 0.37 | 0.20 | 0.43 | 2.73 | 0.32 | 0.13 | 0.08 | 0.15 |
| **20** | 0.21 | 0.55 | 0.25 | 0.08 | 0.31 | 1.74 | 0.35 | 0.16 | 0.16 | 0.45 |
| **21** | 0.31 | 0.07 | 0.39 | 0.24 | 0.45 | 2.71 | 0.31 | 0.09 | 0.08 | 0.39 |
| **22** | 0.17 | 0.15 | 0.44 | 0.12 | 0.44 | 2.41 | 0.35 | 0.11 | 0.12 | 0.54 |
| **23** | 0.42 | 0.21 | 0.37 | 0.12 | 0.58 | 2.62 | 0.22 | 0.13 | 0.11 | 0.26 |
| **24** | 0.21 | 0.46 | 0.52 | 0.04 | 0.65 | 2.03 | 0.47 | 0.15 | 0.14 | 0.37 |
| **25** | 0.11 | 0.25 | 0.52 | 0.12 | 0.77 | 2.29 | 0.43 | 0.09 | 0.14 | 0.53 |
| **26** | 0.23 | 0.42 | 0.18 | 0.08 | 0.34 | 1.75 | 0.29 | 0.19 | 0.16 | 0.38 |
| **27** | 0.27 | 0.46 | 0.15 | 0.09 | 0.38 | 2.20 | 0.28 | 0.16 | 0.18 | 0.59 |
| **28** | 0.15 | 0.58 | 0.40 | 0.10 | 0.47 | 1.68 | 0.36 | 0.15 | 0.11 | 0.40 |
| **29** | 0.37 | 0.36 | 0.52 | 0.12 | 0.44 | 2.04 | 0.37 | 0.14 | 0.13 | 0.33 |
| **30** | 0.11 | 0.27 | 0.36 | 0.13 | 0.52 | 1.98 | 0.40 | 0.16 | 0.15 | 0.49 |
| **31** | 0.08 | 0.34 | 0.49 | 0.08 | 0.56 | 1.89 | 0.44 | 0.14 | 0.13 | 0.39 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **32** | 0.09 | 0.29 | 0.34 | 0.06 | 0.76 | 1.93 | 0.51 | 0.11 | 0.22 | 0.37 |
| **33** | 0.16 | 0.38 | 0.64 | 0.13 | 0.72 | 2.01 | 0.36 | 0.11 | 0.10 | 0.47 |
| **34** | 0.12 | 0.43 | 0.44 | 0.13 | 0.28 | 1.55 | 0.44 | 0.09 | 0.13 | 0.54 |
| **35** | 0.07 | 0.25 | 0.48 | 0.15 | 0.67 | 1.89 | 0.43 | 0.11 | 0.09 | 0.40 |
| **36** | 0.10 | 0.26 | 0.57 | 0.12 | 0.55 | 2.08 | 0.46 | 0.08 | 0.09 | 0.51 |
| **37** | 0.10 | 0.28 | 0.56 | 0.20 | 0.68 | 1.70 | 0.38 | 0.10 | 0.09 | 0.58 |
| **38** | 0.20 | 0.47 | 0.32 | 0.13 | 0.55 | 1.32 | 0.34 | 0.18 | 0.15 | 0.61 |
| **39** | 0.12 | 0.36 | 0.67 | 0.08 | 0.66 | 2.02 | 0.40 | 0.10 | 0.07 | 0.44 |
| **40** | 0.07 | 0.39 | 0.62 | 0.09 | 0.51 | 1.48 | 0.42 | 0.10 | 0.10 | 0.59 |
| **41** | 0.14 | 0.42 | 0.29 | 0.08 | 0.51 | 1.89 | 0.60 | 0.13 | 0.16 | 0.51 |
| **42** | 0.13 | 0.35 | 0.65 | 0.10 | 0.55 | 1.76 | 0.45 | 0.13 | 0.10 | 0.46 |
| **43** | 0.16 | 0.54 | 0.48 | 0.04 | 0.56 | 1.85 | 0.41 | 0.13 | 0.12 | 0.37 |
| **44** | 0.07 | 0.36 | 0.25 | 0.11 | 0.52 | 1.79 | 0.41 | 0.11 | 0.23 | 0.48 |
| **45** | 0.41 | 0.12 | 0.37 | 0.19 | 0.36 | 2.76 | 0.27 | 0.12 | 0.11 | 0.22 |
| **46** | 0.34 | 0.16 | 0.40 | 0.09 | 0.73 | 2.68 | 0.38 | 0.13 | 0.09 | 0.19 |
| **47** | 0.46 | 0.25 | 0.36 | 0.17 | 0.35 | 2.22 | 0.25 | 0.14 | 0.14 | 0.32 |
| **48** | 0.35 | 0.10 | 0.56 | 0.17 | 0.71 | 2.57 | 0.48 | 0.08 | 0.15 | 0.43 |
| **49** | 0.12 | 0.37 | 0.50 | 0.06 | 0.49 | 1.92 | 0.47 | 0.12 | 0.11 | 0.48 |
| **μ** | **0.19** | **0.35** | **0.46** | **0.11** | **0.55** | **2.00** | **0.40** | **0.12** | **0.12** | **0.42** |

**40% Noise**

| **Subject** | ***A*** | ***C*** | ***μTa*** | ***μFl*** | ***μSS*** | ***μRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.22 | 0.03 | 0.43 | 0.22 | 1.14 | 2.96 | 0.30 | 0.09 | 0.04 | 0.16 |
| **2** | 0.35 | 0.19 | 0.38 | 0.09 | 0.72 | 2.51 | 0.26 | 0.13 | 0.09 | 0.19 |
| **3** | 0.35 | 0.10 | 0.42 | 0.21 | 0.67 | 2.75 | 0.36 | 0.14 | 0.10 | 0.35 |
| **4** | 0.25 | 0.06 | 0.63 | 0.25 | 0.55 | 1.93 | 0.45 | 0.08 | 0.17 | 0.24 |
| **5** | 0.11 | 0.33 | 0.72 | 0.06 | 0.63 | 1.77 | 0.42 | 0.08 | 0.05 | 0.26 |
| **6** | 0.18 | 0.38 | 0.50 | 0.09 | 0.41 | 2.09 | 0.41 | 0.14 | 0.13 | 0.50 |
| **7** | 0.29 | 0.13 | 0.43 | 0.16 | 0.83 | 2.56 | 0.19 | 0.09 | 0.06 | 0.17 |
| **8** | 0.34 | 0.14 | 0.41 | 0.08 | 0.71 | 2.83 | 0.37 | 0.11 | 0.07 | 0.22 |
| **9** | 0.41 | 0.16 | 0.40 | 0.10 | 0.62 | 2.93 | 0.26 | 0.11 | 0.08 | 0.24 |
| **10** | 0.03 | 0.28 | 0.89 | 0.32 | 0.54 | 1.70 | 0.44 | 0.03 | 0.08 | 0.23 |
| **11** | 0.18 | 0.39 | 0.67 | 0.07 | 0.49 | 1.72 | 0.43 | 0.12 | 0.11 | 0.26 |
| **12** | 0.21 | 0.49 | 0.65 | 0.11 | 0.57 | 1.78 | 0.34 | 0.12 | 0.09 | 0.30 |
| **13** | 0.11 | 0.22 | 0.41 | 0.10 | 1.05 | 2.46 | 0.44 | 0.11 | 0.19 | 0.39 |
| **14** | 0.32 | 0.16 | 0.46 | 0.22 | 0.74 | 2.55 | 0.19 | 0.12 | 0.08 | 0.18 |
| **15** | 0.38 | 0.10 | 0.35 | 0.14 | 0.61 | 3.19 | 0.28 | 0.08 | 0.06 | 0.37 |
| **16** | 0.07 | 0.30 | 0.50 | 0.07 | 0.76 | 1.89 | 0.42 | 0.07 | 0.09 | 0.32 |
| **17** | 0.09 | 0.32 | 0.64 | 0.08 | 0.58 | 1.90 | 0.54 | 0.08 | 0.19 | 0.49 |
| **18** | 0.28 | 0.11 | 0.44 | 0.19 | 0.90 | 2.70 | 0.34 | 0.07 | 0.05 | 0.22 |
| **19** | 0.31 | 0.15 | 0.40 | 0.12 | 0.83 | 2.37 | 0.25 | 0.11 | 0.10 | 0.18 |
| **20** | 0.15 | 0.46 | 0.58 | 0.02 | 0.54 | 1.79 | 0.38 | 0.12 | 0.11 | 0.41 |
| **21** | 0.10 | 0.17 | 0.41 | 0.10 | 0.98 | 2.36 | 0.38 | 0.11 | 0.15 | 0.38 |
| **22** | 0.07 | 0.33 | 0.58 | 0.05 | 0.63 | 1.97 | 0.41 | 0.10 | 0.09 | 0.42 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **23** | 0.13 | 0.34 | 0.65 | 0.06 | 0.83 | 2.10 | 0.41 | 0.13 | 0.14 | 0.43 |
| **24** | 0.39 | 0.20 | 0.35 | 0.06 | 0.67 | 2.68 | 0.30 | 0.15 | 0.12 | 0.17 |
| **25** | 0.18 | 0.10 | 0.41 | 0.28 | 0.77 | 2.29 | 0.35 | 0.09 | 0.08 | 0.34 |
| **26** | 0.23 | 0.37 | 0.24 | 0.07 | 0.71 | 2.02 | 0.28 | 0.16 | 0.14 | 0.49 |
| **27** | 0.19 | 0.45 | 0.07 | 0.06 | 0.60 | 1.97 | 0.26 | 0.17 | 0.20 | 0.43 |
| **28** | 0.36 | 0.11 | 0.43 | 0.22 | 0.42 | 2.71 | 0.25 | 0.14 | 0.11 | 0.22 |
| **29** | 0.50 | 0.21 | 0.38 | 0.14 | 0.55 | 2.88 | 0.28 | 0.11 | 0.09 | 0.24 |
| **30** | 0.27 | 0.12 | 0.46 | 0.33 | 0.68 | 2.41 | 0.29 | 0.12 | 0.13 | 0.39 |
| **31** | 0.06 | 0.24 | 0.58 | 0.08 | 0.66 | 1.95 | 0.44 | 0.07 | 0.15 | 0.39 |
| **32** | 0.32 | 0.17 | 0.39 | 0.10 | 0.85 | 2.38 | 0.26 | 0.11 | 0.12 | 0.18 |
| **33** | 0.30 | 0.16 | 0.52 | 0.32 | 0.81 | 2.31 | 0.25 | 0.10 | 0.08 | 0.22 |
| **34** | 0.12 | 0.38 | 0.91 | 0.30 | 0.41 | 1.60 | 0.43 | 0.11 | 0.11 | 0.45 |
| **35** | 0.29 | 0.12 | 0.44 | 0.13 | 0.92 | 2.76 | 0.29 | 0.08 | 0.06 | 0.21 |
| **36** | 0.12 | 0.36 | 0.68 | 0.07 | 0.73 | 2.01 | 0.41 | 0.11 | 0.08 | 0.45 |
| **37** | 0.07 | 0.34 | 0.64 | 0.07 | 0.76 | 1.94 | 0.38 | 0.06 | 0.05 | 0.40 |
| **38** | 0.10 | 0.35 | 0.48 | 0.05 | 0.68 | 1.88 | 0.39 | 0.16 | 0.11 | 0.28 |
| **39** | 0.12 | 0.26 | 0.86 | 0.12 | 0.60 | 1.72 | 0.36 | 0.08 | 0.12 | 0.13 |
| **40** | 0.05 | 0.29 | 0.60 | 0.03 | 0.68 | 1.93 | 0.39 | 0.06 | 0.07 | 0.37 |
| **41** | 0.10 | 0.40 | 0.44 | 0.05 | 0.79 | 1.78 | 0.52 | 0.10 | 0.09 | 0.22 |
| **42** | 0.33 | 0.17 | 0.41 | 0.16 | 0.73 | 2.28 | 0.25 | 0.13 | 0.12 | 0.16 |
| **43** | 0.16 | 0.35 | 0.68 | 0.11 | 0.72 | 1.91 | 0.34 | 0.10 | 0.06 | 0.24 |
| **44** | 0.10 | 0.29 | 0.84 | 0.16 | 0.84 | 2.13 | 0.44 | 0.22 | 0.20 | 0.17 |
| **45** | 0.32 | 0.16 | 0.43 | 0.05 | 0.90 | 2.50 | 0.27 | 0.13 | 0.12 | 0.15 |
| **46** | 0.24 | 0.18 | 0.54 | 0.14 | 0.90 | 2.16 | 0.39 | 0.10 | 0.09 | 0.13 |
| **47** | 0.39 | 0.19 | 0.39 | 0.07 | 0.65 | 2.57 | 0.30 | 0.13 | 0.12 | 0.25 |
| **48** | 0.31 | 0.16 | 0.42 | 0.16 | 0.98 | 2.33 | 0.37 | 0.09 | 0.09 | 0.16 |
| **49** | 0.13 | 0.39 | 0.61 | 0.05 | 0.58 | 1.87 | 0.46 | 0.25 | 0.15 | 0.27 |
| **μ** | **0.22** | **0.24** | **0.51** | **0.13** | **0.71** | **2.24** | **0.35** | **0.11** | **0.11** | **0.29** |

**10% Noise**

| **Subject** | ***A*** | ***C*** | ***μTa*** | ***μFl*** | ***μSS*** | ***μRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.03 | 0.29 | 0.83 | 0.06 | 0.63 | 1.83 | 0.36 | 0.03 | 0.04 | 0.18 |
| **2** | 0.30 | 0.16 | 0.45 | 0.24 | 0.99 | 2.36 | 0.30 | 0.09 | 0.07 | 0.15 |
| **3** | 0.15 | 0.23 | 0.57 | 0.06 | 0.80 | 2.22 | 0.40 | 0.11 | 0.11 | 0.46 |
| **4** | 0.29 | 0.14 | 0.44 | 0.18 | 1.01 | 2.27 | 0.38 | 0.09 | 0.13 | 0.15 |
| **5** | 0.32 | 0.17 | 0.41 | 0.11 | 0.87 | 2.58 | 0.27 | 0.13 | 0.09 | 0.16 |
| **6** | 0.38 | 0.11 | 0.64 | 0.26 | 0.40 | 2.45 | 0.31 | 0.11 | 0.19 | 0.37 |
| **7** | 0.27 | 0.11 | 0.41 | 0.09 | 0.91 | 2.46 | 0.20 | 0.09 | 0.08 | 0.15 |
| **8** | 0.33 | 0.13 | 0.41 | 0.13 | 0.73 | 2.89 | 0.36 | 0.11 | 0.05 | 0.20 |
| **9** | 0.17 | 0.38 | 0.73 | 0.02 | 0.59 | 1.76 | 0.37 | 0.10 | 0.08 | 0.28 |
| **10** | 0.24 | 0.06 | 0.48 | 0.19 | 1.17 | 2.68 | 0.32 | 0.05 | 0.05 | 0.14 |
| **11** | 0.18 | 0.60 | 0.78 | 0.08 | 0.44 | 1.72 | 0.45 | 0.11 | 0.08 | 0.42 |
| **12** | 0.12 | 0.36 | 0.77 | 0.10 | 0.56 | 1.73 | 0.39 | 0.09 | 0.05 | 0.23 |
| **13** | 0.32 | 0.17 | 0.42 | 0.11 | 0.81 | 2.39 | 0.28 | 0.12 | 0.12 | 0.20 |

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|---|---|---|---|---|---|---|---|---|---|---|
| **14** | 0.31 | 0.14 | 0.49 | 0.16 | 0.79 | 2.83 | 0.23 | 0.12 | 0.08 | 0.20 |
| **15** | 0.11 | 0.35 | 0.77 | 0.10 | 0.57 | 1.82 | 0.38 | 0.08 | 0.06 | 0.25 |
| **16** | 0.08 | 0.35 | 0.52 | 0.07 | 0.60 | 1.85 | 0.46 | 0.18 | 0.12 | 0.19 |
| **17** | 0.31 | 0.23 | 0.51 | 0.24 | 0.70 | 2.05 | 0.31 | 0.11 | 0.10 | 0.22 |
| **18** | 0.30 | 0.12 | 0.42 | 0.14 | 0.92 | 2.39 | 0.30 | 0.10 | 0.09 | 0.17 |
| **19** | 0.12 | 0.32 | 0.88 | 0.09 | 0.56 | 1.72 | 0.39 | 0.11 | 0.11 | 0.13 |
| **20** | 0.37 | 0.14 | 0.44 | 0.13 | 0.62 | 3.01 | 0.23 | 0.11 | 0.07 | 0.20 |
| **21** | 0.27 | 0.08 | 0.41 | 0.19 | 0.69 | 2.31 | 0.30 | 0.13 | 0.13 | 0.22 |
| **22** | 0.05 | 0.29 | 0.63 | 0.10 | 0.55 | 1.87 | 0.42 | 0.08 | 0.15 | 0.39 |
| **23** | 0.30 | 0.15 | 0.42 | 0.08 | 0.97 | 2.32 | 0.30 | 0.12 | 0.16 | 0.14 |
| **24** | 0.38 | 0.16 | 0.40 | 0.16 | 0.62 | 2.78 | 0.34 | 0.13 | 0.08 | 0.17 |
| **25** | 0.26 | 0.11 | 0.43 | 0.12 | 1.01 | 2.59 | 0.32 | 0.09 | 0.12 | 0.14 |
| **26** | 0.13 | 0.22 | 0.49 | 0.13 | 0.95 | 0.64 | 0.41 | 0.14 | 0.13 | 0.61 |
| **27** | 0.20 | 0.40 | 0.28 | 0.06 | 0.48 | 1.90 | 0.33 | 0.15 | 0.20 | 0.60 |
| **28** | 0.25 | 0.08 | 0.47 | 0.20 | 1.09 | 2.61 | 0.35 | 0.06 | 0.20 | 0.14 |
| **29** | 0.37 | 0.19 | 0.41 | 0.12 | 0.70 | 2.42 | 0.32 | 0.13 | 0.11 | 0.25 |
| **30** | 0.21 | 0.10 | 0.42 | 0.24 | 0.76 | 2.37 | 0.31 | 0.11 | 0.08 | 0.29 |
| **31** | 0.05 | 0.26 | 0.62 | 0.05 | 0.75 | 1.99 | 0.42 | 0.06 | 0.11 | 0.27 |
| **32** | 0.15 | 0.33 | 0.82 | 0.07 | 0.58 | 1.77 | 0.37 | 0.13 | 0.12 | 0.15 |
| **33** | 0.07 | 0.26 | 0.64 | 0.10 | 0.64 | 1.75 | 0.40 | 0.12 | 0.09 | 0.18 |
| **34** | 0.08 | 0.33 | 0.89 | 0.28 | 0.50 | 1.70 | 0.45 | 0.10 | 0.14 | 0.28 |
| **35** | 0.28 | 0.05 | 0.47 | 0.24 | 0.73 | 2.17 | 0.33 | 0.07 | 0.11 | 0.23 |
| **36** | 0.07 | 0.30 | 0.66 | 0.04 | 0.75 | 1.97 | 0.44 | 0.08 | 0.11 | 0.33 |
| **37** | 0.08 | 0.37 | 0.62 | 0.06 | 0.76 | 1.92 | 0.38 | 0.07 | 0.04 | 0.37 |
| **38** | 0.14 | 0.41 | 0.61 | 0.08 | 0.62 | 1.77 | 0.34 | 0.11 | 0.08 | 0.31 |
| **39** | 0.28 | 0.13 | 0.45 | 0.10 | 0.94 | 2.56 | 0.26 | 0.11 | 0.12 | 0.15 |
| **40** | 0.04 | 0.25 | 0.68 | 0.09 | 0.65 | 1.91 | 0.39 | 0.05 | 0.16 | 0.28 |
| **41** | 0.35 | 0.17 | 0.40 | 0.14 | 0.80 | 2.69 | 0.34 | 0.11 | 0.07 | 0.21 |
| **42** | 0.32 | 0.14 | 0.45 | 0.17 | 0.79 | 2.51 | 0.30 | 0.11 | 0.13 | 0.23 |
| **43** | 0.30 | 0.14 | 0.38 | 0.12 | 0.83 | 2.66 | 0.27 | 0.10 | 0.07 | 0.20 |
| **44** | 0.09 | 0.18 | 0.47 | 0.09 | 0.71 | 2.11 | 0.41 | 0.18 | 0.16 | 0.37 |
| **45** | 0.30 | 0.13 | 0.42 | 0.14 | 0.94 | 2.41 | 0.30 | 0.09 | 0.09 | 0.18 |
| **46** | 0.28 | 0.12 | 0.43 | 0.11 | 0.91 | 2.58 | 0.39 | 0.08 | 0.07 | 0.19 |
| **47** | 0.36 | 0.17 | 0.40 | 0.11 | 0.86 | 2.77 | 0.34 | 0.11 | 0.08 | 0.23 |
| **48** | 0.29 | 0.12 | 0.45 | 0.07 | 1.08 | 2.46 | 0.41 | 0.08 | 0.10 | 0.15 |
| **49** | 0.14 | 0.35 | 0.51 | 0.06 | 0.59 | 1.95 | 0.40 | 0.18 | 0.11 | 0.52 |
| **μ** | **0.22** | **0.21** | **0.53** | **0.13** | **0.75** | **2.21** | **0.35** | **0.10** | **0.10** | **0.25** |

**$SSP_{pFl}$**
**80% Noise**

| **Subject** | ***A*** | ***ter*** | ***pTarget*** | ***pFlanker*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.02 | 0.42 | 0.90 | 0.48 | 77.91 | 0.68 | 0.04 | 0.16 | 0.32 |
| **2** | 0.12 | 0.42 | 0.16 | 0.45 | 86.73 | 2.92 | 0.14 | 0.13 | 0.05 |
| **3** | 0.14 | 0.43 | 0.33 | 0.37 | 82.29 | 5.09 | 0.13 | 0.15 | 0.26 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **4** | 0.09 | 0.61 | 0.45 | 0.47 | 84.57 | 1.80 | 0.09 | 0.24 | 0.40 |
| **5** | 0.15 | 0.47 | 0.41 | 0.59 | 86.96 | 3.83 | 0.10 | 0.15 | 0.35 |
| **6** | 0.14 | 0.51 | 0.21 | 0.39 | 81.32 | 4.90 | 0.15 | 0.20 | 0.42 |
| **7** | 0.10 | 0.32 | 0.40 | 0.37 | 88.65 | 5.27 | 0.13 | 0.09 | 0.31 |
| **8** | 0.16 | 0.55 | 0.42 | 0.45 | 87.04 | 3.20 | 0.12 | 0.14 | 0.35 |
| **9** | 0.20 | 0.40 | 0.38 | 0.51 | 83.10 | 4.72 | 0.13 | 0.15 | 0.24 |
| **10** | 0.08 | 0.41 | 0.39 | 0.49 | 89.20 | 2.14 | 0.07 | 0.08 | 0.39 |
| **11** | 0.26 | 0.38 | 0.45 | 0.47 | 88.72 | 4.98 | 0.15 | 0.14 | 0.29 |
| **12** | 0.24 | 0.48 | 0.51 | 0.51 | 80.83 | 5.69 | 0.14 | 0.14 | 0.30 |
| **13** | 0.13 | 0.48 | 0.49 | 0.50 | 89.95 | 3.48 | 0.13 | 0.16 | 0.44 |
| **14** | 0.18 | 0.29 | 0.52 | 0.49 | 87.08 | 4.44 | 0.15 | 0.15 | 0.32 |
| **15** | 0.10 | 0.41 | 0.33 | 0.57 | 90.61 | 2.91 | 0.08 | 0.12 | 0.33 |
| **16** | 0.10 | 0.42 | 0.55 | 0.33 | 83.40 | 5.31 | 0.12 | 0.14 | 0.41 |
| **17** | 0.07 | 0.57 | 0.26 | 0.42 | 85.14 | 1.82 | 0.08 | 0.15 | 0.23 |
| **18** | 0.19 | 0.35 | 0.43 | 0.45 | 85.99 | 5.09 | 0.14 | 0.13 | 0.24 |
| **19** | 0.14 | 0.36 | 0.49 | 0.52 | 86.10 | 4.75 | 0.11 | 0.12 | 0.32 |
| **20** | 0.11 | 0.54 | 0.10 | 0.43 | 86.32 | 2.60 | 0.15 | 0.15 | 0.05 |
| **21** | 0.08 | 0.39 | 0.43 | 0.44 | 85.05 | 2.70 | 0.09 | 0.16 | 0.36 |
| **22** | 0.08 | 0.44 | 0.47 | 0.33 | 87.50 | 2.78 | 0.14 | 0.09 | 0.45 |
| **23** | 0.16 | 0.43 | 0.59 | 0.46 | 84.77 | 3.68 | 0.12 | 0.15 | 0.35 |
| **24** | 0.12 | 0.54 | 0.26 | 0.41 | 86.30 | 2.98 | 0.10 | 0.15 | 0.12 |
| **25** | 0.08 | 0.48 | 0.42 | 0.54 | 89.20 | 3.14 | 0.10 | 0.20 | 0.40 |
| **26** | 0.12 | 0.40 | 0.13 | 0.37 | 84.80 | 4.00 | 0.17 | 0.16 | 0.11 |
| **27** | 0.12 | 0.41 | 0.10 | 0.40 | 83.41 | 3.59 | 0.14 | 0.19 | 0.23 |
| **28** | 0.11 | 0.37 | 0.22 | 0.46 | 83.66 | 3.64 | 0.11 | 0.15 | 0.19 |
| **29** | 0.29 | 0.47 | 0.68 | 0.53 | 85.43 | 4.79 | 0.15 | 0.16 | 0.41 |
| **30** | 0.11 | 0.39 | 0.44 | 0.41 | 83.79 | 5.42 | 0.13 | 0.20 | 0.46 |
| **31** | 0.08 | 0.46 | 0.55 | 0.37 | 89.33 | 3.07 | 0.13 | 0.10 | 0.50 |
| **32** | 0.06 | 0.60 | 0.41 | 0.48 | 82.66 | 1.10 | 0.06 | 0.29 | 0.37 |
| **33** | 0.09 | 0.40 | 0.34 | 0.53 | 86.66 | 3.54 | 0.07 | 0.18 | 0.19 |
| **34** | 0.09 | 0.45 | 0.17 | 0.63 | 89.98 | 3.40 | 0.08 | 0.12 | 0.31 |
| **35** | 0.07 | 0.43 | 0.61 | 0.44 | 85.48 | 1.84 | 0.07 | 0.09 | 0.45 |
| **36** | 0.09 | 0.47 | 0.41 | 0.42 | 85.27 | 2.92 | 0.11 | 0.17 | 0.34 |
| **37** | 0.08 | 0.40 | 0.51 | 0.46 | 87.84 | 2.06 | 0.07 | 0.08 | 0.37 |
| **38** | 0.13 | 0.42 | 0.29 | 0.37 | 84.55 | 4.21 | 0.16 | 0.16 | 0.42 |
| **39** | 0.13 | 0.40 | 0.69 | 0.46 | 88.42 | 3.17 | 0.11 | 0.15 | 0.44 |
| **40** | 0.07 | 0.41 | 0.42 | 0.59 | 88.97 | 3.16 | 0.08 | 0.15 | 0.41 |
| **41** | 0.10 | 0.72 | 0.15 | 0.40 | 84.26 | 4.96 | 0.16 | 0.17 | 0.34 |
| **42** | 0.12 | 0.45 | 0.53 | 0.47 | 89.64 | 3.23 | 0.12 | 0.12 | 0.40 |
| **43** | 0.14 | 0.38 | 0.33 | 0.48 | 87.84 | 3.78 | 0.11 | 0.15 | 0.26 |
| **44** | 0.06 | 0.40 | 0.24 | 0.47 | 84.53 | 1.63 | 0.09 | 0.22 | 0.51 |
| **45** | 0.13 | 0.49 | 0.52 | 0.57 | 88.60 | 2.25 | 0.10 | 0.13 | 0.52 |
| **46** | 0.20 | 0.50 | 0.83 | 0.64 | 91.04 | 4.84 | 0.13 | 0.14 | 0.47 |
| **47** | 0.20 | 0.48 | 0.30 | 0.51 | 85.47 | 4.81 | 0.13 | 0.16 | 0.20 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **48** | 0.10 | 0.58 | 0.45 | 0.58 | 89.14 | 3.33 | 0.08 | 0.13 | 0.31 |
| **49** | 0.11 | 0.48 | 0.45 | 0.48 | 88.03 | 2.57 | 0.10 | 0.16 | 0.51 |
| ***μ*** | **0.12** | **0.45** | **0.41** | **0.47** | **86.20** | **3.51** | **0.11** | **0.15** | **0.33** |

**70% Noise**

| **Subject** | ***A*** | ***ter*** | ***pTarget*** | ***pFlanker*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.04 | 0.35 | 0.59 | 0.49 | 85.40 | 1.09 | 0.05 | 0.06 | 0.23 |
| **2** | 0.15 | 0.42 | 0.50 | 0.47 | 87.64 | 4.21 | 0.12 | 0.12 | 0.24 |
| **3** | 0.15 | 0.46 | 0.59 | 0.35 | 85.84 | 4.87 | 0.14 | 0.18 | 0.43 |
| **4** | 0.09 | 0.60 | 0.65 | 0.57 | 88.88 | 1.61 | 0.07 | 0.25 | 0.49 |
| **5** | 0.36 | 0.26 | 0.92 | 0.54 | 82.53 | 5.63 | 0.14 | 0.10 | 0.29 |
| **6** | 0.11 | 0.47 | 0.18 | 0.42 | 86.65 | 3.75 | 0.11 | 0.14 | 0.33 |
| **7** | 0.08 | 0.34 | 0.62 | 0.41 | 87.97 | 3.91 | 0.10 | 0.08 | 0.39 |
| **8** | 0.17 | 0.47 | 0.54 | 0.50 | 85.49 | 4.05 | 0.12 | 0.13 | 0.36 |
| **9** | 0.27 | 0.39 | 0.77 | 0.50 | 84.27 | 5.16 | 0.16 | 0.17 | 0.38 |
| **10** | 0.28 | 0.28 | 1.16 | 0.43 | 82.41 | 2.87 | 0.11 | 0.07 | 0.25 |
| **11** | 0.43 | 0.25 | 0.79 | 0.46 | 84.82 | 4.71 | 0.15 | 0.12 | 0.28 |
| **12** | 0.42 | 0.27 | 0.73 | 0.48 | 83.63 | 4.38 | 0.14 | 0.12 | 0.26 |
| **13** | 0.09 | 0.46 | 0.48 | 0.54 | 86.64 | 3.88 | 0.08 | 0.12 | 0.34 |
| **14** | 0.33 | 0.18 | 0.97 | 0.47 | 86.01 | 4.72 | 0.14 | 0.09 | 0.32 |
| **15** | 0.11 | 0.39 | 0.56 | 0.49 | 89.85 | 3.25 | 0.09 | 0.11 | 0.35 |
| **16** | 0.08 | 0.42 | 0.48 | 0.48 | 87.13 | 3.36 | 0.07 | 0.10 | 0.32 |
| **17** | 0.09 | 0.55 | 0.68 | 0.40 | 87.47 | 2.87 | 0.11 | 0.15 | 0.42 |
| **18** | 0.17 | 0.44 | 0.86 | 0.55 | 90.16 | 3.67 | 0.11 | 0.09 | 0.48 |
| **19** | 0.31 | 0.26 | 0.97 | 0.42 | 83.62 | 3.52 | 0.13 | 0.08 | 0.24 |
| **20** | 0.14 | 0.40 | 0.24 | 0.42 | 87.26 | 4.23 | 0.14 | 0.16 | 0.30 |
| **21** | 0.08 | 0.40 | 0.68 | 0.51 | 88.19 | 2.80 | 0.08 | 0.09 | 0.43 |
| **22** | 0.08 | 0.41 | 0.57 | 0.50 | 86.19 | 2.02 | 0.08 | 0.16 | 0.42 |
| **23** | 0.34 | 0.25 | 0.88 | 0.43 | 82.45 | 3.90 | 0.13 | 0.11 | 0.26 |
| **24** | 0.20 | 0.48 | 0.64 | 0.44 | 88.78 | 3.06 | 0.17 | 0.17 | 0.30 |
| **25** | 0.08 | 0.46 | 0.70 | 0.54 | 88.02 | 3.16 | 0.08 | 0.14 | 0.43 |
| **26** | 0.12 | 0.41 | 0.17 | 0.39 | 82.53 | 3.87 | 0.17 | 0.17 | 0.15 |
| **27** | 0.16 | 0.43 | 0.25 | 0.44 | 85.97 | 4.91 | 0.18 | 0.20 | 0.46 |
| **28** | 0.13 | 0.35 | 0.41 | 0.44 | 87.67 | 5.02 | 0.12 | 0.13 | 0.33 |
| **29** | 0.28 | 0.44 | 0.71 | 0.55 | 84.09 | 5.63 | 0.15 | 0.13 | 0.32 |
| **30** | 0.08 | 0.43 | 0.45 | 0.41 | 87.08 | 3.52 | 0.13 | 0.19 | 0.37 |
| **31** | 0.07 | 0.44 | 0.46 | 0.40 | 87.20 | 1.90 | 0.11 | 0.13 | 0.30 |
| **32** | 0.07 | 0.56 | 0.46 | 0.37 | 83.70 | 2.32 | 0.11 | 0.29 | 0.24 |
| **33** | 0.13 | 0.37 | 0.73 | 0.65 | 88.48 | 4.59 | 0.10 | 0.11 | 0.37 |
| **34** | 0.10 | 0.45 | 0.38 | 0.60 | 88.51 | 2.08 | 0.07 | 0.13 | 0.44 |
| **35** | 0.06 | 0.43 | 0.58 | 0.47 | 84.28 | 3.63 | 0.08 | 0.11 | 0.33 |
| **36** | 0.07 | 0.47 | 0.61 | 0.54 | 87.54 | 2.18 | 0.06 | 0.11 | 0.41 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **37** | 0.08 | 0.38 | 0.61 | 0.69 | 90.06 | 3.86 | 0.07 | 0.09 | 0.43 |
| **38** | 0.13 | 0.38 | 0.31 | 0.44 | 87.06 | 4.74 | 0.16 | 0.14 | 0.39 |
| **39** | 0.10 | 0.40 | 0.67 | 0.50 | 87.94 | 2.87 | 0.09 | 0.08 | 0.34 |
| **40** | 0.07 | 0.41 | 0.68 | 0.53 | 90.79 | 2.18 | 0.08 | 0.10 | 0.59 |
| **41** | 0.10 | 0.64 | 0.31 | 0.41 | 85.93 | 3.82 | 0.11 | 0.19 | 0.35 |
| **42** | 0.12 | 0.45 | 0.76 | 0.40 | 88.57 | 3.40 | 0.12 | 0.10 | 0.43 |
| **43** | 0.12 | 0.42 | 0.38 | 0.42 | 85.89 | 2.20 | 0.10 | 0.13 | 0.22 |
| **44** | 0.06 | 0.44 | 0.32 | 0.43 | 83.41 | 3.28 | 0.10 | 0.27 | 0.40 |
| **45** | 0.13 | 0.39 | 0.55 | 0.44 | 85.52 | 3.90 | 0.12 | 0.14 | 0.25 |
| **46** | 0.30 | 0.39 | 1.06 | 0.40 | 81.29 | 2.28 | 0.13 | 0.09 | 0.22 |
| **47** | 0.18 | 0.44 | 0.43 | 0.54 | 85.26 | 4.82 | 0.13 | 0.15 | 0.26 |
| **48** | 0.12 | 0.60 | 1.06 | 0.53 | 88.99 | 1.88 | 0.10 | 0.18 | 0.48 |
| **49** | 0.09 | 0.48 | 0.51 | 0.40 | 85.55 | 2.82 | 0.10 | 0.12 | 0.37 |
| ***μ*** | **0.15** | **0.41** | **0.60** | **0.47** | **86.34** | **3.52** | **0.11** | **0.13** | **0.35** |

**40% Noise**

| **Subject** | ***A*** | ***ter*** | ***pTarget*** | ***pFlanker*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.03 | 0.36 | 1.44 | 0.47 | 90.98 | 2.86 | 0.05 | 0.06 | 0.20 |
| **2** | 0.29 | 0.30 | 0.97 | 0.40 | 80.86 | 3.17 | 0.14 | 0.09 | 0.21 |
| **3** | 0.12 | 0.46 | 0.93 | 0.43 | 88.42 | 3.47 | 0.13 | 0.13 | 0.40 |
| **4** | 0.17 | 0.47 | 1.12 | 0.51 | 81.69 | 3.62 | 0.11 | 0.18 | 0.22 |
| **5** | 0.24 | 0.35 | 1.15 | 0.44 | 84.78 | 2.77 | 0.11 | 0.06 | 0.30 |
| **6** | 0.12 | 0.45 | 0.44 | 0.44 | 87.74 | 2.81 | 0.11 | 0.15 | 0.34 |
| **7** | 0.22 | 0.22 | 1.15 | 0.42 | 81.98 | 3.05 | 0.10 | 0.06 | 0.20 |
| **8** | 0.27 | 0.40 | 1.07 | 0.38 | 83.15 | 2.24 | 0.12 | 0.07 | 0.24 |
| **9** | 0.31 | 0.30 | 1.04 | 0.37 | 85.53 | 2.75 | 0.12 | 0.08 | 0.30 |
| **10** | 0.04 | 0.43 | 1.21 | 0.65 | 84.22 | 2.16 | 0.04 | 0.09 | 0.28 |
| **11** | 0.31 | 0.33 | 0.98 | 0.45 | 82.68 | 3.83 | 0.12 | 0.10 | 0.29 |
| **12** | 0.36 | 0.23 | 0.97 | 0.57 | 84.45 | 5.85 | 0.14 | 0.10 | 0.31 |
| **13** | 0.07 | 0.50 | 0.83 | 0.44 | 85.91 | 2.88 | 0.08 | 0.25 | 0.35 |
| **14** | 0.27 | 0.21 | 1.12 | 0.51 | 84.49 | 4.42 | 0.12 | 0.09 | 0.23 |
| **15** | 0.11 | 0.38 | 0.78 | 0.44 | 89.30 | 2.78 | 0.09 | 0.07 | 0.36 |
| **16** | 0.06 | 0.42 | 0.51 | 0.48 | 85.44 | 1.84 | 0.06 | 0.10 | 0.24 |
| **17** | 0.08 | 0.54 | 0.73 | 0.50 | 85.30 | 1.86 | 0.07 | 0.19 | 0.47 |
| **18** | 0.18 | 0.37 | 1.26 | 0.47 | 83.41 | 3.39 | 0.09 | 0.05 | 0.24 |
| **19** | 0.25 | 0.29 | 1.08 | 0.41 | 81.91 | 3.20 | 0.12 | 0.09 | 0.19 |
| **20** | 0.13 | 0.38 | 0.57 | 0.39 | 86.03 | 2.09 | 0.12 | 0.12 | 0.33 |
| **21** | 0.08 | 0.42 | 1.07 | 0.40 | 86.07 | 3.15 | 0.12 | 0.18 | 0.37 |
| **22** | 0.07 | 0.41 | 0.64 | 0.42 | 89.36 | 2.16 | 0.08 | 0.09 | 0.38 |
| **23** | 0.12 | 0.43 | 0.89 | 0.47 | 87.88 | 2.63 | 0.13 | 0.19 | 0.41 |
| **24** | 0.33 | 0.33 | 0.90 | 0.38 | 85.40 | 2.86 | 0.17 | 0.12 | 0.19 |
| **25** | 0.08 | 0.41 | 0.89 | 0.56 | 87.85 | 3.67 | 0.08 | 0.10 | 0.33 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **26** | 0.13 | 0.40 | 0.45 | 0.29 | 81.01 | 5.59 | 0.16 | 0.15 | 0.35 |
| **27** | 0.13 | 0.46 | 0.30 | 0.24 | 69.72 | 6.90 | 0.24 | 0.29 | 0.37 |
| **28** | 0.12 | 0.36 | 0.67 | 0.43 | 87.27 | 3.74 | 0.13 | 0.14 | 0.31 |
| **29** | 0.40 | 0.32 | 0.98 | 0.48 | 85.38 | 4.51 | 0.13 | 0.10 | 0.31 |
| **30** | 0.11 | 0.38 | 0.91 | 0.66 | 90.71 | 4.14 | 0.11 | 0.15 | 0.44 |
| **31** | 0.05 | 0.44 | 0.69 | 0.48 | 86.57 | 1.82 | 0.06 | 0.16 | 0.36 |
| **32** | 0.27 | 0.29 | 1.09 | 0.40 | 82.10 | 2.80 | 0.13 | 0.12 | 0.18 |
| **33** | 0.25 | 0.27 | 1.20 | 0.65 | 81.88 | 5.52 | 0.10 | 0.08 | 0.25 |
| **34** | 0.12 | 0.42 | 0.96 | 0.72 | 93.00 | 3.10 | 0.09 | 0.09 | 0.55 |
| **35** | 0.21 | 0.33 | 1.26 | 0.41 | 84.75 | 2.61 | 0.10 | 0.06 | 0.21 |
| **36** | 0.12 | 0.40 | 0.82 | 0.47 | 88.36 | 3.13 | 0.11 | 0.10 | 0.41 |
| **37** | 0.07 | 0.37 | 0.70 | 0.43 | 88.43 | 2.36 | 0.06 | 0.05 | 0.36 |
| **38** | 0.10 | 0.38 | 0.55 | 0.34 | 85.99 | 3.42 | 0.15 | 0.12 | 0.21 |
| **39** | 0.22 | 0.28 | 1.25 | 0.47 | 81.46 | 3.58 | 0.11 | 0.11 | 0.16 |
| **40** | 0.05 | 0.39 | 0.66 | 0.43 | 83.48 | 1.18 | 0.06 | 0.08 | 0.34 |
| **41** | 0.10 | 0.52 | 0.48 | 0.43 | 85.50 | 2.79 | 0.12 | 0.11 | 0.14 |
| **42** | 0.29 | 0.27 | 1.02 | 0.44 | 81.57 | 4.15 | 0.13 | 0.12 | 0.18 |
| **43** | 0.27 | 0.26 | 1.04 | 0.56 | 83.03 | 5.10 | 0.13 | 0.08 | 0.24 |
| **44** | 0.12 | 0.40 | 1.24 | 0.21 | 81.94 | 6.01 | 0.24 | 0.17 | 0.24 |
| **45** | 0.27 | 0.31 | 1.15 | 0.39 | 83.90 | 1.78 | 0.14 | 0.12 | 0.15 |
| **46** | 0.24 | 0.39 | 1.22 | 0.48 | 80.83 | 3.70 | 0.13 | 0.08 | 0.14 |
| **47** | 0.34 | 0.31 | 0.94 | 0.39 | 82.38 | 2.19 | 0.13 | 0.11 | 0.24 |
| **48** | 0.26 | 0.40 | 1.25 | 0.44 | 82.62 | 3.74 | 0.11 | 0.09 | 0.16 |
| **49** | 0.15 | 0.38 | 0.87 | 0.12 | 76.17 | 7.58 | 0.20 | 0.14 | 0.34 |
| ***μ*** | **0.18** | **0.37** | **0.93** | **0.44** | **84.55** | **3.41** | **0.12** | **0.11** | **0.29** |

**10% Noise**

| **Subject** | ***A*** | ***ter*** | ***pTarget*** | ***pFlanker*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.03 | 0.36 | 1.14 | 0.49 | 84.13 | 1.03 | 0.04 | 0.04 | 0.26 |
| **2** | 0.22 | 0.35 | 1.27 | 0.55 | 79.29 | 4.79 | 0.10 | 0.07 | 0.16 |
| **3** | 0.11 | 0.44 | 0.85 | 0.41 | 86.32 | 2.53 | 0.11 | 0.13 | 0.39 |
| **4** | 0.24 | 0.39 | 1.25 | 0.47 | 80.27 | 3.66 | 0.11 | 0.11 | 0.13 |
| **5** | 0.28 | 0.30 | 1.14 | 0.41 | 82.90 | 2.80 | 0.13 | 0.09 | 0.18 |
| **6** | 0.11 | 0.47 | 0.73 | 0.56 | 88.02 | 1.87 | 0.09 | 0.21 | 0.50 |
| **7** | 0.21 | 0.23 | 1.20 | 0.39 | 80.50 | 1.76 | 0.11 | 0.08 | 0.16 |
| **8** | 0.24 | 0.39 | 1.10 | 0.45 | 84.55 | 2.38 | 0.13 | 0.06 | 0.25 |
| **9** | 0.29 | 0.31 | 1.08 | 0.36 | 84.87 | 2.41 | 0.12 | 0.08 | 0.30 |
| **10** | 0.17 | 0.34 | 1.64 | 0.44 | 82.04 | 1.54 | 0.07 | 0.05 | 0.13 |
| **11** | 0.25 | 0.41 | 1.09 | 0.48 | 91.77 | 3.23 | 0.11 | 0.08 | 0.49 |
| **12** | 0.22 | 0.33 | 1.15 | 0.47 | 85.10 | 3.40 | 0.10 | 0.06 | 0.29 |
| **13** | 0.28 | 0.29 | 1.07 | 0.39 | 81.30 | 2.89 | 0.13 | 0.12 | 0.19 |
| **14** | 0.25 | 0.24 | 1.20 | 0.41 | 84.81 | 2.31 | 0.13 | 0.08 | 0.23 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **15** | | 0.21 | 0.32 | 1.20 | 0.48 | 84.90 | 3.55 | 0.09 | 0.05 | 0.33 |
| **16** | | 0.09 | 0.46 | 0.66 | 0.53 | 87.17 | 2.05 | 0.21 | 0.14 | 0.19 |
| **17** | | 0.29 | 0.32 | 1.01 | 0.64 | 77.65 | 6.22 | 0.12 | 0.10 | 0.22 |
| **18** | | 0.26 | 0.31 | 1.25 | 0.39 | 82.47 | 2.49 | 0.11 | 0.08 | 0.17 |
| **19** | | 0.23 | 0.31 | 1.21 | 0.46 | 82.83 | 3.24 | 0.14 | 0.10 | 0.16 |
| **20** | | 0.30 | 0.24 | 1.09 | 0.42 | 83.94 | 2.68 | 0.13 | 0.07 | 0.26 |
| **21** | | 0.25 | 0.26 | 1.08 | 0.40 | 82.93 | 2.98 | 0.13 | 0.12 | 0.19 |
| **22** | | 0.05 | 0.42 | 0.74 | 0.45 | 84.21 | 1.40 | 0.07 | 0.15 | 0.43 |
| **23** | | 0.26 | 0.32 | 1.15 | 0.39 | 81.49 | 2.01 | 0.15 | 0.13 | 0.13 |
| **24** | | 0.30 | 0.36 | 0.99 | 0.45 | 85.80 | 3.82 | 0.14 | 0.08 | 0.23 |
| **25** | | 0.21 | 0.34 | 1.33 | 0.42 | 82.47 | 2.19 | 0.13 | 0.10 | 0.14 |
| **26** | | 0.12 | 0.41 | 0.66 | 0.53 | 87.78 | 4.19 | 0.13 | 0.13 | 0.57 |
| **27** | | 0.13 | 0.42 | 0.42 | 0.35 | 83.52 | 3.96 | 0.14 | 0.20 | 0.54 |
| **28** | | 0.19 | 0.36 | 1.43 | 0.45 | 80.81 | 2.56 | 0.10 | 0.18 | 0.14 |
| **29** | | 0.33 | 0.34 | 0.99 | 0.43 | 82.66 | 3.46 | 0.13 | 0.11 | 0.25 |
| **30** | | 0.21 | 0.29 | 1.08 | 0.46 | 84.86 | 3.56 | 0.11 | 0.08 | 0.23 |
| **31** | | 0.08 | 0.40 | 0.86 | 0.41 | 85.06 | 1.68 | 0.09 | 0.10 | 0.27 |
| **32** | | 0.27 | 0.29 | 1.18 | 0.42 | 84.94 | 2.95 | 0.15 | 0.12 | 0.18 |
| **33** | | 0.09 | 0.39 | 0.91 | 0.40 | 83.42 | 2.43 | 0.16 | 0.08 | 0.20 |
| **34** | | 0.12 | 0.39 | 1.18 | 0.54 | 83.65 | 5.85 | 0.13 | 0.12 | 0.22 |
| **35** | | 0.05 | 0.43 | 0.92 | 0.48 | 84.68 | 2.11 | 0.06 | 0.13 | 0.28 |
| **36** | | 0.10 | 0.42 | 0.89 | 0.41 | 88.42 | 2.05 | 0.09 | 0.10 | 0.33 |
| **37** | | 0.08 | 0.37 | 0.71 | 0.47 | 87.67 | 2.70 | 0.07 | 0.05 | 0.34 |
| **38** | | 0.33 | 0.20 | 0.99 | 0.43 | 84.34 | 3.66 | 0.13 | 0.09 | 0.28 |
| **39** | | 0.22 | 0.28 | 1.21 | 0.41 | 82.73 | 2.03 | 0.15 | 0.10 | 0.15 |
| **40** | | 0.05 | 0.39 | 1.05 | 0.43 | 84.61 | 1.59 | 0.07 | 0.17 | 0.31 |
| **41** | | 0.28 | 0.38 | 1.13 | 0.45 | 85.49 | 3.47 | 0.13 | 0.07 | 0.24 |
| **42** | | 0.29 | 0.31 | 1.14 | 0.40 | 81.81 | 2.85 | 0.12 | 0.12 | 0.23 |
| **43** | | 0.23 | 0.31 | 1.12 | 0.44 | 82.54 | 2.74 | 0.12 | 0.06 | 0.22 |
| **44** | | 0.08 | 0.41 | 0.81 | 0.28 | 85.83 | 3.90 | 0.16 | 0.17 | 0.39 |
| **45** | | 0.24 | 0.33 | 1.28 | 0.41 | 81.35 | 2.73 | 0.11 | 0.09 | 0.19 |
| **46** | | 0.25 | 0.40 | 1.27 | 0.42 | 81.82 | 1.93 | 0.10 | 0.07 | 0.19 |
| **47** | | 0.28 | 0.38 | 1.17 | 0.42 | 84.55 | 2.88 | 0.12 | 0.08 | 0.25 |
| **48** | | 0.23 | 0.44 | 1.36 | 0.39 | 82.52 | 1.66 | 0.11 | 0.09 | 0.13 |
| **49** | | 0.11 | 0.42 | 0.71 | 0.30 | 90.08 | 3.90 | 0.16 | 0.11 | 0.48 |
| | ***μ*** | **0.20** | **0.35** | **1.06** | **0.44** | **84.02** | **2.86** | **0.12** | **0.10** | **0.26** |

## Log marginal likelihoods and log Bayes Factor (ln(BF))

| Subject | Noise Level | | | | | |
|---|---|---|---|---|---|---|
| | 80% | | | 70% | | |
| | SSP | DSTP | ln(BF) | SSP | DSTP | ln(BF) |
| **1** | -382.93 | -381.76 | 1.17 | -345.67 | -344.90 | 0.76 |
| **2** | -598.50 | -601.13 | -2.64 | -520.07 | -515.58 | 4.49 |
| **3** | -540.08 | -541.63 | -1.55 | -531.22 | -531.35 | -0.12 |
| **4** | -515.99 | -515.45 | 0.54 | -483.12 | -482.01 | 1.12 |
| **5** | -571.84 | -574.62 | -2.78 | -488.45 | -484.36 | 4.09 |
| **6** | -583.01 | -586.02 | -3.01 | -605.35 | -603.89 | 1.46 |
| **7** | -538.25 | -538.33 | -0.08 | -455.70 | -452.39 | 3.31 |
| **8** | -560.18 | -560.80 | -0.62 | -529.23 | -530.06 | -0.83 |
| **9** | -572.81 | -572.27 | 0.55 | -507.82 | -508.42 | -0.60 |
| **10** | -499.56 | -497.30 | 2.26 | -418.38 | -417.88 | 0.50 |
| **11** | -555.17 | -552.08 | 3.09 | -496.39 | -497.62 | -1.23 |
| **12** | -530.67 | -528.55 | 2.12 | -516.36 | -516.14 | 0.21 |
| **13** | -555.08 | -554.18 | 0.90 | -496.67 | -497.53 | -0.87 |
| **14** | -549.53 | -548.50 | 1.03 | -460.57 | -460.92 | -0.35 |
| **15** | -549.80 | -545.10 | 4.70 | -491.83 | -491.80 | 0.03 |
| **16** | -503.11 | -503.16 | -0.05 | -468.37 | -466.08 | 2.28 |
| **17** | -518.64 | -515.34 | 3.30 | -465.43 | -465.12 | 0.31 |
| **18** | -539.72 | -536.38 | 3.34 | -485.48 | -486.81 | -1.33 |
| **19** | -534.92 | -536.58 | -1.66 | -443.83 | -441.62 | 2.21 |
| **20** | -608.91 | -608.29 | 0.62 | -610.04 | -611.58 | -1.54 |
| **21** | -497.03 | -498.49 | -1.45 | -457.18 | -450.97 | 6.21 |
| **22** | -508.47 | -506.18 | 2.29 | -476.96 | -472.35 | 4.62 |
| **23** | -515.94 | -516.02 | -0.09 | -465.11 | -465.72 | -0.61 |
| **24** | -538.41 | -534.19 | 4.22 | -499.42 | -497.26 | 2.16 |
| **25** | -508.74 | -503.13 | 5.60 | -433.27 | -433.20 | 0.07 |
| **26** | -581.43 | -578.01 | 3.41 | -593.82 | -592.58 | 1.23 |
| **27** | -626.60 | -626.78 | -0.18 | -621.87 | -622.70 | -0.84 |
| **28** | -592.81 | -591.85 | 0.96 | -562.83 | -561.70 | 1.13 |
| **29** | -494.55 | -490.48 | 4.07 | -518.54 | -514.22 | 4.32 |
| **30** | -547.92 | -550.21 | -2.29 | -507.54 | -505.73 | 1.81 |
| **31** | -483.61 | -483.79 | -0.17 | -468.58 | -466.38 | 2.20 |
| **32** | -497.68 | -496.04 | 1.64 | -487.93 | -484.63 | 3.30 |
| **33** | -514.63 | -510.31 | 4.32 | -452.08 | -452.80 | -0.72 |
| **34** | -575.83 | -571.16 | 4.67 | -536.71 | -533.67 | 3.04 |
| **35** | -438.50 | -437.64 | 0.86 | -430.10 | -428.95 | 1.15 |
| **36** | -535.34 | -535.23 | 0.11 | -459.72 | -457.01 | 2.70 |
| **37** | -466.65 | -465.26 | 1.39 | -454.47 | -457.60 | -3.13 |
| **38** | -575.39 | -579.06 | -3.67 | -591.93 | -595.18 | -3.25 |
| **39** | -500.11 | -503.47 | -3.36 | -436.09 | -435.31 | 0.78 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **40** | -499.66 | -495.84 | 3.82 | -448.94 | -452.69 | -3.75 |
| **41** | -591.61 | -590.42 | 1.19 | -560.74 | -561.12 | -0.38 |
| **42** | -523.69 | -525.00 | -1.32 | -468.95 | -468.77 | 0.18 |
| **43** | -583.37 | -580.29 | 3.08 | -531.27 | -530.75 | 0.52 |
| **44** | -525.45 | -524.33 | 1.12 | -517.00 | -515.93 | 1.07 |
| **45** | -554.02 | -555.84 | -1.82 | -484.90 | -478.47 | 6.43 |
| **46** | -503.91 | -496.99 | 6.93 | -396.53 | -397.28 | -0.75 |
| **47** | -593.19 | -588.83 | 4.36 | -552.49 | -545.32 | 7.17 |
| **48** | -501.18 | -490.11 | 11.06 | -421.76 | -414.46 | 7.30 |
| **49** | -537.14 | -537.35 | -0.21 | -510.98 | -511.93 | -0.95 |

| **Subject** | **Noise Level** | | | | | |
|---|---|---|---|---|---|---|
| | **40%** | | | **10%** | | |
| | **SSP** | **DSTP** | **ln(BF)** | **SSP** | **DSTP** | **ln(BF)** |
| **1** | -281.03 | -283.82 | -2.80 | -250.50 | -250.28 | 0.22 |
| **2** | -399.45 | -400.86 | -1.42 | -325.85 | -326.16 | -0.31 |
| **3** | -428.07 | -423.34 | 4.73 | -410.94 | -411.06 | -0.11 |
| **4** | -381.26 | -374.20 | 7.06 | -348.22 | -348.27 | -0.05 |
| **5** | -373.55 | -372.99 | 0.56 | -359.80 | -360.09 | -0.29 |
| **6** | -530.99 | -529.26 | 1.72 | -468.39 | -462.11 | 6.27 |
| **7** | -344.30 | -344.20 | 0.10 | -331.57 | -331.71 | -0.14 |
| **8** | -388.50 | -389.14 | -0.64 | -372.79 | -373.17 | -0.38 |
| **9** | -426.27 | -426.16 | 0.11 | -418.57 | -419.54 | -0.96 |
| **10** | -286.58 | -278.20 | 8.37 | -267.93 | -267.36 | 0.58 |
| **11** | -430.51 | -430.12 | 0.39 | -498.33 | -498.01 | 0.32 |
| **12** | -461.32 | -459.68 | 1.65 | -405.83 | -404.37 | 1.45 |
| **13** | -429.99 | -427.72 | 2.27 | -389.94 | -389.87 | 0.07 |
| **14** | -368.22 | -367.10 | 1.12 | -369.84 | -369.20 | 0.64 |
| **15** | -429.30 | -425.90 | 3.40 | -359.40 | -358.34 | 1.06 |
| **16** | -402.82 | -400.47 | 2.35 | -457.83 | -456.68 | 1.14 |
| **17** | -450.17 | -451.01 | -0.84 | -404.98 | -404.54 | 0.44 |
| **18** | -326.69 | -327.09 | -0.40 | -326.38 | -326.07 | 0.31 |
| **19** | -376.23 | -376.65 | -0.42 | -341.96 | -341.81 | 0.14 |
| **20** | -496.67 | -496.78 | -0.11 | -427.34 | -427.30 | 0.05 |
| **21** | -395.53 | -394.66 | 0.87 | -399.51 | -396.83 | 2.67 |
| **22** | -420.17 | -421.27 | -1.10 | -393.92 | -392.67 | 1.25 |
| **23** | -425.24 | -424.21 | 1.03 | -357.47 | -358.03 | -0.56 |
| **24** | -423.71 | -425.03 | -1.32 | -410.88 | -410.78 | 0.10 |
| **25** | -366.38 | -361.67 | 4.71 | -319.90 | -320.68 | -0.77 |
| **26** | -533.59 | -534.91 | -1.32 | -515.99 | -521.98 | -5.99 |
| **27** | -600.74 | -598.14 | 2.60 | -574.25 | -576.13 | -1.89 |
| **28** | -446.60 | -441.45 | 5.15 | -344.79 | -344.95 | -0.16 |
| **29** | -471.30 | -471.20 | 0.11 | -434.18 | -434.20 | -0.03 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **30** | -426.71 | -420.98 | 5.73 | -375.33 | -371.71 | 3.62 |
| **31** | -403.13 | -401.04 | 2.10 | -371.83 | -370.34 | 1.49 |
| **32** | -381.69 | -381.75 | -0.05 | -375.03 | -375.19 | -0.15 |
| **33** | -364.68 | -363.67 | 1.01 | -377.97 | -373.43 | 4.54 |
| **34** | -431.65 | -427.12 | 4.53 | -379.06 | -375.32 | 3.74 |
| **35** | -324.21 | -324.61 | -0.40 | -356.37 | -351.56 | 4.81 |
| **36** | -433.43 | -433.91 | -0.48 | -403.55 | -403.35 | 0.20 |
| **37** | -393.43 | -390.85 | 2.58 | -415.08 | -413.72 | 1.35 |
| **38** | -475.74 | -474.97 | 0.77 | -437.57 | -435.91 | 1.66 |
| **39** | -337.38 | -336.97 | 0.40 | -352.33 | -353.41 | -1.08 |
| **40** | -382.67 | -382.78 | -0.10 | -357.05 | -355.49 | 1.56 |
| **41** | -445.29 | -441.87 | 3.42 | -373.91 | -374.10 | -0.19 |
| **42** | -394.72 | -394.53 | 0.19 | -399.41 | -398.82 | 0.59 |
| **43** | -399.02 | -398.85 | 0.17 | -355.25 | -355.59 | -0.34 |
| **44** | -424.77 | -422.46 | 2.31 | -450.01 | -447.95 | 2.06 |
| **45** | -369.79 | -370.65 | -0.86 | -351.49 | -351.30 | 0.19 |
| **46** | -334.05 | -334.54 | -0.49 | -328.97 | -328.88 | 0.09 |
| **47** | -436.24 | -436.91 | -0.67 | -390.80 | -391.26 | -0.46 |
| **48** | -337.86 | -337.89 | -0.03 | -305.19 | -306.08 | -0.89 |
| **49** | -501.31 | -502.42 | -1.12 | -496.68 | -499.01 | -2.33 |

# Appendix C: Study 3

## Expected a-posteriori estimates (High Noise Target)

**SSP$_{pFl}$**

**80% Noise**

| **Subject** | ***A*** | ***ter*** | ***pTarget*** | ***pFlanker*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** | ***IR*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.11 | 0.43 | 0.44 | 0.39 | 85.34 | 2.91 | 0.13 | 0.16 | 0.34 | 0.03 |
| **2** | 0.21 | 0.47 | 0.24 | 0.40 | 82.92 | 3.69 | 0.13 | 0.14 | 0.07 | 0.04 |
| **3** | 0.11 | 0.53 | 0.18 | 0.39 | 87.02 | 3.94 | 0.12 | 0.15 | 0.19 | 0.05 |
| **4** | 0.18 | 0.67 | 0.33 | 0.41 | 83.69 | 3.85 | 0.13 | 0.16 | 0.20 | 0.05 |
| **5** | 0.14 | 0.64 | 0.27 | 0.41 | 84.66 | 3.47 | 0.13 | 0.17 | 0.14 | 0.04 |
| **6** | 0.15 | 0.63 | 0.15 | 0.40 | 80.96 | 4.58 | 0.14 | 0.16 | 0.06 | 0.06 |
| **7** | 0.15 | 0.60 | 0.21 | 0.56 | 85.96 | 5.10 | 0.10 | 0.15 | 0.13 | 0.06 |
| **8** | 0.12 | 0.58 | 0.15 | 0.43 | 88.33 | 2.88 | 0.11 | 0.17 | 0.19 | 0.03 |
| **9** | 0.29 | 0.34 | 0.24 | 0.48 | 81.71 | 4.48 | 0.22 | 0.14 | 0.03 | 0.05 |
| **10** | 0.14 | 0.51 | 0.32 | 0.44 | 85.29 | 3.80 | 0.11 | 0.13 | 0.20 | 0.04 |
| **11** | 0.10 | 0.51 | 0.37 | 0.44 | 87.11 | 3.11 | 0.13 | 0.14 | 0.51 | 0.04 |
| **12** | 0.11 | 0.60 | 0.13 | 0.46 | 86.94 | 3.47 | 0.08 | 0.16 | 0.06 | 0.04 |
| **13** | 0.13 | 0.49 | 0.17 | 0.35 | 84.68 | 3.64 | 0.14 | 0.18 | 0.25 | 0.04 |
| **14** | 0.15 | 0.40 | 0.46 | 0.47 | 87.12 | 4.07 | 0.12 | 0.14 | 0.36 | 0.05 |
| **15** | 0.13 | 0.49 | 0.21 | 0.50 | 85.58 | 4.25 | 0.10 | 0.14 | 0.19 | 0.05 |
| **16** | 0.16 | 0.38 | 0.31 | 0.48 | 86.81 | 3.73 | 0.11 | 0.15 | 0.24 | 0.04 |
| **17** | 0.18 | 0.46 | 0.56 | 0.54 | 85.29 | 4.52 | 0.13 | 0.15 | 0.32 | 0.05 |
| **18** | 0.20 | 0.33 | 0.19 | 0.44 | 81.23 | 4.06 | 0.14 | 0.15 | 0.22 | 0.05 |
| **19** | 0.10 | 0.50 | 0.14 | 0.40 | 85.37 | 3.54 | 0.16 | 0.17 | 0.16 | 0.04 |
| **20** | 0.13 | 0.45 | 0.16 | 0.42 | 83.38 | 4.71 | 0.14 | 0.16 | 0.06 | 0.06 |
| **21** | 0.13 | 0.54 | 0.09 | 0.39 | 87.04 | 3.32 | 0.13 | 0.18 | 0.10 | 0.04 |
| **22** | 0.14 | 0.55 | 0.13 | 0.46 | 83.22 | 4.36 | 0.12 | 0.16 | 0.05 | 0.05 |
| **23** | 0.13 | 0.43 | 0.17 | 0.38 | 86.29 | 2.92 | 0.13 | 0.14 | 0.07 | 0.03 |
| **24** | 0.14 | 0.52 | 0.18 | 0.40 | 85.84 | 3.39 | 0.13 | 0.17 | 0.20 | 0.04 |
| **25** | 0.10 | 0.44 | 0.19 | 0.44 | 83.68 | 4.04 | 0.12 | 0.18 | 0.13 | 0.05 |
| **26** | 0.28 | 0.21 | 0.23 | 0.45 | 81.91 | 3.95 | 0.18 | 0.14 | 0.05 | 0.05 |
| **27** | 0.23 | 0.46 | 0.27 | 0.56 | 77.65 | 6.36 | 0.15 | 0.15 | 0.11 | 0.08 |
| **28** | 0.13 | 0.43 | 0.18 | 0.41 | 85.76 | 3.05 | 0.12 | 0.18 | 0.19 | 0.04 |
| **29** | 0.13 | 0.56 | 0.12 | 0.42 | 86.53 | 3.03 | 0.12 | 0.18 | 0.18 | 0.04 |
| **30** | 0.12 | 0.39 | 0.35 | 0.46 | 87.13 | 1.89 | 0.10 | 0.18 | 0.37 | 0.02 |
| **31** | 0.16 | 0.36 | 0.29 | 0.52 | 85.03 | 4.99 | 0.11 | 0.15 | 0.23 | 0.06 |
| **32** | 0.11 | 0.59 | 0.51 | 0.55 | 90.89 | 3.42 | 0.10 | 0.17 | 0.39 | 0.04 |
| **33** | 0.11 | 0.59 | 0.19 | 0.44 | 84.92 | 3.52 | 0.10 | 0.16 | 0.16 | 0.04 |
| **34** | 0.41 | 0.36 | 0.61 | 0.57 | 74.73 | 6.41 | 0.14 | 0.14 | 0.22 | 0.09 |
| **35** | 0.22 | 0.47 | 0.56 | 0.35 | 86.34 | 4.01 | 0.17 | 0.19 | 0.33 | 0.05 |
| **36** | 0.12 | 0.69 | 0.10 | 0.45 | 86.42 | 3.48 | 0.11 | 0.16 | 0.14 | 0.04 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **37** | 0.21 | 0.54 | 0.46 | 0.43 | 83.59 | 4.69 | 0.14 | 0.18 | 0.35 | 0.06 |
| **38** | 0.16 | 0.50 | 0.39 | 0.49 | 82.43 | 4.94 | 0.14 | 0.17 | 0.25 | 0.06 |
| **39** | 0.13 | 0.50 | 0.19 | 0.51 | 86.20 | 4.00 | 0.12 | 0.19 | 0.20 | 0.05 |
| **40** | 0.14 | 0.46 | 0.30 | 0.42 | 87.08 | 2.68 | 0.11 | 0.15 | 0.23 | 0.03 |
| **41** | 0.12 | 0.61 | 0.15 | 0.43 | 84.44 | 4.02 | 0.11 | 0.15 | 0.11 | 0.05 |
| **42** | 0.20 | 0.41 | 0.52 | 0.44 | 83.47 | 4.17 | 0.14 | 0.16 | 0.30 | 0.05 |
| **43** | 0.14 | 0.38 | 0.28 | 0.44 | 86.69 | 3.99 | 0.12 | 0.17 | 0.21 | 0.05 |
| **44** | 0.07 | 0.39 | 0.22 | 0.45 | 85.89 | 1.54 | 0.08 | 0.12 | 0.35 | 0.02 |
| **45** | 0.30 | 0.42 | 0.60 | 0.58 | 81.92 | 6.41 | 0.15 | 0.15 | 0.34 | 0.08 |
| **μ** | **0.16** | **0.48** | **0.28** | **0.45** | **84.77** | **3.92** | **0.13** | **0.16** | **0.20** | **0.05** |

**70% Noise**

| **Subject** | ***A*** | ***ter*** | ***pTarget*** | ***pFlanker*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** | ***IR*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.08 | 0.45 | 0.37 | 0.50 | 88.06 | 3.44 | 0.08 | 0.13 | 0.28 | 0.04 |
| **2** | 0.16 | 0.54 | 0.18 | 0.49 | 85.24 | 4.42 | 0.14 | 0.14 | 0.05 | 0.05 |
| **3** | 0.12 | 0.56 | 0.20 | 0.43 | 82.46 | 4.80 | 0.13 | 0.18 | 0.21 | 0.06 |
| **4** | 0.15 | 0.64 | 0.26 | 0.50 | 84.95 | 4.71 | 0.14 | 0.19 | 0.13 | 0.06 |
| **5** | 0.15 | 0.64 | 0.35 | 0.48 | 81.62 | 5.18 | 0.12 | 0.15 | 0.20 | 0.06 |
| **6** | 0.15 | 0.64 | 0.15 | 0.40 | 79.00 | 4.83 | 0.17 | 0.15 | 0.04 | 0.06 |
| **7** | 0.16 | 0.55 | 0.28 | 0.54 | 83.85 | 5.29 | 0.13 | 0.17 | 0.18 | 0.06 |
| **8** | 0.12 | 0.56 | 0.14 | 0.45 | 87.13 | 3.61 | 0.11 | 0.16 | 0.10 | 0.04 |
| **9** | 0.35 | 0.26 | 0.24 | 0.40 | 83.17 | 3.33 | 0.31 | 0.15 | 0.02 | 0.04 |
| **10** | 0.13 | 0.53 | 0.33 | 0.61 | 86.73 | 4.80 | 0.09 | 0.13 | 0.24 | 0.06 |
| **11** | 0.08 | 0.49 | 0.37 | 0.42 | 85.40 | 2.54 | 0.10 | 0.19 | 0.33 | 0.03 |
| **12** | 0.14 | 0.65 | 0.23 | 0.39 | 86.77 | 3.40 | 0.14 | 0.17 | 0.14 | 0.04 |
| **13** | 0.11 | 0.47 | 0.11 | 0.38 | 85.76 | 3.06 | 0.12 | 0.15 | 0.11 | 0.04 |
| **14** | 0.15 | 0.43 | 0.54 | 0.42 | 83.62 | 4.18 | 0.17 | 0.18 | 0.29 | 0.05 |
| **15** | 0.12 | 0.52 | 0.18 | 0.47 | 87.58 | 3.67 | 0.10 | 0.15 | 0.19 | 0.04 |
| **16** | 0.14 | 0.38 | 0.27 | 0.42 | 87.66 | 3.52 | 0.13 | 0.16 | 0.24 | 0.04 |
| **17** | 0.15 | 0.46 | 0.39 | 0.47 | 86.14 | 3.67 | 0.12 | 0.16 | 0.28 | 0.04 |
| **18** | 0.14 | 0.40 | 0.09 | 0.32 | 80.29 | 3.61 | 0.17 | 0.15 | 0.07 | 0.04 |
| **19** | 0.09 | 0.51 | 0.08 | 0.47 | 83.86 | 4.30 | 0.10 | 0.19 | 0.12 | 0.05 |
| **20** | 0.13 | 0.45 | 0.17 | 0.47 | 83.81 | 3.87 | 0.11 | 0.15 | 0.12 | 0.05 |
| **21** | 0.13 | 0.53 | 0.14 | 0.42 | 83.92 | 3.78 | 0.12 | 0.16 | 0.11 | 0.04 |
| **22** | 0.18 | 0.41 | 0.18 | 0.44 | 85.60 | 3.78 | 0.15 | 0.17 | 0.07 | 0.04 |
| **23** | 0.13 | 0.39 | 0.15 | 0.49 | 87.97 | 4.09 | 0.11 | 0.16 | 0.05 | 0.05 |
| **24** | 0.13 | 0.45 | 0.16 | 0.41 | 84.41 | 2.40 | 0.11 | 0.16 | 0.13 | 0.03 |
| **25** | 0.09 | 0.41 | 0.22 | 0.41 | 84.72 | 2.36 | 0.09 | 0.16 | 0.17 | 0.03 |
| **26** | 0.26 | 0.19 | 0.22 | 0.50 | 79.68 | 4.61 | 0.21 | 0.14 | 0.03 | 0.06 |
| **27** | 0.11 | 0.68 | 0.14 | 0.42 | 87.44 | 2.48 | 0.09 | 0.15 | 0.07 | 0.03 |
| **28** | 0.13 | 0.48 | 0.23 | 0.48 | 86.57 | 2.74 | 0.11 | 0.17 | 0.33 | 0.03 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **29** | 0.11 | 0.56 | 0.11 | 0.45 | 85.11 | 3.35 | 0.09 | 0.17 | 0.08 | 0.04 |
| **30** | 0.11 | 0.37 | 0.28 | 0.60 | 87.59 | 4.06 | 0.09 | 0.16 | 0.26 | 0.05 |
| **31** | 0.13 | 0.45 | 0.33 | 0.63 | 91.71 | 3.21 | 0.11 | 0.17 | 0.42 | 0.03 |
| **32** | 0.09 | 0.62 | 0.40 | 0.65 | 88.28 | 2.68 | 0.07 | 0.18 | 0.37 | 0.03 |
| **33** | 0.15 | 0.55 | 0.24 | 0.59 | 83.72 | 5.18 | 0.10 | 0.16 | 0.15 | 0.06 |
| **34** | 0.34 | 0.49 | 0.69 | 0.65 | 76.82 | 6.60 | 0.17 | 0.18 | 0.27 | 0.09 |
| **35** | 0.19 | 0.41 | 0.38 | 0.50 | 82.29 | 5.46 | 0.13 | 0.14 | 0.22 | 0.07 |
| **36** | 0.11 | 0.66 | 0.09 | 0.40 | 85.94 | 2.68 | 0.11 | 0.18 | 0.14 | 0.03 |
| **37** | 0.23 | 0.31 | 0.26 | 0.51 | 83.24 | 5.01 | 0.15 | 0.14 | 0.09 | 0.06 |
| **38** | 0.22 | 0.40 | 0.41 | 0.54 | 82.47 | 5.85 | 0.14 | 0.14 | 0.25 | 0.07 |
| **39** | 0.13 | 0.62 | 0.18 | 0.42 | 82.44 | 4.54 | 0.15 | 0.20 | 0.27 | 0.06 |
| **40** | 0.14 | 0.49 | 0.30 | 0.52 | 85.16 | 3.44 | 0.10 | 0.17 | 0.27 | 0.04 |
| **41** | 0.13 | 0.54 | 0.14 | 0.42 | 83.33 | 3.51 | 0.11 | 0.18 | 0.08 | 0.04 |
| **42** | 0.23 | 0.38 | 0.54 | 0.59 | 77.99 | 6.30 | 0.14 | 0.16 | 0.33 | 0.08 |
| **43** | 0.11 | 0.39 | 0.28 | 0.44 | 82.24 | 4.76 | 0.12 | 0.16 | 0.22 | 0.06 |
| **44** | 0.08 | 0.41 | 0.37 | 0.38 | 86.15 | 4.08 | 0.13 | 0.17 | 0.42 | 0.05 |
| **45** | 0.26 | 0.39 | 0.51 | 0.50 | 80.20 | 5.87 | 0.16 | 0.19 | 0.24 | 0.07 |
| **μ** | **0.15** | **0.48** | **0.26** | **0.48** | **84.40** | **4.07** | **0.13** | **0.16** | **0.19** | **0.05** |

**40% Noise**

| **Subject** | ***A*** | ***ter*** | ***pTarget*** | ***pFlanker*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** | ***IR*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.10 | 0.44 | 0.40 | 0.94 | 92.06 | 5.67 | 0.12 | 0.13 | 0.36 | 0.06 |
| **2** | 0.21 | 0.50 | 0.27 | 0.62 | 77.52 | 6.53 | 0.13 | 0.15 | 0.11 | 0.08 |
| **3** | 0.10 | 0.54 | 0.19 | 0.43 | 85.49 | 1.75 | 0.10 | 0.18 | 0.26 | 0.02 |
| **4** | 0.15 | 0.65 | 0.32 | 0.43 | 85.71 | 3.52 | 0.13 | 0.17 | 0.19 | 0.04 |
| **5** | 0.14 | 0.58 | 0.24 | 0.68 | 82.76 | 5.61 | 0.08 | 0.14 | 0.15 | 0.07 |
| **6** | 0.16 | 0.48 | 0.18 | 0.73 | 81.09 | 6.52 | 0.12 | 0.17 | 0.14 | 0.08 |
| **7** | 0.16 | 0.51 | 0.28 | 0.58 | 83.00 | 5.54 | 0.13 | 0.17 | 0.20 | 0.07 |
| **8** | 0.12 | 0.56 | 0.15 | 0.48 | 83.50 | 4.38 | 0.12 | 0.16 | 0.12 | 0.05 |
| **9** | 0.28 | 0.26 | 0.22 | 0.48 | 82.39 | 4.66 | 0.22 | 0.14 | 0.03 | 0.06 |
| **10** | 0.14 | 0.50 | 0.30 | 0.60 | 81.98 | 6.18 | 0.14 | 0.18 | 0.23 | 0.08 |
| **11** | 0.10 | 0.46 | 0.28 | 0.55 | 88.34 | 3.04 | 0.10 | 0.17 | 0.41 | 0.03 |
| **12** | 0.12 | 0.52 | 0.13 | 0.49 | 83.65 | 4.54 | 0.12 | 0.16 | 0.07 | 0.05 |
| **13** | 0.11 | 0.49 | 0.14 | 0.42 | 86.39 | 4.21 | 0.15 | 0.15 | 0.23 | 0.05 |
| **14** | 0.10 | 0.47 | 0.35 | 0.75 | 88.06 | 5.26 | 0.12 | 0.16 | 0.28 | 0.06 |
| **15** | 0.11 | 0.50 | 0.13 | 0.76 | 82.30 | 6.58 | 0.09 | 0.14 | 0.04 | 0.08 |
| **16** | 0.16 | 0.43 | 0.40 | 0.48 | 89.71 | 3.16 | 0.14 | 0.20 | 0.42 | 0.04 |
| **17** | 0.15 | 0.47 | 0.49 | 0.66 | 86.04 | 5.16 | 0.11 | 0.15 | 0.32 | 0.06 |
| **18** | 0.15 | 0.31 | 0.14 | 0.29 | 81.75 | 4.24 | 0.17 | 0.16 | 0.15 | 0.05 |
| **19** | 0.11 | 0.46 | 0.10 | 0.38 | 83.69 | 4.19 | 0.16 | 0.15 | 0.20 | 0.05 |
| **20** | 0.13 | 0.48 | 0.21 | 0.54 | 81.14 | 5.75 | 0.13 | 0.18 | 0.15 | 0.07 |
| **21** | 0.12 | 0.44 | 0.12 | 0.53 | 85.91 | 3.85 | 0.10 | 0.17 | 0.11 | 0.04 |
| **22** | 0.16 | 0.45 | 0.18 | 0.54 | 81.02 | 5.46 | 0.11 | 0.16 | 0.10 | 0.07 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **23** | 0.13 | 0.44 | 0.18 | 0.41 | 86.30 | 3.48 | 0.13 | 0.16 | 0.11 | 0.04 |
| **24** | 0.12 | 0.48 | 0.19 | 0.68 | 86.78 | 5.62 | 0.09 | 0.15 | 0.17 | 0.06 |
| **25** | 0.11 | 0.40 | 0.27 | 0.45 | 84.82 | 3.68 | 0.11 | 0.18 | 0.26 | 0.04 |
| **26** | 0.20 | 0.27 | 0.17 | 0.62 | 81.74 | 6.58 | 0.20 | 0.16 | 0.05 | 0.08 |
| **27** | 0.12 | 0.57 | 0.14 | 0.51 | 80.90 | 4.98 | 0.11 | 0.15 | 0.05 | 0.06 |
| **28** | 0.14 | 0.46 | 0.24 | 0.51 | 88.48 | 3.61 | 0.12 | 0.15 | 0.37 | 0.04 |
| **29** | 0.12 | 0.58 | 0.09 | 0.52 | 87.13 | 4.50 | 0.10 | 0.16 | 0.14 | 0.05 |
| **30** | 0.13 | 0.39 | 0.44 | 0.77 | 91.91 | 3.79 | 0.10 | 0.14 | 0.46 | 0.04 |
| **31** | 0.11 | 0.37 | 0.16 | 0.75 | 86.77 | 6.07 | 0.10 | 0.15 | 0.15 | 0.07 |
| **32** | 0.10 | 0.57 | 0.42 | 0.71 | 96.40 | 2.91 | 0.10 | 0.16 | 0.54 | 0.03 |
| **33** | 0.15 | 0.63 | 0.30 | 0.70 | 83.99 | 5.73 | 0.10 | 0.17 | 0.21 | 0.07 |
| **34** | 0.21 | 0.47 | 0.38 | 0.82 | 70.66 | 8.16 | 0.11 | 0.17 | 0.16 | 0.12 |
| **35** | 0.13 | 0.48 | 0.30 | 0.67 | 80.99 | 6.24 | 0.10 | 0.18 | 0.23 | 0.08 |
| **36** | 0.11 | 0.65 | 0.09 | 0.55 | 82.35 | 5.55 | 0.11 | 0.16 | 0.08 | 0.07 |
| **37** | 0.14 | 0.46 | 0.20 | 0.65 | 83.19 | 5.76 | 0.09 | 0.15 | 0.07 | 0.07 |
| **38** | 0.12 | 0.51 | 0.27 | 0.88 | 90.66 | 5.56 | 0.11 | 0.19 | 0.30 | 0.06 |
| **39** | 0.12 | 0.61 | 0.13 | 0.59 | 76.78 | 6.87 | 0.15 | 0.16 | 0.20 | 0.09 |
| **40** | 0.12 | 0.46 | 0.24 | 0.64 | 80.72 | 5.70 | 0.10 | 0.17 | 0.21 | 0.07 |
| **41** | 0.15 | 0.48 | 0.18 | 0.64 | 84.56 | 5.10 | 0.11 | 0.17 | 0.19 | 0.06 |
| **42** | 0.14 | 0.45 | 0.46 | 0.69 | 79.07 | 6.99 | 0.12 | 0.16 | 0.35 | 0.09 |
| **43** | 0.13 | 0.33 | 0.35 | 0.59 | 88.01 | 4.45 | 0.10 | 0.14 | 0.33 | 0.05 |
| **44** | 0.08 | 0.46 | 0.34 | 0.35 | 84.45 | 4.22 | 0.18 | 0.15 | 0.39 | 0.05 |
| **45** | 0.13 | 0.43 | 0.16 | 0.85 | 83.64 | 6.48 | 0.07 | 0.16 | 0.07 | 0.08 |
| **μ** | **0.13** | **0.48** | **0.24** | **0.60** | **84.31** | **5.06** | **0.12** | **0.16** | **0.21** | **0.06** |

**10% Noise**

| **Subject** | ***A*** | ***ter*** | ***pTarget*** | ***pFlanker*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** | ***IR*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.09 | 0.42 | 0.38 | 0.79 | 89.22 | 5.13 | 0.12 | 0.13 | 0.32 | 0.06 |
| **2** | 0.17 | 0.48 | 0.18 | 0.69 | 75.55 | 6.86 | 0.10 | 0.15 | 0.04 | 0.09 |
| **3** | 0.11 | 0.50 | 0.15 | 0.38 | 86.17 | 2.40 | 0.14 | 0.16 | 0.18 | 0.03 |
| **4** | 0.22 | 0.60 | 0.47 | 0.72 | 82.42 | 6.17 | 0.14 | 0.17 | 0.31 | 0.07 |
| **5** | 0.21 | 0.43 | 0.29 | 0.85 | 72.48 | 7.85 | 0.10 | 0.16 | 0.15 | 0.11 |
| **6** | 0.14 | 0.49 | 0.23 | 0.62 | 83.01 | 6.00 | 0.12 | 0.17 | 0.14 | 0.07 |
| **7** | 0.13 | 0.50 | 0.19 | 0.61 | 84.74 | 5.32 | 0.10 | 0.17 | 0.18 | 0.06 |
| **8** | 0.11 | 0.53 | 0.12 | 0.42 | 85.08 | 2.52 | 0.11 | 0.16 | 0.13 | 0.03 |
| **9** | 0.35 | 0.25 | 0.26 | 0.58 | 77.88 | 6.00 | 0.27 | 0.16 | 0.03 | 0.08 |
| **10** | 0.13 | 0.50 | 0.35 | 0.70 | 89.26 | 5.01 | 0.11 | 0.14 | 0.28 | 0.06 |
| **11** | 0.10 | 0.46 | 0.37 | 0.44 | 88.02 | 2.39 | 0.10 | 0.18 | 0.44 | 0.03 |
| **12** | 0.12 | 0.50 | 0.12 | 0.49 | 87.25 | 4.28 | 0.12 | 0.19 | 0.10 | 0.05 |
| **13** | 0.12 | 0.45 | 0.19 | 0.49 | 85.69 | 4.39 | 0.12 | 0.17 | 0.24 | 0.05 |
| **14** | 0.10 | 0.46 | 0.40 | 0.83 | 78.76 | 6.82 | 0.10 | 0.19 | 0.20 | 0.09 |
| **15** | 0.11 | 0.49 | 0.13 | 0.83 | 79.69 | 6.76 | 0.09 | 0.15 | 0.06 | 0.08 |
| **16** | 0.11 | 0.36 | 0.20 | 0.40 | 85.60 | 3.75 | 0.12 | 0.16 | 0.10 | 0.04 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **17** | 0.14 | 0.44 | 0.32 | 0.54 | 84.81 | 5.11 | 0.11 | 0.18 | 0.27 | 0.06 |
| **18** | 0.18 | 0.45 | 0.17 | 0.43 | 84.33 | 3.93 | 0.15 | 0.17 | 0.41 | 0.05 |
| **19** | 0.10 | 0.47 | 0.13 | 0.55 | 88.51 | 4.99 | 0.18 | 0.16 | 0.29 | 0.06 |
| **20** | 0.11 | 0.46 | 0.15 | 0.61 | 79.07 | 6.68 | 0.12 | 0.18 | 0.05 | 0.08 |
| **21** | 0.13 | 0.44 | 0.13 | 0.35 | 85.77 | 3.18 | 0.17 | 0.18 | 0.07 | 0.04 |
| **22** | 0.15 | 0.40 | 0.15 | 0.56 | 84.23 | 5.25 | 0.11 | 0.17 | 0.11 | 0.06 |
| **23** | 0.13 | 0.43 | 0.18 | 0.56 | 84.89 | 4.89 | 0.10 | 0.15 | 0.12 | 0.06 |
| **24** | 0.14 | 0.42 | 0.22 | 0.54 | 87.55 | 4.74 | 0.12 | 0.16 | 0.19 | 0.05 |
| **25** | 0.09 | 0.43 | 0.18 | 0.54 | 86.17 | 4.31 | 0.11 | 0.14 | 0.22 | 0.05 |
| **26** | 0.17 | 0.31 | 0.17 | 0.56 | 82.17 | 5.00 | 0.13 | 0.16 | 0.07 | 0.06 |
| **27** | 0.12 | 0.51 | 0.12 | 0.63 | 82.80 | 6.13 | 0.10 | 0.18 | 0.04 | 0.07 |
| **28** | 0.10 | 0.38 | 0.10 | 0.41 | 87.05 | 2.76 | 0.12 | 0.16 | 0.08 | 0.03 |
| **29** | 0.13 | 0.58 | 0.18 | 0.44 | 86.79 | 2.54 | 0.13 | 0.16 | 0.25 | 0.03 |
| **30** | 0.10 | 0.42 | 0.28 | 0.83 | 91.60 | 5.12 | 0.13 | 0.11 | 0.34 | 0.06 |
| **31** | 0.10 | 0.38 | 0.19 | 0.85 | 89.67 | 5.68 | 0.09 | 0.15 | 0.19 | 0.06 |
| **32** | 0.10 | 0.56 | 0.37 | 1.00 | 89.26 | 5.23 | 0.08 | 0.20 | 0.26 | 0.06 |
| **33** | 0.10 | 0.61 | 0.11 | 0.88 | 86.52 | 7.12 | 0.08 | 0.16 | 0.07 | 0.08 |
| **34** | 0.25 | 0.44 | 0.48 | 1.14 | 72.51 | 8.81 | 0.11 | 0.15 | 0.25 | 0.12 |
| **35** | 0.16 | 0.39 | 0.32 | 0.90 | 71.05 | 8.03 | 0.08 | 0.14 | 0.17 | 0.11 |
| **36** | 0.11 | 0.56 | 0.11 | 0.58 | 86.40 | 4.71 | 0.11 | 0.18 | 0.16 | 0.05 |
| **37** | 0.12 | 0.47 | 0.16 | 0.63 | 84.27 | 5.49 | 0.08 | 0.14 | 0.05 | 0.07 |
| **38** | 0.12 | 0.56 | 0.14 | 0.88 | 58.04 | 9.16 | 0.24 | 0.22 | 0.10 | 0.16 |
| **39** | 0.12 | 0.54 | 0.17 | 0.39 | 86.08 | 4.03 | 0.13 | 0.16 | 0.26 | 0.05 |
| **40** | 0.13 | 0.47 | 0.26 | 1.01 | 87.21 | 6.63 | 0.08 | 0.16 | 0.21 | 0.08 |
| **41** | 0.13 | 0.46 | 0.17 | 0.59 | 87.23 | 4.39 | 0.10 | 0.16 | 0.17 | 0.05 |
| **42** | 0.13 | 0.43 | 0.33 | 0.73 | 80.17 | 6.80 | 0.10 | 0.15 | 0.19 | 0.08 |
| **43** | 0.11 | 0.37 | 0.32 | 0.48 | 89.58 | 3.33 | 0.11 | 0.14 | 0.41 | 0.04 |
| **44** | 0.07 | 0.39 | 0.32 | 0.36 | 84.63 | 3.18 | 0.12 | 0.14 | 0.32 | 0.04 |
| **45** | 0.12 | 0.48 | 0.14 | 0.97 | 83.75 | 6.44 | 0.06 | 0.15 | 0.09 | 0.08 |
| **μ** | **0.13** | **0.46** | **0.22** | **0.64** | **83.62** | **5.23** | **0.12** | **0.16** | **0.19** | **0.06** |

## DSTP

**DSTP**
**80% Noise**

| Subject | *A* | *C* | *μTa* | *μFl* | *μSS* | *μRS2* | *ter* | *sz* | *ster* | *sv* |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.15 | 0.40 | 0.42 | 0.06 | 0.51 | 1.95 | 0.41 | 0.16 | 0.15 | 0.46 |
| **2** | 0.20 | 0.61 | 0.24 | 0.04 | 0.38 | 1.36 | 0.57 | 0.13 | 0.13 | 0.15 |
| **3** | 0.21 | 0.53 | 0.23 | 0.07 | 0.39 | 1.79 | 0.47 | 0.14 | 0.14 | 0.45 |
| **4** | 0.35 | 0.45 | 0.37 | 0.06 | 0.43 | 1.83 | 0.55 | 0.16 | 0.16 | 0.38 |
| **5** | 0.27 | 0.48 | 0.32 | 0.05 | 0.55 | 1.83 | 0.53 | 0.16 | 0.16 | 0.35 |
| **6** | 0.22 | 0.48 | 0.14 | 0.05 | 0.28 | 1.64 | 0.49 | 0.18 | 0.16 | 0.13 |
| **7** | 0.27 | 0.59 | 0.31 | 0.09 | 0.39 | 1.73 | 0.53 | 0.14 | 0.14 | 0.30 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **8** | 0.24 | 0.53 | 0.21 | 0.07 | 0.30 | 1.91 | 0.51 | 0.16 | 0.17 | 0.42 |
| **9** | 0.23 | 0.62 | 0.18 | 0.02 | 0.32 | 1.51 | 0.42 | 0.15 | 0.13 | 0.06 |
| **10** | 0.22 | 0.55 | 0.42 | 0.06 | 0.44 | 1.68 | 0.49 | 0.14 | 0.13 | 0.37 |
| **11** | 0.12 | 0.39 | 0.35 | 0.08 | 0.47 | 1.32 | 0.50 | 0.13 | 0.14 | 0.62 |
| **12** | 0.18 | 0.58 | 0.20 | 0.07 | 0.40 | 1.45 | 0.57 | 0.13 | 0.15 | 0.23 |
| **13** | 0.23 | 0.47 | 0.17 | 0.06 | 0.31 | 1.83 | 0.40 | 0.16 | 0.17 | 0.45 |
| **14** | 0.22 | 0.51 | 0.49 | 0.11 | 0.41 | 1.61 | 0.38 | 0.16 | 0.14 | 0.47 |
| **15** | 0.25 | 0.50 | 0.32 | 0.11 | 0.29 | 1.83 | 0.42 | 0.14 | 0.14 | 0.41 |
| **16** | 0.26 | 0.52 | 0.40 | 0.07 | 0.29 | 1.83 | 0.33 | 0.14 | 0.15 | 0.39 |
| **17** | 0.42 | 0.22 | 0.45 | 0.18 | 0.37 | 2.24 | 0.31 | 0.15 | 0.13 | 0.34 |
| **18** | 0.29 | 0.50 | 0.22 | 0.05 | 0.40 | 0.82 | 0.28 | 0.16 | 0.15 | 0.37 |
| **19** | 0.20 | 0.36 | 0.13 | 0.07 | 0.30 | 1.89 | 0.39 | 0.19 | 0.16 | 0.42 |
| **20** | 0.28 | 0.54 | 0.21 | 0.08 | 0.49 | 1.35 | 0.30 | 0.17 | 0.16 | 0.30 |
| **21** | 0.26 | 0.57 | 0.11 | 0.03 | 0.32 | 1.81 | 0.40 | 0.18 | 0.17 | 0.30 |
| **22** | 0.25 | 0.59 | 0.16 | 0.06 | 0.39 | 1.29 | 0.41 | 0.16 | 0.16 | 0.21 |
| **23** | 0.19 | 0.57 | 0.23 | 0.03 | 0.34 | 1.56 | 0.39 | 0.16 | 0.14 | 0.18 |
| **24** | 0.28 | 0.53 | 0.25 | 0.05 | 0.29 | 1.69 | 0.43 | 0.16 | 0.16 | 0.42 |
| **25** | 0.22 | 0.38 | 0.20 | 0.10 | 0.50 | 1.96 | 0.33 | 0.16 | 0.17 | 0.41 |
| **26** | 0.29 | 0.52 | 0.22 | 0.02 | 0.23 | 1.37 | 0.24 | 0.16 | 0.15 | 0.10 |
| **27** | 0.41 | 0.53 | 0.30 | 0.10 | 0.41 | 1.45 | 0.33 | 0.16 | 0.15 | 0.25 |
| **28** | 0.24 | 0.51 | 0.24 | 0.05 | 0.33 | 1.90 | 0.35 | 0.15 | 0.17 | 0.41 |
| **29** | 0.22 | 0.56 | 0.16 | 0.04 | 0.26 | 1.83 | 0.50 | 0.16 | 0.17 | 0.35 |
| **30** | 0.18 | 0.42 | 0.41 | 0.07 | 0.25 | 1.94 | 0.36 | 0.13 | 0.16 | 0.51 |
| **31** | 0.22 | 0.57 | 0.34 | 0.10 | 0.31 | 1.69 | 0.33 | 0.15 | 0.14 | 0.34 |
| **32** | 0.37 | 0.15 | 0.39 | 0.21 | 0.38 | 2.48 | 0.44 | 0.12 | 0.13 | 0.47 |
| **33** | 0.23 | 0.45 | 0.27 | 0.08 | 0.36 | 1.93 | 0.52 | 0.14 | 0.16 | 0.42 |
| **34** | 0.45 | 0.40 | 0.37 | 0.11 | 0.52 | 1.67 | 0.31 | 0.14 | 0.14 | 0.28 |
| **35** | 0.35 | 0.42 | 0.36 | 0.04 | 0.62 | 2.16 | 0.33 | 0.17 | 0.17 | 0.44 |
| **36** | 0.24 | 0.48 | 0.17 | 0.07 | 0.21 | 1.69 | 0.60 | 0.15 | 0.15 | 0.38 |
| **37** | 0.40 | 0.44 | 0.36 | 0.06 | 0.44 | 2.38 | 0.39 | 0.15 | 0.17 | 0.46 |
| **38** | 0.28 | 0.42 | 0.41 | 0.12 | 0.47 | 1.83 | 0.41 | 0.16 | 0.16 | 0.40 |
| **39** | 0.29 | 0.44 | 0.23 | 0.10 | 0.33 | 2.15 | 0.37 | 0.16 | 0.17 | 0.46 |
| **40** | 0.27 | 0.45 | 0.41 | 0.05 | 0.29 | 1.99 | 0.39 | 0.14 | 0.14 | 0.44 |
| **41** | 0.20 | 0.57 | 0.20 | 0.05 | 0.38 | 1.70 | 0.55 | 0.16 | 0.15 | 0.28 |
| **42** | 0.49 | 0.20 | 0.29 | 0.14 | 0.36 | 2.51 | 0.22 | 0.14 | 0.15 | 0.29 |
| **43** | 0.23 | 0.52 | 0.36 | 0.09 | 0.40 | 1.75 | 0.34 | 0.16 | 0.17 | 0.40 |
| **44** | 0.09 | 0.44 | 0.25 | 0.05 | 0.40 | 1.77 | 0.39 | 0.11 | 0.12 | 0.45 |
| **45** | 0.35 | 0.57 | 0.50 | 0.10 | 0.45 | 1.78 | 0.39 | 0.16 | 0.15 | 0.39 |
| **μ** | **0.26** | **0.48** | **0.29** | **0.08** | **0.38** | **1.77** | **0.41** | **0.15** | **0.15** | **0.36** |

**70% Noise**

| **Subject** | ***A*** | ***C*** | ***μTa*** | ***μFl*** | ***μSS*** | ***μRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.12 | 0.38 | 0.42 | 0.15 | 0.53 | 1.82 | 0.45 | 0.12 | 0.11 | 0.44 |
| **2** | 0.56 | 0.15 | 0.15 | 0.08 | 0.14 | 2.50 | 0.37 | 0.16 | 0.14 | 0.05 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **3** | 0.24 | 0.50 | 0.21 | 0.10 | 0.42 | 1.83 | 0.46 | 0.16 | 0.16 | 0.45 |
| **4** | 0.44 | 0.33 | 0.23 | 0.13 | 0.38 | 1.98 | 0.38 | 0.16 | 0.18 | 0.30 |
| **5** | 0.44 | 0.23 | 0.30 | 0.17 | 0.33 | 2.08 | 0.45 | 0.15 | 0.14 | 0.30 |
| **6** | 0.23 | 0.46 | 0.13 | 0.04 | 0.33 | 1.44 | 0.44 | 0.18 | 0.15 | 0.13 |
| **7** | 0.42 | 0.25 | 0.28 | 0.18 | 0.26 | 2.14 | 0.37 | 0.17 | 0.15 | 0.21 |
| **8** | 0.29 | 0.53 | 0.22 | 0.06 | 0.35 | 1.76 | 0.44 | 0.15 | 0.16 | 0.38 |
| **9** | 0.27 | 0.60 | 0.16 | 0.01 | 0.29 | 1.64 | 0.32 | 0.23 | 0.14 | 0.03 |
| **10** | 0.23 | 0.46 | 0.40 | 0.17 | 0.36 | 1.78 | 0.49 | 0.12 | 0.12 | 0.37 |
| **11** | 0.14 | 0.26 | 0.36 | 0.09 | 0.42 | 2.07 | 0.45 | 0.13 | 0.15 | 0.52 |
| **12** | 0.35 | 0.42 | 0.31 | 0.07 | 0.40 | 1.80 | 0.49 | 0.16 | 0.17 | 0.38 |
| **13** | 0.17 | 0.55 | 0.16 | 0.04 | 0.34 | 1.62 | 0.42 | 0.15 | 0.15 | 0.30 |
| **14** | 0.42 | 0.13 | 0.35 | 0.22 | 0.31 | 2.83 | 0.30 | 0.19 | 0.14 | 0.20 |
| **15** | 0.20 | 0.57 | 0.25 | 0.08 | 0.31 | 1.58 | 0.48 | 0.14 | 0.14 | 0.38 |
| **16** | 0.26 | 0.50 | 0.36 | 0.06 | 0.36 | 1.80 | 0.31 | 0.15 | 0.15 | 0.46 |
| **17** | 0.23 | 0.45 | 0.45 | 0.11 | 0.38 | 1.86 | 0.42 | 0.15 | 0.15 | 0.41 |
| **18** | 0.22 | 0.51 | 0.08 | 0.02 | 0.26 | 1.38 | 0.22 | 0.18 | 0.15 | 0.20 |
| **19** | 0.18 | 0.45 | 0.10 | 0.11 | 0.29 | 1.84 | 0.43 | 0.15 | 0.17 | 0.39 |
| **20** | 0.20 | 0.58 | 0.25 | 0.08 | 0.31 | 1.54 | 0.44 | 0.16 | 0.15 | 0.27 |
| **21** | 0.25 | 0.56 | 0.19 | 0.06 | 0.36 | 1.65 | 0.43 | 0.16 | 0.16 | 0.31 |
| **22** | 0.40 | 0.22 | 0.06 | 0.13 | 0.17 | 2.47 | 0.21 | 0.20 | 0.15 | 0.05 |
| **23** | 0.17 | 0.63 | 0.18 | 0.05 | 0.36 | 1.56 | 0.37 | 0.15 | 0.15 | 0.14 |
| **24** | 0.34 | 0.41 | 0.27 | 0.05 | 0.18 | 1.68 | 0.31 | 0.16 | 0.15 | 0.37 |
| **25** | 0.13 | 0.45 | 0.30 | 0.06 | 0.44 | 1.83 | 0.41 | 0.16 | 0.15 | 0.34 |
| **26** | 0.24 | 0.50 | 0.19 | 0.03 | 0.20 | 1.53 | 0.22 | 0.18 | 0.14 | 0.04 |
| **27** | 0.20 | 0.55 | 0.25 | 0.05 | 0.44 | 1.76 | 0.64 | 0.15 | 0.15 | 0.30 |
| **28** | 0.18 | 0.44 | 0.29 | 0.09 | 0.31 | 1.20 | 0.46 | 0.15 | 0.17 | 0.46 |
| **29** | 0.19 | 0.52 | 0.16 | 0.07 | 0.33 | 1.67 | 0.50 | 0.16 | 0.16 | 0.26 |
| **30** | 0.19 | 0.47 | 0.37 | 0.16 | 0.41 | 1.87 | 0.33 | 0.13 | 0.15 | 0.47 |
| **31** | 0.23 | 0.37 | 0.38 | 0.24 | 0.15 | 2.01 | 0.38 | 0.14 | 0.16 | 0.50 |
| **32** | 0.13 | 0.36 | 0.47 | 0.16 | 0.43 | 2.01 | 0.60 | 0.10 | 0.17 | 0.53 |
| **33** | 0.33 | 0.43 | 0.33 | 0.14 | 0.33 | 1.73 | 0.42 | 0.14 | 0.15 | 0.34 |
| **34** | 0.42 | 0.33 | 0.48 | 0.16 | 0.47 | 1.75 | 0.43 | 0.16 | 0.18 | 0.29 |
| **35** | 0.26 | 0.51 | 0.40 | 0.09 | 0.39 | 1.73 | 0.37 | 0.15 | 0.13 | 0.32 |
| **36** | 0.17 | 0.48 | 0.12 | 0.05 | 0.18 | 1.81 | 0.63 | 0.16 | 0.16 | 0.30 |
| **37** | 0.28 | 0.61 | 0.30 | 0.06 | 0.39 | 1.56 | 0.34 | 0.15 | 0.14 | 0.22 |
| **38** | 0.28 | 0.56 | 0.40 | 0.09 | 0.35 | 1.68 | 0.36 | 0.14 | 0.13 | 0.30 |
| **39** | 0.25 | 0.45 | 0.15 | 0.09 | 0.38 | 1.91 | 0.50 | 0.17 | 0.18 | 0.50 |
| **40** | 0.22 | 0.49 | 0.37 | 0.08 | 0.31 | 1.89 | 0.46 | 0.13 | 0.16 | 0.43 |
| **41** | 0.24 | 0.58 | 0.17 | 0.03 | 0.38 | 1.78 | 0.41 | 0.15 | 0.17 | 0.23 |
| **42** | 0.31 | 0.37 | 0.44 | 0.16 | 0.32 | 1.86 | 0.30 | 0.16 | 0.15 | 0.31 |
| **43** | 0.18 | 0.48 | 0.31 | 0.12 | 0.52 | 1.78 | 0.35 | 0.15 | 0.15 | 0.43 |
| **44** | 0.10 | 0.37 | 0.31 | 0.10 | 0.52 | 1.91 | 0.40 | 0.16 | 0.17 | 0.50 |
| **45** | 0.17 | 0.45 | 0.33 | 0.11 | 0.31 | 1.73 | 0.48 | 0.22 | 0.17 | 0.12 |
| **μ** | **0.26** | **0.44** | **0.28** | **0.10** | **0.34** | **1.81** | **0.41** | **0.16** | **0.15** | **0.32** |

**40% Noise**

| **Subject** | ***A*** | ***C*** | ***μTa*** | ***μFl*** | ***μSS*** | ***μRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.09 | 0.48 | 0.40 | 0.35 | 0.34 | 1.61 | 0.45 | 0.17 | 0.13 | 0.20 |
| **2** | 0.31 | 0.55 | 0.28 | 0.10 | 0.38 | 1.62 | 0.41 | 0.14 | 0.14 | 0.19 |
| **3** | 0.15 | 0.50 | 0.23 | 0.02 | 0.40 | 1.80 | 0.52 | 0.12 | 0.18 | 0.43 |
| **4** | 0.46 | 0.16 | 0.27 | 0.13 | 0.21 | 2.26 | 0.45 | 0.13 | 0.14 | 0.22 |
| **5** | 0.20 | 0.55 | 0.31 | 0.16 | 0.39 | 1.57 | 0.55 | 0.13 | 0.14 | 0.27 |
| **6** | 0.39 | 0.52 | 0.28 | 0.21 | 0.30 | 1.74 | 0.30 | 0.16 | 0.17 | 0.36 |
| **7** | 0.37 | 0.42 | 0.32 | 0.16 | 0.40 | 1.81 | 0.35 | 0.15 | 0.16 | 0.41 |
| **8** | 0.28 | 0.50 | 0.23 | 0.10 | 0.33 | 1.56 | 0.45 | 0.16 | 0.15 | 0.38 |
| **9** | 0.33 | 0.24 | 0.42 | 0.09 | 0.80 | 0.23 | 0.30 | 0.22 | 0.14 | 0.02 |
| **10** | 0.48 | 0.13 | 0.27 | 0.23 | 0.14 | 2.14 | 0.33 | 0.22 | 0.15 | 0.17 |
| **11** | 0.14 | 0.44 | 0.32 | 0.14 | 0.36 | 1.58 | 0.44 | 0.12 | 0.16 | 0.55 |
| **12** | 0.20 | 0.53 | 0.16 | 0.08 | 0.37 | 1.71 | 0.42 | 0.18 | 0.16 | 0.23 |
| **13** | 0.16 | 0.52 | 0.15 | 0.11 | 0.24 | 1.66 | 0.45 | 0.16 | 0.14 | 0.38 |
| **14** | 0.35 | 0.11 | 0.38 | 0.34 | 0.15 | 2.21 | 0.35 | 0.21 | 0.12 | 0.28 |
| **15** | 0.21 | 0.70 | 0.23 | 0.22 | 0.55 | 1.23 | 0.38 | 0.13 | 0.13 | 0.27 |
| **16** | 0.23 | 0.38 | 0.43 | 0.11 | 0.48 | 1.06 | 0.39 | 0.16 | 0.19 | 0.56 |
| **17** | 0.35 | 0.23 | 0.44 | 0.27 | 0.35 | 2.09 | 0.34 | 0.15 | 0.13 | 0.37 |
| **18** | 0.28 | 0.54 | 0.14 | 0.04 | 0.39 | 1.35 | 0.18 | 0.18 | 0.16 | 0.37 |
| **19** | 0.16 | 0.50 | 0.12 | 0.08 | 0.30 | 1.78 | 0.42 | 0.19 | 0.15 | 0.39 |
| **20** | 0.26 | 0.46 | 0.25 | 0.17 | 0.44 | 1.58 | 0.37 | 0.18 | 0.16 | 0.36 |
| **21** | 0.35 | 0.42 | 0.22 | 0.11 | 0.19 | 1.86 | 0.29 | 0.15 | 0.16 | 0.40 |
| **22** | 0.30 | 0.57 | 0.26 | 0.11 | 0.36 | 1.36 | 0.36 | 0.15 | 0.16 | 0.28 |
| **23** | 0.26 | 0.47 | 0.25 | 0.07 | 0.34 | 1.74 | 0.35 | 0.17 | 0.15 | 0.32 |
| **24** | 0.24 | 0.54 | 0.30 | 0.23 | 0.35 | 1.69 | 0.42 | 0.14 | 0.15 | 0.43 |
| **25** | 0.17 | 0.47 | 0.30 | 0.11 | 0.53 | 1.79 | 0.37 | 0.15 | 0.15 | 0.44 |
| **26** | 0.34 | 0.13 | 0.61 | 0.29 | 0.62 | 0.22 | 0.27 | 0.30 | 0.14 | 0.02 |
| **27** | 0.27 | 0.51 | 0.18 | 0.13 | 0.49 | 1.34 | 0.41 | 0.15 | 0.15 | 0.30 |
| **28** | 0.20 | 0.50 | 0.27 | 0.15 | 0.18 | 1.64 | 0.43 | 0.14 | 0.14 | 0.48 |
| **29** | 0.18 | 0.59 | 0.13 | 0.07 | 0.23 | 1.71 | 0.54 | 0.13 | 0.16 | 0.30 |
| **30** | 0.15 | 0.45 | 0.49 | 0.33 | 0.27 | 1.22 | 0.39 | 0.13 | 0.16 | 0.46 |
| **31** | 0.16 | 0.58 | 0.27 | 0.27 | 0.39 | 1.45 | 0.34 | 0.16 | 0.13 | 0.34 |
| **32** | 0.40 | 0.10 | 0.52 | 0.32 | 0.09 | 2.15 | 0.39 | 0.12 | 0.12 | 0.42 |
| **33** | 0.35 | 0.29 | 0.32 | 0.23 | 0.24 | 1.90 | 0.46 | 0.16 | 0.15 | 0.28 |
| **34** | 0.32 | 0.42 | 0.32 | 0.23 | 0.44 | 1.59 | 0.35 | 0.16 | 0.16 | 0.20 |
| **35** | 0.17 | 0.47 | 0.33 | 0.22 | 0.42 | 1.66 | 0.47 | 0.18 | 0.19 | 0.34 |
| **36** | 0.25 | 0.48 | 0.12 | 0.16 | 0.27 | 1.71 | 0.49 | 0.15 | 0.15 | 0.36 |
| **37** | 0.21 | 0.56 | 0.27 | 0.11 | 0.40 | 1.37 | 0.43 | 0.14 | 0.13 | 0.17 |
| **38** | 0.38 | 0.15 | 0.34 | 0.41 | 0.08 | 2.24 | 0.31 | 0.17 | 0.14 | 0.28 |
| **39** | 0.20 | 0.48 | 0.14 | 0.24 | 0.41 | 1.15 | 0.52 | 0.16 | 0.16 | 0.46 |
| **40** | 0.21 | 0.50 | 0.32 | 0.21 | 0.53 | 1.61 | 0.41 | 0.15 | 0.16 | 0.46 |
| **41** | 0.34 | 0.52 | 0.28 | 0.15 | 0.27 | 1.81 | 0.36 | 0.15 | 0.17 | 0.46 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **42** | 0.22 | 0.44 | 0.38 | 0.25 | 0.61 | 1.74 | 0.40 | 0.14 | 0.14 | 0.48 |
| **43** | 0.20 | 0.47 | 0.42 | 0.16 | 0.36 | 1.92 | 0.29 | 0.14 | 0.13 | 0.50 |
| **44** | 0.09 | 0.32 | 0.28 | 0.11 | 0.46 | 1.83 | 0.46 | 0.21 | 0.15 | 0.47 |
| **45** | 0.15 | 0.53 | 0.19 | 0.15 | 0.33 | 1.63 | 0.39 | 0.16 | 0.13 | 0.09 |
| **μ** | **0.25** | **0.43** | **0.29** | **0.18** | **0.36** | **1.62** | **0.39** | **0.16** | **0.15** | **0.34** |

**10% Noise**

| **Subject** | ***A*** | ***C*** | ***μTa*** | ***μFl*** | ***μSS*** | ***μRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.37 | 0.09 | 0.39 | 0.32 | 0.17 | 2.44 | 0.33 | 0.25 | 0.11 | 0.26 |
| **2** | 0.26 | 0.61 | 0.21 | 0.12 | 0.43 | 1.01 | 0.36 | 0.13 | 0.14 | 0.16 |
| **3** | 0.17 | 0.61 | 0.18 | 0.02 | 0.38 | 1.62 | 0.46 | 0.15 | 0.15 | 0.36 |
| **4** | 0.44 | 0.28 | 0.41 | 0.22 | 0.25 | 1.73 | 0.38 | 0.14 | 0.15 | 0.30 |
| **5** | 0.31 | 0.49 | 0.29 | 0.20 | 0.33 | 1.48 | 0.30 | 0.14 | 0.16 | 0.19 |
| **6** | 0.41 | 0.20 | 0.23 | 0.19 | 0.16 | 1.94 | 0.29 | 0.18 | 0.16 | 0.19 |
| **7** | 0.22 | 0.55 | 0.26 | 0.16 | 0.31 | 1.63 | 0.45 | 0.15 | 0.16 | 0.35 |
| **8** | 0.22 | 0.48 | 0.20 | 0.07 | 0.23 | 1.76 | 0.46 | 0.16 | 0.16 | 0.37 |
| **9** | 0.27 | 0.64 | 0.16 | 0.03 | 0.34 | 1.62 | 0.29 | 0.18 | 0.15 | 0.04 |
| **10** | 0.28 | 0.35 | 0.42 | 0.25 | 0.37 | 2.04 | 0.40 | 0.14 | 0.13 | 0.47 |
| **11** | 0.19 | 0.24 | 0.32 | 0.10 | 0.27 | 2.38 | 0.39 | 0.13 | 0.14 | 0.59 |
| **12** | 0.35 | 0.33 | 0.14 | 0.13 | 0.16 | 1.76 | 0.30 | 0.18 | 0.16 | 0.36 |
| **13** | 0.22 | 0.49 | 0.24 | 0.14 | 0.29 | 1.60 | 0.40 | 0.16 | 0.16 | 0.46 |
| **14** | 0.17 | 0.23 | 0.23 | 0.47 | 0.76 | 0.94 | 0.39 | 0.15 | 0.11 | 0.34 |
| **15** | 0.15 | 0.53 | 0.22 | 0.24 | 0.36 | 1.54 | 0.46 | 0.19 | 0.12 | 0.16 |
| **16** | 0.25 | 0.46 | 0.28 | 0.08 | 0.49 | 1.81 | 0.27 | 0.17 | 0.16 | 0.37 |
| **17** | 0.43 | 0.23 | 0.32 | 0.20 | 0.26 | 2.35 | 0.26 | 0.15 | 0.16 | 0.41 |
| **18** | 0.23 | 0.34 | 0.19 | 0.06 | 0.70 | 0.23 | 0.44 | 0.16 | 0.17 | 0.54 |
| **19** | 0.14 | 0.45 | 0.15 | 0.21 | 0.27 | 1.85 | 0.40 | 0.16 | 0.14 | 0.53 |
| **20** | 0.15 | 0.45 | 0.20 | 0.16 | 0.35 | 1.33 | 0.47 | 0.24 | 0.15 | 0.11 |
| **21** | 0.17 | 0.43 | 0.14 | 0.06 | 0.25 | 1.88 | 0.45 | 0.27 | 0.17 | 0.12 |
| **22** | 0.33 | 0.53 | 0.25 | 0.14 | 0.26 | 1.52 | 0.29 | 0.17 | 0.16 | 0.32 |
| **23** | 0.18 | 0.54 | 0.23 | 0.11 | 0.27 | 1.63 | 0.42 | 0.16 | 0.14 | 0.20 |
| **24** | 0.19 | 0.57 | 0.26 | 0.13 | 0.28 | 1.77 | 0.40 | 0.17 | 0.16 | 0.29 |
| **25** | 0.13 | 0.40 | 0.23 | 0.18 | 0.29 | 1.79 | 0.39 | 0.14 | 0.13 | 0.43 |
| **26** | 0.49 | 0.16 | 0.15 | 0.13 | 0.12 | 2.38 | 0.17 | 0.19 | 0.14 | 0.05 |
| **27** | 0.21 | 0.48 | 0.11 | 0.12 | 0.33 | 1.78 | 0.32 | 0.17 | 0.14 | 0.13 |
| **28** | 0.17 | 0.55 | 0.14 | 0.06 | 0.31 | 1.53 | 0.33 | 0.16 | 0.15 | 0.28 |
| **29** | 0.26 | 0.45 | 0.24 | 0.07 | 0.19 | 1.82 | 0.48 | 0.16 | 0.15 | 0.46 |
| **30** | 0.13 | 0.49 | 0.38 | 0.36 | 0.33 | 1.59 | 0.39 | 0.12 | 0.09 | 0.52 |
| **31** | 0.15 | 0.51 | 0.29 | 0.30 | 0.31 | 1.77 | 0.33 | 0.12 | 0.13 | 0.32 |
| **32** | 0.19 | 0.24 | 0.36 | 0.44 | 0.46 | 2.08 | 0.46 | 0.15 | 0.15 | 0.34 |
| **33** | 0.24 | 0.37 | 0.19 | 0.36 | 0.22 | 1.85 | 0.45 | 0.17 | 0.12 | 0.26 |
| **34** | 0.36 | 0.46 | 0.40 | 0.32 | 0.47 | 1.69 | 0.31 | 0.13 | 0.13 | 0.27 |
| **35** | 0.23 | 0.45 | 0.29 | 0.34 | 0.74 | 0.76 | 0.32 | 0.15 | 0.12 | 0.29 |
| **36** | 0.23 | 0.48 | 0.16 | 0.13 | 0.26 | 1.87 | 0.46 | 0.15 | 0.17 | 0.43 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **37** | 0.21 | 0.61 | 0.26 | 0.15 | 0.50 | 1.38 | 0.43 | 0.13 | 0.13 | 0.25 |
| **38** | 0.13 | 0.51 | 0.31 | 0.42 | 0.39 | 0.95 | 0.48 | 0.18 | 0.15 | 0.23 |
| **39** | 0.19 | 0.50 | 0.18 | 0.11 | 0.26 | 1.83 | 0.48 | 0.16 | 0.15 | 0.43 |
| **40** | 0.18 | 0.41 | 0.35 | 0.32 | 0.32 | 1.70 | 0.44 | 0.18 | 0.14 | 0.25 |
| **41** | 0.22 | 0.54 | 0.25 | 0.13 | 0.26 | 1.62 | 0.41 | 0.15 | 0.15 | 0.36 |
| **42** | 0.23 | 0.33 | 0.31 | 0.30 | 0.51 | 1.57 | 0.35 | 0.17 | 0.14 | 0.32 |
| **43** | 0.15 | 0.43 | 0.34 | 0.18 | 0.28 | 1.85 | 0.34 | 0.13 | 0.11 | 0.53 |
| **44** | 0.08 | 0.38 | 0.32 | 0.11 | 0.58 | 1.85 | 0.40 | 0.16 | 0.14 | 0.40 |
| **45** | 0.21 | 0.50 | 0.27 | 0.29 | 0.32 | 1.61 | 0.38 | 0.14 | 0.13 | 0.24 |
| **μ** | **0.23** | **0.43** | **0.25** | **0.19** | **0.34** | **1.67** | **0.38** | **0.16** | **0.14** | **0.32** |

## Expected a-posteriori estimates (Low Noise Target)

### $\mathbf{SSP_{pFl}}$

**80% Noise**

| **Subject** | ***A*** | ***ter*** | ***pTarget*** | ***pFlanker*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** | ***IR*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.06 | 0.42 | 1.36 | 0.51 | 87.70 | 3.47 | 0.08 | 0.16 | 0.22 | 0.04 |
| **2** | 0.27 | 0.33 | 1.17 | 0.41 | 82.24 | 2.89 | 0.12 | 0.09 | 0.16 | 0.04 |
| **3** | 0.11 | 0.45 | 0.83 | 0.46 | 87.89 | 4.54 | 0.13 | 0.10 | 0.38 | 0.05 |
| **4** | 0.34 | 0.29 | 0.94 | 0.45 | 82.26 | 3.99 | 0.13 | 0.09 | 0.25 | 0.05 |
| **5** | 0.13 | 0.48 | 0.64 | 0.31 | 82.57 | 3.98 | 0.13 | 0.10 | 0.29 | 0.05 |
| **6** | 0.28 | 0.33 | 1.02 | 0.40 | 81.65 | 2.96 | 0.12 | 0.08 | 0.23 | 0.04 |
| **7** | 0.33 | 0.27 | 0.88 | 0.43 | 81.63 | 4.24 | 0.13 | 0.10 | 0.23 | 0.05 |
| **8** | 0.24 | 0.38 | 1.13 | 0.43 | 81.43 | 3.38 | 0.11 | 0.08 | 0.23 | 0.04 |
| **9** | 0.39 | 0.28 | 0.76 | 0.40 | 84.38 | 3.43 | 0.16 | 0.14 | 0.20 | 0.04 |
| **10** | 0.29 | 0.31 | 1.09 | 0.38 | 82.04 | 2.10 | 0.12 | 0.10 | 0.21 | 0.03 |
| **11** | 0.26 | 0.26 | 1.19 | 0.42 | 83.77 | 3.03 | 0.13 | 0.11 | 0.15 | 0.04 |
| **12** | 0.28 | 0.27 | 0.75 | 0.40 | 81.26 | 2.67 | 0.18 | 0.11 | 0.14 | 0.03 |
| **13** | 0.08 | 0.50 | 1.09 | 0.50 | 87.24 | 3.45 | 0.13 | 0.22 | 0.36 | 0.04 |
| **14** | 0.23 | 0.31 | 1.17 | 0.45 | 84.12 | 3.40 | 0.12 | 0.07 | 0.20 | 0.04 |
| **15** | 0.12 | 0.41 | 0.59 | 0.44 | 85.91 | 2.82 | 0.12 | 0.10 | 0.22 | 0.03 |
| **16** | 0.20 | 0.32 | 1.31 | 0.42 | 83.76 | 2.41 | 0.09 | 0.05 | 0.20 | 0.03 |
| **17** | 0.31 | 0.29 | 1.01 | 0.43 | 83.39 | 3.48 | 0.15 | 0.16 | 0.16 | 0.04 |
| **18** | 0.19 | 0.38 | 0.73 | 0.29 | 86.01 | 4.05 | 0.15 | 0.11 | 0.41 | 0.05 |
| **19** | 0.07 | 0.43 | 0.55 | 0.47 | 84.83 | 1.04 | 0.07 | 0.11 | 0.28 | 0.01 |
| **20** | 0.21 | 0.33 | 0.96 | 0.43 | 81.29 | 2.02 | 0.19 | 0.07 | 0.13 | 0.02 |
| **21** | 0.31 | 0.27 | 0.95 | 0.40 | 82.31 | 2.57 | 0.15 | 0.14 | 0.17 | 0.03 |
| **22** | 0.27 | 0.31 | 1.03 | 0.53 | 81.98 | 5.09 | 0.11 | 0.08 | 0.30 | 0.06 |
| **23** | 0.27 | 0.35 | 0.99 | 0.37 | 81.37 | 2.17 | 0.16 | 0.14 | 0.12 | 0.03 |
| **24** | 0.16 | 0.38 | 0.75 | 0.41 | 90.63 | 3.68 | 0.15 | 0.14 | 0.38 | 0.04 |
| **25** | 0.09 | 0.45 | 1.02 | 0.35 | 83.57 | 2.07 | 0.16 | 0.21 | 0.21 | 0.02 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **26** | 0.27 | 0.33 | 1.14 | 0.39 | 83.19 | 2.19 | 0.12 | 0.08 | 0.26 | 0.03 |
| **27** | 0.37 | 0.20 | 0.68 | 0.41 | 84.17 | 2.79 | 0.14 | 0.12 | 0.21 | 0.03 |
| **28** | 0.29 | 0.28 | 1.23 | 0.38 | 82.80 | 2.56 | 0.15 | 0.19 | 0.14 | 0.03 |
| **29** | 0.11 | 0.48 | 0.23 | 0.44 | 86.34 | 2.26 | 0.10 | 0.12 | 0.09 | 0.03 |
| **30** | 0.25 | 0.26 | 1.12 | 0.39 | 81.70 | 2.52 | 0.11 | 0.09 | 0.17 | 0.03 |
| **31** | 0.21 | 0.26 | 1.35 | 0.40 | 81.48 | 1.82 | 0.10 | 0.09 | 0.13 | 0.02 |
| **32** | 0.28 | 0.36 | 1.17 | 0.40 | 82.27 | 2.26 | 0.16 | 0.15 | 0.13 | 0.03 |
| **33** | 0.31 | 0.36 | 0.91 | 0.37 | 80.39 | 2.90 | 0.15 | 0.13 | 0.16 | 0.04 |
| **34** | 0.24 | 0.38 | 1.21 | 0.42 | 83.87 | 2.29 | 0.12 | 0.07 | 0.20 | 0.03 |
| **35** | 0.23 | 0.35 | 1.28 | 0.40 | 83.35 | 2.07 | 0.11 | 0.09 | 0.16 | 0.02 |
| **36** | 0.10 | 0.50 | 0.89 | 0.47 | 87.76 | 2.26 | 0.11 | 0.18 | 0.42 | 0.03 |
| **37** | 0.18 | 0.40 | 1.15 | 0.45 | 83.43 | 2.68 | 0.10 | 0.06 | 0.25 | 0.03 |
| **38** | 0.25 | 0.30 | 1.10 | 0.38 | 82.15 | 1.89 | 0.12 | 0.09 | 0.15 | 0.02 |
| **39** | 0.17 | 0.44 | 0.73 | 0.34 | 83.84 | 4.18 | 0.15 | 0.19 | 0.34 | 0.05 |
| **40** | 0.22 | 0.33 | 1.22 | 0.40 | 81.87 | 2.12 | 0.11 | 0.07 | 0.19 | 0.03 |
| **41** | 0.13 | 0.44 | 0.87 | 0.42 | 87.20 | 2.06 | 0.13 | 0.18 | 0.44 | 0.02 |
| **42** | 0.30 | 0.27 | 1.06 | 0.39 | 82.86 | 2.50 | 0.15 | 0.14 | 0.14 | 0.03 |
| **43** | 0.26 | 0.22 | 1.11 | 0.41 | 81.75 | 2.65 | 0.15 | 0.11 | 0.15 | 0.03 |
| **44** | 0.09 | 0.40 | 1.06 | 0.39 | 83.35 | 1.74 | 0.20 | 0.11 | 0.19 | 0.02 |
| **45** | 0.25 | 0.31 | 1.00 | 0.42 | 81.61 | 2.54 | 0.16 | 0.10 | 0.19 | 0.03 |
| **μ** | **0.22** | **0.35** | **0.99** | **0.41** | **83.57** | **2.83** | **0.13** | **0.12** | **0.22** | **0.03** |

**70% Noise**

| **Subject** | ***A*** | ***ter*** | ***pTarget*** | ***pFlanker*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** | ***IR*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.25 | 0.27 | 1.15 | 0.40 | 81.80 | 2.24 | 0.11 | 0.10 | 0.17 | 0.03 |
| **2** | 0.24 | 0.35 | 1.10 | 0.42 | 82.62 | 2.59 | 0.12 | 0.07 | 0.19 | 0.03 |
| **3** | 0.29 | 0.33 | 1.04 | 0.37 | 80.14 | 2.26 | 0.15 | 0.10 | 0.17 | 0.03 |
| **4** | 0.34 | 0.27 | 0.83 | 0.41 | 81.37 | 3.21 | 0.15 | 0.11 | 0.20 | 0.04 |
| **5** | 0.35 | 0.32 | 0.96 | 0.42 | 84.72 | 3.48 | 0.13 | 0.10 | 0.28 | 0.04 |
| **6** | 0.14 | 0.46 | 0.89 | 0.39 | 86.61 | 3.41 | 0.19 | 0.15 | 0.28 | 0.04 |
| **7** | 0.34 | 0.26 | 0.95 | 0.39 | 86.29 | 3.54 | 0.13 | 0.10 | 0.27 | 0.04 |
| **8** | 0.27 | 0.35 | 1.08 | 0.39 | 84.09 | 2.57 | 0.12 | 0.08 | 0.26 | 0.03 |
| **9** | 0.38 | 0.31 | 0.80 | 0.43 | 80.02 | 3.94 | 0.14 | 0.15 | 0.24 | 0.05 |
| **10** | 0.26 | 0.32 | 1.14 | 0.47 | 81.66 | 3.90 | 0.12 | 0.08 | 0.20 | 0.05 |
| **11** | 0.23 | 0.33 | 1.29 | 0.40 | 82.02 | 2.02 | 0.13 | 0.14 | 0.13 | 0.02 |
| **12** | 0.31 | 0.27 | 0.87 | 0.37 | 81.82 | 2.59 | 0.13 | 0.10 | 0.23 | 0.03 |
| **13** | 0.09 | 0.48 | 0.79 | 0.26 | 83.77 | 3.53 | 0.15 | 0.16 | 0.35 | 0.04 |
| **14** | 0.25 | 0.30 | 1.11 | 0.40 | 82.33 | 1.84 | 0.13 | 0.08 | 0.20 | 0.02 |
| **15** | 0.35 | 0.26 | 1.03 | 0.43 | 84.83 | 3.26 | 0.14 | 0.10 | 0.27 | 0.04 |
| **16** | 0.24 | 0.29 | 1.21 | 0.41 | 83.69 | 1.62 | 0.11 | 0.06 | 0.25 | 0.02 |
| **17** | 0.32 | 0.28 | 1.02 | 0.39 | 83.98 | 2.24 | 0.14 | 0.11 | 0.22 | 0.03 |
| **18** | 0.20 | 0.37 | 0.73 | 0.34 | 86.76 | 4.16 | 0.16 | 0.15 | 0.45 | 0.05 |
| **19** | 0.07 | 0.43 | 0.69 | 0.40 | 85.38 | 2.90 | 0.09 | 0.11 | 0.33 | 0.03 |
| **20** | 0.27 | 0.30 | 1.16 | 0.44 | 83.66 | 3.65 | 0.14 | 0.11 | 0.15 | 0.04 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **21** | 0.28 | 0.28 | 0.83 | 0.41 | 80.36 | 3.50 | 0.13 | 0.11 | 0.23 | 0.04 |
| **22** | 0.32 | 0.28 | 0.99 | 0.41 | 82.59 | 3.39 | 0.13 | 0.11 | 0.21 | 0.04 |
| **23** | 0.29 | 0.34 | 1.02 | 0.39 | 82.70 | 2.19 | 0.15 | 0.18 | 0.12 | 0.03 |
| **24** | 0.32 | 0.22 | 0.81 | 0.40 | 83.91 | 2.45 | 0.16 | 0.11 | 0.24 | 0.03 |
| **25** | 0.09 | 0.39 | 0.63 | 0.37 | 85.54 | 1.97 | 0.12 | 0.12 | 0.28 | 0.02 |
| **26** | 0.22 | 0.36 | 1.11 | 0.43 | 83.22 | 2.70 | 0.12 | 0.06 | 0.22 | 0.03 |
| **27** | 0.36 | 0.20 | 0.63 | 0.46 | 81.95 | 4.82 | 0.15 | 0.12 | 0.19 | 0.06 |
| **28** | 0.28 | 0.26 | 1.10 | 0.39 | 81.90 | 2.50 | 0.13 | 0.13 | 0.17 | 0.03 |
| **29** | 0.13 | 0.55 | 0.36 | 0.39 | 87.73 | 2.50 | 0.13 | 0.20 | 0.25 | 0.03 |
| **30** | 0.20 | 0.32 | 1.08 | 0.42 | 82.89 | 1.76 | 0.15 | 0.05 | 0.19 | 0.02 |
| **31** | 0.21 | 0.27 | 1.32 | 0.43 | 81.99 | 1.56 | 0.13 | 0.08 | 0.15 | 0.02 |
| **32** | 0.28 | 0.36 | 1.25 | 0.44 | 81.95 | 3.36 | 0.14 | 0.16 | 0.11 | 0.04 |
| **33** | 0.32 | 0.37 | 0.85 | 0.43 | 82.47 | 3.28 | 0.18 | 0.13 | 0.14 | 0.04 |
| **34** | 0.23 | 0.40 | 1.22 | 0.41 | 82.50 | 1.98 | 0.14 | 0.08 | 0.16 | 0.02 |
| **35** | 0.19 | 0.37 | 1.30 | 0.46 | 86.27 | 2.29 | 0.14 | 0.06 | 0.18 | 0.03 |
| **36** | 0.12 | 0.45 | 0.75 | 0.43 | 85.40 | 3.58 | 0.10 | 0.11 | 0.34 | 0.04 |
| **37** | 0.24 | 0.37 | 1.31 | 0.37 | 81.66 | 2.09 | 0.10 | 0.08 | 0.16 | 0.03 |
| **38** | 0.21 | 0.32 | 1.13 | 0.42 | 84.03 | 2.90 | 0.11 | 0.06 | 0.21 | 0.03 |
| **39** | 0.14 | 0.50 | 0.77 | 0.48 | 85.52 | 2.99 | 0.12 | 0.18 | 0.43 | 0.03 |
| **40** | 0.20 | 0.33 | 1.19 | 0.45 | 84.97 | 3.08 | 0.10 | 0.05 | 0.25 | 0.04 |
| **41** | 0.35 | 0.25 | 1.02 | 0.42 | 84.32 | 2.80 | 0.15 | 0.10 | 0.24 | 0.03 |
| **42** | 0.29 | 0.27 | 1.09 | 0.44 | 82.97 | 3.80 | 0.15 | 0.18 | 0.12 | 0.05 |
| **43** | 0.22 | 0.24 | 1.12 | 0.51 | 83.22 | 4.09 | 0.10 | 0.06 | 0.29 | 0.05 |
| **44** | 0.08 | 0.38 | 1.01 | 0.41 | 88.91 | 4.41 | 0.12 | 0.14 | 0.29 | 0.05 |
| **45** | 0.26 | 0.29 | 0.96 | 0.41 | 81.88 | 2.90 | 0.15 | 0.09 | 0.18 | 0.04 |
| **μ** | **0.24** | **0.33** | **0.99** | **0.41** | **83.52** | **2.93** | **0.13** | **0.11** | **0.23** | **0.04** |

**40% Noise**

| **Subject** | ***A*** | ***ter*** | ***pTarget*** | ***pFlanker*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** | ***IR*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.24 | 0.30 | 1.28 | 0.41 | 84.07 | 2.33 | 0.12 | 0.10 | 0.18 | 0.03 |
| **2** | 0.28 | 0.33 | 1.25 | 0.47 | 81.91 | 3.97 | 0.12 | 0.10 | 0.12 | 0.05 |
| **3** | 0.27 | 0.31 | 1.00 | 0.43 | 80.57 | 3.93 | 0.12 | 0.09 | 0.22 | 0.05 |
| **4** | 0.29 | 0.36 | 1.09 | 0.39 | 83.88 | 2.75 | 0.11 | 0.08 | 0.28 | 0.03 |
| **5** | 0.39 | 0.27 | 0.87 | 0.46 | 83.05 | 4.12 | 0.14 | 0.11 | 0.27 | 0.05 |
| **6** | 0.28 | 0.37 | 1.07 | 0.37 | 83.02 | 2.18 | 0.11 | 0.07 | 0.27 | 0.03 |
| **7** | 0.34 | 0.24 | 0.77 | 0.37 | 82.86 | 3.16 | 0.16 | 0.14 | 0.16 | 0.04 |
| **8** | 0.15 | 0.49 | 0.96 | 0.47 | 91.01 | 2.33 | 0.12 | 0.12 | 0.50 | 0.03 |
| **9** | 0.38 | 0.24 | 0.66 | 0.40 | 82.24 | 3.10 | 0.16 | 0.15 | 0.17 | 0.04 |
| **10** | 0.31 | 0.29 | 1.12 | 0.45 | 85.45 | 3.86 | 0.13 | 0.10 | 0.25 | 0.05 |
| **11** | 0.10 | 0.43 | 1.25 | 0.38 | 85.87 | 1.99 | 0.20 | 0.14 | 0.18 | 0.02 |
| **12** | 0.34 | 0.26 | 0.96 | 0.39 | 84.97 | 2.11 | 0.14 | 0.13 | 0.23 | 0.02 |
| **13** | 0.07 | 0.51 | 0.70 | 0.40 | 86.13 | 2.47 | 0.10 | 0.23 | 0.43 | 0.03 |
| **14** | 0.26 | 0.27 | 1.20 | 0.59 | 79.65 | 5.17 | 0.12 | 0.10 | 0.15 | 0.06 |
| **15** | 0.29 | 0.30 | 0.99 | 0.39 | 82.84 | 3.00 | 0.13 | 0.11 | 0.18 | 0.04 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **16** | 0.24 | 0.26 | 1.12 | 0.42 | 82.44 | 2.84 | 0.12 | 0.08 | 0.18 | 0.03 |
| **17** | 0.26 | 0.35 | 1.07 | 0.38 | 81.73 | 2.18 | 0.16 | 0.20 | 0.15 | 0.03 |
| **18** | 0.15 | 0.36 | 0.52 | 0.23 | 82.58 | 4.90 | 0.18 | 0.15 | 0.37 | 0.06 |
| **19** | 0.07 | 0.43 | 0.74 | 0.51 | 85.10 | 1.53 | 0.06 | 0.14 | 0.42 | 0.02 |
| **20** | 0.27 | 0.31 | 1.08 | 0.38 | 81.40 | 2.85 | 0.14 | 0.12 | 0.16 | 0.03 |
| **21** | 0.19 | 0.39 | 0.83 | 0.39 | 84.88 | 2.78 | 0.14 | 0.15 | 0.30 | 0.03 |
| **22** | 0.28 | 0.29 | 0.86 | 0.40 | 81.16 | 2.66 | 0.14 | 0.10 | 0.19 | 0.03 |
| **23** | 0.30 | 0.31 | 0.97 | 0.38 | 82.25 | 1.78 | 0.16 | 0.17 | 0.14 | 0.02 |
| **24** | 0.11 | 0.41 | 0.57 | 0.39 | 86.46 | 2.78 | 0.10 | 0.10 | 0.32 | 0.03 |
| **25** | 0.11 | 0.42 | 0.79 | 0.36 | 86.92 | 2.38 | 0.21 | 0.15 | 0.19 | 0.03 |
| **26** | 0.24 | 0.37 | 1.20 | 0.43 | 85.24 | 2.74 | 0.11 | 0.06 | 0.28 | 0.03 |
| **27** | 0.40 | 0.23 | 0.68 | 0.41 | 82.23 | 3.40 | 0.14 | 0.13 | 0.22 | 0.04 |
| **28** | 0.32 | 0.24 | 1.08 | 0.41 | 86.31 | 1.88 | 0.13 | 0.09 | 0.28 | 0.02 |
| **29** | 0.14 | 0.50 | 0.36 | 0.42 | 87.63 | 4.37 | 0.13 | 0.15 | 0.23 | 0.05 |
| **30** | 0.25 | 0.26 | 1.15 | 0.39 | 82.36 | 2.68 | 0.13 | 0.10 | 0.16 | 0.03 |
| **31** | 0.08 | 0.36 | 1.27 | 0.56 | 89.14 | 3.01 | 0.10 | 0.12 | 0.29 | 0.03 |
| **32** | 0.27 | 0.37 | 1.28 | 0.37 | 83.28 | 2.08 | 0.14 | 0.13 | 0.12 | 0.02 |
| **33** | 0.34 | 0.33 | 0.87 | 0.44 | 81.27 | 3.75 | 0.14 | 0.12 | 0.22 | 0.05 |
| **34** | 0.25 | 0.38 | 1.27 | 0.42 | 84.21 | 2.85 | 0.11 | 0.07 | 0.20 | 0.03 |
| **35** | 0.25 | 0.32 | 1.21 | 0.42 | 84.29 | 2.89 | 0.12 | 0.09 | 0.18 | 0.03 |
| **36** | 0.10 | 0.48 | 0.94 | 0.43 | 90.29 | 2.60 | 0.11 | 0.13 | 0.43 | 0.03 |
| **37** | 0.23 | 0.37 | 1.26 | 0.46 | 82.46 | 3.64 | 0.09 | 0.07 | 0.20 | 0.04 |
| **38** | 0.26 | 0.29 | 1.17 | 0.40 | 81.41 | 2.74 | 0.12 | 0.09 | 0.15 | 0.03 |
| **39** | 0.15 | 0.46 | 0.65 | 0.43 | 87.95 | 3.27 | 0.12 | 0.13 | 0.40 | 0.04 |
| **40** | 0.07 | 0.45 | 1.01 | 0.43 | 86.94 | 1.86 | 0.11 | 0.12 | 0.29 | 0.02 |
| **41** | 0.32 | 0.26 | 0.97 | 0.42 | 83.90 | 3.48 | 0.12 | 0.08 | 0.28 | 0.04 |
| **42** | 0.32 | 0.23 | 0.92 | 0.38 | 82.74 | 2.67 | 0.15 | 0.17 | 0.16 | 0.03 |
| **43** | 0.11 | 0.33 | 0.87 | 0.42 | 88.09 | 2.32 | 0.10 | 0.09 | 0.39 | 0.03 |
| **44** | 0.21 | 0.30 | 1.27 | 0.43 | 81.35 | 2.70 | 0.13 | 0.13 | 0.14 | 0.03 |
| **45** | 0.27 | 0.31 | 1.02 | 0.39 | 83.14 | 1.77 | 0.16 | 0.09 | 0.22 | 0.02 |
| **μ** | **0.23** | **0.34** | **0.98** | **0.42** | **84.15** | **2.88** | **0.13** | **0.12** | **0.24** | **0.03** |

**10% Noise**

| **Subject** | ***A*** | ***ter*** | ***pTarget*** | ***pFlanker*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** | ***IR*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.08 | 0.41 | 1.10 | 0.46 | 84.95 | 3.71 | 0.12 | 0.15 | 0.26 | 0.04 |
| **2** | 0.23 | 0.39 | 1.12 | 0.42 | 81.31 | 1.75 | 0.12 | 0.06 | 0.23 | 0.02 |
| **3** | 0.30 | 0.32 | 0.95 | 0.41 | 84.46 | 2.20 | 0.15 | 0.08 | 0.22 | 0.03 |
| **4** | 0.30 | 0.33 | 0.98 | 0.42 | 81.93 | 3.81 | 0.12 | 0.10 | 0.25 | 0.05 |
| **5** | 0.36 | 0.27 | 0.90 | 0.42 | 82.26 | 3.66 | 0.14 | 0.12 | 0.27 | 0.04 |
| **6** | 0.30 | 0.31 | 1.01 | 0.37 | 82.95 | 2.53 | 0.14 | 0.13 | 0.15 | 0.03 |
| **7** | 0.34 | 0.28 | 0.96 | 0.36 | 83.13 | 2.85 | 0.13 | 0.10 | 0.28 | 0.03 |
| **8** | 0.27 | 0.36 | 1.01 | 0.43 | 83.16 | 2.72 | 0.14 | 0.08 | 0.19 | 0.03 |
| **9** | 0.40 | 0.21 | 0.70 | 0.44 | 83.47 | 4.33 | 0.15 | 0.15 | 0.23 | 0.05 |
| **10** | 0.08 | 0.47 | 0.91 | 0.60 | 84.39 | 3.93 | 0.08 | 0.13 | 0.24 | 0.05 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **11** | 0.28 | 0.27 | 1.11 | 0.42 | 82.85 | 1.61 | 0.13 | 0.11 | 0.17 | 0.02 |
| **12** | 0.31 | 0.30 | 0.88 | 0.40 | 81.11 | 2.15 | 0.15 | 0.10 | 0.20 | 0.03 |
| **13** | 0.09 | 0.48 | 0.65 | 0.49 | 88.99 | 2.52 | 0.10 | 0.15 | 0.46 | 0.03 |
| **14** | 0.25 | 0.29 | 1.16 | 0.41 | 80.31 | 1.84 | 0.12 | 0.09 | 0.16 | 0.02 |
| **15** | 0.30 | 0.32 | 1.04 | 0.46 | 83.20 | 4.10 | 0.12 | 0.09 | 0.27 | 0.05 |
| **16** | 0.21 | 0.31 | 1.25 | 0.42 | 82.28 | 3.08 | 0.10 | 0.09 | 0.15 | 0.04 |
| **17** | 0.31 | 0.28 | 0.96 | 0.40 | 82.85 | 3.41 | 0.13 | 0.08 | 0.25 | 0.04 |
| **18** | 0.16 | 0.38 | 0.70 | 0.41 | 85.87 | 2.28 | 0.12 | 0.12 | 0.42 | 0.03 |
| **19** | 0.08 | 0.41 | 0.58 | 0.64 | 88.33 | 3.10 | 0.07 | 0.15 | 0.47 | 0.04 |
| **20** | 0.24 | 0.33 | 1.01 | 0.41 | 82.18 | 2.81 | 0.15 | 0.09 | 0.18 | 0.03 |
| **21** | 0.12 | 0.43 | 0.83 | 0.43 | 88.57 | 3.35 | 0.12 | 0.11 | 0.47 | 0.04 |
| **22** | 0.09 | 0.47 | 0.79 | 0.41 | 82.64 | 4.24 | 0.11 | 0.20 | 0.32 | 0.05 |
| **23** | 0.33 | 0.30 | 0.99 | 0.40 | 82.06 | 2.89 | 0.13 | 0.10 | 0.24 | 0.04 |
| **24** | 0.11 | 0.41 | 0.63 | 0.36 | 85.52 | 2.58 | 0.10 | 0.11 | 0.35 | 0.03 |
| **25** | 0.29 | 0.24 | 0.97 | 0.37 | 82.16 | 2.42 | 0.16 | 0.11 | 0.17 | 0.03 |
| **26** | 0.26 | 0.33 | 1.09 | 0.36 | 82.83 | 2.44 | 0.11 | 0.07 | 0.25 | 0.03 |
| **27** | 0.39 | 0.21 | 0.69 | 0.42 | 86.39 | 3.46 | 0.16 | 0.13 | 0.23 | 0.04 |
| **28** | 0.10 | 0.36 | 0.67 | 0.25 | 85.71 | 3.82 | 0.14 | 0.14 | 0.28 | 0.04 |
| **29** | 0.16 | 0.51 | 0.55 | 0.38 | 86.62 | 3.80 | 0.15 | 0.16 | 0.31 | 0.04 |
| **30** | 0.25 | 0.27 | 1.31 | 0.46 | 84.00 | 3.59 | 0.14 | 0.12 | 0.13 | 0.04 |
| **31** | 0.24 | 0.23 | 1.23 | 0.41 | 83.39 | 1.96 | 0.12 | 0.09 | 0.17 | 0.02 |
| **32** | 0.26 | 0.38 | 1.20 | 0.40 | 81.54 | 2.90 | 0.13 | 0.15 | 0.12 | 0.04 |
| **33** | 0.30 | 0.36 | 0.88 | 0.41 | 80.62 | 3.37 | 0.14 | 0.10 | 0.20 | 0.04 |
| **34** | 0.24 | 0.38 | 1.23 | 0.41 | 83.18 | 2.59 | 0.13 | 0.10 | 0.17 | 0.03 |
| **35** | 0.21 | 0.36 | 1.33 | 0.44 | 83.87 | 1.95 | 0.10 | 0.06 | 0.22 | 0.02 |
| **36** | 0.10 | 0.48 | 0.61 | 0.46 | 88.84 | 3.12 | 0.11 | 0.14 | 0.31 | 0.04 |
| **37** | 0.22 | 0.39 | 1.21 | 0.39 | 80.90 | 1.96 | 0.12 | 0.07 | 0.15 | 0.02 |
| **38** | 0.27 | 0.28 | 1.14 | 0.43 | 83.70 | 3.50 | 0.11 | 0.06 | 0.28 | 0.04 |
| **39** | 0.13 | 0.44 | 0.46 | 0.46 | 87.12 | 3.64 | 0.10 | 0.12 | 0.29 | 0.04 |
| **40** | 0.21 | 0.36 | 1.24 | 0.41 | 79.93 | 1.83 | 0.12 | 0.08 | 0.18 | 0.02 |
| **41** | 0.27 | 0.32 | 1.10 | 0.41 | 83.79 | 3.27 | 0.15 | 0.18 | 0.18 | 0.04 |
| **42** | 0.30 | 0.26 | 1.03 | 0.38 | 81.93 | 3.21 | 0.14 | 0.15 | 0.15 | 0.04 |
| **43** | 0.10 | 0.34 | 0.83 | 0.39 | 90.27 | 2.30 | 0.10 | 0.07 | 0.38 | 0.03 |
| **44** | 0.07 | 0.42 | 1.07 | 0.45 | 82.98 | 1.60 | 0.15 | 0.17 | 0.25 | 0.02 |
| **45** | 0.29 | 0.27 | 1.02 | 0.40 | 82.71 | 2.81 | 0.15 | 0.12 | 0.18 | 0.03 |
| **μ** | **0.23** | **0.35** | **0.96** | **0.42** | **83.81** | **2.91** | **0.13** | **0.11** | **0.25** | **0.03** |

## DSTP

**DSTP**
**80% Noise**

| **Subject** | ***A*** | ***C*** | ***μTa*** | ***μFl*** | ***μSS*** | ***μRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.25 | 0.04 | 0.48 | 0.26 | 0.87 | 2.29 | 0.35 | 0.08 | 0.13 | 0.19 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **2** | 0.30 | 0.15 | 0.41 | 0.12 | 0.90 | 2.51 | 0.32 | 0.11 | 0.10 | 0.15 |
| **3** | 0.12 | 0.31 | 0.61 | 0.10 | 0.77 | 1.92 | 0.45 | 0.12 | 0.09 | 0.42 |
| **4** | 0.19 | 0.42 | 0.63 | 0.06 | 0.55 | 1.68 | 0.39 | 0.12 | 0.09 | 0.23 |
| **5** | 0.40 | 0.13 | 0.29 | 0.10 | 0.54 | 2.71 | 0.37 | 0.12 | 0.10 | 0.31 |
| **6** | 0.36 | 0.18 | 0.38 | 0.09 | 0.77 | 2.54 | 0.28 | 0.11 | 0.08 | 0.22 |
| **7** | 0.41 | 0.22 | 0.36 | 0.12 | 0.61 | 2.52 | 0.23 | 0.12 | 0.10 | 0.21 |
| **8** | 0.32 | 0.15 | 0.39 | 0.13 | 0.85 | 2.48 | 0.34 | 0.09 | 0.08 | 0.21 |
| **9** | 0.44 | 0.25 | 0.32 | 0.06 | 0.55 | 2.60 | 0.26 | 0.16 | 0.14 | 0.19 |
| **10** | 0.32 | 0.17 | 0.43 | 0.07 | 0.80 | 2.52 | 0.29 | 0.12 | 0.10 | 0.20 |
| **11** | 0.30 | 0.14 | 0.44 | 0.19 | 0.89 | 2.48 | 0.26 | 0.13 | 0.10 | 0.14 |
| **12** | 0.38 | 0.18 | 0.32 | 0.09 | 0.54 | 2.67 | 0.24 | 0.17 | 0.11 | 0.11 |
| **13** | 0.34 | 0.07 | 0.55 | 0.17 | 0.60 | 2.31 | 0.37 | 0.11 | 0.18 | 0.38 |
| **14** | 0.30 | 0.13 | 0.41 | 0.19 | 0.85 | 2.53 | 0.28 | 0.11 | 0.07 | 0.17 |
| **15** | 0.37 | 0.09 | 0.38 | 0.17 | 0.40 | 3.04 | 0.32 | 0.11 | 0.08 | 0.18 |
| **16** | 0.25 | 0.10 | 0.45 | 0.19 | 0.91 | 2.64 | 0.31 | 0.08 | 0.06 | 0.18 |
| **17** | 0.32 | 0.18 | 0.43 | 0.14 | 0.77 | 2.25 | 0.29 | 0.14 | 0.17 | 0.16 |
| **18** | 0.25 | 0.41 | 0.55 | 0.04 | 0.55 | 1.97 | 0.34 | 0.14 | 0.11 | 0.44 |
| **19** | 0.08 | 0.34 | 0.55 | 0.04 | 0.82 | 2.18 | 0.42 | 0.08 | 0.09 | 0.36 |
| **20** | 0.32 | 0.14 | 0.37 | 0.10 | 0.74 | 2.72 | 0.28 | 0.15 | 0.09 | 0.12 |
| **21** | 0.10 | 0.29 | 0.54 | 0.04 | 0.84 | 2.05 | 0.46 | 0.09 | 0.19 | 0.34 |
| **22** | 0.13 | 0.36 | 0.63 | 0.11 | 0.62 | 1.80 | 0.43 | 0.11 | 0.07 | 0.29 |
| **23** | 0.31 | 0.16 | 0.39 | 0.08 | 0.84 | 2.27 | 0.34 | 0.14 | 0.17 | 0.14 |
| **24** | 0.45 | 0.16 | 0.34 | 0.13 | 0.60 | 2.85 | 0.24 | 0.14 | 0.12 | 0.38 |
| **25** | 0.08 | 0.26 | 0.68 | 0.06 | 0.73 | 1.91 | 0.44 | 0.14 | 0.18 | 0.20 |
| **26** | 0.34 | 0.16 | 0.40 | 0.08 | 0.83 | 2.76 | 0.29 | 0.10 | 0.08 | 0.24 |
| **27** | 0.25 | 0.50 | 0.51 | 0.01 | 0.46 | 1.65 | 0.31 | 0.13 | 0.11 | 0.22 |
| **28** | 0.31 | 0.15 | 0.43 | 0.12 | 1.01 | 2.44 | 0.28 | 0.12 | 0.21 | 0.13 |
| **29** | 0.16 | 0.58 | 0.35 | 0.04 | 0.57 | 1.59 | 0.47 | 0.13 | 0.12 | 0.29 |
| **30** | 0.08 | 0.30 | 0.74 | 0.08 | 0.62 | 1.79 | 0.39 | 0.12 | 0.10 | 0.16 |
| **31** | 0.26 | 0.11 | 0.43 | 0.10 | 1.08 | 2.46 | 0.24 | 0.08 | 0.10 | 0.14 |
| **32** | 0.31 | 0.16 | 0.43 | 0.09 | 0.95 | 2.38 | 0.34 | 0.13 | 0.16 | 0.13 |
| **33** | 0.36 | 0.20 | 0.38 | 0.09 | 0.71 | 2.36 | 0.34 | 0.15 | 0.13 | 0.16 |
| **34** | 0.30 | 0.13 | 0.44 | 0.14 | 0.87 | 2.69 | 0.35 | 0.11 | 0.08 | 0.17 |
| **35** | 0.30 | 0.12 | 0.44 | 0.14 | 0.99 | 2.57 | 0.32 | 0.10 | 0.09 | 0.16 |
| **36** | 0.14 | 0.26 | 0.64 | 0.06 | 0.83 | 2.21 | 0.46 | 0.12 | 0.13 | 0.49 |
| **37** | 0.28 | 0.12 | 0.39 | 0.16 | 0.88 | 2.68 | 0.35 | 0.09 | 0.06 | 0.18 |
| **38** | 0.30 | 0.14 | 0.38 | 0.07 | 0.86 | 2.39 | 0.27 | 0.11 | 0.09 | 0.15 |
| **39** | 0.35 | 0.17 | 0.38 | 0.14 | 0.54 | 2.52 | 0.32 | 0.16 | 0.18 | 0.29 |
| **40** | 0.28 | 0.11 | 0.41 | 0.15 | 0.88 | 2.64 | 0.31 | 0.10 | 0.07 | 0.17 |
| **41** | 0.36 | 0.12 | 0.39 | 0.10 | 0.70 | 2.59 | 0.32 | 0.12 | 0.16 | 0.42 |
| **42** | 0.32 | 0.19 | 0.42 | 0.07 | 0.89 | 2.32 | 0.25 | 0.14 | 0.15 | 0.14 |
| **43** | 0.31 | 0.16 | 0.41 | 0.12 | 0.92 | 2.59 | 0.20 | 0.14 | 0.13 | 0.14 |
| **44** | 0.08 | 0.30 | 0.77 | 0.05 | 0.63 | 1.77 | 0.41 | 0.17 | 0.11 | 0.16 |
| **45** | 0.35 | 0.16 | 0.38 | 0.11 | 0.75 | 2.68 | 0.26 | 0.13 | 0.11 | 0.18 |

| μ | **0.28** | **0.20** | **0.45** | **0.11** | **0.75** | **2.37** | **0.33** | **0.12** | **0.11** | **0.22** |
|---|---|---|---|---|---|---|---|---|---|---|

**70% Noise**

| **Subject** | ***A*** | ***C*** | ***μTa*** | ***μFl*** | ***μSS*** | ***μRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.27 | 0.06 | 0.48 | 0.18 | 0.69 | 2.05 | 0.30 | 0.08 | 0.12 | 0.25 |
| **2** | 0.32 | 0.13 | 0.41 | 0.15 | 0.77 | 2.70 | 0.33 | 0.12 | 0.07 | 0.16 |
| **3** | 0.33 | 0.16 | 0.38 | 0.06 | 0.79 | 2.54 | 0.31 | 0.14 | 0.10 | 0.17 |
| **4** | 0.40 | 0.22 | 0.33 | 0.08 | 0.61 | 2.49 | 0.23 | 0.14 | 0.11 | 0.19 |
| **5** | 0.41 | 0.19 | 0.40 | 0.11 | 0.60 | 2.74 | 0.30 | 0.12 | 0.10 | 0.26 |
| **6** | 0.32 | 0.11 | 0.45 | 0.16 | 0.61 | 2.57 | 0.37 | 0.15 | 0.15 | 0.30 |
| **7** | 0.40 | 0.17 | 0.36 | 0.10 | 0.59 | 2.77 | 0.25 | 0.12 | 0.10 | 0.24 |
| **8** | 0.33 | 0.17 | 0.41 | 0.07 | 0.79 | 2.61 | 0.31 | 0.10 | 0.08 | 0.24 |
| **9** | 0.41 | 0.29 | 0.41 | 0.08 | 0.58 | 2.11 | 0.28 | 0.15 | 0.15 | 0.24 |
| **10** | 0.31 | 0.16 | 0.43 | 0.16 | 0.84 | 2.40 | 0.29 | 0.10 | 0.09 | 0.19 |
| **11** | 0.27 | 0.11 | 0.44 | 0.09 | 1.04 | 2.54 | 0.32 | 0.09 | 0.17 | 0.15 |
| **12** | 0.20 | 0.37 | 0.63 | 0.02 | 0.52 | 1.66 | 0.34 | 0.11 | 0.11 | 0.22 |
| **13** | 0.12 | 0.21 | 0.42 | 0.06 | 0.80 | 2.18 | 0.44 | 0.15 | 0.13 | 0.41 |
| **14** | 0.31 | 0.14 | 0.41 | 0.08 | 0.79 | 2.70 | 0.27 | 0.12 | 0.08 | 0.17 |
| **15** | 0.21 | 0.41 | 0.71 | 0.04 | 0.62 | 1.88 | 0.35 | 0.12 | 0.11 | 0.26 |
| **16** | 0.31 | 0.13 | 0.41 | 0.05 | 0.85 | 2.77 | 0.25 | 0.09 | 0.06 | 0.22 |
| **17** | 0.37 | 0.19 | 0.39 | 0.05 | 0.76 | 2.56 | 0.24 | 0.13 | 0.12 | 0.21 |
| **18** | 0.29 | 0.40 | 0.51 | 0.05 | 0.75 | 1.80 | 0.30 | 0.16 | 0.14 | 0.54 |
| **19** | 0.07 | 0.27 | 0.55 | 0.07 | 0.70 | 1.84 | 0.44 | 0.10 | 0.12 | 0.36 |
| **20** | 0.32 | 0.16 | 0.43 | 0.16 | 0.88 | 2.54 | 0.29 | 0.13 | 0.12 | 0.16 |
| **21** | 0.31 | 0.12 | 0.33 | 0.17 | 0.51 | 2.40 | 0.32 | 0.14 | 0.12 | 0.25 |
| **22** | 0.27 | 0.11 | 0.41 | 0.19 | 0.57 | 2.34 | 0.36 | 0.13 | 0.13 | 0.26 |
| **23** | 0.31 | 0.15 | 0.41 | 0.12 | 0.88 | 2.35 | 0.36 | 0.14 | 0.21 | 0.14 |
| **24** | 0.41 | 0.20 | 0.36 | 0.07 | 0.55 | 2.71 | 0.18 | 0.14 | 0.11 | 0.25 |
| **25** | 0.11 | 0.31 | 0.56 | 0.02 | 0.70 | 2.00 | 0.38 | 0.12 | 0.11 | 0.37 |
| **26** | 0.31 | 0.12 | 0.41 | 0.16 | 0.78 | 2.79 | 0.33 | 0.11 | 0.06 | 0.19 |
| **27** | 0.47 | 0.18 | 0.25 | 0.13 | 0.34 | 2.64 | 0.20 | 0.14 | 0.10 | 0.11 |
| **28** | 0.32 | 0.17 | 0.42 | 0.09 | 0.86 | 2.36 | 0.23 | 0.12 | 0.13 | 0.17 |
| **29** | 0.23 | 0.40 | 0.37 | 0.04 | 0.51 | 2.16 | 0.46 | 0.15 | 0.17 | 0.43 |
| **30** | 0.30 | 0.11 | 0.41 | 0.13 | 0.73 | 3.07 | 0.28 | 0.12 | 0.05 | 0.15 |
| **31** | 0.12 | 0.26 | 0.89 | 0.03 | 0.63 | 1.71 | 0.31 | 0.09 | 0.07 | 0.13 |
| **32** | 0.31 | 0.15 | 0.44 | 0.18 | 1.02 | 2.31 | 0.35 | 0.13 | 0.16 | 0.11 |
| **33** | 0.18 | 0.35 | 0.63 | 0.05 | 0.58 | 1.70 | 0.50 | 0.18 | 0.11 | 0.12 |
| **34** | 0.12 | 0.28 | 0.84 | 0.04 | 0.60 | 1.73 | 0.46 | 0.11 | 0.08 | 0.14 |
| **35** | 0.29 | 0.12 | 0.46 | 0.16 | 0.98 | 2.86 | 0.33 | 0.10 | 0.08 | 0.17 |
| **36** | 0.12 | 0.35 | 0.62 | 0.06 | 0.65 | 1.89 | 0.46 | 0.10 | 0.11 | 0.38 |
| **37** | 0.29 | 0.12 | 0.43 | 0.11 | 1.00 | 2.50 | 0.35 | 0.09 | 0.08 | 0.15 |
| **38** | 0.13 | 0.28 | 0.78 | 0.04 | 0.60 | 1.69 | 0.37 | 0.08 | 0.07 | 0.16 |
| **39** | 0.22 | 0.30 | 0.58 | 0.10 | 0.64 | 2.08 | 0.44 | 0.14 | 0.16 | 0.48 |
| **40** | 0.09 | 0.29 | 0.73 | 0.11 | 0.67 | 1.77 | 0.41 | 0.07 | 0.04 | 0.17 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **41** | 0.39 | 0.16 | 0.44 | 0.14 | 0.61 | 2.93 | 0.26 | 0.15 | 0.09 | 0.18 |
| **42** | 0.31 | 0.16 | 0.42 | 0.18 | 0.91 | 2.29 | 0.28 | 0.14 | 0.20 | 0.14 |
| **43** | 0.11 | 0.32 | 0.70 | 0.11 | 0.64 | 1.72 | 0.32 | 0.08 | 0.06 | 0.23 |
| **44** | 0.29 | 0.07 | 0.43 | 0.23 | 0.76 | 2.31 | 0.29 | 0.16 | 0.11 | 0.26 |
| **45** | 0.14 | 0.33 | 0.68 | 0.05 | 0.57 | 1.70 | 0.38 | 0.14 | 0.08 | 0.14 |
| **μ** | **0.27** | **0.21** | **0.49** | **0.10** | **0.71** | **2.30** | **0.33** | **0.12** | **0.11** | **0.23** |

**40% Noise**

| **Subject** | ***A*** | ***C*** | ***μTa*** | ***μFl*** | ***μSS*** | ***μRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.07 | 0.30 | 0.78 | 0.08 | 0.69 | 1.96 | 0.42 | 0.09 | 0.13 | 0.28 |
| **2** | 0.31 | 0.18 | 0.42 | 0.15 | 1.03 | 2.29 | 0.30 | 0.10 | 0.10 | 0.12 |
| **3** | 0.32 | 0.17 | 0.41 | 0.14 | 0.75 | 2.37 | 0.29 | 0.11 | 0.09 | 0.23 |
| **4** | 0.15 | 0.38 | 0.71 | 0.04 | 0.61 | 1.76 | 0.44 | 0.09 | 0.08 | 0.24 |
| **5** | 0.21 | 0.47 | 0.57 | 0.07 | 0.52 | 1.63 | 0.40 | 0.12 | 0.10 | 0.26 |
| **6** | 0.15 | 0.36 | 0.72 | 0.03 | 0.59 | 1.72 | 0.45 | 0.10 | 0.07 | 0.24 |
| **7** | 0.25 | 0.34 | 0.56 | 0.03 | 0.53 | 1.79 | 0.32 | 0.16 | 0.14 | 0.18 |
| **8** | 0.14 | 0.39 | 0.79 | 0.04 | 0.65 | 1.76 | 0.49 | 0.11 | 0.11 | 0.50 |
| **9** | 0.34 | 0.37 | 0.46 | 0.03 | 0.52 | 1.85 | 0.28 | 0.15 | 0.15 | 0.21 |
| **10** | 0.37 | 0.20 | 0.42 | 0.14 | 0.79 | 2.71 | 0.25 | 0.12 | 0.10 | 0.22 |
| **11** | 0.26 | 0.14 | 0.41 | 0.08 | 0.99 | 2.54 | 0.30 | 0.12 | 0.11 | 0.16 |
| **12** | 0.37 | 0.21 | 0.40 | 0.04 | 0.74 | 2.39 | 0.24 | 0.13 | 0.13 | 0.24 |
| **13** | 0.08 | 0.24 | 0.48 | 0.08 | 0.62 | 1.98 | 0.50 | 0.11 | 0.21 | 0.43 |
| **14** | 0.32 | 0.17 | 0.47 | 0.29 | 0.91 | 2.26 | 0.25 | 0.12 | 0.10 | 0.13 |
| **15** | 0.32 | 0.18 | 0.39 | 0.10 | 0.76 | 2.32 | 0.29 | 0.13 | 0.12 | 0.19 |
| **16** | 0.32 | 0.14 | 0.43 | 0.16 | 0.81 | 2.65 | 0.23 | 0.11 | 0.08 | 0.16 |
| **17** | 0.29 | 0.13 | 0.43 | 0.11 | 0.95 | 2.42 | 0.38 | 0.09 | 0.28 | 0.17 |
| **18** | 0.30 | 0.39 | 0.30 | 0.04 | 0.69 | 1.99 | 0.21 | 0.17 | 0.15 | 0.52 |
| **19** | 0.07 | 0.33 | 0.67 | 0.09 | 0.57 | 1.80 | 0.43 | 0.06 | 0.13 | 0.43 |
| **20** | 0.31 | 0.16 | 0.38 | 0.11 | 0.86 | 2.51 | 0.30 | 0.13 | 0.14 | 0.15 |
| **21** | 0.33 | 0.13 | 0.44 | 0.11 | 0.57 | 2.29 | 0.31 | 0.12 | 0.14 | 0.32 |
| **22** | 0.36 | 0.19 | 0.35 | 0.09 | 0.66 | 2.51 | 0.25 | 0.14 | 0.10 | 0.19 |
| **23** | 0.32 | 0.19 | 0.39 | 0.04 | 0.82 | 2.24 | 0.29 | 0.14 | 0.19 | 0.15 |
| **24** | 0.13 | 0.42 | 0.58 | 0.04 | 0.56 | 1.81 | 0.41 | 0.10 | 0.10 | 0.41 |
| **25** | 0.10 | 0.32 | 0.65 | 0.09 | 0.61 | 1.89 | 0.43 | 0.20 | 0.13 | 0.16 |
| **26** | 0.33 | 0.13 | 0.44 | 0.15 | 0.82 | 2.96 | 0.33 | 0.09 | 0.06 | 0.24 |
| **27** | 0.49 | 0.25 | 0.30 | 0.07 | 0.43 | 2.66 | 0.19 | 0.14 | 0.14 | 0.19 |
| **28** | 0.38 | 0.19 | 0.42 | 0.05 | 0.76 | 2.87 | 0.21 | 0.12 | 0.08 | 0.26 |
| **29** | 0.20 | 0.48 | 0.42 | 0.09 | 0.47 | 1.78 | 0.48 | 0.16 | 0.13 | 0.38 |
| **30** | 0.30 | 0.13 | 0.42 | 0.14 | 0.91 | 2.52 | 0.25 | 0.11 | 0.12 | 0.15 |
| **31** | 0.25 | 0.05 | 0.61 | 0.26 | 0.74 | 2.47 | 0.29 | 0.06 | 0.12 | 0.32 |
| **32** | 0.31 | 0.15 | 0.44 | 0.09 | 1.03 | 2.40 | 0.35 | 0.12 | 0.13 | 0.13 |
| **33** | 0.40 | 0.22 | 0.36 | 0.11 | 0.62 | 2.44 | 0.29 | 0.13 | 0.12 | 0.20 |
| **34** | 0.31 | 0.15 | 0.42 | 0.10 | 0.98 | 2.65 | 0.35 | 0.09 | 0.07 | 0.19 |
| **35** | 0.31 | 0.14 | 0.42 | 0.15 | 0.92 | 2.58 | 0.29 | 0.11 | 0.08 | 0.16 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **36** | 0.33 | 0.08 | 0.44 | 0.17 | 0.68 | 2.79 | 0.38 | 0.09 | 0.12 | 0.39 |
| **37** | 0.10 | 0.29 | 0.82 | 0.11 | 0.57 | 1.70 | 0.46 | 0.07 | 0.07 | 0.17 |
| **38** | 0.30 | 0.14 | 0.42 | 0.13 | 0.89 | 2.44 | 0.27 | 0.11 | 0.09 | 0.14 |
| **39** | 0.18 | 0.46 | 0.63 | 0.07 | 0.44 | 1.71 | 0.45 | 0.14 | 0.13 | 0.45 |
| **40** | 0.27 | 0.05 | 0.47 | 0.12 | 0.69 | 2.66 | 0.36 | 0.08 | 0.10 | 0.30 |
| **41** | 0.15 | 0.44 | 0.61 | 0.04 | 0.70 | 1.82 | 0.37 | 0.09 | 0.07 | 0.28 |
| **42** | 0.33 | 0.21 | 0.39 | 0.06 | 0.76 | 2.13 | 0.21 | 0.15 | 0.17 | 0.18 |
| **43** | 0.10 | 0.35 | 0.71 | 0.05 | 0.65 | 1.87 | 0.34 | 0.09 | 0.08 | 0.39 |
| **44** | 0.27 | 0.12 | 0.42 | 0.15 | 0.99 | 2.44 | 0.27 | 0.10 | 0.14 | 0.14 |
| **45** | 0.33 | 0.10 | 0.44 | 0.09 | 0.67 | 2.63 | 0.33 | 0.09 | 0.13 | 0.36 |
| **μ** | **0.26** | **0.24** | **0.49** | **0.10** | **0.72** | **2.24** | **0.33** | **0.12** | **0.12** | **0.25** |

**10% Noise**

| **Subject** | ***A*** | ***C*** | ***μTa*** | ***μFl*** | ***μSS*** | ***μRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.27 | 0.06 | 0.44 | 0.21 | 0.71 | 2.33 | 0.33 | 0.12 | 0.12 | 0.25 |
| **2** | 0.31 | 0.13 | 0.42 | 0.08 | 0.80 | 2.86 | 0.35 | 0.10 | 0.06 | 0.20 |
| **3** | 0.36 | 0.14 | 0.38 | 0.08 | 0.57 | 2.94 | 0.32 | 0.14 | 0.08 | 0.17 |
| **4** | 0.37 | 0.18 | 0.41 | 0.14 | 0.68 | 2.50 | 0.30 | 0.12 | 0.10 | 0.24 |
| **5** | 0.39 | 0.23 | 0.39 | 0.09 | 0.65 | 2.31 | 0.24 | 0.13 | 0.13 | 0.28 |
| **6** | 0.33 | 0.18 | 0.40 | 0.08 | 0.82 | 2.31 | 0.30 | 0.14 | 0.14 | 0.15 |
| **7** | 0.39 | 0.18 | 0.37 | 0.08 | 0.65 | 2.58 | 0.25 | 0.12 | 0.11 | 0.29 |
| **8** | 0.14 | 0.32 | 0.61 | 0.04 | 0.79 | 1.90 | 0.44 | 0.10 | 0.07 | 0.19 |
| **9** | 0.36 | 0.41 | 0.49 | 0.05 | 0.44 | 1.91 | 0.24 | 0.15 | 0.15 | 0.23 |
| **10** | 0.15 | 0.09 | 0.41 | 0.30 | 0.67 | 1.99 | 0.43 | 0.12 | 0.08 | 0.19 |
| **11** | 0.16 | 0.31 | 0.80 | 0.02 | 0.60 | 1.79 | 0.35 | 0.11 | 0.11 | 0.16 |
| **12** | 0.19 | 0.36 | 0.63 | 0.02 | 0.57 | 1.69 | 0.38 | 0.13 | 0.10 | 0.20 |
| **13** | 0.12 | 0.26 | 0.54 | 0.11 | 0.65 | 2.17 | 0.45 | 0.12 | 0.12 | 0.59 |
| **14** | 0.29 | 0.14 | 0.44 | 0.08 | 0.90 | 2.40 | 0.28 | 0.11 | 0.09 | 0.17 |
| **15** | 0.37 | 0.21 | 0.39 | 0.12 | 0.81 | 2.45 | 0.26 | 0.11 | 0.10 | 0.28 |
| **16** | 0.27 | 0.11 | 0.43 | 0.20 | 0.96 | 2.42 | 0.29 | 0.09 | 0.09 | 0.14 |
| **17** | 0.37 | 0.16 | 0.39 | 0.12 | 0.61 | 2.63 | 0.27 | 0.12 | 0.08 | 0.22 |
| **18** | 0.17 | 0.48 | 0.65 | 0.03 | 0.50 | 1.31 | 0.38 | 0.13 | 0.13 | 0.45 |
| **19** | 0.09 | 0.24 | 0.51 | 0.20 | 0.59 | 1.82 | 0.40 | 0.09 | 0.14 | 0.57 |
| **20** | 0.30 | 0.15 | 0.38 | 0.10 | 0.74 | 2.61 | 0.30 | 0.13 | 0.09 | 0.17 |
| **21** | 0.15 | 0.32 | 0.64 | 0.10 | 0.59 | 1.94 | 0.42 | 0.12 | 0.11 | 0.50 |
| **22** | 0.29 | 0.08 | 0.41 | 0.26 | 0.56 | 1.96 | 0.37 | 0.16 | 0.16 | 0.22 |
| **23** | 0.38 | 0.18 | 0.41 | 0.09 | 0.66 | 2.57 | 0.28 | 0.13 | 0.11 | 0.21 |
| **24** | 0.11 | 0.45 | 0.57 | 0.04 | 0.57 | 1.81 | 0.42 | 0.10 | 0.10 | 0.38 |
| **25** | 0.17 | 0.32 | 0.68 | 0.03 | 0.61 | 1.78 | 0.32 | 0.14 | 0.10 | 0.17 |
| **26** | 0.34 | 0.16 | 0.43 | 0.08 | 0.80 | 2.78 | 0.29 | 0.10 | 0.07 | 0.24 |
| **27** | 0.26 | 0.52 | 0.51 | 0.02 | 0.52 | 1.70 | 0.32 | 0.14 | 0.11 | 0.25 |
| **28** | 0.11 | 0.34 | 0.52 | 0.04 | 0.68 | 1.88 | 0.37 | 0.14 | 0.14 | 0.31 |
| **29** | 0.44 | 0.16 | 0.32 | 0.11 | 0.43 | 2.51 | 0.35 | 0.14 | 0.15 | 0.33 |
| **30** | 0.31 | 0.14 | 0.44 | 0.20 | 0.96 | 2.45 | 0.25 | 0.12 | 0.10 | 0.13 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **31** | 0.29 | 0.11 | 0.44 | 0.16 | 0.89 | 2.59 | 0.22 | 0.11 | 0.09 | 0.16 |
| **32** | 0.29 | 0.15 | 0.43 | 0.12 | 0.97 | 2.33 | 0.37 | 0.11 | 0.16 | 0.14 |
| **33** | 0.37 | 0.21 | 0.36 | 0.09 | 0.68 | 2.33 | 0.32 | 0.13 | 0.10 | 0.20 |
| **34** | 0.29 | 0.13 | 0.44 | 0.15 | 0.94 | 2.66 | 0.37 | 0.12 | 0.11 | 0.16 |
| **35** | 0.28 | 0.12 | 0.45 | 0.10 | 1.00 | 2.70 | 0.32 | 0.08 | 0.07 | 0.21 |
| **36** | 0.35 | 0.09 | 0.42 | 0.19 | 0.37 | 2.69 | 0.37 | 0.11 | 0.10 | 0.25 |
| **37** | 0.29 | 0.12 | 0.43 | 0.12 | 0.92 | 2.66 | 0.37 | 0.10 | 0.08 | 0.15 |
| **38** | 0.34 | 0.15 | 0.42 | 0.14 | 0.72 | 2.90 | 0.25 | 0.10 | 0.06 | 0.23 |
| **39** | 0.17 | 0.52 | 0.51 | 0.09 | 0.46 | 1.71 | 0.44 | 0.12 | 0.12 | 0.39 |
| **40** | 0.11 | 0.29 | 0.84 | 0.05 | 0.57 | 1.74 | 0.42 | 0.08 | 0.08 | 0.16 |
| **41** | 0.15 | 0.34 | 0.74 | 0.08 | 0.53 | 1.68 | 0.40 | 0.15 | 0.14 | 0.16 |
| **42** | 0.32 | 0.19 | 0.38 | 0.09 | 0.86 | 2.20 | 0.24 | 0.13 | 0.16 | 0.17 |
| **43** | 0.09 | 0.35 | 0.68 | 0.04 | 0.70 | 2.06 | 0.35 | 0.09 | 0.06 | 0.38 |
| **44** | 0.06 | 0.30 | 0.81 | 0.12 | 0.61 | 1.73 | 0.43 | 0.12 | 0.17 | 0.18 |
| **45** | 0.34 | 0.16 | 0.41 | 0.14 | 0.76 | 2.58 | 0.27 | 0.15 | 0.13 | 0.16 |
| **μ** | **0.26** | **0.23** | **0.49** | **0.11** | **0.69** | **2.24** | **0.33** | **0.12** | **0.11** | **0.24** |

## Log Marginal Likelihoods and log Bayes Factor (ln(BF)).

**High Noise Target**

| | **80% Noise** | | | **70% Noise** | | |
|---|---|---|---|---|---|---|
| **Subject** | SSPpFl | DSTP | ln(BF) | SSPpFl | DSTP | ln(BF) |
| **1** | -526.68 | -525.61 | 1.07 | -504.92 | -501.23 | 3.69 |
| **2** | -515.05 | -513.95 | 1.10 | -536.86 | -535.47 | 1.39 |
| **3** | -601.18 | -600.85 | 0.33 | -600.55 | -601.06 | -0.51 |
| **4** | -565.60 | -563.23 | 2.37 | -573.20 | -564.48 | 8.72 |
| **5** | -539.67 | -536.88 | 2.79 | -512.59 | -505.56 | 7.03 |
| **6** | -559.82 | -556.92 | 2.90 | -515.73 | -515.29 | 0.44 |
| **7** | -600.58 | -598.24 | 2.35 | -557.16 | -551.41 | 5.75 |
| **8** | -579.10 | -575.67 | 3.43 | -571.85 | -571.91 | -0.05 |
| **9** | -507.36 | -510.23 | -2.87 | -538.48 | -537.89 | 0.59 |
| **10** | -554.89 | -553.64 | 1.25 | -548.48 | -541.08 | 7.40 |
| **11** | -551.74 | -555.42 | -3.68 | -523.50 | -521.16 | 2.34 |
| **12** | -608.31 | -604.76 | 3.56 | -600.41 | -594.33 | 6.08 |
| **13** | -610.39 | -611.74 | -1.35 | -629.93 | -630.42 | -0.49 |
| **14** | -569.89 | -570.71 | -0.82 | -513.32 | -509.40 | 3.93 |
| **15** | -597.52 | -594.63 | 2.89 | -585.12 | -583.22 | 1.90 |
| **16** | -599.78 | -597.97 | 1.81 | -598.65 | -598.87 | -0.22 |
| **17** | -531.57 | -522.37 | 9.20 | -551.51 | -548.20 | 3.31 |
| **18** | -475.00 | -477.33 | -2.33 | -508.70 | -506.75 | 1.95 |
| **19** | -603.73 | -600.53 | 3.20 | -622.94 | -620.81 | 2.13 |
| **20** | -596.18 | -598.49 | -2.31 | -613.26 | -609.55 | 3.71 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **21** | -646.60 | -645.95 | 0.65 | -576.55 | -576.11 | 0.44 |
| **22** | -545.14 | -544.00 | 1.14 | -505.75 | -500.60 | 5.15 |
| **23** | -578.31 | -577.38 | 0.93 | -594.17 | -592.38 | 1.79 |
| **24** | -615.62 | -615.66 | -0.05 | -623.39 | -617.07 | 6.32 |
| **25** | -581.01 | -578.87 | 2.14 | -558.96 | -557.22 | 1.75 |
| **26** | -484.11 | -486.93 | -2.83 | -496.77 | -497.68 | -0.91 |
| **27** | -543.98 | -544.06 | -0.08 | -581.19 | -579.42 | 1.77 |
| **28** | -621.66 | -621.44 | 0.22 | -612.09 | -612.19 | -0.10 |
| **29** | -616.94 | -616.91 | 0.03 | -609.64 | -604.91 | 4.73 |
| **30** | -567.33 | -565.57 | 1.77 | -569.27 | -566.05 | 3.21 |
| **31** | -584.34 | -583.27 | 1.07 | -575.79 | -562.55 | 13.24 |
| **32** | -506.22 | -496.39 | 9.83 | -510.47 | -507.95 | 2.52 |
| **33** | -594.41 | -593.22 | 1.20 | -570.68 | -564.94 | 5.74 |
| **34** | -521.48 | -523.94 | -2.45 | -509.38 | -504.40 | 4.98 |
| **35** | -533.48 | -532.17 | 1.31 | -563.69 | -562.49 | 1.20 |
| **36** | -641.61 | -639.22 | 2.39 | -649.39 | -649.04 | 0.35 |
| **37** | -550.25 | -551.44 | -1.19 | -575.19 | -577.34 | -2.15 |
| **38** | -543.83 | -540.76 | 3.07 | -550.22 | -548.19 | 2.02 |
| **39** | -612.22 | -610.00 | 2.22 | -608.44 | -607.98 | 0.46 |
| **40** | -581.20 | -578.03 | 3.17 | -589.65 | -588.91 | 0.74 |
| **41** | -613.40 | -614.19 | -0.79 | -620.64 | -619.13 | 1.51 |
| **42** | -540.47 | -535.33 | 5.14 | -537.03 | -532.28 | 4.75 |
| **43** | -573.16 | -571.11 | 2.05 | -547.50 | -546.43 | 1.07 |
| **44** | -530.47 | -529.86 | 0.61 | -535.75 | -535.30 | 0.45 |
| **45** | -571.32 | -572.95 | -1.63 | -533.45 | -524.50 | 8.95 |

| | **40% Noise** | | | **10% Noise** | | |
|---|---|---|---|---|---|---|
| **Subject** | SSPpFl | DSTP | ln(BF) | SSPpFl | DSTP | ln(BF) |
| **1** | -517.60 | -499.91 | 17.70 | -513.09 | -502.17 | 10.92 |
| **2** | -494.80 | -492.00 | 2.80 | -496.69 | -494.83 | 1.85 |
| **3** | -588.15 | -587.98 | 0.17 | -616.41 | -617.12 | -0.71 |
| **4** | -549.63 | -539.00 | 10.63 | -556.28 | -542.60 | 13.68 |
| **5** | -565.47 | -558.39 | 7.08 | -564.33 | -555.86 | 8.47 |
| **6** | -591.89 | -585.84 | 6.05 | -561.10 | -550.97 | 10.12 |
| **7** | -572.03 | -566.20 | 5.83 | -588.42 | -582.18 | 6.23 |
| **8** | -594.05 | -591.82 | 2.23 | -603.07 | -600.13 | 2.94 |
| **9** | -519.78 | -521.85 | -2.07 | -519.92 | -519.73 | 0.19 |
| **10** | -585.20 | -576.92 | 8.28 | -559.95 | -552.54 | 7.40 |
| **11** | -572.23 | -571.64 | 0.59 | -553.98 | -550.85 | 3.12 |
| **12** | -611.86 | -612.64 | -0.78 | -625.44 | -613.05 | 12.39 |
| **13** | -605.13 | -602.04 | 3.09 | -618.97 | -617.35 | 1.62 |
| **14** | -528.03 | -514.54 | 13.49 | -488.26 | -487.30 | 0.96 |
| **15** | -580.88 | -579.96 | 0.93 | -573.90 | -560.02 | 13.89 |
| **16** | -585.29 | -586.35 | -1.06 | -582.58 | -582.37 | 0.21 |
| **17** | -519.88 | -509.36 | 10.52 | -555.09 | -546.33 | 8.76 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **18** | -544.22 | -545.53 | -1.31 | -558.39 | -561.69 | -3.30 |
| **19** | -627.01 | -626.18 | 0.83 | -594.22 | -590.74 | 3.48 |
| **20** | -576.06 | -572.60 | 3.46 | -576.90 | -572.63 | 4.27 |
| **21** | -613.94 | -607.17 | 6.77 | -606.88 | -602.55 | 4.32 |
| **22** | -538.47 | -537.16 | 1.31 | -574.43 | -567.87 | 6.56 |
| **23** | -577.89 | -577.37 | 0.53 | -584.94 | -576.60 | 8.34 |
| **24** | -605.38 | -598.97 | 6.40 | -609.36 | -602.96 | 6.40 |
| **25** | -580.53 | -578.19 | 2.34 | -577.09 | -571.62 | 5.47 |
| **26** | -517.07 | -510.71 | 6.36 | -499.55 | -492.76 | 6.79 |
| **27** | -552.81 | -553.53 | -0.71 | -593.20 | -585.90 | 7.30 |
| **28** | -625.00 | -620.88 | 4.12 | -641.25 | -638.04 | 3.20 |
| **29** | -647.13 | -648.20 | -1.06 | -565.14 | -561.27 | 3.87 |
| **30** | -541.53 | -525.30 | 16.24 | -563.87 | -550.32 | 13.54 |
| **31** | -584.19 | -570.80 | 13.39 | -561.74 | -544.49 | 17.25 |
| **32** | -540.03 | -514.46 | 25.58 | -507.29 | -490.30 | 16.99 |
| **33** | -538.95 | -525.87 | 13.07 | -538.48 | -522.88 | 15.60 |
| **34** | -536.57 | -531.05 | 5.53 | -544.34 | -533.88 | 10.46 |
| **35** | -573.41 | -568.76 | 4.65 | -542.94 | -542.82 | 0.11 |
| **36** | -622.40 | -618.97 | 3.43 | -632.25 | -630.33 | 1.92 |
| **37** | -561.35 | -555.69 | 5.67 | -568.15 | -565.99 | 2.16 |
| **38** | -562.87 | -537.09 | 25.78 | -531.82 | -507.21 | 24.61 |
| **39** | -603.80 | -602.16 | 1.65 | -598.89 | -595.55 | 3.35 |
| **40** | -580.25 | -578.54 | 1.70 | -566.46 | -546.43 | 20.04 |
| **41** | -629.74 | -628.81 | 0.93 | -604.59 | -600.16 | 4.44 |
| **42** | -549.20 | -549.74 | -0.54 | -528.59 | -524.59 | 4.00 |
| **43** | -572.65 | -571.29 | 1.35 | -561.94 | -556.55 | 5.40 |
| **44** | -519.52 | -519.65 | -0.13 | -505.09 | -503.50 | 1.59 |
| **45** | -596.04 | -583.06 | 12.99 | -591.19 | -572.70 | 18.50 |

**Low Noise Target**

| | **80% Noise** | | | **70% Noise** | | |
|---|---|---|---|---|---|---|
| **Subject** | SSPpFl | DSTP | ln(BF) | SSPpFl | DSTP | ln(BF) |
| **1** | -334.29 | -328.87 | 5.42 | -357.58 | -355.59 | 1.99 |
| **2** | -352.95 | -353.89 | -0.93 | -364.73 | -365.37 | -0.64 |
| **3** | -437.52 | -439.87 | -2.35 | -371.93 | -373.70 | -1.76 |
| **4** | -431.95 | -432.99 | -1.04 | -444.56 | -446.26 | -1.70 |
| **5** | -471.50 | -470.61 | 0.90 | -445.22 | -446.69 | -1.48 |
| **6** | -402.70 | -403.87 | -1.17 | -437.37 | -433.65 | 3.72 |
| **7** | -431.92 | -433.23 | -1.31 | -437.16 | -438.26 | -1.10 |
| **8** | -381.78 | -382.81 | -1.03 | -396.58 | -397.91 | -1.33 |
| **9** | -478.76 | -480.80 | -2.04 | -491.25 | -492.72 | -1.47 |
| **10** | -383.60 | -384.90 | -1.29 | -366.03 | -367.27 | -1.23 |
| **11** | -341.62 | -341.86 | -0.24 | -333.00 | -334.52 | -1.51 |
| **12** | -422.97 | -424.40 | -1.43 | -440.51 | -442.30 | -1.79 |
| **13** | -419.36 | -414.98 | 4.37 | -432.14 | -433.22 | -1.08 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **14** | -355.47 | -355.68 | -0.20 | -350.47 | -351.70 | -1.24 |
| **15** | -444.37 | -440.68 | 3.69 | -433.23 | -434.88 | -1.65 |
| **16** | -311.78 | -312.01 | -0.23 | -344.62 | -346.31 | -1.69 |
| **17** | -389.45 | -390.03 | -0.58 | -399.29 | -401.60 | -2.31 |
| **18** | -475.18 | -476.88 | -1.70 | -496.34 | -501.39 | -5.04 |
| **19** | -427.30 | -425.10 | 2.20 | -411.02 | -411.11 | -0.09 |
| **20** | -368.29 | -370.36 | -2.07 | -371.58 | -372.43 | -0.85 |
| **21** | -414.38 | -414.39 | 0.00 | -447.94 | -445.46 | 2.49 |
| **22** | -426.67 | -426.89 | -0.22 | -413.10 | -410.35 | 2.74 |
| **23** | -375.15 | -376.59 | -1.45 | -377.44 | -378.49 | -1.04 |
| **24** | -491.32 | -488.75 | 2.57 | -475.59 | -477.37 | -1.78 |
| **25** | -408.16 | -407.43 | 0.73 | -425.94 | -425.13 | 0.81 |
| **26** | -377.45 | -378.98 | -1.53 | -372.16 | -372.90 | -0.74 |
| **27** | -500.18 | -501.91 | -1.72 | -502.92 | -503.03 | -0.11 |
| **28** | -391.59 | -393.36 | -1.77 | -387.52 | -389.08 | -1.57 |
| **29** | -546.57 | -544.49 | 2.08 | -553.33 | -550.93 | 2.40 |
| **30** | -363.82 | -364.49 | -0.68 | -349.49 | -350.74 | -1.26 |
| **31** | -321.07 | -322.34 | -1.27 | -308.61 | -310.02 | -1.41 |
| **32** | -355.56 | -356.71 | -1.15 | -355.27 | -355.51 | -0.24 |
| **33** | -406.87 | -408.14 | -1.27 | -422.14 | -422.69 | -0.56 |
| **34** | -340.14 | -340.43 | -0.29 | -334.07 | -335.37 | -1.29 |
| **35** | -328.22 | -328.52 | -0.30 | -329.43 | -330.51 | -1.08 |
| **36** | -420.67 | -421.44 | -0.77 | -427.17 | -428.66 | -1.49 |
| **37** | -352.65 | -353.68 | -1.03 | -318.22 | -319.11 | -0.89 |
| **38** | -356.89 | -357.98 | -1.09 | -353.31 | -354.45 | -1.14 |
| **39** | -478.06 | -474.75 | 3.31 | -478.42 | -478.28 | 0.14 |
| **40** | -324.49 | -325.16 | -0.67 | -337.60 | -336.05 | 1.55 |
| **41** | -437.45 | -434.96 | 2.50 | -425.57 | -426.23 | -0.66 |
| **42** | -382.52 | -384.08 | -1.56 | -381.49 | -381.99 | -0.50 |
| **43** | -360.02 | -361.69 | -1.68 | -384.09 | -383.74 | 0.35 |
| **44** | -374.27 | -375.75 | -1.48 | -372.91 | -370.41 | 2.49 |
| **45** | -396.02 | -397.69 | -1.68 | -389.25 | -390.32 | -1.06 |

| | **40% Noise** | | | **10% Noise** | | |
|---|---|---|---|---|---|---|
| **Subject** | SSPpFl | DSTP | ln(BF) | SSPpFl | DSTP | ln(BF) |
| **1** | -359.89 | -360.61 | -0.73 | -379.17 | -375.69 | 3.49 |
| **2** | -327.63 | -328.74 | -1.11 | -357.61 | -358.88 | -1.28 |
| **3** | -423.20 | -424.17 | -0.97 | -405.98 | -407.20 | -1.22 |
| **4** | -411.22 | -412.79 | -1.57 | -418.95 | -419.48 | -0.52 |
| **5** | -477.02 | -477.06 | -0.05 | -457.90 | -459.26 | -1.36 |
| **6** | -402.72 | -404.18 | -1.47 | -397.86 | -398.77 | -0.91 |
| **7** | -460.90 | -462.18 | -1.29 | -437.04 | -438.55 | -1.51 |
| **8** | -448.21 | -451.47 | -3.26 | -387.90 | -389.40 | -1.50 |
| **9** | -484.34 | -486.63 | -2.29 | -516.96 | -519.32 | -2.36 |
| **10** | -388.70 | -390.22 | -1.53 | -366.19 | -360.05 | 6.14 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **11** | -350.19 | -351.61 | -1.42 | -362.40 | -364.36 | -1.96 |
| **12** | -433.77 | -436.04 | -2.27 | -432.13 | -433.88 | -1.74 |
| **13** | -461.08 | -460.72 | 0.36 | -465.97 | -467.12 | -1.14 |
| **14** | -351.69 | -350.83 | 0.86 | -336.04 | -337.11 | -1.07 |
| **15** | -406.45 | -407.36 | -0.91 | -434.94 | -436.80 | -1.86 |
| **16** | -374.10 | -374.88 | -0.78 | -326.11 | -326.11 | 0.00 |
| **17** | -401.93 | -403.49 | -1.56 | -411.22 | -412.53 | -1.31 |
| **18** | -497.24 | -499.11 | -1.87 | -453.87 | -458.77 | -4.90 |
| **19** | -410.10 | -410.14 | -0.04 | -469.35 | -468.69 | 0.66 |
| **20** | -379.29 | -380.24 | -0.96 | -381.15 | -382.58 | -1.43 |
| **21** | -440.71 | -435.92 | 4.79 | -452.40 | -453.49 | -1.09 |
| **22** | -430.46 | -431.80 | -1.35 | -435.33 | -429.90 | 5.43 |
| **23** | -391.73 | -393.58 | -1.85 | -416.56 | -417.86 | -1.30 |
| **24** | -483.85 | -483.66 | 0.19 | -480.47 | -480.06 | 0.40 |
| **25** | -423.52 | -420.37 | 3.16 | -396.13 | -397.35 | -1.22 |
| **26** | -371.71 | -372.49 | -0.78 | -384.67 | -385.95 | -1.28 |
| **27** | -519.15 | -521.34 | -2.20 | -514.79 | -516.63 | -1.84 |
| **28** | -405.45 | -407.68 | -2.23 | -438.20 | -437.71 | 0.49 |
| **29** | -555.79 | -553.10 | 2.69 | -507.31 | -501.38 | 5.93 |
| **30** | -351.81 | -352.81 | -0.99 | -338.48 | -338.67 | -0.19 |
| **31** | -341.66 | -335.52 | 6.14 | -334.25 | -334.33 | -0.07 |
| **32** | -334.71 | -335.84 | -1.13 | -347.69 | -348.54 | -0.85 |
| **33** | -451.48 | -452.89 | -1.41 | -434.06 | -435.91 | -1.86 |
| **34** | -335.83 | -337.30 | -1.47 | -353.98 | -354.54 | -0.56 |
| **35** | -348.25 | -348.93 | -0.69 | -330.61 | -332.19 | -1.58 |
| **36** | -410.81 | -404.85 | 5.96 | -452.55 | -444.28 | 8.26 |
| **37** | -344.44 | -344.13 | 0.31 | -320.23 | -321.06 | -0.83 |
| **38** | -352.85 | -353.27 | -0.41 | -376.16 | -377.27 | -1.11 |
| **39** | -508.89 | -510.54 | -1.65 | -531.68 | -528.87 | 2.81 |
| **40** | -364.08 | -358.25 | 5.83 | -335.61 | -336.52 | -0.91 |
| **41** | -434.91 | -435.01 | -0.09 | -412.22 | -412.45 | -0.23 |
| **42** | -403.21 | -404.60 | -1.39 | -386.60 | -387.80 | -1.20 |
| **43** | -403.64 | -403.67 | -0.03 | -400.40 | -398.66 | 1.74 |
| **44** | -349.57 | -350.51 | -0.94 | -401.55 | -400.39 | 1.16 |
| **45** | -404.78 | -403.46 | 1.32 | -389.04 | -389.55 | -0.51 |

**2 x 2 x 4 ANOVA on RT and arcsine transformed error rates from Study 3.**

| **Predictor** | **df** | ***F*** | ***p*** | $\eta_p^2$ |
|---|---|---|---|---|
| **RT** | | | | |
| **Con.** | (1,44) | 95.57*** | < .001 | .69 |
| **Target Noise** | (1,44) | 257.41*** | < .001 | .85 |
| **Con. x Target Noise** | (1,44) | 116.85*** | <.001 | .73 |
| **Flanker Noise** | (3,132) | 5.77*** | <.001 | .12 |
| **Target Noise x Flanker Noise** | (3,132) | 9.19*** | <.001 | .17 |
| **Con. x Flanker Noise** | (3,132) | 21.38*** | <.001 | .33 |
| **Con. x Target Noise x Flanker Noise** | (3,132) | 18.47*** | <.001 | .30 |
| **Error Rate** | | | | |
| **Con.** | (1,44) | 90.06*** | < .001 | .67 |
| **Target Noise** | (1,44) | 425.97*** | < .001 | .91 |
| **Congruency x Target Noise** | (1,44) | 133.84*** | <.001 | .75 |
| **Flanker Noise** | (3,132) | 8.38*** | < .001 | .16 |
| **Target Noise x Flanker Noise** | (3,132) | 3.43* | .019 | .07 |
| **Con. x Flanker Noise** | (3, 132) | 24.21*** | <.001 | .36 |
| **Con. x Target Noise x Flanker Noise** | (3,132) | 23.13*** | <.001 | .35 |

Note: Con = Congruency, Flanker Noise = Flanker Noise Level.

$^{*}p < .05$. $^{***}p < .001$.

# Appendix D: Study 4

## Expected a-posteriori estimates for Study 4 (Color Noise Task)

**SSP**

**SSP**
**80% Noise**

| **Subject** | ***A*** | ***ter*** | ***p*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** | ***IR*** |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.06 | 0.41 | 0.40 | 86.72 | 2.51 | 0.07 | 0.08 | 0.19 | 0.03 |
| **2** | 0.06 | 0.38 | 0.84 | 83.73 | 1.12 | 0.09 | 0.21 | 0.26 | 0.01 |
| **3** | 0.08 | 0.46 | 0.57 | 85.53 | 2.06 | 0.11 | 0.16 | 0.20 | 0.02 |
| **4** | 0.06 | 0.43 | 0.43 | 88.08 | 2.28 | 0.07 | 0.13 | 0.30 | 0.03 |
| **5** | 0.06 | 0.41 | 0.78 | 84.68 | 0.87 | 0.10 | 0.13 | 0.31 | 0.01 |
| **6** | 0.09 | 0.36 | 1.21 | 81.34 | 0.74 | 0.20 | 0.17 | 0.18 | 0.01 |
| **7** | 0.10 | 0.48 | 0.47 | 89.55 | 4.23 | 0.12 | 0.14 | 0.40 | 0.05 |
| **8** | 0.24 | 0.25 | 1.16 | 85.41 | 1.70 | 0.11 | 0.09 | 0.22 | 0.02 |
| **9** | 0.25 | 0.20 | 1.01 | 81.83 | 1.63 | 0.13 | 0.11 | 0.16 | 0.02 |
| **10** | 0.07 | 0.40 | 0.65 | 84.89 | 1.29 | 0.11 | 0.18 | 0.28 | 0.02 |
| **11** | 0.22 | 0.29 | 1.30 | 79.17 | 0.86 | 0.10 | 0.08 | 0.14 | 0.01 |
| **12** | 0.07 | 0.36 | 1.27 | 86.41 | 1.81 | 0.17 | 0.16 | 0.19 | 0.02 |
| **13** | 0.06 | 0.31 | 0.72 | 84.38 | 0.85 | 0.11 | 0.11 | 0.19 | 0.01 |
| **14** | 0.08 | 0.37 | 0.89 | 86.44 | 3.01 | 0.12 | 0.25 | 0.27 | 0.03 |
| **15** | 0.07 | 0.33 | 0.56 | 85.33 | 1.52 | 0.12 | 0.07 | 0.16 | 0.02 |
| **16** | 0.06 | 0.43 | 0.48 | 86.83 | 1.47 | 0.08 | 0.13 | 0.17 | 0.02 |
| **17** | 0.06 | 0.42 | 0.67 | 87.45 | 1.49 | 0.12 | 0.09 | 0.27 | 0.02 |
| **18** | 0.37 | 0.26 | 0.87 | 86.48 | 1.32 | 0.14 | 0.10 | 0.29 | 0.02 |
| **19** | 0.09 | 0.35 | 1.03 | 82.62 | 0.88 | 0.21 | 0.20 | 0.19 | 0.01 |
| **20** | 0.07 | 0.44 | 0.44 | 87.66 | 2.32 | 0.15 | 0.17 | 0.33 | 0.03 |
| **21** | 0.08 | 0.37 | 0.80 | 89.99 | 1.99 | 0.16 | 0.13 | 0.33 | 0.02 |
| **22** | 0.20 | 0.31 | 1.15 | 80.12 | 0.78 | 0.12 | 0.10 | 0.16 | 0.01 |
| **23** | 0.06 | 0.33 | 0.51 | 86.09 | 2.26 | 0.08 | 0.15 | 0.30 | 0.03 |
| **24** | 0.09 | 0.34 | 1.17 | 87.40 | 1.52 | 0.18 | 0.11 | 0.17 | 0.02 |
| **25** | 0.28 | 0.27 | 1.01 | 82.44 | 1.08 | 0.12 | 0.10 | 0.26 | 0.01 |
| **26** | 0.27 | 0.30 | 1.07 | 84.52 | 0.92 | 0.13 | 0.09 | 0.20 | 0.01 |
| **27** | 0.24 | 0.30 | 0.99 | 85.28 | 1.44 | 0.12 | 0.07 | 0.22 | 0.02 |
| **28** | 0.10 | 0.39 | 0.58 | 87.19 | 2.06 | 0.24 | 0.16 | 0.25 | 0.02 |
| **29** | 0.09 | 0.38 | 0.76 | 83.86 | 1.23 | 0.19 | 0.11 | 0.20 | 0.01 |
| **30** | 0.08 | 0.34 | 0.51 | 88.07 | 2.97 | 0.12 | 0.12 | 0.29 | 0.03 |
| **31** | 0.07 | 0.41 | 1.16 | 84.90 | 1.52 | 0.16 | 0.15 | 0.22 | 0.02 |
| **32** | 0.24 | 0.21 | 0.98 | 83.81 | 2.20 | 0.13 | 0.10 | 0.18 | 0.03 |
| **33** | 0.08 | 0.36 | 0.99 | 85.23 | 1.46 | 0.18 | 0.10 | 0.17 | 0.02 |
| **34** | 0.09 | 0.40 | 0.62 | 89.77 | 2.72 | 0.13 | 0.18 | 0.25 | 0.03 |
| **35** | 0.04 | 0.38 | 0.58 | 84.06 | 1.63 | 0.04 | 0.08 | 0.24 | 0.02 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **36** | 0.05 | 0.42 | 0.73 | 88.71 | 1.77 | 0.07 | 0.20 | 0.38 | 0.02 |
| **µ** | **0.12** | **0.36** | **0.82** | **85.44** | **1.71** | **0.13** | **0.13** | **0.24** | **0.02** |

**70% Noise**

| **Subject** | ***A*** | ***ter*** | ***p*** | ***rd*** | ***sdA*** | ***sz*** | ***ster*** | ***sv*** | ***IR*** |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.05 | 0.40 | 0.51 | 83.83 | 1.01 | 0.06 | 0.10 | 0.24 | 0.01 |
| **2** | 0.09 | 0.34 | 0.98 | 87.87 | 2.37 | 0.16 | 0.20 | 0.21 | 0.03 |
| **3** | 0.28 | 0.28 | 0.91 | 84.56 | 0.98 | 0.12 | 0.08 | 0.27 | 0.01 |
| **4** | 0.05 | 0.41 | 0.48 | 88.32 | 2.69 | 0.08 | 0.09 | 0.19 | 0.03 |
| **5** | 0.05 | 0.43 | 1.03 | 86.72 | 1.31 | 0.05 | 0.14 | 0.32 | 0.02 |
| **6** | 0.06 | 0.32 | 0.61 | 88.51 | 2.70 | 0.09 | 0.13 | 0.26 | 0.03 |
| **7** | 0.08 | 0.46 | 0.51 | 90.31 | 3.16 | 0.09 | 0.12 | 0.26 | 0.03 |
| **8** | 0.16 | 0.30 | 1.36 | 80.11 | 0.83 | 0.08 | 0.06 | 0.15 | 0.01 |
| **9** | 0.08 | 0.32 | 0.63 | 87.27 | 1.21 | 0.12 | 0.12 | 0.20 | 0.01 |
| **10** | 0.07 | 0.40 | 0.66 | 83.34 | 1.03 | 0.09 | 0.16 | 0.29 | 0.01 |
| **11** | 0.20 | 0.27 | 1.28 | 80.36 | 0.79 | 0.10 | 0.08 | 0.16 | 0.01 |
| **12** | 0.06 | 0.37 | 1.07 | 88.16 | 2.29 | 0.15 | 0.16 | 0.26 | 0.03 |
| **13** | 0.24 | 0.18 | 1.15 | 82.31 | 0.89 | 0.13 | 0.09 | 0.19 | 0.01 |
| **14** | 0.11 | 0.31 | 0.69 | 89.12 | 1.60 | 0.12 | 0.15 | 0.32 | 0.02 |
| **15** | 0.23 | 0.23 | 1.26 | 83.24 | 0.93 | 0.13 | 0.12 | 0.16 | 0.01 |
| **16** | 0.27 | 0.27 | 1.05 | 80.33 | 0.81 | 0.13 | 0.12 | 0.14 | 0.01 |
| **17** | 0.06 | 0.40 | 0.71 | 86.81 | 2.61 | 0.08 | 0.11 | 0.22 | 0.03 |
| **18** | 0.32 | 0.27 | 0.88 | 86.38 | 1.99 | 0.13 | 0.11 | 0.31 | 0.02 |
| **19** | 0.07 | 0.36 | 1.08 | 83.59 | 1.53 | 0.16 | 0.19 | 0.23 | 0.02 |
| **20** | 0.07 | 0.41 | 0.37 | 88.38 | 2.74 | 0.11 | 0.18 | 0.25 | 0.03 |
| **21** | 0.07 | 0.40 | 1.23 | 81.69 | 1.12 | 0.16 | 0.19 | 0.19 | 0.01 |
| **22** | 0.25 | 0.27 | 1.16 | 82.68 | 0.66 | 0.12 | 0.10 | 0.18 | 0.01 |
| **23** | 0.05 | 0.36 | 0.75 | 82.05 | 0.83 | 0.09 | 0.16 | 0.27 | 0.01 |
| **24** | 0.08 | 0.34 | 1.23 | 84.25 | 1.18 | 0.16 | 0.12 | 0.22 | 0.01 |
| **25** | 0.10 | 0.40 | 0.66 | 91.21 | 2.53 | 0.17 | 0.12 | 0.18 | 0.03 |
| **26** | 0.29 | 0.28 | 1.14 | 84.81 | 2.02 | 0.15 | 0.14 | 0.14 | 0.02 |
| **27** | 0.09 | 0.41 | 0.88 | 82.04 | 1.00 | 0.11 | 0.10 | 0.23 | 0.01 |
| **28** | 0.07 | 0.32 | 0.58 | 85.90 | 2.18 | 0.11 | 0.14 | 0.24 | 0.03 |
| **29** | 0.07 | 0.38 | 1.03 | 85.23 | 1.24 | 0.15 | 0.13 | 0.23 | 0.01 |
| **30** | 0.21 | 0.26 | 1.03 | 85.89 | 1.35 | 0.09 | 0.06 | 0.32 | 0.02 |
| **31** | 0.07 | 0.38 | 1.03 | 87.81 | 1.70 | 0.13 | 0.08 | 0.21 | 0.02 |
| **32** | 0.24 | 0.21 | 1.10 | 83.65 | 1.14 | 0.13 | 0.08 | 0.19 | 0.01 |
| **33** | 0.06 | 0.37 | 0.96 | 82.22 | 0.88 | 0.13 | 0.12 | 0.18 | 0.01 |
| **34** | 0.30 | 0.21 | 0.91 | 84.99 | 2.17 | 0.13 | 0.10 | 0.25 | 0.03 |
| **35** | 0.05 | 0.36 | 0.72 | 82.99 | 2.76 | 0.05 | 0.07 | 0.26 | 0.03 |
| **36** | 0.06 | 0.40 | 0.76 | 88.28 | 1.95 | 0.06 | 0.14 | 0.38 | 0.02 |
| **µ** | **0.13** | **0.34** | **0.90** | **85.14** | **1.62** | **0.11** | **0.12** | **0.23** | **0.02** |

**40% Noise**

| Subject | *A* | *ter* | *p* | *rd* | *sdA* | *sz* | *ster* | *sv* | *IR* |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.21 | 0.32 | 1.18 | 80.17 | 0.75 | 0.13 | 0.09 | 0.14 | 0.01 |
| **2** | 0.06 | 0.34 | 0.92 | 87.38 | 0.87 | 0.09 | 0.11 | 0.36 | 0.01 |
| **3** | 0.30 | 0.28 | 0.96 | 84.11 | 1.17 | 0.13 | 0.09 | 0.23 | 0.01 |
| **4** | 0.05 | 0.40 | 0.68 | 85.68 | 2.20 | 0.06 | 0.09 | 0.28 | 0.03 |
| **5** | 0.22 | 0.28 | 1.26 | 81.63 | 0.94 | 0.11 | 0.10 | 0.15 | 0.01 |
| **6** | 0.08 | 0.33 | 1.14 | 85.48 | 1.62 | 0.17 | 0.14 | 0.18 | 0.02 |
| **7** | 0.08 | 0.44 | 0.67 | 89.38 | 2.43 | 0.14 | 0.10 | 0.33 | 0.03 |
| **8** | 0.17 | 0.28 | 1.33 | 82.33 | 1.08 | 0.08 | 0.05 | 0.16 | 0.01 |
| **9** | 0.24 | 0.19 | 1.16 | 86.59 | 2.10 | 0.14 | 0.09 | 0.17 | 0.02 |
| **10** | 0.06 | 0.38 | 0.71 | 85.79 | 1.11 | 0.08 | 0.12 | 0.33 | 0.01 |
| **11** | 0.15 | 0.29 | 1.27 | 84.63 | 1.48 | 0.08 | 0.04 | 0.18 | 0.02 |
| **12** | 0.08 | 0.33 | 1.29 | 87.17 | 2.64 | 0.12 | 0.14 | 0.19 | 0.03 |
| **13** | 0.18 | 0.22 | 1.21 | 84.33 | 1.06 | 0.09 | 0.04 | 0.26 | 0.01 |
| **14** | 0.22 | 0.20 | 1.04 | 82.79 | 1.28 | 0.12 | 0.08 | 0.20 | 0.02 |
| **15** | 0.18 | 0.26 | 1.51 | 78.40 | 0.58 | 0.10 | 0.08 | 0.13 | 0.01 |
| **16** | 0.25 | 0.26 | 1.10 | 83.48 | 1.35 | 0.13 | 0.09 | 0.19 | 0.02 |
| **17** | 0.18 | 0.32 | 1.11 | 80.66 | 0.90 | 0.09 | 0.05 | 0.23 | 0.01 |
| **18** | 0.28 | 0.28 | 0.99 | 88.40 | 2.83 | 0.12 | 0.08 | 0.32 | 0.03 |
| **19** | 0.07 | 0.32 | 0.78 | 84.84 | 1.99 | 0.13 | 0.14 | 0.21 | 0.02 |
| **20** | 0.06 | 0.42 | 0.49 | 86.47 | 1.17 | 0.06 | 0.15 | 0.43 | 0.01 |
| **21** | 0.05 | 0.39 | 1.18 | 83.82 | 1.25 | 0.12 | 0.13 | 0.21 | 0.01 |
| **22** | 0.21 | 0.27 | 1.15 | 81.53 | 0.82 | 0.10 | 0.08 | 0.20 | 0.01 |
| **23** | 0.07 | 0.31 | 0.61 | 87.30 | 1.81 | 0.12 | 0.10 | 0.22 | 0.02 |
| **24** | 0.09 | 0.33 | 1.30 | 86.09 | 1.65 | 0.10 | 0.13 | 0.19 | 0.02 |
| **25** | 0.24 | 0.26 | 1.06 | 84.18 | 1.38 | 0.11 | 0.07 | 0.22 | 0.02 |
| **26** | 0.25 | 0.31 | 1.07 | 80.72 | 0.80 | 0.13 | 0.09 | 0.19 | 0.01 |
| **27** | 0.27 | 0.27 | 1.23 | 82.52 | 0.94 | 0.12 | 0.10 | 0.17 | 0.01 |
| **28** | 0.06 | 0.30 | 0.50 | 87.38 | 1.81 | 0.07 | 0.12 | 0.30 | 0.02 |
| **29** | 0.06 | 0.35 | 0.84 | 83.84 | 2.97 | 0.06 | 0.14 | 0.29 | 0.04 |
| **30** | 0.07 | 0.34 | 0.84 | 83.43 | 1.10 | 0.11 | 0.09 | 0.26 | 0.01 |
| **31** | 0.25 | 0.25 | 1.33 | 83.24 | 1.08 | 0.11 | 0.09 | 0.19 | 0.01 |
| **32** | 0.24 | 0.23 | 1.27 | 82.95 | 1.16 | 0.13 | 0.14 | 0.16 | 0.01 |
| **33** | 0.20 | 0.24 | 1.28 | 85.25 | 2.04 | 0.10 | 0.06 | 0.18 | 0.02 |
| **34** | 0.18 | 0.29 | 0.82 | 88.49 | 3.47 | 0.11 | 0.11 | 0.36 | 0.04 |
| **35** | 0.16 | 0.29 | 1.46 | 84.52 | 2.34 | 0.09 | 0.06 | 0.16 | 0.03 |
| **36** | 0.05 | 0.37 | 0.55 | 83.18 | 0.91 | 0.05 | 0.11 | 0.33 | 0.01 |
| **μ** | **0.15** | **0.30** | **1.04** | **84.39** | **1.53** | **0.11** | **0.10** | **0.23** | **0.02** |

**10% Noise**

| Subject | *A* | *ter* | *p* | *rd* | *sdA* | *sz* | *ster* | *sv* | *IR* |
|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.25 | 0.27 | 1.17 | 82.91 | 1.07 | 0.10 | 0.07 | 0.20 | 0.01 |
| **2** | 0.07 | 0.35 | 1.16 | 83.38 | 0.98 | 0.13 | 0.15 | 0.26 | 0.01 |
| **3** | 0.26 | 0.31 | 1.06 | 82.05 | 1.28 | 0.16 | 0.19 | 0.13 | 0.02 |

| | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|
| **4** | 0.04 | 0.42 | 0.61 | 82.56 | 0.84 | 0.04 | 0.16 | 0.31 | 0.01 |
| **5** | 0.05 | 0.40 | 1.45 | 83.86 | 1.66 | 0.06 | 0.12 | 0.20 | 0.02 |
| **6** | 0.05 | 0.37 | 1.24 | 83.70 | 1.22 | 0.09 | 0.21 | 0.21 | 0.01 |
| **7** | 0.06 | 0.42 | 0.44 | 86.52 | 2.88 | 0.07 | 0.09 | 0.22 | 0.03 |
| **8** | 0.17 | 0.29 | 1.47 | 80.59 | 0.69 | 0.09 | 0.06 | 0.15 | 0.01 |
| **9** | 0.21 | 0.22 | 1.11 | 83.55 | 1.28 | 0.16 | 0.08 | 0.16 | 0.02 |
| **10** | 0.09 | 0.34 | 0.66 | 86.71 | 2.54 | 0.13 | 0.13 | 0.19 | 0.03 |
| **11** | 0.15 | 0.31 | 1.41 | 80.75 | 0.85 | 0.09 | 0.05 | 0.15 | 0.01 |
| **12** | 0.05 | 0.33 | 0.76 | 81.88 | 0.85 | 0.08 | 0.11 | 0.28 | 0.01 |
| **13** | 0.17 | 0.22 | 1.17 | 81.99 | 0.85 | 0.10 | 0.05 | 0.24 | 0.01 |
| **14** | 0.24 | 0.19 | 0.98 | 84.46 | 1.49 | 0.16 | 0.08 | 0.20 | 0.02 |
| **15** | 0.20 | 0.22 | 1.30 | 84.74 | 1.94 | 0.09 | 0.07 | 0.17 | 0.02 |
| **16** | 0.09 | 0.40 | 0.98 | 88.93 | 2.37 | 0.12 | 0.19 | 0.32 | 0.03 |
| **17** | 0.20 | 0.33 | 1.44 | 81.86 | 1.43 | 0.10 | 0.09 | 0.13 | 0.02 |
| **18** | 0.29 | 0.26 | 0.97 | 88.84 | 2.43 | 0.12 | 0.09 | 0.35 | 0.03 |
| **19** | 0.06 | 0.33 | 0.65 | 84.63 | 1.45 | 0.12 | 0.14 | 0.21 | 0.02 |
| **20** | 0.06 | 0.42 | 0.50 | 88.25 | 3.86 | 0.07 | 0.21 | 0.39 | 0.04 |
| **21** | 0.06 | 0.38 | 0.85 | 81.99 | 1.31 | 0.11 | 0.12 | 0.21 | 0.02 |
| **22** | 0.25 | 0.23 | 1.10 | 81.53 | 1.34 | 0.11 | 0.09 | 0.20 | 0.02 |
| **23** | 0.05 | 0.31 | 0.62 | 83.70 | 0.86 | 0.06 | 0.08 | 0.25 | 0.01 |
| **24** | 0.15 | 0.28 | 1.41 | 79.67 | 0.98 | 0.08 | 0.18 | 0.14 | 0.01 |
| **25** | 0.07 | 0.38 | 0.78 | 83.30 | 0.97 | 0.09 | 0.13 | 0.36 | 0.01 |
| **26** | 0.23 | 0.31 | 1.05 | 85.15 | 2.00 | 0.11 | 0.07 | 0.25 | 0.02 |
| **27** | 0.22 | 0.30 | 1.26 | 82.16 | 1.09 | 0.10 | 0.08 | 0.16 | 0.01 |
| **28** | 0.27 | 0.19 | 1.15 | 86.32 | 1.94 | 0.11 | 0.09 | 0.22 | 0.02 |
| **29** | 0.08 | 0.33 | 0.82 | 86.32 | 1.67 | 0.08 | 0.08 | 0.37 | 0.02 |
| **30** | 0.06 | 0.32 | 0.57 | 89.69 | 2.30 | 0.06 | 0.09 | 0.30 | 0.03 |
| **31** | 0.05 | 0.36 | 0.68 | 85.04 | 1.17 | 0.07 | 0.11 | 0.22 | 0.01 |
| **32** | 0.27 | 0.18 | 1.06 | 81.48 | 0.93 | 0.13 | 0.11 | 0.19 | 0.01 |
| **33** | 0.23 | 0.22 | 1.23 | 84.69 | 1.36 | 0.11 | 0.07 | 0.19 | 0.02 |
| **34** | 0.30 | 0.19 | 0.86 | 85.07 | 1.82 | 0.13 | 0.10 | 0.26 | 0.02 |
| **35** | 0.04 | 0.38 | 0.87 | 88.18 | 2.06 | 0.07 | 0.13 | 0.26 | 0.02 |
| **36** | 0.05 | 0.37 | 0.42 | 84.64 | 1.30 | 0.05 | 0.10 | 0.31 | 0.02 |
| **μ** | **0.14** | **0.31** | **0.98** | **84.20** | **1.53** | **0.10** | **0.11** | **0.23** | **0.02** |

## DSTP

**DSTP**
**80% Noise**

| **Subject** | ***A*** | ***C*** | ***μTa*** | ***μFl*** | ***μSS*** | ***μRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.07 | 0.32 | 0.44 | 0.08 | 0.81 | 1.87 | 0.42 | 0.10 | 0.08 | 0.30 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **2** | 0.05 | 0.29 | 0.66 | 0.12 | 0.63 | 1.87 | 0.38 | 0.09 | 0.20 | 0.25 |
| **3** | 0.14 | 0.21 | 0.30 | 0.08 | 0.91 | 2.10 | 0.37 | 0.12 | 0.12 | 0.34 |
| **4** | 0.07 | 0.28 | 0.42 | 0.09 | 0.61 | 1.87 | 0.43 | 0.09 | 0.12 | 0.42 |
| **5** | 0.06 | 0.27 | 0.63 | 0.06 | 0.76 | 2.07 | 0.40 | 0.09 | 0.13 | 0.33 |
| **6** | 0.07 | 0.28 | 0.82 | 0.05 | 0.67 | 1.85 | 0.36 | 0.15 | 0.16 | 0.16 |
| **7** | 0.11 | 0.42 | 0.55 | 0.22 | 0.41 | 1.82 | 0.52 | 0.23 | 0.15 | 0.40 |
| **8** | 0.29 | 0.12 | 0.47 | 0.22 | 0.80 | 2.43 | 0.22 | 0.11 | 0.09 | 0.19 |
| **9** | 0.15 | 0.20 | 0.56 | 0.08 | 0.72 | 1.83 | 0.28 | 0.13 | 0.12 | 0.17 |
| **10** | 0.11 | 0.19 | 0.41 | 0.07 | 0.82 | 2.13 | 0.35 | 0.10 | 0.15 | 0.37 |
| **11** | 0.26 | 0.10 | 0.42 | 0.13 | 0.99 | 2.37 | 0.25 | 0.08 | 0.08 | 0.13 |
| **12** | 0.06 | 0.12 | 0.34 | 0.15 | 1.13 | 2.24 | 0.33 | 0.12 | 0.13 | 0.20 |
| **13** | 0.06 | 0.29 | 0.60 | 0.04 | 0.72 | 1.89 | 0.31 | 0.09 | 0.11 | 0.21 |
| **14** | 0.06 | 0.26 | 0.62 | 0.21 | 0.59 | 1.75 | 0.38 | 0.09 | 0.25 | 0.23 |
| **15** | 0.07 | 0.29 | 0.53 | 0.08 | 0.77 | 1.81 | 0.34 | 0.12 | 0.06 | 0.19 |
| **16** | 0.07 | 0.28 | 0.47 | 0.04 | 0.85 | 1.87 | 0.42 | 0.07 | 0.12 | 0.27 |
| **17** | 0.06 | 0.32 | 0.57 | 0.05 | 0.65 | 1.76 | 0.43 | 0.11 | 0.08 | 0.28 |
| **18** | 0.22 | 0.50 | 0.63 | 0.02 | 0.51 | 1.80 | 0.35 | 0.12 | 0.10 | 0.29 |
| **19** | 0.07 | 0.28 | 0.77 | 0.06 | 0.65 | 1.81 | 0.35 | 0.16 | 0.19 | 0.17 |
| **20** | 0.09 | 0.38 | 0.46 | 0.14 | 0.57 | 1.91 | 0.44 | 0.20 | 0.15 | 0.40 |
| **21** | 0.08 | 0.24 | 0.53 | 0.09 | 0.83 | 2.09 | 0.36 | 0.13 | 0.14 | 0.36 |
| **22** | 0.24 | 0.12 | 0.41 | 0.09 | 0.96 | 2.48 | 0.28 | 0.10 | 0.10 | 0.18 |
| **23** | 0.07 | 0.26 | 0.44 | 0.09 | 0.68 | 1.93 | 0.32 | 0.10 | 0.14 | 0.38 |
| **24** | 0.26 | 0.06 | 0.42 | 0.13 | 0.92 | 2.58 | 0.26 | 0.13 | 0.12 | 0.22 |
| **25** | 0.35 | 0.17 | 0.41 | 0.08 | 0.75 | 2.54 | 0.22 | 0.11 | 0.10 | 0.28 |
| **26** | 0.33 | 0.17 | 0.41 | 0.07 | 0.83 | 2.76 | 0.26 | 0.12 | 0.08 | 0.20 |
| **27** | 0.13 | 0.32 | 0.69 | 0.04 | 0.64 | 1.74 | 0.36 | 0.09 | 0.07 | 0.19 |
| **28** | 0.10 | 0.39 | 0.56 | 0.05 | 0.52 | 1.69 | 0.39 | 0.24 | 0.17 | 0.29 |
| **29** | 0.08 | 0.35 | 0.68 | 0.09 | 0.60 | 1.76 | 0.39 | 0.18 | 0.11 | 0.19 |
| **30** | 0.08 | 0.40 | 0.54 | 0.12 | 0.61 | 1.73 | 0.37 | 0.17 | 0.14 | 0.30 |
| **31** | 0.06 | 0.15 | 0.47 | 0.11 | 0.94 | 2.07 | 0.39 | 0.10 | 0.13 | 0.26 |
| **32** | 0.09 | 0.30 | 0.69 | 0.09 | 0.61 | 1.77 | 0.35 | 0.16 | 0.12 | 0.18 |
| **33** | 0.06 | 0.18 | 0.59 | 0.11 | 0.82 | 1.92 | 0.36 | 0.11 | 0.11 | 0.19 |
| **34** | 0.16 | 0.26 | 0.29 | 0.08 | 0.97 | 2.30 | 0.30 | 0.13 | 0.14 | 0.38 |
| **35** | 0.04 | 0.21 | 0.50 | 0.12 | 0.79 | 1.81 | 0.38 | 0.04 | 0.07 | 0.26 |
| **36** | 0.05 | 0.27 | 0.58 | 0.08 | 0.71 | 2.02 | 0.41 | 0.07 | 0.18 | 0.41 |
| **μ** | **0.12** | **0.26** | **0.53** | **0.10** | **0.74** | **2.01** | **0.35** | **0.12** | **0.13** | **0.26** |

**70% Noise**

| **Subject** | ***A*** | ***C*** | ***μTa*** | ***μFl*** | ***μSS*** | ***μRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.06 | 0.31 | 0.53 | 0.07 | 0.74 | 1.91 | 0.40 | 0.07 | 0.10 | 0.32 |
| **2** | 0.31 | 0.08 | 0.41 | 0.24 | 0.76 | 2.23 | 0.23 | 0.19 | 0.17 | 0.18 |
| **3** | 0.40 | 0.14 | 0.36 | 0.07 | 0.60 | 2.83 | 0.24 | 0.10 | 0.08 | 0.28 |
| **4** | 0.06 | 0.26 | 0.45 | 0.10 | 0.76 | 1.87 | 0.42 | 0.11 | 0.09 | 0.28 |
| **5** | 0.27 | 0.04 | 0.53 | 0.19 | 0.64 | 2.17 | 0.31 | 0.05 | 0.10 | 0.29 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **6** | 0.07 | 0.33 | 0.77 | 0.24 | 0.60 | 1.74 | 0.34 | 0.15 | 0.14 | 0.19 |
| **7** | 0.10 | 0.29 | 0.47 | 0.10 | 0.83 | 1.93 | 0.45 | 0.11 | 0.10 | 0.41 |
| **8** | 0.23 | 0.08 | 0.45 | 0.17 | 1.03 | 2.50 | 0.27 | 0.06 | 0.05 | 0.14 |
| **9** | 0.07 | 0.33 | 0.59 | 0.07 | 0.70 | 1.87 | 0.32 | 0.12 | 0.12 | 0.22 |
| **10** | 0.08 | 0.23 | 0.52 | 0.04 | 0.78 | 2.09 | 0.37 | 0.09 | 0.15 | 0.35 |
| **11** | 0.27 | 0.04 | 0.45 | 0.17 | 0.80 | 2.43 | 0.27 | 0.05 | 0.11 | 0.24 |
| **12** | 0.05 | 0.23 | 0.70 | 0.24 | 0.67 | 1.90 | 0.37 | 0.12 | 0.15 | 0.21 |
| **13** | 0.30 | 0.15 | 0.42 | 0.06 | 0.93 | 2.72 | 0.14 | 0.11 | 0.09 | 0.19 |
| **14** | 0.10 | 0.37 | 0.61 | 0.07 | 0.71 | 1.98 | 0.31 | 0.13 | 0.15 | 0.35 |
| **15** | 0.27 | 0.13 | 0.45 | 0.14 | 1.00 | 2.52 | 0.20 | 0.12 | 0.11 | 0.17 |
| **16** | 0.32 | 0.17 | 0.41 | 0.06 | 0.91 | 2.31 | 0.22 | 0.12 | 0.13 | 0.15 |
| **17** | 0.25 | 0.07 | 0.43 | 0.31 | 0.65 | 2.20 | 0.32 | 0.16 | 0.07 | 0.17 |
| **18** | 0.44 | 0.21 | 0.37 | 0.11 | 0.63 | 2.72 | 0.20 | 0.12 | 0.11 | 0.31 |
| **19** | 0.05 | 0.28 | 0.72 | 0.18 | 0.65 | 1.76 | 0.35 | 0.12 | 0.18 | 0.20 |
| **20** | 0.09 | 0.31 | 0.39 | 0.14 | 0.52 | 1.84 | 0.41 | 0.18 | 0.14 | 0.34 |
| **21** | 0.05 | 0.27 | 0.84 | 0.14 | 0.64 | 1.80 | 0.40 | 0.11 | 0.18 | 0.16 |
| **22** | 0.30 | 0.13 | 0.43 | 0.09 | 0.90 | 2.71 | 0.25 | 0.12 | 0.11 | 0.19 |
| **23** | 0.05 | 0.24 | 0.55 | 0.05 | 0.71 | 1.86 | 0.35 | 0.08 | 0.15 | 0.30 |
| **24** | 0.08 | 0.13 | 0.31 | 0.09 | 1.17 | 2.35 | 0.29 | 0.10 | 0.09 | 0.24 |
| **25** | 0.08 | 0.33 | 0.53 | 0.09 | 0.73 | 1.88 | 0.40 | 0.14 | 0.08 | 0.22 |
| **26** | 0.32 | 0.19 | 0.41 | 0.14 | 0.97 | 2.30 | 0.25 | 0.13 | 0.15 | 0.15 |
| **27** | 0.28 | 0.05 | 0.43 | 0.12 | 0.72 | 2.10 | 0.31 | 0.08 | 0.10 | 0.25 |
| **28** | 0.12 | 0.19 | 0.33 | 0.08 | 0.85 | 2.13 | 0.26 | 0.11 | 0.11 | 0.38 |
| **29** | 0.06 | 0.24 | 0.68 | 0.09 | 0.68 | 1.83 | 0.37 | 0.12 | 0.12 | 0.22 |
| **30** | 0.08 | 0.40 | 0.62 | 0.05 | 0.75 | 1.83 | 0.33 | 0.07 | 0.05 | 0.36 |
| **31** | 0.28 | 0.06 | 0.40 | 0.19 | 0.79 | 2.57 | 0.30 | 0.13 | 0.06 | 0.19 |
| **32** | 0.14 | 0.30 | 0.75 | 0.04 | 0.60 | 1.76 | 0.26 | 0.10 | 0.08 | 0.15 |
| **33** | 0.05 | 0.25 | 0.67 | 0.05 | 0.68 | 1.79 | 0.36 | 0.09 | 0.11 | 0.15 |
| **34** | 0.19 | 0.39 | 0.67 | 0.06 | 0.52 | 1.77 | 0.28 | 0.13 | 0.10 | 0.23 |
| **35** | 0.05 | 0.20 | 0.65 | 0.28 | 0.79 | 1.85 | 0.36 | 0.09 | 0.05 | 0.19 |
| **36** | 0.10 | 0.13 | 0.43 | 0.14 | 0.81 | 2.43 | 0.35 | 0.08 | 0.11 | 0.47 |
| **μ** | **0.17** | **0.21** | **0.52** | **0.12** | **0.76** | **2.12** | **0.31** | **0.11** | **0.11** | **0.25** |

**40% Noise**

| **Subject** | ***A*** | ***C*** | ***μTa*** | ***μFl*** | ***μSS*** | ***μRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.28 | 0.11 | 0.43 | 0.12 | 0.94 | 2.59 | 0.29 | 0.11 | 0.10 | 0.15 |
| **2** | 0.06 | 0.29 | 0.74 | 0.05 | 0.71 | 1.95 | 0.33 | 0.08 | 0.11 | 0.35 |
| **3** | 0.36 | 0.17 | 0.39 | 0.08 | 0.69 | 2.63 | 0.25 | 0.12 | 0.10 | 0.24 |
| **4** | 0.05 | 0.25 | 0.62 | 0.14 | 0.67 | 1.84 | 0.42 | 0.08 | 0.10 | 0.26 |
| **5** | 0.29 | 0.12 | 0.45 | 0.12 | 1.01 | 2.47 | 0.24 | 0.09 | 0.10 | 0.16 |
| **6** | 0.28 | 0.07 | 0.41 | 0.21 | 0.90 | 2.53 | 0.23 | 0.17 | 0.11 | 0.15 |
| **7** | 0.08 | 0.38 | 0.60 | 0.06 | 0.60 | 1.86 | 0.45 | 0.15 | 0.10 | 0.36 |
| **8** | 0.26 | 0.10 | 0.44 | 0.14 | 1.06 | 2.61 | 0.23 | 0.06 | 0.05 | 0.15 |
| **9** | 0.29 | 0.17 | 0.46 | 0.16 | 0.95 | 2.53 | 0.15 | 0.11 | 0.10 | 0.17 |

| | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| **10** | 0.06 | 0.23 | 0.58 | 0.07 | 0.73 | 1.94 | 0.37 | 0.07 | 0.12 | 0.34 |
| **11** | 0.08 | 0.28 | 0.93 | 0.11 | 0.57 | 1.72 | 0.33 | 0.06 | 0.05 | 0.13 |
| **12** | 0.25 | 0.07 | 0.48 | 0.32 | 0.97 | 2.44 | 0.25 | 0.16 | 0.10 | 0.14 |
| **13** | 0.29 | 0.10 | 0.44 | 0.14 | 0.85 | 3.07 | 0.17 | 0.06 | 0.04 | 0.23 |
| **14** | 0.12 | 0.30 | 0.74 | 0.07 | 0.56 | 1.70 | 0.26 | 0.11 | 0.07 | 0.16 |
| **15** | 0.25 | 0.08 | 0.46 | 0.13 | 1.18 | 2.73 | 0.23 | 0.07 | 0.09 | 0.13 |
| **16** | 0.32 | 0.15 | 0.42 | 0.13 | 0.85 | 2.65 | 0.22 | 0.12 | 0.10 | 0.17 |
| **17** | 0.27 | 0.10 | 0.42 | 0.13 | 0.80 | 2.83 | 0.28 | 0.08 | 0.05 | 0.22 |
| **18** | 0.15 | 0.43 | 0.68 | 0.09 | 0.57 | 1.74 | 0.35 | 0.10 | 0.08 | 0.29 |
| **19** | 0.06 | 0.27 | 0.60 | 0.14 | 0.65 | 1.80 | 0.32 | 0.12 | 0.13 | 0.23 |
| **20** | 0.07 | 0.30 | 0.50 | 0.12 | 0.45 | 1.81 | 0.42 | 0.08 | 0.15 | 0.48 |
| **21** | 0.04 | 0.25 | 0.71 | 0.17 | 0.63 | 1.77 | 0.38 | 0.08 | 0.13 | 0.17 |
| **22** | 0.29 | 0.13 | 0.40 | 0.08 | 0.90 | 2.57 | 0.22 | 0.09 | 0.08 | 0.19 |
| **23** | 0.06 | 0.31 | 0.56 | 0.09 | 0.73 | 1.80 | 0.31 | 0.12 | 0.10 | 0.25 |
| **24** | 0.21 | 0.04 | 0.56 | 0.30 | 0.83 | 2.36 | 0.27 | 0.06 | 0.13 | 0.23 |
| **25** | 0.32 | 0.15 | 0.41 | 0.12 | 0.78 | 2.78 | 0.22 | 0.10 | 0.07 | 0.20 |
| **26** | 0.32 | 0.15 | 0.41 | 0.08 | 0.82 | 2.69 | 0.27 | 0.12 | 0.10 | 0.18 |
| **27** | 0.31 | 0.15 | 0.46 | 0.08 | 1.02 | 2.57 | 0.24 | 0.10 | 0.10 | 0.19 |
| **28** | 0.07 | 0.27 | 0.50 | 0.06 | 0.74 | 2.00 | 0.30 | 0.08 | 0.11 | 0.40 |
| **29** | 0.18 | 0.06 | 0.46 | 0.35 | 0.62 | 1.80 | 0.28 | 0.12 | 0.10 | 0.21 |
| **30** | 0.27 | 0.06 | 0.38 | 0.16 | 0.72 | 2.65 | 0.25 | 0.10 | 0.08 | 0.26 |
| **31** | 0.31 | 0.13 | 0.47 | 0.12 | 1.01 | 2.65 | 0.22 | 0.09 | 0.09 | 0.21 |
| **32** | 0.30 | 0.13 | 0.46 | 0.14 | 1.05 | 2.55 | 0.20 | 0.10 | 0.17 | 0.15 |
| **33** | 0.28 | 0.13 | 0.48 | 0.22 | 0.99 | 2.51 | 0.18 | 0.08 | 0.06 | 0.17 |
| **34** | 0.16 | 0.39 | 0.64 | 0.08 | 0.68 | 1.98 | 0.31 | 0.11 | 0.11 | 0.40 |
| **35** | 0.23 | 0.11 | 0.50 | 0.32 | 1.12 | 2.34 | 0.24 | 0.07 | 0.05 | 0.14 |
| **36** | 0.05 | 0.31 | 0.55 | 0.05 | 0.71 | 1.94 | 0.36 | 0.06 | 0.10 | 0.38 |
| **μ** | **0.20** | **0.19** | **0.52** | **0.14** | **0.81** | **2.29** | **0.28** | **0.10** | **0.10** | **0.23** |

**10% Noise**

| **Subject** | ***A*** | ***C*** | ***μTa*** | ***μFl*** | ***μSS*** | ***μRS2*** | ***ter*** | ***sz*** | ***ster*** | ***sv*** |
|---|---|---|---|---|---|---|---|---|---|---|
| **1** | 0.32 | 0.14 | 0.45 | 0.13 | 0.86 | 2.79 | 0.23 | 0.10 | 0.07 | 0.18 |
| **2** | 0.05 | 0.28 | 0.85 | 0.11 | 0.68 | 1.87 | 0.35 | 0.10 | 0.15 | 0.21 |
| **3** | 0.32 | 0.15 | 0.41 | 0.13 | 0.90 | 2.41 | 0.29 | 0.13 | 0.22 | 0.15 |
| **4** | 0.04 | 0.27 | 0.56 | 0.07 | 0.65 | 1.75 | 0.41 | 0.04 | 0.15 | 0.31 |
| **5** | 0.05 | 0.23 | 0.80 | 0.19 | 0.68 | 1.89 | 0.39 | 0.06 | 0.10 | 0.19 |
| **6** | 0.22 | 0.04 | 0.43 | 0.24 | 0.92 | 2.79 | 0.31 | 0.07 | 0.21 | 0.19 |
| **7** | 0.08 | 0.29 | 0.43 | 0.09 | 0.76 | 1.91 | 0.41 | 0.09 | 0.08 | 0.37 |
| **8** | 0.25 | 0.08 | 0.45 | 0.17 | 1.14 | 2.67 | 0.25 | 0.06 | 0.06 | 0.14 |
| **9** | 0.30 | 0.13 | 0.40 | 0.14 | 0.83 | 2.85 | 0.18 | 0.14 | 0.09 | 0.14 |
| **10** | 0.29 | 0.09 | 0.36 | 0.20 | 0.58 | 2.57 | 0.26 | 0.18 | 0.09 | 0.16 |
| **11** | 0.24 | 0.08 | 0.45 | 0.16 | 1.11 | 2.68 | 0.27 | 0.06 | 0.06 | 0.15 |
| **12** | 0.04 | 0.23 | 0.58 | 0.07 | 0.63 | 1.82 | 0.33 | 0.07 | 0.11 | 0.28 |
| **13** | 0.09 | 0.30 | 0.81 | 0.05 | 0.58 | 1.72 | 0.25 | 0.08 | 0.05 | 0.19 |

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|---|---|---|---|---|---|---|---|---|---|---|
| **14** | 0.33 | 0.16 | 0.39 | 0.11 | 0.75 | 2.83 | 0.13 | 0.13 | 0.08 | 0.18 |
| **15** | 0.27 | 0.11 | 0.49 | 0.27 | 0.99 | 2.32 | 0.18 | 0.08 | 0.07 | 0.14 |
| **16** | 0.29 | 0.08 | 0.43 | 0.20 | 0.72 | 2.43 | 0.29 | 0.11 | 0.14 | 0.35 |
| **17** | 0.26 | 0.10 | 0.47 | 0.21 | 1.12 | 2.49 | 0.29 | 0.07 | 0.10 | 0.13 |
| **18** | 0.47 | 0.17 | 0.39 | 0.16 | 0.65 | 3.03 | 0.19 | 0.10 | 0.08 | 0.34 |
| **19** | 0.06 | 0.26 | 0.55 | 0.08 | 0.64 | 1.76 | 0.33 | 0.11 | 0.13 | 0.24 |
| **20** | 0.06 | 0.32 | 0.47 | 0.32 | 0.50 | 1.78 | 0.43 | 0.09 | 0.21 | 0.34 |
| **21** | 0.05 | 0.24 | 0.59 | 0.11 | 0.65 | 1.78 | 0.37 | 0.08 | 0.11 | 0.21 |
| **22** | 0.29 | 0.13 | 0.43 | 0.16 | 0.80 | 2.49 | 0.20 | 0.10 | 0.08 | 0.17 |
| **23** | 0.06 | 0.26 | 0.58 | 0.04 | 0.73 | 1.86 | 0.31 | 0.06 | 0.08 | 0.30 |
| **24** | 0.14 | 0.16 | 0.75 | 0.13 | 0.80 | 2.05 | 0.29 | 0.05 | 0.19 | 0.13 |
| **25** | 0.11 | 0.17 | 0.47 | 0.06 | 0.82 | 2.34 | 0.33 | 0.09 | 0.10 | 0.43 |
| **26** | 0.31 | 0.16 | 0.40 | 0.17 | 0.85 | 2.64 | 0.27 | 0.10 | 0.07 | 0.27 |
| **27** | 0.28 | 0.12 | 0.44 | 0.12 | 0.99 | 2.52 | 0.26 | 0.08 | 0.08 | 0.16 |
| **28** | 0.06 | 0.25 | 0.55 | 0.05 | 0.81 | 1.94 | 0.33 | 0.06 | 0.11 | 0.35 |
| **29** | 0.28 | 0.07 | 0.48 | 0.28 | 0.61 | 2.67 | 0.23 | 0.08 | 0.06 | 0.30 |
| **30** | 0.08 | 0.22 | 0.43 | 0.10 | 0.78 | 2.17 | 0.30 | 0.07 | 0.08 | 0.42 |
| **31** | 0.05 | 0.27 | 0.60 | 0.06 | 0.71 | 1.79 | 0.36 | 0.07 | 0.11 | 0.24 |
| **32** | 0.29 | 0.21 | 0.54 | 0.05 | 0.76 | 2.32 | 0.16 | 0.11 | 0.11 | 0.20 |
| **33** | 0.30 | 0.14 | 0.44 | 0.14 | 0.95 | 2.63 | 0.17 | 0.09 | 0.06 | 0.18 |
| **34** | 0.40 | 0.17 | 0.37 | 0.13 | 0.56 | 2.74 | 0.16 | 0.12 | 0.10 | 0.26 |
| **35** | 0.05 | 0.11 | 0.35 | 0.16 | 0.95 | 2.26 | 0.36 | 0.06 | 0.10 | 0.33 |
| **36** | 0.05 | 0.28 | 0.44 | 0.07 | 0.60 | 1.79 | 0.37 | 0.07 | 0.10 | 0.39 |
| **μ** | **0.19** | **0.18** | **0.50** | **0.14** | **0.78** | **2.29** | **0.28** | **0.09** | **0.11** | **0.24** |

## Log Marginal Likelihoods and Log Bayes Factor (ln(BF)).

| | **80% Noise** | | | **70% Noise** | | |
|---|---|---|---|---|---|---|
| **Subject** | SSP | DSTP | ln(BF) | SSP | DSTP | ln(BF) |
| **1** | -434.24 | -433.29 | 0.95 | -398.74 | -396.29 | 2.45 |
| **2** | -402.33 | -399.91 | 2.42 | -395.85 | -392.74 | 3.11 |
| **3** | -442.34 | -440.81 | 1.53 | -433.87 | -433.97 | -0.11 |
| **4** | -448.67 | -447.18 | 1.49 | -414.26 | -413.69 | 0.57 |
| **5** | -372.10 | -371.48 | 0.61 | -349.33 | -340.42 | 8.90 |
| **6** | -372.80 | -373.87 | -1.07 | -404.35 | -402.80 | 1.55 |
| **7** | -521.90 | -519.83 | 2.07 | -463.84 | -464.05 | -0.21 |
| **8** | -361.92 | -360.72 | 1.20 | -298.08 | -297.56 | 0.52 |
| **9** | -388.52 | -388.46 | 0.06 | -401.25 | -398.42 | 2.83 |
| **10** | -441.95 | -440.05 | 1.90 | -402.54 | -402.16 | 0.38 |
| **11** | -307.28 | -307.18 | 0.10 | -334.62 | -332.77 | 1.85 |
| **12** | -370.49 | -371.08 | -0.59 | -398.90 | -397.13 | 1.77 |
| **13** | -370.73 | -368.40 | 2.33 | -342.82 | -344.28 | -1.46 |
| **14** | -424.98 | -421.62 | 3.35 | -437.28 | -436.34 | 0.94 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **15** | -402.59 | -399.92 | 2.67 | -371.49 | -371.10 | 0.39 |
| **16** | -417.57 | -415.19 | 2.38 | -373.74 | -374.60 | -0.86 |
| **17** | -410.90 | -411.70 | -0.79 | -373.76 | -367.65 | 6.12 |
| **18** | -481.60 | -482.42 | -0.82 | -468.54 | -469.15 | -0.60 |
| **19** | -410.30 | -410.57 | -0.27 | -412.61 | -410.77 | 1.83 |
| **20** | -502.99 | -499.32 | 3.67 | -492.63 | -487.02 | 5.61 |
| **21** | -406.55 | -406.17 | 0.38 | -375.45 | -374.16 | 1.29 |
| **22** | -355.62 | -356.15 | -0.54 | -359.49 | -360.48 | -0.99 |
| **23** | -443.86 | -443.09 | 0.76 | -403.68 | -403.45 | 0.23 |
| **24** | -345.35 | -345.84 | -0.48 | -358.46 | -359.02 | -0.56 |
| **25** | -418.75 | -419.32 | -0.57 | -437.07 | -431.29 | 5.77 |
| **26** | -386.68 | -388.46 | -1.78 | -368.34 | -368.45 | -0.11 |
| **27** | -387.88 | -388.17 | -0.29 | -362.19 | -358.28 | 3.91 |
| **28** | -486.56 | -487.34 | -0.78 | -431.04 | -430.08 | 0.97 |
| **29** | -425.88 | -424.65 | 1.23 | -381.73 | -382.91 | -1.18 |
| **30** | -478.60 | -477.72 | 0.88 | -410.41 | -409.35 | 1.06 |
| **31** | -396.95 | -397.13 | -0.18 | -347.11 | -343.03 | 4.07 |
| **32** | -395.27 | -395.19 | 0.09 | -351.84 | -352.35 | -0.51 |
| **33** | -369.19 | -368.18 | 1.01 | -345.43 | -343.34 | 2.09 |
| **34** | -449.87 | -447.41 | 2.46 | -436.15 | -435.92 | 0.22 |
| **35** | -353.94 | -352.30 | 1.64 | -350.61 | -346.25 | 4.36 |
| **36** | -408.63 | -409.78 | -1.15 | -384.26 | -384.18 | 0.08 |

| | **40% Noise** | | | **10% Noise** | | |
|---|---|---|---|---|---|---|
| **Subject** | SSP | DSTP | ln(BF) | SSP | DSTP | ln(BF) |
| **1** | -349.59 | -350.18 | -0.59 | -350.81 | -351.59 | -0.78 |
| **2** | -381.17 | -380.56 | 0.61 | -356.41 | -356.60 | -0.18 |
| **3** | -408.84 | -409.36 | -0.52 | -377.49 | -377.92 | -0.43 |
| **4** | -370.59 | -369.82 | 0.77 | -386.61 | -384.92 | 1.69 |
| **5** | -341.86 | -341.92 | -0.06 | -332.95 | -331.42 | 1.53 |
| **6** | -353.88 | -352.33 | 1.54 | -347.96 | -346.54 | 1.42 |
| **7** | -454.86 | -457.37 | -2.51 | -441.91 | -441.19 | 0.72 |
| **8** | -297.56 | -298.43 | -0.86 | -270.69 | -270.85 | -0.15 |
| **9** | -340.16 | -341.15 | -1.00 | -348.20 | -348.84 | -0.64 |
| **10** | -396.79 | -396.50 | 0.30 | -429.07 | -425.89 | 3.18 |
| **11** | -294.89 | -293.80 | 1.09 | -262.92 | -263.02 | -0.10 |
| **12** | -334.39 | -333.81 | 0.57 | -360.31 | -358.69 | 1.62 |
| **13** | -345.81 | -346.48 | -0.67 | -336.42 | -336.64 | -0.22 |
| **14** | -370.67 | -369.84 | 0.83 | -388.66 | -389.66 | -0.99 |
| **15** | -272.87 | -273.43 | -0.55 | -327.25 | -326.30 | 0.94 |
| **16** | -387.99 | -388.82 | -0.84 | -405.55 | -400.73 | 4.81 |
| **17** | -349.83 | -350.24 | -0.42 | -313.43 | -313.28 | 0.15 |
| **18** | -445.13 | -444.31 | 0.82 | -467.74 | -467.48 | 0.26 |
| **19** | -394.13 | -392.42 | 1.71 | -404.15 | -402.74 | 1.42 |
| **20** | -452.88 | -449.25 | 3.64 | -478.60 | -467.22 | 11.38 |

| | | | | | | |
|---|---|---|---|---|---|---|
| **21** | -359.37 | -358.56 | 0.81 | -372.87 | -370.97 | 1.90 |
| **22** | -343.89 | -344.38 | -0.48 | -351.91 | -351.40 | 0.51 |
| **23** | -411.95 | -410.69 | 1.26 | -379.68 | -379.41 | 0.27 |
| **24** | -341.10 | -337.25 | 3.85 | -324.58 | -324.58 | 0.00 |
| **25** | -371.85 | -372.62 | -0.77 | -390.06 | -390.35 | -0.28 |
| **26** | -378.22 | -379.01 | -0.79 | -398.00 | -398.14 | -0.15 |
| **27** | -342.70 | -343.19 | -0.49 | -333.94 | -334.08 | -0.14 |
| **28** | -424.10 | -423.86 | 0.23 | -398.79 | -399.34 | -0.55 |
| **29** | -377.83 | -373.49 | 4.34 | -379.33 | -375.92 | 3.41 |
| **30** | -366.20 | -363.89 | 2.31 | -413.95 | -414.32 | -0.37 |
| **31** | -337.50 | -337.71 | -0.21 | -373.81 | -372.98 | 0.82 |
| **32** | -375.78 | -376.43 | -0.65 | -378.95 | -379.84 | -0.89 |
| **33** | -324.44 | -324.59 | -0.15 | -336.95 | -337.24 | -0.28 |
| **34** | -478.86 | -480.17 | -1.31 | -444.78 | -444.97 | -0.19 |
| **35** | -319.48 | -320.24 | -0.76 | -358.79 | -359.11 | -0.31 |
| **36** | -420.94 | -419.99 | 0.96 | -429.37 | -427.99 | 1.38 |