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Abstract

Understanding the dynamics of selective attention has been a central research goal in the cognitive sciences. One account proposes that attention is unitary and increases in selectivity *continuously* over time. An alternative account proposes that attention switches from a low to a high state of selectivity at a *discrete* point in time when a distinct selective attention mechanism is engaged. Despite posing fundamentally different theoretical perspectives on selective attention, both accounts have successfully explained outcome-based data, such as reaction time. Here, we used mouse-tracking which provides high temporal resolution to record movement trajectories in a flanker task. We examined spatial and temporal movement dynamics for characteristics of continuous and discrete shifts in attentional selectivity. Our results showed that attentional selectivity increases gradually over time, rather than abruptly, demonstrating a continuous process of selective attention.

Keywords: selective attention; mouse-tracking; flanker task; continuous selection; discrete selection; flanker congruency effect

Public Significance Statement

Selective attention is typically investigated with outcome-based measures (e.g., reaction time). In this study, we examined changes in selective attention by recording real-time movement trajectories. Our results suggested that selective attention increases continuously over time, as opposed to discretely over time.

Tracking Flanker Task Dynamics: Evidence for Continuous Attentional Selectivity

Selective attention involves both bringing focus to goal-relevant information and suppressing conflicting, goal-irrelevant information. A standard tool for assessing selective attention is the flanker task (Eriksen & Eriksen, 1974). In the canonical flanker task, participants are instructed to attend to a central target object (e.g., an arrow pointing left) and to execute a left/right response based on its identity. The target object is typically flanked by distractors that are either the same (e.g., $\leftarrow\leftarrow\leftarrow\leftarrow\leftarrow$, congruent) or different (e.g., $\rightarrow\rightarrow\leftarrow\rightarrow\rightarrow$, incongruent) in relation to the target object. In cases where the target and distractors contain conflicting information (incongruent), reaction times (RTs) are reliably slower, and error rates are higher compared to when there is no conflict, a finding commonly termed the *flanker congruency effect*. This effect is reliable even though the location of the target remains constant, indicating that the distractors inevitably interfere with target processing during selective attention (Eriksen & Schultz, 1979).

A foundational study on the flanker congruency effect found that errors on incongruent trials are associated with faster RTs (Gratton et al., 1988). This finding indicates that distractor interference is strong soon after trial onset, promoting errors during early processing. Thus, attentional selectivity requires additional time to select target information and override distractor information. In other words, attention needs time to transition from low to high selectivity, which increases the likelihood that target information is correctly identified. This notion that attentional selectivity increases over time has been well-established (e.g., Eriksen & St. James, 1986; Heitz & Engle, 2007; Servant et al., 2014). More recent studies have instead focused on investigating the processes related to *how* attention reaches a high state of selectivity.

Two main accounts have been proposed that explain the temporal dynamics of attentional selectivity in the flanker task: *discrete* and *continuous* selection. Although both discrete and continuous selection accounts propose that attentional selectivity increases over time, they differ in terms of how this selectivity unfolds (Fig. 1). Discrete selection accounts suggest that attention increases in stages, such that processes involved in low and high selectivity are distinct (Reeves & Sperling, 1986; Shih & Sperling, 2002). These accounts assume that during early processing,

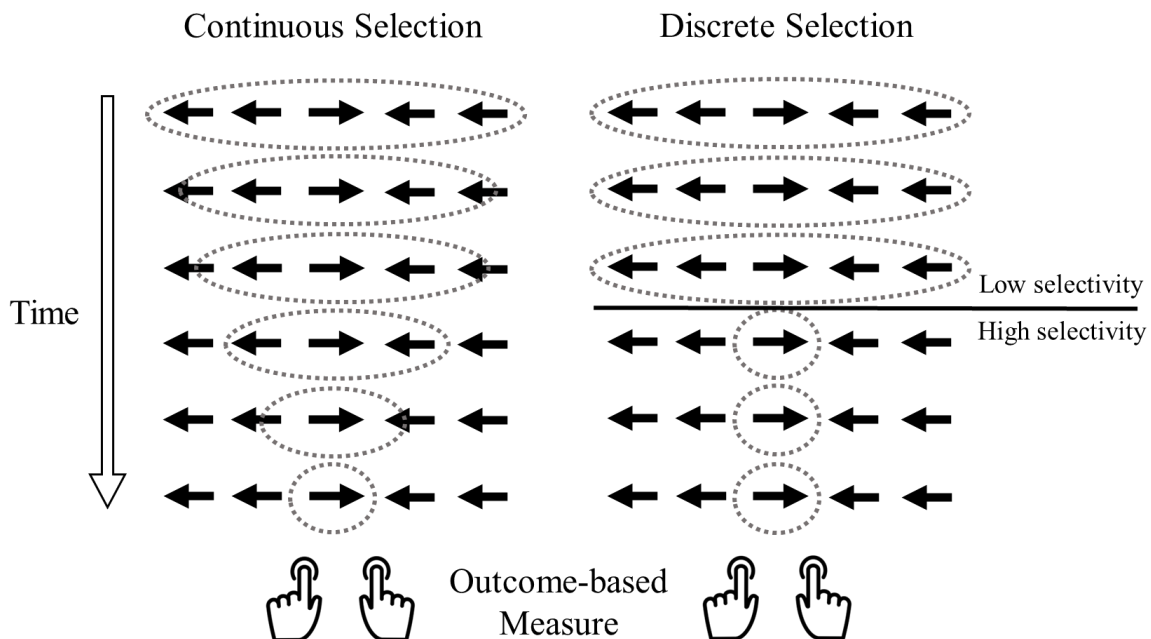


Fig 1. Main theoretical accounts of attentional selectivity in the flanker task. Continuous selection (left) proposes that attention gradually narrows onto the target over time. Discrete selection (right) proposes that attention shifts to a state of high selectivity for target processing at a discrete point in time (solid black bar). Outcome-based measurements, such as reaction times (bottom), capture the summed result of processing, traditionally used to infer changes in attentional selectivity over time.

attention is broadly distributed to both target and distractor information. Then, a discrete shift from low to high selectivity occurs, after which only target information is selected for further processing. From this perspective, a highly selective attentional mechanism is activated at a discrete point in time between these stages. Alternatively, continuous selection accounts propose that attention presents itself on a continuum that ranges from low to high selectivity (Cohen et

al., 1992; Liu et al., 2009). In this view, attention gradually narrows onto the target as distractor information is progressively suppressed. Importantly, continuous selection assumes that one dynamic process, as opposed to two distinct processes, is involved in both target selection and distractor suppression.

The dominant approach for testing a discrete versus continuous selection process in the flanker task has been the examination of RT and accuracy data. That is, the temporal dynamics underlying attentional selectivity are inferred by examining the relationship between RT and accuracy. Due to the slow temporal resolution of RT and accuracy (~1 measurement/second), these data are typically fit with conflict diffusion models (Grange, 2016; Servant et al., 2014; Servant & Evans, 2020) in an attempt to decompose their underlying cognitive processes. These conflict diffusion models are commonly implemented in either a discrete (e.g., dual-stage two-phase model; Hübner et al., 2010) or continuous selection (e.g., shrinking spotlight model; Heitz & Engle, 2007) framework that account for changes in attentional selectivity. Each of the models assume that evidence is accumulated from target and distractor information until a decision threshold is reached. Importantly, these models vary in how target and distractor decision evidence is accumulated over time with a parameter known as the drift rate. For example, in the shrinking spotlight model, RT and accuracy scores result from a continuous time-varying drift rate that specifies the relative strength of target and distractor information as attention gradually narrows (White et al., 2011). In the dual-stage two-phase model, the drift rate varies based on a discrete transition from a first and second phase of response selection (Hübner et al., 2010). Decision evidence during the first phase of response selection is provided by the perceptual processing (early stage of stimulus selection) of both targets and distractor features, whereas decision evidence during the second phase of response selection is exclusively provided by target

information after it has been identified (late stage of stimulus selection). The drift rate of these models therefore reflects the different theoretical processing assumptions of discrete and continuous selection.

Several previous studies have compared discrete and continuous selection models by examining how well they fit RT and accuracy data in the flanker task. For example, White et al. (2011) found that the shrinking spotlight model provided an overall better account of the flanker task data than the dual-stage two-phase model, supporting continuous selection. Other studies have instead found that the dual-stage two-phase model provides a better fit of data from the flanker task (Hübner & Töbel, 2012; Servant et al., 2014; Servant et al., 2015), supporting discrete selection. Providing evidence for either continuous or discrete selection has proven challenging based on these mixed findings. As another example, Hübner and Töbel (2012) showed that whether the dual-stage two-phase or the shrinking spotlight model showed superiority may depend on methodological differences in the flanker task (e.g., response-stimulus interval). Moreover, both discrete and continuous selection models have been found to capture the main patterns of RT and accuracy data in the flanker task (Hübner et al., 2010; White et al., 2011), to the extent that their behavioral predictions largely mirror each other (Evans & Servant, 2020; White et al., 2018). These findings indicate that changes in attentional selectivity are not easily identified using this particular model-based approach.

Distinguishing between continuous and discrete selection is a critical step for uncovering the dynamics that govern selective attention. To this end, several lines of work have compared computational models to understand the underlying processes of attentional selectivity. A critical limitation impeding these efforts has been the focus on RT and accuracy data, or outcome-based measures. Outcome-based measures only convey a summary of the cognitive operations that take

place between stimulus onset and response output and, thus, are limited in their capacity to reveal how cognitive processes emerge over time (Fig. 1). As a result, these measures are ill-suited for dissociating fine-grained temporal predictions of different mechanisms underlying attentional selectivity. For example, providing direct evidence for (or against) the proposed time point at which discrete selection arises cannot be achieved with RT measurements. In the present study, we directly compared continuous and discrete selection accounts with a more temporally sensitive measure. Specifically, we assessed changes in attentional selectivity with real-time movement trajectories.

Tracking the dynamics of movements has emerged as a promising tool for investigations into the temporal nature of a broad range of cognitive domains (Spivey et al., 2005; Hehman et al., 2014a; Freeman & Ambady, 2011). One popular implementation of this technique is called mouse-tracking (Freeman, 2018; Magnuson, 2005). As the hand moves to select a response (as opposed to an all-or-none button-press), its real-time location, velocity, and acceleration are recorded until a choice is reached. Information regarding the movement's trajectory can then be examined to infer how the decision emerged. For example, a movement trajectory's spatial attraction (i.e., curvature) toward the distractor response may provide valuable information about the degree of competition among ongoing cognitive processes (Spivey et al., 2008). Additionally, temporal metrics such as movement velocity may be used to explore the time at which there is response competition or activation (for a review, see Hehman et al., 2014b). For example, peak velocity may index the amount of response activation at different time points during response selection (Duran et al., 2010). Whereas RT may reveal differences in overall processing speed, examining mouse trajectories can reveal changes in velocity toward multiple response options over time. Crucially, mouse-tracking can also be informative of response selection processes by

identifying changes in the movement's path (e.g., continuous or discrete-like), relative to its proximity to the target and distractor response locations (e.g., Freeman, 2014). Therefore, measuring mouse trajectories serves as an ideal candidate for differentiating discrete and continuous accounts of attentional selectivity.

In the following experiment, we used mouse-tracking to record real-time movement trajectories in a flanker task. Specifically, we asked participants to move a mouse-cursor to one of two response locations based on the identity of a target. First, we examined whether mouse-tracking measures would replicate the flanker congruency effect commonly found with RT. We predicted that mouse-tracking measures, due to their enhanced spatial and temporal resolution, would be as or more sensitive than RT for detecting the flanker congruency effect. To directly test continuous versus discrete selection, we examined mid-flight characteristics of movement trajectories. According to continuous selection, competition between the distractor and target should be resolved continuously over time, resulting in movement trajectories that gradually transition toward the target response. According to discrete selection, competition should be resolved by discrete activation of the target and suppression of the distractor, resulting in movement trajectories that exhibit an abrupt, mid-flight correction toward the target. Finally, we used an exploratory data analysis approach to examine whether gradual or abrupt trajectories may be associated with fluctuations in attention (e.g., fatigue). To preview our main results, we found evidence to support a continuous process of spatial selective attention: Spatial and temporal movement dynamics were strongly representative of a gradual path toward the target.

Methods

Participants

Twenty-four undergraduate students (15 female) ranging from 18 to 30 years of age ($M = 19.7$) from the University of Tennessee, Knoxville participated in this study. Three additional participants were enrolled but were dropped because they did not complete the study due to technical malfunctions. To calculate the required sample size, we conducted a pilot study ($N = 5$) with a similar flanker task used in this experiment, except with different target-distractor color combinations (e.g., a yellow target and red distractors)¹. Power analyses were run with the MorePower 6.0 program (Campbell & Thompson, 2012). Results showed that for a one-factor, 3-level within-subjects design, we needed a minimum of 24 participants to achieve a power of .95 to detect an RT effect of $\eta_p^2 = .256$. We also conducted an additional a priori power analysis that showed we needed a minimum of 12 participants to detect an area under the curve (see Mouse-tracking data preprocessing) effect of $\eta_p^2 = .434$. We chose a sample size of 24 participants as it was the more conservative estimate between the two power analyses. Participants provided informed consent, completed a demographics survey upon arrival and were compensated with course credit upon completion. The University of Tennessee Institutional Review Board approved the study's protocol.

¹ While pilot studies may lead to unstable effect sizes for power calculations, we opted to conduct a pilot study to estimate our required sample size for two reasons. First, typical flanker RT effects in the literature are very large (e.g., $\eta_p^2 = .88$; Hübner & Töbel, 2012, Experiment 1) which would result in small sample size estimates (e.g., $N = 4$) to achieve .95 power. Second, our mouse-tracking design is novel in the context of the flanker task; therefore, the similar design of our pilot study provided more compatible effect sizes for our power analysis. We note that the effect sizes found in the pilot study were overall smaller than those found in our study, suggesting that our power calculation was rather conservative.

Apparatus and stimuli

Participants were seated approximately 60 cm from a 23-inch LCD computer monitor with a resolution of 1920 x 1080 and a refresh rate of 60Hz. The MouseTracker software (Freeman & Ambady, 2010) was used for stimulus presentation and for recording the x, y coordinates of the mouse cursor on the screen at a sampling rate of approximately 60-75Hz. Participants began each trial by clicking on a “Start” button, which subtended $\sim 4.9 \times 1.7$ degrees of visual angle (dva). A fixation cross that subtended $\sim 0.45 \times 0.45$ dva was presented at the center of the screen at the start of each trial. The response locations were marked by white rectangles that subtended $\sim 7.2 \times 3.5$ dva at the top-left and top-right corner of the screen. Stimuli for the flanker task were discs that varied in color. We used color space metrics to control for the distance and relationship between the target and flanker stimuli. Target stimuli were either yellow (RGB: 178, 178, 53) or blue (RGB: 53, 53, 178) discs, and were 180° apart in HSV color space. Flanker stimuli (distractors) were either yellow, blue, or black discs. Each disc had a diameter of ~ 1.5 dva. Stimuli were presented on a gray (RGB: 148, 148, 148) background. The target and flanker stimuli were presented in a horizontal array subtending ~ 8.5 dva centered on the screen.

Design and procedure

Participants initiated each trial by clicking on a “Start” button at the center bottom of the screen (Fig. 2a). After trial initiation, a fixation cross was presented at the center of the screen for 250 ms, followed by the presentation of five circular stimuli arranged horizontally for the duration of the trial. The central stimulus served as the target, and the surrounding stimuli were distractors. The color of the target stimulus corresponded to one of the two response locations (stimulus color and response location pairing was counter-balanced across participants), located

in the upper-left and upper-right corners of the screen. Therefore, we used a 1-1 mapping of stimuli onto responses, as is common in previous studies testing continuous and discrete selection (e.g., White et al., 2011; Hübner & Töbel, 2012; White et al., 2018).

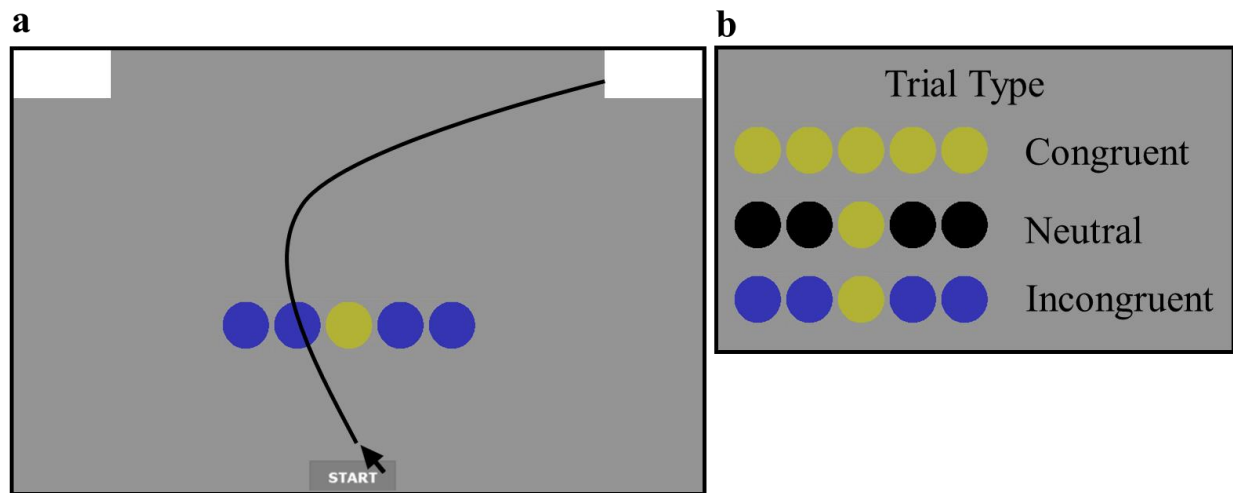


Fig 2. Flanker task design used in the current experiment. **a.** Participants initiated each trial by clicking on the “Start” button. A central target object was then presented. In this example, yellow is associated with the top-right response location (i.e., target location). **b.** Flankers surrounding the central target object could be associated with the same (congruent) response, with the opposite (incongruent) response or be unrelated (neutral).

Participants were instructed to attend to the color of the target stimulus while ignoring the color of the distractors. The target stimulus was flanked by distractor stimuli that were either the same color (congruent), the color that was mapped to the opposite response location (incongruent), or black (neutral; see Fig. 2b). Target-distractor congruity was randomly mixed with 144 trials per trial type, resulting in 432 trials total. The task was administered in three blocks of 144 trials with an equal number of trials per trial type in each block. Participants were offered a break in between blocks. Participants were encouraged to initiate moving the mouse cursor as quickly as possible after trial onset, with instructions to begin moving even if they were still undecided on which response location to select. A warning signal was presented at the end of the trial if participants were too slow to initiate movement (more than 400ms), stating “Please start moving earlier, even if you are not fully certain of a response yet!”. As is standard in the

mouse-tracking literature (e.g., Freeman & Ambady, 2009), this was done to ensure movements coincided with ongoing selective attention processes (also see data preprocessing for exclusion criteria), as opposed to participants having decided which response to select before initiating a movement. Inter-trial intervals depended on the pace of the participant (i.e., the amount of time to press the “Start” button to initiate each trial), but we implemented a minimum inter-trial interval of 1s. Altogether, the session lasted approximately 25 minutes.

Mouse-tracking data preprocessing

Movement trajectories along the x and y axes were rescaled into a standard coordinate space (bottom left: [-1,0]; top right: [1,1.5]). Trajectories to the left response location were remapped to the right location, resulting in the overlay of all trajectories to the same response location. We extracted both spatial (e.g., proximity to the target and distractor response locations) and temporal (e.g., velocity and acceleration along the x-axis) mouse-tracking data for our analyses. For spatial analyses, trajectories were normalized into 101 time-steps to allow for comparisons across trials of different lengths. We calculated average trajectories for each trial type by averaging the x and y coordinates of the mouse cursor at each time step (see Freeman & Ambady, 2010 for more information on mouse-tracking preprocessing). We examined the area under the curve (AUC) as our measure of trajectory curvature, or degree of spatial attraction. AUC was calculated separately for each trial by taking the geometric area under the observed response trajectory in relation to the idealized trajectory (i.e., a straight path from the “Start” location to the target response location). As a result, AUC quantifies the extent to which the observed trajectory deviated from the idealized trajectory path. We also calculated the maximum deviation of each trajectory, or the peak perpendicular deviation away from the idealized path to the target response location. For temporal analyses, we generated 22 bins consisting of 60 ms

each to capture a time window of up to approximately two standard deviations above the mean RT. On each trial, we calculated the bin at which maximum x-coordinate velocity toward the target location occurred.

Incorrect trials were excluded from the RT and movement trajectory analyses (0.5% of trials). Additional trials were excluded if RT was two standard deviations above the mean (longer than 1326 ms, $M = 833.62$ ms; 3% of trials), if movement initiations were slower than two standard deviations above the mean (longer than 387 ms, $M = 147.8$ ms; 2.5% of trials), or if the area under the curve was two standard deviations above or below the mean (more than 3.4 or less than -1.9, $M = 0.77$; 8% of trials). Thus, a total of 8,935 trials were included in the following analyses (87% of total trials), with an average of 372 trials per participant. All data and materials have been made publicly available and can be accessed at <https://osf.io/ysqfv/>

Results

We first report the effects of trial type on traditional outcome-based measures (RT and accuracy) in addition to spatial and temporal mouse-tracking measures in the flanker task. For these analyses, we ran one-factor repeated measures ANOVAs with three levels (congruent, incongruent, neutral) to test the effects of trial type on accuracy, RT, maximum velocity time, and AUC. We then shift to our primary focus and test predictions of the continuous and discrete selection accounts of attentional selectivity. To do that, we compared spatial and temporal mouse-tracking measures for trajectories that exhibit mid-flight continuous and discrete-like transitions. In the following analyses, all pairwise comparisons were corrected with Bonferroni-Holm correction.

Outcome-based analyses

Accuracy and reaction time. Overall accuracy in the flanker task was high ($M = 99.5\%$). There was no effect of trial type on accuracy, $F < 1$. There was a significant effect of trial type on RT (Fig. 3a), $F(2,46) = 72.3$, $p < .001$, $\eta_p^2 = .759$. Pairwise comparisons showed that RTs on incongruent trial ($M = 821$ ms) were significantly longer than on both congruent ($M =$

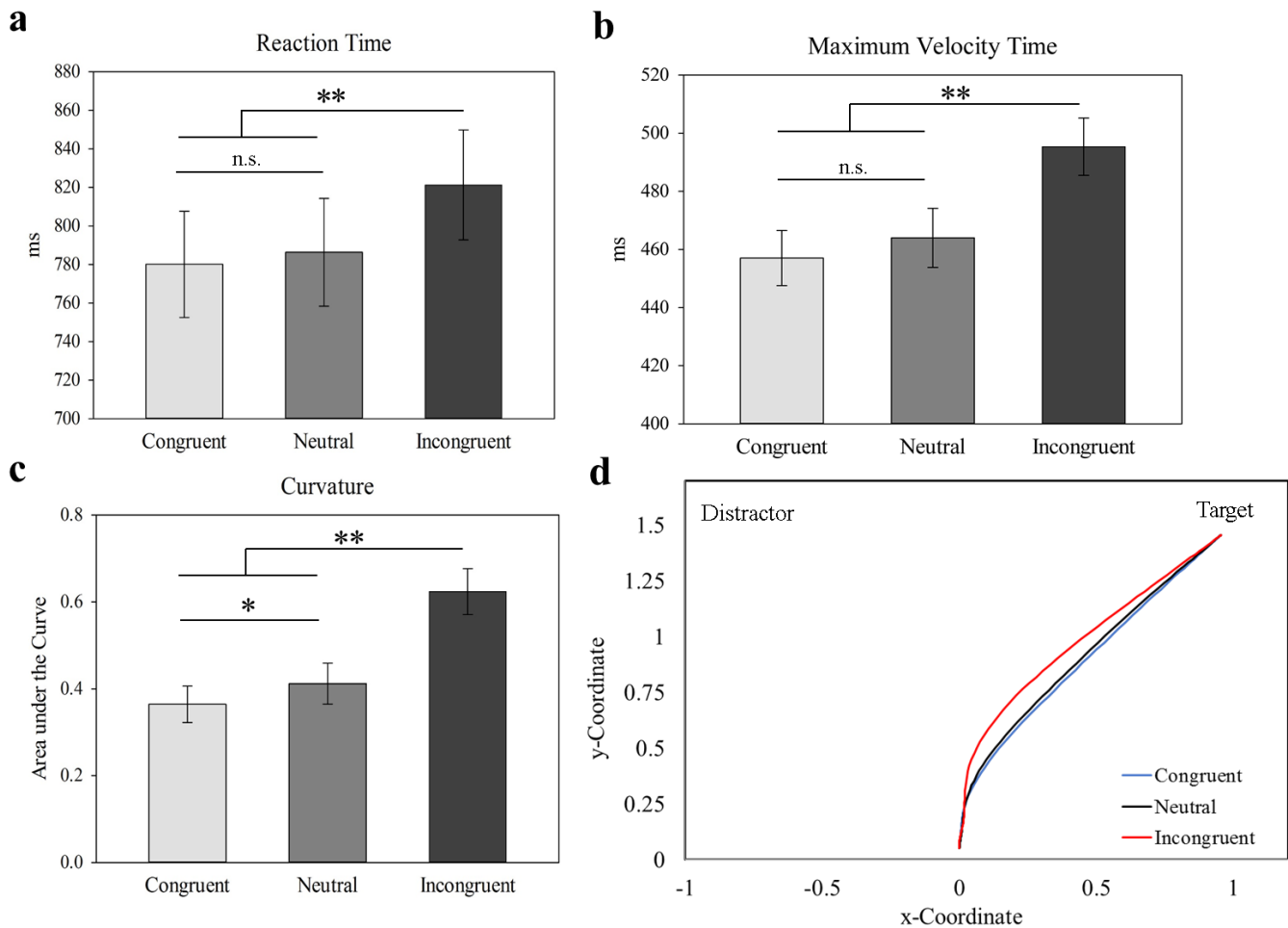


Fig 3 Outcome-based and mouse-tracking results. **a.** Reaction times plotted as a function of trial type. **b.** Maximum x-coordinate velocity plotted as a function of trial type. **c.** Curvature as measured with area under the curve plotted as a function of trial type. **d.** Mean trajectories for each trial type. In each data figure, error bars display the standard error of the mean (SEM). * $p < .05$, ** $p < .01$.

780 ms, $p < .001$) and neutral trials ($M = 786$ ms, $p < .001$). RTs did not significantly differ between the congruent and neutral flankers ($p = .265$).

Mouse-tracking analyses

Temporal dynamics. There was a significant effect of trial type on the time at which maximum x-coordinate velocity occurred, $F(2,46) = 97.16, p < .001, \eta_p^2 = .809$ (Fig. 3b). Maximum velocity occurred significantly later for incongruent ($M = 495$ ms) compared to congruent ($M = 457$ ms, $p < .001$) and neutral trials ($M = 464$ ms, $p < .001$). Participants reached maximum movement velocity earlier on congruent than on neutral trials, but this effect was not significant ($p = .064$).

Spatial attraction. We found a significant main effect of trial type on AUC, $F(2,46) = 53.4, p < .001, \eta_p^2 = .710$ (Fig. 3c). Pairwise comparisons revealed AUC was significantly larger for incongruent ($M = 0.626$) than both congruent ($M = 0.364, p < .001$) and neutral trials ($M = 0.413, p < .001$). Further, AUC was significantly larger for neutral than congruent trials ($p = .015$). Mean trajectories for each trial type are shown in Figure 3d.

Our mouse-tracking results replicated the flanker congruency effect commonly found in manual response settings, such that incongruent trials elicited distractor interference, indicated by greater AUC and more time to reach maximum movement velocity. We also note that our RT results replicated the flanker congruency effect (Eriksen & Eriksen, 1974), in which incongruent trials had longer RTs than congruent and neutral trials. However, we did not find an effect of trial type on accuracy, possibly because our mouse-tracking design allowed more time for participants to make their response decisions compared to responses collected with button presses. In fact, the average RTs in our study were 833 ms, while average RTs in studies using button presses are typically in the range of 400-500 ms (e.g., Eriksen & Eriksen, 1974; Hübner & Töbel, 2019).

Interestingly, we found a facilitation effect with AUC (less curvature for congruent than neutral trials) but not for RT and maximum velocity time. We note that we are not the first to show a curvature effect in the absence of an RT effect (e.g., Stillman et al., 2017; Wojnowicz et al., 2009). To our knowledge, however, these are the first data to show a facilitation effect in the flanker task with AUC but not with RT. These results suggest that AUC may have greater sensitivity to detect distinct differences in selective attention processes, even when RT and maximum velocity time indicate similar temporal dynamics. The offloading of selective attention processing into the path of the trajectory, rather than an outcome-based measure, may identify additional details about information processing. While the facilitation effect is beyond the scope of this paper, this finding adds to a growing literature demonstrating that continuous measures are capable of exposing fine-grained information about cognition (e.g., Stillman et al., 2017). Future research may benefit from using continuous mouse-tracking measures to investigate the selective attention dynamics underlying facilitation and interference. In the next section, we focus on examining whether movement trajectories in the flanker task provide evidence for continuous or discrete changes in attentional selectivity.

Continuous versus discrete selection analyses

The following analyses tested predictions of continuous and discrete selection accounts. First, we calculated the number of trials in which movement trajectories reflected either gradual (as predicted by continuous selection) or abrupt (as predicted by discrete selection) mid-flight transitions away from the distractor location and toward the target location. We then compared movement velocity profiles and the frequency of these types of trajectories across trial types. We also examined whether changes in attention over the course of the task were associated with gradual or abrupt trajectories. Lastly, we tested an important assumption of the discrete selection

account: The strength of distractor interference should depend on when during a trial attentional selectivity increases.

Assessing gradual versus abrupt trajectories. First, we assessed whether trajectories gradually (continuous selection) or abruptly (discrete selection) transitioned toward the target response location. We first focused on trajectory divergences in incongruent trials since these trials should provide the most sensitive measure of overcoming distractor interference. For each

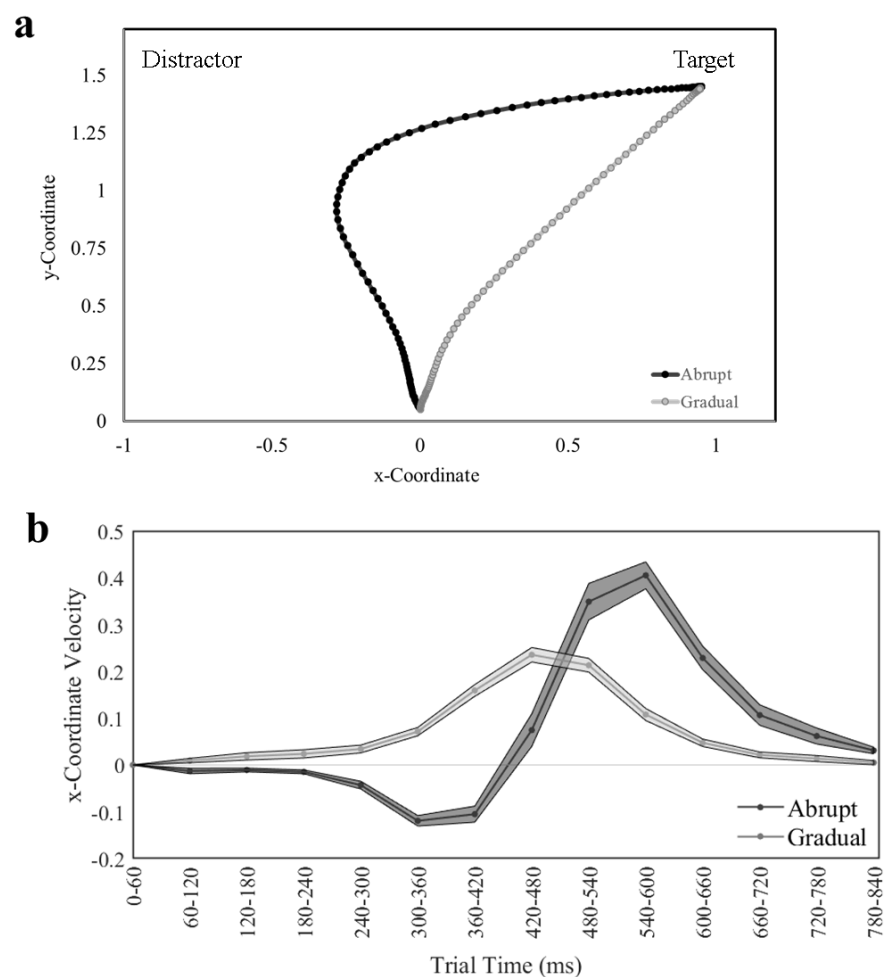


Fig 4. Characteristics of gradual and abrupt trajectories on incongruent trials. **a.** Mean trajectories for trials that exhibited abrupt shifts and gradual changes toward the target response location. **b.** Velocity profiles for gradual and abrupt trajectories. Positive x-Coordinate velocity values indicate movement toward the target response, whereas negative values indicate movement toward the distractor response. Filled-in area represents the standard error of the mean at each time bin.

trajectory, we calculated maximum deviation as the peak perpendicular deviation between the actual path of the trajectory and the idealized path to the target response location. We then applied a threshold to maximum deviation to quantitatively code trajectories as abrupt ($> .9$ maximum deviation) or gradual ($< .9$ maximum deviation). These criteria are based on previous research, showing that this maximum deviation threshold was in high agreement with manually coding trajectories as gradual or abrupt (Freeman, 2014). The majority of incongruent trials exhibited gradual trajectories (84.4%) as opposed to abrupt trajectory shifts (15.6%, see Fig. 4a). For comparison, the majority of congruent and neutral trials also exhibited gradual trajectories (92.5% and 90.9%, respectively). Additionally, across participants the majority of incongruent trials displayed gradual trajectories (range: 72% - 97%). Thus, most movement trajectories on incongruent trials displayed gradual changes in trajectory, consistent with the continuous selection account. However, our data also showed that a subset of trials displayed abrupt shifts. Next, we attempted to further characterize these relatively infrequent occurrences of abrupt shifts.

Analysis of movement velocity has been shown to provide valuable information on the temporal dynamics of target and distractor response selection and competition (e.g., Wojnowicz et al., 2009; Duran et al., 2010). Therefore, we used movement velocity profiles to examine changes in selective attention processing between gradual and abrupt trajectories. Specifically, we expected that abrupt trajectories would reach peak velocity toward the distractor location at an earlier time point compared to gradual trajectories, indicative of uniquely strong and early distractor interference on these trials. Following the analysis approach of Freeman (2014), we examined x-coordinate movement velocity profiles between 0 and 840 ms (approximate mean RT) in bins of 60 ms. We ran Bonferroni-Holm corrected paired-sample t-tests to compare the x-

coordinate velocities between trajectories characterized as abrupt and gradual for each bin separately. Gradual trajectories moved toward the target location throughout the trial, showing no divergence toward the distractor location. Abrupt trajectories, on the other hand, moved toward the distractor location early in the trial (60-420 ms), then sharply and quickly shifted direction toward the target location (see Fig. 4b)². Comparisons of velocities between the abrupt and gradual trajectories revealed a significant difference for all bins, except the two earliest bins between 0-60 ms ($p = .678$) and 60-120 ms ($p = .037$).

One explanation for our movement velocity findings is that distractor interference was strong early in the trial, and the reversal back toward the target reflects the engagement of selective attention to suppress processing of the distractor. From this perspective, abrupt trajectories should be more likely to occur when there is distractor interference (i.e., incongruent trials). To test whether the frequency of abrupt trajectories was dependent on trial type, we ran a chi-square test of independence. The results showed that the frequency of abrupt trajectories significantly differed across trial types, $\chi^2(2) = 116.24, p < .001$ (see Fig. 5). Bonferroni-corrected post hoc comparisons (p threshold = .016) revealed that there were more abrupt trajectories for incongruent trials than congruent ($p < .001$) and neutral ($p < .001$) trials. The number of abrupt trajectories did not significantly differ between congruent and neutral trials ($p = .023$). Together, these results suggest that abrupt trajectories were more likely to occur when there was distractor interference. This explanation would be consistent with the discrete model of selective attention. Interestingly, however, abrupt trajectory shifts were not exclusive to incongruent trials. Although less frequent than incongruent trials (15.6%), we also found abrupt

² See Supplemental Materials for an RT analysis of gradual and abrupt trajectories

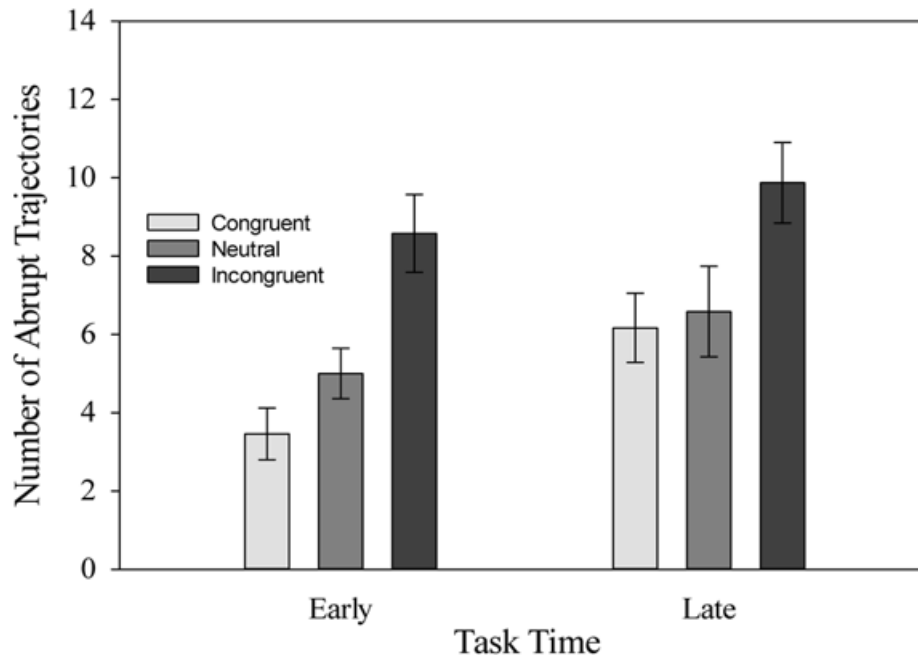


Fig 5. The number of abrupt trajectories plotted as a function of task time (early: the first 216 trials and late: the last 216 trials) and trial type. Error bars display SEM.

trajectories on a small number of trials for congruent (7.5%) and neutral conditions (9.1%), indicating that abrupt shifts cannot be simply explained by distractor interference.

Given the prevalence of abrupt trajectories across all trial types, including trials in which no distractor interference was present, we next examined whether more global aspects of the task are associated with the frequency of abrupt trajectories. For instance, abrupt trajectories may be due to a lapse in attention which leads to movement trajectories on a subset of trials to initially proceed unguided by stimulus processing. In this case, we would expect a higher prevalence of abrupt trajectories later in the experiment as attention becomes fatigued (e.g., Boksem et al., 2005; Faber et al., 2012). Alternatively, we might find that attention improves as participants gain experience in the task. That is, strong distractor interference early in the experiment could result in fewer abrupt trajectories as the experiment progresses (e.g., Vatterott et al., 2018). Lastly, it may be that attentional selectivity fluctuates throughout the experiment leading to

similar number of trials with abrupt trajectories throughout the experiment (e.g., deBettencourt et al., 2018). To test whether abrupt trajectories occurred more frequently in the early (i.e., the first 216 trials) or late (i.e., the last 216 trials) stage of the flanker task, we ran a chi-square test of independence. The results showed that the frequency of abrupt trajectories significantly differed based on task time, $\chi^2(1) = 23.48, p < .001$ (see Fig. 5). There were more abrupt trajectories in the late stage than in the early stage of the flanker task. This increase in abrupt trajectories across task time was significant for congruent, $\chi^2(1) = 19.77, p < .001$, and neutral trials, $\chi^2(1) = 7.05, p = .008$, but not for incongruent trials, $\chi^2(1) = 2.93, p = .08$. These results suggest lapses in attention increased over the course of the experiment, potentially due to factors such as fatigue or boredom, resulting in an increased number of trials with abrupt trajectories.³

Testing assumptions of discrete selection. Theoretically, discrete selection should produce an abrupt trajectory. However, we found that abrupt trajectories are infrequent (10.74%) and are associated with other factors related to lapses in attention. The majority of trials instead favored continuous selection (89.26%), displaying gradual movement trajectories. To better characterize the nature of abrupt trajectories and to comprehensively examine the assumptions of discrete selection, we ran an additional analysis on the relationship between AUC and the time point at which abrupt trajectories changed direction. This test is based on the assumption of discrete selection accounts that attention shifts to a highly selective state at an abrupt time point. Based on this assumption, discrete selection would occur when the response trajectory deviates most from the direct path to the target location (the maximum deviation point; Fig. 6). That is, attention is initially diffuse, allowing interference from flankers, which results in manual

³ See Supplemental Materials for additional task phase results, which include AUC, RT, and accuracy findings.

responses to move toward the distractor location. Later in the trial, at a discrete point in time, attention becomes highly selective, only allowing for the processing of target information in which the movement changes its course toward the correct target location. According to discrete selection accounts, the strength of distractor interference should be related to the amount of time spent in a low state of attentional selectivity, where distractor information strongly influences processing. That is, more time spent before the discrete shift (maximum deviation point) to high selectivity should be associated with greater curvature toward the distractor location.

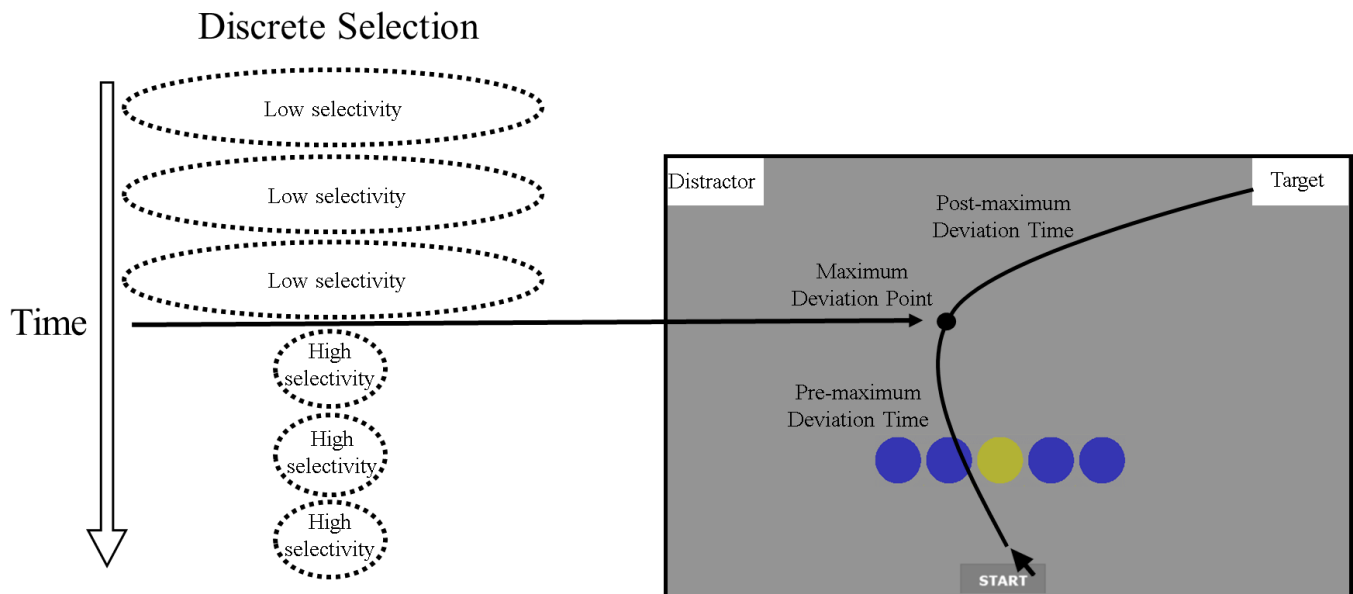


Fig 6. We characterized the time point at which attentional selectivity supposedly transitions from a low- to a high-state of selectivity (i.e., the time at which the discrete shift occurred, according to discrete selection) as the maximum deviation point (black dot).

For this analysis, we only included incongruent trials because they directly induce distractor interference. We also excluded trials in which the trajectory curved maximally toward the target location (21.7%) as opposed to toward the distractor location, because the maximum deviation point on these trials did not indicate distractor interference. To test whether AUC is related to the duration of time before a shift toward the target occurred, we first calculated the proportion of trial time spent before the maximum deviation point for each incongruent trial's

trajectory. Next, we performed a tri-median split to categorize trials as having either a high or low proportion of time spent pre-maximum deviation. We chose to trichotomize the data to directly compare trials with substantially high and low time spent pre-maximum deviation above or below the median, respectively (but see Supplemental Materials for results obtained with a regression analysis). We then ran a paired-sample *t*-test to compare AUC between trials that were categorized as having low ($M = 365.04$ ms) and high ($M = 486.09$ ms) proportions of time spent pre-maximum deviation. Discrete selection accounts would predict that AUC for trials that had a high proportion of pre-maximum deviation time would be significantly larger than AUC for trials that had a low proportion of time spent pre-maximum deviation. Contrary to this prediction, however, AUC did not significantly differ for trajectories that had a low ($M = 0.84$) or high ($M = 0.67$) proportion of trial time spent pre-maximum deviation, $t(23) = 1.69$, $p = .102$, $d = 0.72$ (Fig. 7), indicating that the strength of distractor interference was not affected by the

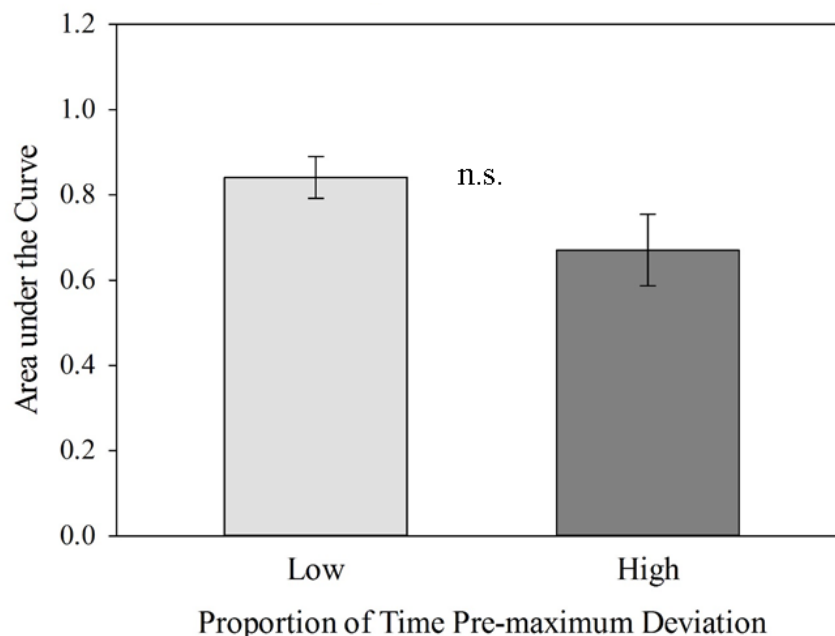


Fig 7. Curvature results (area under the curve) for incongruent trials that had a low proportion of pre-maximum deviation time compared to trials that had a high proportion of pre-maximum deviation time. Error bars display SEM.

amount of time spent before an abrupt trajectory shift occurred. Bayes factor indicated anecdotal evidence in favor of the null hypothesis $BF_{01} = 1.73$ (Keysers et al., 2020).

Discussion

The present study examined how attentional selectivity improves over the time course of response selection. We employed a novel approach to uncovering the temporal dynamics of attentional selectivity using mouse-tracking in the context of a flanker task. We conducted several analyses to test for continuous and discrete changes in attentional selectivity and found strong evidence in favor of continuous dynamics in the deployment of selective attention. First, we quantified spatial aspects of movement trajectories to characterize movement toward the target response as unfolding either gradually or abruptly, consistent with continuous and discrete selection, respectively. The analysis of gradual versus abrupt trajectories revealed that the majority of trajectories were representative of paths that gradually moved toward the target response location.

Although we found that most trajectories were characterized as gradual, strongly supporting continuous selection, we also found that abrupt trajectory shifts occurred on a small subset of trials. Consistent with previous research (Barca & Pezzulo, 2015; Freeman, 2014), we found that these trajectories with abrupt shifts were associated with early increases in movement velocity toward the distractor location, followed by a sharp increase in movement velocity toward the target location. These movement dynamics suggested that abrupt trajectories resulted from strong, early activation of the distractor. Accordingly, we also found that abrupt trajectory shifts occurred more often when distractor information was directly linked to the distractor location (incongruent trials). These results are in line with those of Freeman (2014), which found

that the likelihood of abrupt trajectories increased as competition between the stimulus and response alternatives increased.

We explored three possible reasons for these abrupt trajectory shifts that did not involve discrete selection processes: attentional fluctuations that occur early in the task, late in the task due to fatigue or boredom, or throughout the task. We found significantly more abrupt shifts during the last half of the flanker task compared to the first half. Therefore, one possible explanation for abrupt shifts is that mental fatigue negatively affected attention, leading to more decisive, early movements toward the distractor location as the task progressed. Indeed, it has previously been shown that mental fatigue can impair visual selective attention (Faber et al., 2012). It is important to note that we found significantly more abrupt shifts as the task progressed despite the short duration of our experiment (~25 minutes). Flanker task research has also shown that mental fatigue is typically associated with increased error rates (Csathó et al., 2012), which we also found in our experiment (see Supplemental Materials). Thus, the abrupt trajectory shifts we observed may have resulted from a lapse in attention at the start of the trial followed by a large corrective movement to the target location once selective attention was finally engaged. That view is consistent with our movement velocity findings discussed above, in which the distractor is strongly represented at the beginning of the movement, before sharply reversing toward the target location. Another possibility is that muscle fatigue led to abrupt trajectory shifts. Huysmans et al. (2008) found that a muscle fatigue intervention during a mouse-tracking task promotes movements that are further from the target with higher variability, and, importantly, with larger corrective shifts back toward the target. Thus, it is also possible that muscle fatigue in our mouse-tracking paradigm may have led to movement errors that presented as abrupt trajectories. Whether it may be due to mental or muscle fatigue, boredom, or other

fluctuations in attention, our results indicate that abrupt shifts were associated with trials in later stages of the flanker task and early, decisive movement toward the distractor.

We highlight again that the characteristics of trajectories strongly favored continuous selection, yet a small portion of trials still required an abrupt shift to suppress distractor interference. While we found evidence to suggest that abrupt shifts may have been the result of attentional lapses (e.g., fatigue or boredom) on those trials, we ran an additional analysis to test whether signatures of discrete selection are evident in abrupt trajectories. Specifically, we tested a key assumption of discrete selection: The strength of attentional selectivity should vary before and after a discrete point in time. We used the mouse-tracking measure of maximum deviation time as the time point of a discrete shift in attention to calculate the amount of trial time spent pre-maximum deviation. We found that the proportion of trial time spent pre-maximum deviation, or in a supposedly low state of attentional selectivity, did not affect the amount of distractor interference as measured with AUC, providing no evidence for the idea of two distinct states of attentional selectivity. A potential limitation of these exploratory analyses is that our power analysis was directly applied to capture the congruency effect. Although our pilot study had smaller effect sizes for RT and AUC than those in the current study, suggesting that our sample size estimates were most likely conservative, it remains a possibility that our exploratory analyses were underpowered to detect meaningful effects. It is an important avenue for future studies to investigate the effect of time before maximum deviation on the amount of curvature and how it relates to selective attention processes.

The aim of the current study was to examine spatial attentional selectivity processes in the flanker task, due to the focus of conflict diffusion models on this task for differentiating continuous and discrete selection (e.g., White et al., 2011; Hübner & Töbel, 2012). Therefore,

our results account for changes specifically in spatial selective attention, but it is an open question whether similar dynamics are at play when selective attention is not spatially distributed (e.g., the Stroop task). In future work, mouse-tracking data could be informative for examining whether the dynamics of attentional selectivity identified here generalize across selective attention tasks, or whether continuous or discrete selection processes are recruited depending on the type of selective attention.

Conclusion

In sum, the present study used a novel approach to address the widely raised question of how selective attention changes over response selection. The dominant theories of selective attention have debated whether selectivity unfolds as a continuous or discrete process; however, to-date these accounts have each successfully explained empirical data. The traditional approach to differentiating between continuous and discrete selection accounts relies on outcome-based measures that have limited temporal sensitivity. By examining real-time movement measures with mouse-tracking in the flanker task, we found strong evidence in favor of the continuous selection account of attentional selectivity.

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