

Past Experiences Shape Attentional Priorities: The Combined Effects of Reward and Statistical Learning

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Abstract

Visual attention is guided not only by bottom-up capture and top-down control, but also by selection history – comprising multiple mechanisms that influence attentional control (AC) based on prior experience with stimuli. We specifically focus on two mechanisms of selection history: reward learning (RL), guiding attention via stimulus-reward associations, and statistical learning (SL), guiding attention based on frequently encountered patterns in the environment. Although both mechanisms influence AC, it remains unclear how they jointly shape attentional prioritization when associated with the same stimulus. The present study investigates whether RL and SL exert additive or interactive effects on AC when converging on the same target feature and whether one mechanism influences attentional prioritization more strongly than the other. Participants completed a visual search task in which they identified a target based on its orientation while the target color was associated with a unique combination of reward magnitude and presentation frequency. Results showed faster response times (RT) for high-reward and high-frequency target colors. Importantly, the effects of RL and SL interacted, producing the fastest RTs in trials in which the target color was related to both a high reward and a high frequency. Together, these findings suggest that RL and SL can jointly shape attentional prioritization, but not necessarily in an independent way. Instead, we argue that their influence appears to depend on how learned associations are represented within the visual context. The results contribute to a more nuanced understanding of how multiple forms of selection history jointly guide attention in complex visual environments.

Nederlandse Samenvatting

Visuele aandacht wordt niet enkel geleid door bottom-up- of top-down-geleide processen, maar ook door selectiegeschiedenis – wat mechanismen omvat die aandachtscontrole (AC) beïnvloeden op basis van eerdere ervaringen met stimuli. We focussen op twee mechanismen die onder selectiegeschiedenis vallen: beloningsleren, waarbij aandacht wordt gestuurd via associaties tussen prikkels en beloningen, en statistisch leren, waarbij de aandacht wordt gestuurd op basis van veelvoorkomende patronen in de omgeving. Hoewel beide mechanismen AC beïnvloeden, blijft het onduidelijk hoe ze gezamenlijk de prioriteit van aandacht bepalen wanneer ze met dezelfde stimulus worden geassocieerd. De huidige studie onderzoekt of beloningsleren en statistisch leren additieve of interactieve effecten op AC uitoefenen wanneer ze op hetzelfde kenmerk van een doelstimulus convergeren en of het ene mechanisme een sterkere invloed heeft op AC dan het andere. Deelnemers voltooiden een visuele zoektaken waarin ze een doel identificeerden op basis van de oriëntatie ervan, terwijl de kleur van het doel werd geassocieerd met een unieke combinatie van beloningsgrootte en presentatiefrequentie. Resultaten toonden snellere reacties aan voor doelen met een hoge beloning en frequentie. Belangrijk is dat de effecten van beloningsleren en statistisch leren elkaar beïnvloedden, wat de snelste reactietijden opleverde voor doelen met zowel een hoge beloning als een hoge frequentie. Deze bevindingen suggereren dat beloningsleren en statistisch leren gezamenlijk de prioriteit van aandacht bepalen, maar dat dit niet noodzakelijkerwijs op een onafhankelijke manier gebeurt. In plaats daarvan stellen we dat hun gezamenlijke invloed lijkt af te hangen van hoe de geleerde associaties zich tot elkaar verhouden in de visuele scène. Deze resultaten dragen bij aan een genuanceerd begrip van hoe verschillende bronnen van selectiegeschiedenis aandacht sturen in complexe visuele omgevingen.

Word of Thanks

Writing this dissertation marks the final stage of my studies. Although this was challenging at times, I feel relieved by the support and encouragement I received. I would therefore like to take this opportunity to express my sincere gratitude to everyone who contributed to this work.

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Visual environments contain more information than the human cognitive system can process at once. To navigate this complexity, visual attention serves as a critical filtering mechanism, prioritizing the most relevant sources of information. This enables efficient perception and behavior (Chun et al., 2011; McMains & Kastner, 2009). As a form of selective attention, visual attention enhances the processing of goal-relevant visual stimuli while actively suppressing distracting or irrelevant inputs (McMains & Kastner, 2009; Stevens & Bavelier, 2012; Wolfe & Horowitz, 2004). Imagine driving home along a busy road. Visual attention is utilized to prioritize goal-relevant stimuli such as traffic signals and crossing pedestrians, in a background of excessive information. This selective filtering of visual information allows completing the task at hand: getting home without accidents. The mechanism directing visual attention toward relevant stimuli is called attentional control (AC). Traditionally, AC has been thought to be driven by two concurrent mechanisms: bottom-up capture, directing attention automatically to salient features (Theeuwes, 2010), and top-down control, directing attention based on goals, prior knowledge, and task demands (Bundesen, 1990; Chun et al., 2011; Corbetta & Shulman, 2002). While influential, this dichotomy fails to capture all ways in which AC can be guided (Abbasi et al., 2022).

A growing body of research highlights a third source of AC that can be simultaneously present with bottom-up and top-down AC: selection history (Table 1). Prior experience with stimuli can automatically bias AC in ways that are not reducible to top-down or bottom-up AC, and its effects persist beyond the context in which that experience was established (Anderson, 2016; Anderson & Yantis, 2013; Awh et al., 2012; Buschman & Kastner, 2015; Failing & Theeuwes, 2018). Importantly, selection history is not a unitary construct: different forms of prior experience, such as previously reinforced selection of stimuli or repeated exposure to stimuli, are believed to represent distinct selection history mechanisms that can

influence AC (Anderson, 2024). Although the influence of selection history on AC is well established, it remains unclear how different selection history mechanisms interact when they are simultaneously present – an important question, given that real-world visual scenes often contain multiple co-occurring learned regularities.

Table 1

Brief overview of findings suggesting independent effects of selection history

Reference	Finding
Anderson et al. (2012)	Previously rewarded features capture attention involuntarily, despite being perceptually non-salient.
Le Pelley et al. (2015)	Previously rewarded features capture attention involuntarily, despite being task-irrelevant.
Failing and Theeuwes (2018)	These effects (Le Pelley et al., 2015) persist even under explicit instructions to ignore reward-related features.
Wang et al. (2013), Le Pelley et al. (2016)	Features associated with punishment are suppressed, attracting less attention.
Wang and Theeuwes (2018)	Targets appearing frequently at a specific location are detected more rapidly, even when spatial probability is irrelevant to the task.
Gaspelin and Luck (2019), Vatterott and Vecera (2012), Zehetleitner et al. (2012)	Distractors recurring frequently in the same color are suppressed, drawing less attention. Even when their physical appearance remains unchanged.
Jiang et al. (2013), Wang et al. (2019)	Distractors recurring at a predictable location are suppressed, drawing less attention. Even when their physical appearance remains unchanged.
Dolci et al. (2024)	Although goals dominate over repeatedly encountered patterns, participants benefited from experience with these patterns in homogeneous displays (absence of salient targets).
Gao & Theeuwes (2020)	Although goals dominate over repeatedly encountered patterns, if there is a reliable cue predicting the target location (Dolci et al., 2023), participants still leverage statistical properties of the search display and ignore the cue if it is not 100% reliable.

Note. This table summarizes empirical findings that highlight the influence of selection history on AC, in addition to traditional bottom-up and top-down mechanisms. These results underscore the importance of

considering selection history as a distinct factor in models of attentional guidance, particularly where effects cannot be fully accounted for by salience-driven or goal-directed processes.

The Role of Selection History in Attentional Control: Insights from the Priority Map Model

One influential framework for understanding how different selection history mechanisms, along with top-down and bottom-up AC, jointly guide visual attention is the Priority Map Model (Awh et al., 2012; Kadel et al., 2017). According to this framework, all AC mechanisms contribute simultaneously to a continuously updated priority map. Visual attention, including overt and covert visual attention, is directed toward whichever stimulus currently holds the highest relative priority within the visual scene, implying that the contribution of each of the different mechanisms shaping shifts in attentional priority according to available information (Awh et al., 2012; Cavanagh et al., 2023; Ferrante et al., 2018). Priority can be directed to stimulus features, such as color or shape, or to spatial locations (Ferrante et al., 2023; Gepperth et al., 2011; Wolfe, 2021). In the context of feature-based priority, stimuli carrying higher-priority features receive enhanced processing, while those carrying lower-priority features are suppressed (Awh et al., 2012; Gepperth et al., 2011).

At the neural level, the Priority Map Model is closely related to the principle of biased competition. During biased competition, neural representations of stimuli mutually inhibit each other across multiple stages of visual processing. Each processing stage involves input from other neural systems (e.g., stimulus-reward associations), which dynamically influence processing of visual information (Beck & Kastner, 2005; Buschman & Kastner, 2015; Chelazzi et al., 2014; J. Duncan, 1996; Ferrante et al., 2023; Sprague et al., 2018; Thayer &

Sprague, 2023). This mechanism offers a biologically plausible account of how attentional priority can shift. Computational models, such as Guided Search 6.0 (Wolfe, 2021), have leveraged this principle to simulate how multiple sources of AC are resolved into a dynamic attentional priority map.

The Guided Search 6.0 model proposes that distinct mechanisms (e.g., goals, salience, learning history) assign weights to signals representing stimuli in the visual system. These weighted signals then converge into a priority map, where competition is resolved through a diffusion process. Signals reaching a threshold value receive attentional priority. Crucially, this process is continuous, involving multiple stimuli simultaneously, explaining how AC can dynamically prioritize different stimuli depending on changes in currently available information. While these integrative models offer empirically grounded predictions for both typical and clinical populations (Hoppenbrouwers et al., 2016; Peschard & Philippot, 2016), they also serve as tools for incorporating novel findings.

Taken together, dominant models of AC conceptualize visual attention as the outcome of a dynamic competition in which top-down goals, bottom-up salience, and selection history jointly shape attentional priority. Although these models increasingly incorporate selection history as a source of attentional bias, the specific contributions of different mechanisms constituting selection history remain underexplored (Anderson, 2024). To fully integrate selection history into models of attentional prioritization, it is essential to clarify how these mechanisms influence attentional prioritization in both an isolated and combined fashion.

Reward Learning and Statistical Learning as Isolated Mechanisms

In this study, we focus on statistical learning (SL) (Folk & Remington, 2015; Zehetleitner et al., 2012) and reward learning (RL) (Chelazzi et al., 2014), as these are the most

theoretically developed and empirically supported selection history mechanisms (Anderson et al., 2021). Both RL and SL meet the criteria for being sources of selection history effects: (1) they stem from prior experience, (2) are not reducible to intentional control, and (3) assign priority to arbitrary stimuli rather than inherently salient ones (Anderson, 2024; Anderson et al., 2021). At their core, both RL and SL are forms of associative learning, relying on predictable patterns in the environment that can be internalized through repeated exposure (Anderson, 2013; Jeong et al., 2023a; Lee & Shomstein, 2014; Ma & Yu, 2015). Despite this shared basis, the isolated effects of RL and SL can be compared along three dimensions that are relevant to how they bias AC: the type of memory associations they form, the neural systems that support them, and the conditions that modulate their effect.

What Is Associated?

The first dimension concerns the content of the associations formed by RL and SL and how these differ. RL forms associations between arbitrary stimuli and external rewards (e.g., money). Consequently, the reward-predictive stimulus is perceived as more salient, leading to increased attentional priority (Anderson et al., 2022; Becker et al., 2020; Hickey & Van Zoest, 2013; Pearson et al., 2016). SL, in contrast, forms associations between arbitrary features that frequently co-occur in the environment (e.g., a stimulus's shape and its location; Kim & Anderson, 2021). The resulting effect is that the presence of one feature predicts the presence of another, thereby guiding attention following these statistical regularities (Aslin & Newport, 2012; D. H. Duncan et al., 2024; Ferrante et al., 2018; Jiang et al., 2015; Kelley & Yantis, 2009; Turk-Browne et al., 2005). These functional differences suggest that RL and SL influence AC through qualitatively distinct associative content. Such differences are likely rooted in the partially distinct neural systems that support each

mechanism. Briefly outlining these systems may therefore help explain why RL and SL influence attention in qualitatively different ways.

What Neural Systems Underlie RL and SL?

The second comparative dimension concerns which neural systems produce the qualitative differences between RL and SL. Reward-driven attentional bias is thought to rely on interconnected dopamine and norepinephrine systems (Zhao et al., 2024). When a stimulus predicts reward, dopamine neurons in the ventral tegmental area and substantia nigra signal its value through projections to regions such as the ventral striatum, caudate tail, and orbitofrontal cortex (Krebs et al., 2012; Qi et al., 2013). An important result of this dopaminergic projection is an increased plasticity of the neurons in the visual cortex, which modulates the salience of the reward-associated stimulus (Anderson et al., 2011a; Becker et al., 2020; Failing & Theeuwes, 2018; Hickey et al., 2010; Hickey & Peelen, 2015). At the same time, the locus coeruleus–norepinephrine (LC–NE) system interacts closely with these dopaminergic circuits, increasing cortical responsiveness to motivationally relevant stimuli (Bouret & Richmond, 2015; Y. Zhang et al., 2023).

The neural system on which SL relies differs from that of RL. For learning environmental regularities, SL depends on the medial temporal lobe. In particular, the hippocampus and nearby cortical regions (Batterink et al., 2019; Turk-Browne et al., 2009) are involved in encoding stimulus-stimulus and stimulus-context relationships (Zhao et al., 2024). Once these relationships are established, they are thought to influence attention via a corticostriatal circuit involving the basal ganglia and posterior parietal cortex (Batterink et al., 2019; Theeuwes et al., 2022). This reshapes the visual cortex's responsiveness in a feature-selective manner, enhancing neural representations of stimuli associated with regularities predictive of targets while proactively suppressing processing of stimuli associated with

frequent distractors (Failing et al., 2019; Van Moorselaar & Slagter, 2020; B. Zhang et al., 2022).

These distinct neural substrates of RL and SL mirror the functional differences described in the previous section. Dopaminergic–noradrenergic circuits implement a salience-driven bias toward motivationally relevant stimuli based on stimulus–outcome regularities (Bachman et al., 2020; Hickey & Peelen, 2015), while medial-temporal–corticostriatal circuits implement a predictive bias derived from learned stimulus–stimulus regularities (B. Zhang et al., 2022). Importantly, their isolated influence on AC is not fixed, but depends on the conditions under which learning is acquired and expressed.

What Modulates the Attentional Bias of RL and SL?

A final dimension to compare RL and SL is how both mechanisms are modulated. Even when studied in isolation, the strength of the attentional bias produced by RL or SL varies with parameters of the learned contingencies. A first source of variability are the parameters of the learned contingency itself. The attentional bias produced by RL is modulated by reward magnitude (Feldmann-Wüstefeld et al., 2016; Jeong et al., 2023b; Le Pelley et al., 2015), frequency of the stimulus–reward contingency (Le Pelley et al., 2016), and the specificity of the arbitrary feature associated with reward (Milner et al., 2023). Similarly the attentional bias produced by SL depends on how deeply participants engage with the regularity during learning (D. H. Duncan et al., 2024; Golan et al., 2024), the frequency of the regularity (Di Caro & Della Libera, 2021), the perceptual dimension along which the regularity is defined (e.g., location typically exerts stronger influence than color; Kovacs & Harris, 2019), and the salience of the statistical regularity and the features involved (Dolci et al., 2024).

A second source of variability in the effects of RL and SL is what has been learned previously via the same mechanism. For RL, previously acquired stimulus–reward associations can interfere with one another. When two stimuli are each paired with a reward during training, neither comes to capture attention as strongly as a single reward-associated stimulus would on its own (Feldmann-Wüstefeld et al., 2016; Liao & Anderson, 2020; Sha & Jiang, 2016). The same logic holds for SL: participants who had first learned one statistical regularity were slower to acquire and express a new regularity than participants who had been exposed to random displays during training (Vaskevich & Luria, 2019). These findings show that the attentional bias produced by RL or SL is not a fixed property of the learning mechanism. Its strength varies with the parameters of the current contingency and with what has previously been learned through the same associative learning mechanism.

Together, the three comparative dimensions above show that RL and SL are related but distinct selection history mechanisms: they form different kinds of associations, rely on different neural systems, and are modulated by different factors. Importantly, how these differences translate into effects on AC has mainly been characterized by studying the effects of each mechanism in isolation. However, as outlined in the Priority Map Framework, multiple selection history mechanisms often contribute simultaneously to a single computation of attentional priority (Ahw et al., 2012; Anderson et al., 2021). How RL and SL contribute on their own, therefore, says little about how they shape priority when both are present simultaneously (Anderson, 2024).

The Combined Influence of Reward and Statistical Learning

While some studies have explored how RL or SL interact with other attentional systems, such as top-down or bottom-up AC (e.g., Abbasi et al., 2022; Dolci et al., 2023, 2024; Feldmann-Wüstefeld et al., 2016; Hickey & Van Zoest, 2013), fewer have looked at the

effects when directly combining RL and SL in the same paradigm. This limitation is significant because attentional selection in real-world environments rarely depends on a single source of selection history in isolation. Instead, visual scenes usually contain multiple statistical and reward-related regularities. Understanding how RL and SL jointly influence AC is therefore necessary for developing models of attentional prioritization that more accurately reflect attentional processing in realistic settings (Anderson, 2024). The few studies that have looked at the combined effects of SL and RL can be grouped into two major lines of research, using distinct experimental paradigms.

Two Lines of Research

The first line of research uses experimental paradigms where participants must rapidly respond to a target that varies simultaneously in its reward value and the frequency with which it appears in a certain location. For instance, the target may appear in two different colors, each one associated with a different reward magnitude. Simultaneously, the target may also appear more frequently in a particular location (e.g., Stankevich & Geng, 2014). Importantly, these contingencies are not known to the participant. Studies implementing this paradigm show that participants are fastest to respond to the target when it reliably appears in one location, and its color predicts a high reward. This indicates that participants leverage both the implicit spatial properties of the target as well as the reward outcome associated with the target when both regularities are present simultaneously (Garner et al., 2021; Stankevich & Geng, 2014).

The second line of research uses paradigms that include a distracting stimulus in the visual scene. Participants must still respond to a target, defined by a unique feature, and ignore a distracting stimulus (Theeuwes, 2026). In this paradigm, SL and RL are not bound to target features, but are associated with the distracting stimulus instead. Studies using this

paradigm have shown that RL and SL exert opposite influences on distractor processing. Reward-associated distractors capture attention and slow target search, while distractors with highly predictable features are proactively suppressed, facilitating search (Kim & Anderson, 2021; Le Pelley et al., 2022; Zhao et al., 2024). When associating RL and SL to the same distractor – for instance, when a high-value distractor frequently appears in the same location – participants showed a reduced slowing effect (Le Pelley et al., 2022). Thus, studies using this paradigm provide additional evidence that people can rely simultaneously on RL and SL to guide their attention.

Both paradigms are theoretically relevant because they can provide complementary insights into how different selection history mechanisms contribute to the selection of task-relevant information and suppression of counterproductive information – two important functions of visual attention (McMains & Kastner, 2009). Studies relying on these paradigms have focused mainly on behavioral measures – response time (RT) and accuracy. However, these behavioral measures represent the end product of a chain of perception, decision, and motor response, therefore providing limited insight into how RL and SL bias AC. A method that captures physiological signatures of these underlying processes – providing qualitative depth – is pupillometry.

Capturing Selection History Effects with Pupillometry

Pupillometry measures the surface area of the pupil, which can offer a window to observe the cognitive processes underlying RL and SL (O'Bryan & Scolari, 2021). RL engages motivational systems that mobilize attentional resources toward valuable stimuli, resulting in an increase in arousal that is reflected in pupil dilation (Cole et al., 2022; Y. Zhang et al., 2023). SL, in contrast, biases attention through expectation: when regularities make a stimulus predictable, it is processed more efficiently than when it is unpredictable. This

results in a pupil constriction (Binda et al., 2025; Richter & De Lange, 2019; Schwiedrzik & Sudmann, 2020). Thus, the pupil response following RL and SL is opposite, reflecting either increased or reduced perceptual processing efforts. Both, however, result in more efficient navigation of perceptual scenes by influencing AC.

Gaps in the Present Understanding of the Joint Effects of Different Selection History Mechanisms

Despite the methodological tools available, our understanding of how RL and SL jointly influence AC remains incomplete. This is because RL and SL are typically linked to different stimulus dimensions: either dimensions from different perceptual modalities (e.g., RL to target color and SL to target location; Garner et al., 2021), or distinct dimensions within the same modality (e.g., RL to color and SL to shape; Ogden et al., 2023). As a result, the effects of RL and SL are difficult to compare. That is because, on the one hand, their effects might compete less than they would when converging on a single feature representation. On the other hand, their effects could also result in an unbalanced input during priority weighting, because some stimulus dimensions (e.g., location) are more heavily weighted than others (e.g., color; Kovacs & Harris, 2009; Ogden et al., 2023). Therefore, to understand how RL and SL jointly contribute to attentional prioritization, it is best to assess this when both selection history mechanisms prioritize the same target feature. Specifically, two questions currently remain unanswered (for an overview, see Anderson, 2024; Awh et al., 2012):

- 1) Do RL and SL independently affect attentional prioritization, or do they influence the effect of one another when prioritizing the same stimulus feature?
- 2) Do RL and SL differ in strength during attentional prioritization?

The present study was designed to address both of these questions empirically.

Research Aims and Hypotheses

Specifically, we examine how RL and SL jointly influence attentional control when both are bound to the same non-salient target feature in a visual search task. On each trial, participants identify a target defined by its orientation and report whether a gap is located at the top or bottom of the target stimulus. This target can appear in four colors, with which RL and SL are factorially combined. Two of those colors are associated with high reward and two with low reward, establishing RL. Independently, the target appears more frequently in two colors and infrequently in the remaining two, establishing SL. This creates four conditions in which each color uniquely combines reward magnitude and statistical predictability of the target (high reward–high frequency, high reward–low frequency, low reward–high frequency, low reward–low frequency). Importantly, the target color is irrelevant for identifying the target. This design allows for a direct test of (1) whether RL and SL effects on AC are additive or interactive, and (2) whether their effects differ in strength. To track behavioral effects of RL and SL on AC, accuracy, and RT will be measured.

It is hypothesized that trials engaging both RL and SL will yield faster RTs and higher accuracy than those involving only one or neither mechanism. Furthermore, when one mechanism strengthens the effect of the other (for example, an increased RL effect in the presence of SL, or vice versa), this would manifest as an interaction effect between SL and RL. Alternatively, if the mechanisms exert additive effects on AC, it is expected that RL and SL independently enhance performance. Based on prior findings (Stankevich & Geng, 2014; Ogden et al., 2023), additive effects are expected. In contrast, no directional hypotheses are proposed for differences in the relative strength of RL and SL. Reward-predictive colors may generate stronger and earlier attentional biases due to their motivational salience (Anderson,

2016; Hickey et al., 2010; Van Zoest et al., 2021). However, these expectations are insufficiently supported by empirical research in the context of visual search and attentional control. Therefore, this effect is treated as exploratory.

In addition to behavioral measures, we use pupillometry to assess the effects of RL and SL on AC. We expect to replicate the opposing effects of RL and SL on pupil size. However, how RL and SL jointly shape pupil size remains speculative. That is because pupillometry has not been implemented to compare how different AC mechanisms contribute to attentional prioritization. In addition, pupil responses are most often studied in anticipation of a task rather than online task processing (Eayrs et al., 2025; Irons et al., 2017). Because of the novelty of the task context in which pupillometry will be implemented, we integrate this as an exploratory measure.

Nevertheless, different pupillometry effects would carry different theoretical meanings. If the combined effects of RL and SL are additive and roughly equal in strength, one would expect little net change in pupil size, because they push pupil size in the opposite direction. If they differ in strength, one mechanism would bias the response toward dilation or constriction. An interactive pattern, in contrast, would imply that the presence of one mechanism alters the strength of the other. For instance, expectancy as a consequence of SL may dampen the arousal response normally evoked by reward. Alternatively, valence-driven arousal as a consequence of RL may lessen the constriction produced by expectation. In either case, the joint pupillary response would deviate from what would be expected based on the isolated contributions of RL and SL.

Methods

Ethical approval

The present study was conducted in accordance with the Declaration of Helsinki and approved by the ethical committee of the Faculty of Psychology and Educational Sciences of Ghent University (code 2025-012A).

Participants

26 participants were recruited – 11 males and 15 females between the ages of 18 and 34 ($M = 22$, $SD = 3.14$). Two participants had an accuracy less than 2 SD s from the overall mean ($N = 26$, $M = 0.86$, $SD = 0.14$), and more than 50% of their trials were rejected based on low-quality eye-tracking data (see Section ‘Preprocessing of Pupil Responses’). Therefore, these participants were excluded from the analysis. Thus, the final sample for the analysis consisted of 24 participants. All participants were right-handed. They reported a good understanding of English, normal or corrected to normal vision, and no known psychiatric disorders. Recruitment happened mainly through SONA – an online recruitment platform used by Ghent University. Additional participants were also recruited via Ghent Erasmus Student Network. All participants provided informed consent and were compensated €30, with a potential bonus of up to €8 based on their task performance.

An a priori power analysis was conducted based on the smallest effect expected from the literature: the difference in attentional bias between RL and SL. Stankevich et al. (2014) reported main effects of $\eta^2_p \approx 0.26$. However, the present study includes methodological features known to reduce attentional bias, such as a larger array size (Gaspelin et al., 2015; Kristjánsson & Egeth, 2020), the use of a contingency between target and color rather than target and location (Kovacs & Harris, 2019; Zehetleitner et al., 2012), and differing frequency

distributions of target color (Le Pelley et al., 2016). Therefore, a more conservative $\eta_p^2 = 0.13$ was used for the main effects of RL and SL in our study. A G*Power analysis indicated that a sample size of 15 participants and a correlation between repeated measures of $r = 0.30$ would provide 80% power at $\alpha = 0.05$ (Faul et al., 2007). More participants than this were recruited to account for potential exclusions and ensure sufficient power.

Materials

The experiment was programmed in PsychoPy (v2024.2.4; Peirce et al., 2019). Pupil size was recorded using an EyeLink 1000 Plus at a sampling rate of 1000 Hz. Only the left eye was recorded unless the right eye yielded a higher-quality signal. Participants were seated in a quiet, dimly lit room. Viewing distance from the monitor (1920 × 1080 resolution, 60 Hz refresh rate) was maintained at 97 cm using a chin rest. EEG data was collected simultaneously but was not included in the present dissertation.

All stimuli were presented on a grey background (RGB: 40, 40, 40). A white fixation cross (0.29°×0.29°; RGB: 255, 255, 255) was present in the middle of the screen throughout the experiment. The search array used in the visual search task consisted of six isoluminant bars (0.50°×2.00°; 38.64 cd/m²) that were evenly spaced in a circular formation with a radius of 7° around the fixation cross. Each bar contained a small gap in the same color as the background (0.25° in diameter) located on one side of the bar. The target was a bar with a distinct orientation (25° tilt from the vertical axis, while filler bars were tilted 25° from the horizontal axis). Target bars could appear in one of four colors: orange (RGB: 180,99,80), light green (RGB: 104, 126, 57), petroleum (RGB: 0, 131, 134), and blue (RGB: 0, 127, 172). Fillers could appear in red (RGB: 182,94,123), yellow (148, 113, 50), green (RGB: 38, 134, 94), pink (RGB: 151, 104, 164), and purple (RGB: 81, 118, 185). The target never appeared in the upper two positions of the search array, because the N2pc, an event-related potential

(ERP) of interest for the EEG study, tends to be smaller for visual information in the upper parts of the visual field (Luck et al., 1997). Thus, the location of the target was randomized across the remaining four positions. Fillers filled the remaining positions in the search array. At the end of each trial – if participants gave a correct response – reward feedback was presented in white (0.48°; RGB: 255, 255, 255) above the fixation cross. The feedback was ‘100’ or ‘001’ in case of a high or low reward, respectively.

Experimental Design

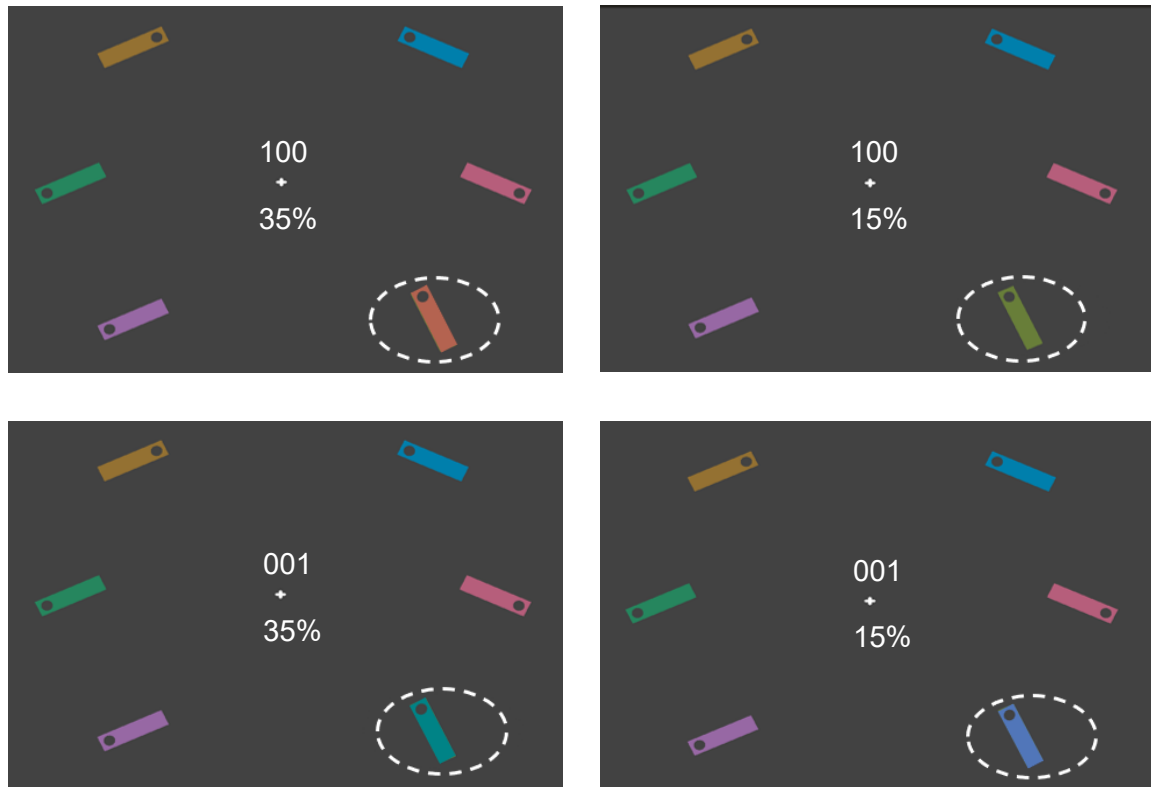
This study employed a within-subjects design to investigate the influence of SL and RL on AC. A within-subjects design was chosen to minimize inter-individual variability between conditions, enhancing statistical power (Charness et al., 2012). Participants first completed a 23-trial practice block to become familiar with the task and fixation requirements. The main experiment consisted of 1216 trials, divided into eight blocks that were separated by self-paced breaks. The task and procedure used in this study were adopted from Dolci et al. (2024) for comparability, but they were adjusted to fit the current research question. During the task used in this study, participants had to discriminate whether a gap in the target bar was located at the top or the bottom of that bar. Participants used a keyboard in front of them to respond with ‘z’ or ‘m’ if the gap was located at the top or at the bottom of the target, respectively.

Crucially, the color of the target was systematically linked to both the number of reward points participants could earn and how often the target appeared in that color. Each of the four target colors represented one unique combination of reward magnitude and target frequency: high reward–high frequency (HRHF), high reward–low frequency (HRLF), low reward–high frequency (LRHF), or low reward–low frequency (LRLF). In high-reward (HR) conditions, correct responses to the target resulted in 100 points, whereas in low-reward

(LR) conditions, correct responses resulted in 1 point. In high-frequency (HF) conditions, the target appeared in that color in 35% of trials, whereas in low-frequency (LF) conditions, it appeared in that color in 15% of trials (Figure 1). For example, if the orange target color was assigned to the HRHF condition, the target appeared in orange relatively often (35% of trials), and correct responses to orange targets earned 100 points. Alternatively, if the blue target color was assigned to the LRLF condition, the target appeared in blue relatively rarely (15% of trials), and correct responses to blue targets earned only 1 point. Importantly, participants were not explicitly told about these color–reward and color–frequency contingencies. Instead, they could only learn them gradually through experience during the experiment.

Figure 1

Experimental Conditions



Note. Example search displays used in the experiment. Participants searched for a uniquely oriented target bar among five filler bars while maintaining fixation on the central fixation cross. The target was defined by its orientation: it was tilted 25° from the vertical axis, whereas distractor bars were tilted 25° from the horizontal axis. This is indicated by the dashed, white ellipse (not present during the experiment). Participants had to respond with a keypress to the location of a small gap in the target bar. The gap in the target could appear at the top or the bottom of the target. The crucial experimental manipulation was that the target could appear in one of four colors, and each color consistently signaled a unique combination of reward magnitude and target frequency throughout the experiment. Specifically, target colors were associated with one of four conditions: high reward–high frequency (HRHF), high reward–low frequency (HRLF), low reward–high frequency (LRHF), or low reward–low frequency (LRLF). Correct responses to high-reward target colors resulted in 100 points, whereas correct responses to low-reward target colors resulted in 1 point. The target was presented in high-frequency colors in

35% of the trials, whereas it appeared in low-frequency colors in only 15% of the trials. Thus, each unique target color simultaneously predicted both the number of points that could be earned and the likelihood that the target would appear in that color. In the exemplary displays shown in the figure, the top row depicts high-reward target colors (100 points), and the bottom row depicts low-reward target colors (1 point). The left column depicts high-frequency target colors (35% of trials), and the right column depicts low-frequency target colors (15% of trials). The assignment of specific colors to conditions was counterbalanced across participants. Distractor colors were never used as target colors.

The four target colors were counterbalanced across participants, such that each color was equally often assigned to each reward–frequency condition (HRHF, HRLF, LRHF, LRLF). To achieve this, participants were divided into four groups, with each group receiving a different mapping between target colors and the four experimental conditions. However, within a participant, these color–condition associations remained constant throughout the experiment. During the practice block, all target colors appeared equally often and were related to both reward outcomes to avoid a priori color preferences. To avoid a pop-out effect that would trigger bottom-up attentional capture, the colorful target was presented in a heterogeneous display amongst colorful fillers (Feldmann-Wüstefeld et al., 2016). Target colors were never used for fillers and vice versa. The order of the conditions was fully randomized within the experiment.

Experimental Procedure

Each experimental trial began with a frame displaying only the fixation cross, which remained visible throughout the trial. After a randomly jittered interval between 400 and 600 ms to avoid anticipatory motor and pupil responses, the search array was presented for 300 ms. Responses were recorded from search array onset until 1000 ms after search array offset. If participants were correct (i.e., correctly and timely identified the gap location), they received feedback about the number of points they collected in this trial. This feedback was

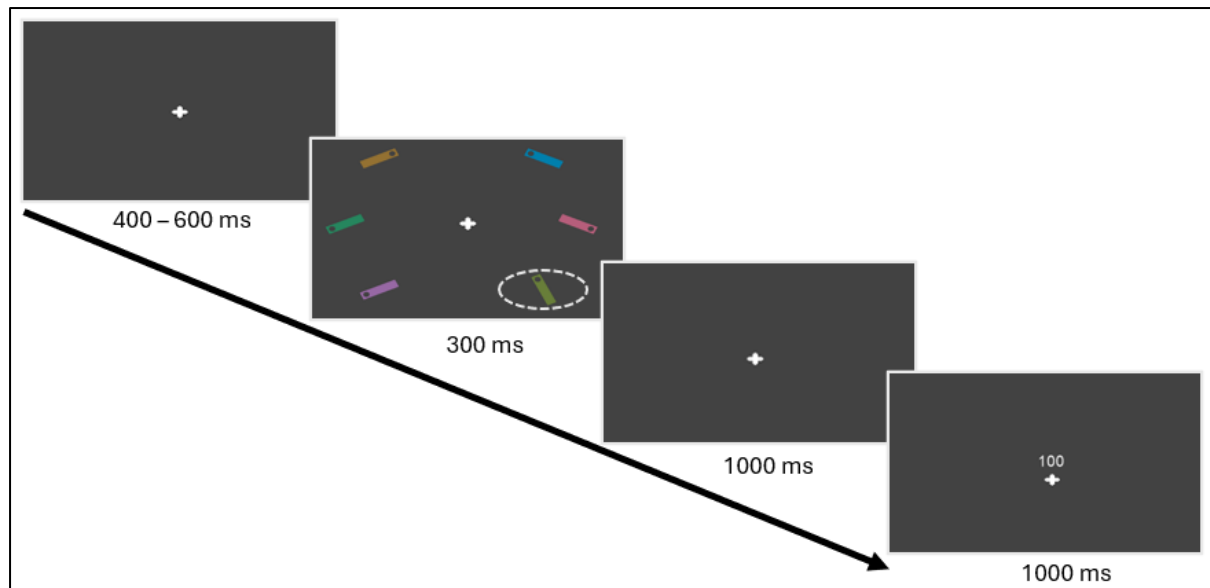
presented for 1000 ms. In case of an incorrect response, no feedback was given, and the next trial started immediately (Figure 2).

During breaks, participants were encouraged to remove their head from the chinrest and relax their eyes to be able to maintain a comfortable position during the task. Eye movements and blinks were monitored during the task by the experimenter. If excessive motion or blinks were detected, participants were reminded during the break to keep looking at the fixation cross and minimize the number of blinks in the next block. A constant fixation was important to ensure that the effects of the manipulation on the pupil size, RT, and accuracy reflected covert attentional shifts without contamination from overt orientation responses. Such responses cause both pupillometric and behavioral artifacts. For instance, the rotation of the eye causes a decrease in the measured pupil area because the pupil image becomes more elliptic (Hayes & Petrov, 2016). A potential behavioral artifact could be the inflation of RTs due to the preparation and execution of eye movements (Bompas et al., 2025).

Before the experiment started, the eye tracker was calibrated using nine-point calibration. After each break, the eye-tracker was recalibrated, and participants were explicitly motivated to keep increasing their score (McLaughlin et al., 2023). After the experiment, participants were asked if they noticed any patterns in the target color during the experiment to test their awareness of the target-color contingencies. In case they reported having noticed a pattern, they were asked to identify the colors related to the high reward and the colors in which the target appeared most frequently.

Figure 2

Experimental Procedure



Note. Each trial started with a fixation cross, presented during a random jittered interval (between 400 and 600 ms). This was followed by the heterogeneous search array. The target is indicated with a dashed, white ellipse (not present during the experiment). The target was tilted 25° along the vertical axis, and fillers were tilted 25° along the horizontal axis. The target appeared equally frequently in the four bottom positions of the search array, but never in the upper two. After the search array offset, participants still had 1000 ms to respond to the location of the gap (at the top or bottom of the target bar) with a keypress. At the end of the trial, feedback was received in case of a correct response. During feedback, participants saw either the number '100' or '001'. In case of an incorrect response, the next trial started immediately.

Preprocessing of Pupil Recordings

Besides behavioral data, we also recorded participants' pupil size during the task. However, before this data could be reliably analyzed, it had to be preprocessed to increase the signal-to-noise ratio. For instance, blinks – periods in which the pupil is (partially) covered – are an important source of noise, because they cause an artificial decrease in the

pupil size that is not task-related. To minimize the noise in the data, we followed a preprocessing procedure based on a method suggested by Kret & Sjak-Shie (2019).

In the first preprocessing step, we detected samples with rapid changes in pupil size that were likely caused by eye blinks or measurement noise rather than by the experimental task itself. To identify such noisy samples, we first calculated the velocity ($d'[i]$) of each sample, reflecting the minimal, normalized change in pupil size from directly adjacent samples. The formula used for this calculation (Equation 1) can be found below. In this formula, $t(i)$ represents the sample number, which was used for normalization. Samples with unusually large changes in pupil size were considered noisy (Figure 3A). To determine which changes were unusually large, a participant-specific velocity threshold (v) was calculated. This threshold was based on the median absolute deviation (MAD ; Equation 2) – the median of the difference between the velocity $d'(i)$ of a sample and the median of the velocities d' of that participant. The velocity threshold v was finally obtained by multiplying the MAD by a constant n , shifting the sensitivity of the velocity threshold (Equation 3). In our analysis, this constant was set at $n = 4$. If at least five noisy samples occurred in a row, this cluster was considered a blink, and its values were replaced with 'not available' (N/A). Because pupil measurements immediately before and after a blink are often distorted as well, an additional padding of 50 samples was applied on both sides of each blink segment. Finally, if fewer than 100 valid samples remained between two blink segments, these segments were merged and treated as a single blink, with all samples in that interval also marked as N/A (Figure 3B).

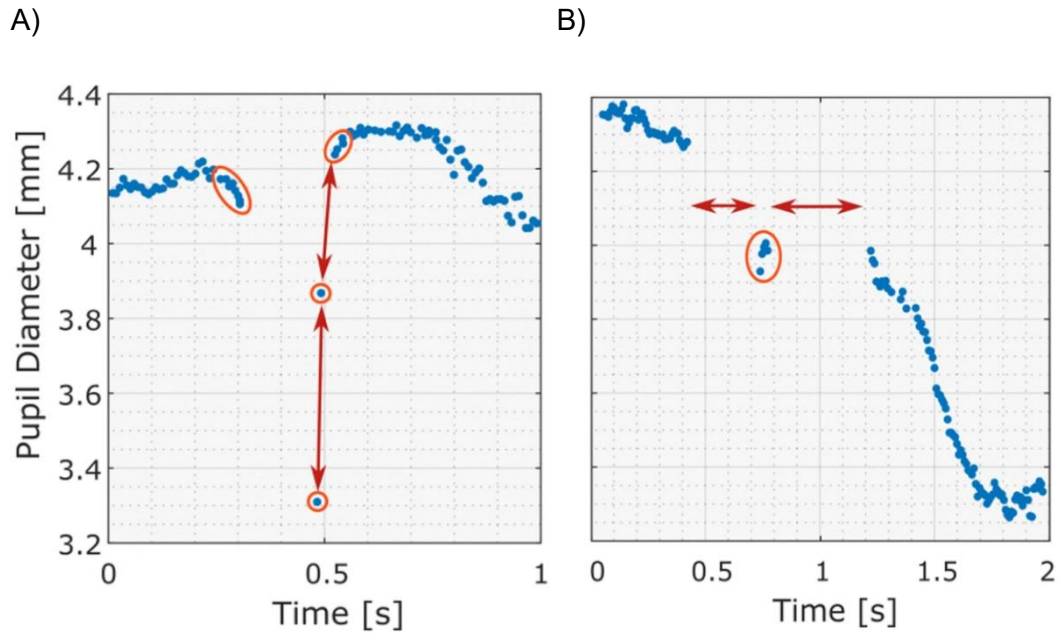
$$d'(i) = \max\left(\frac{d(i) - d(i-1)}{t(i) - t(i-1)}, \frac{d(i+1) - d(i)}{t(i+1) - t(i)}\right) \quad (1)$$

$$MAD = \text{median}(|d'(i) - \text{median}(d')|) \quad (2)$$

$$v = \text{median}(d') + n \cdot MAD \quad (3)$$

Figure 3

Data Cleaning Method



Note: **A)** Artifacts, such as partial blinks, can cause large differences in pupil size between adjacent samples (vertical isolation). The size of this difference can be represented by the dilation speed of each sample. Samples with high velocity are indicated with a red circle. In the present study, such samples were identified when their dilatation exceeded a participant-specific velocity threshold. Consequently, such samples were flagged as noise. **B)** Isolated clusters (horizontally, red circle) typically also contain artifacts. In the present study, clusters with fewer than 100 samples that occurred between blinks, and their values were set to non-available (N/A). Figure

adapted from “Preprocessing pupil size data: Guidelines and code”, by Kret, M., & Sjak-Shie, E.E., 2019, *Behavioral Research Methods*, 51, p. 3 (<https://doi.org/10.3758/s13428-018-1075-y>). Copyright 2026 by Springer Nature.

In the second preprocessing step, linear interpolation was applied to missing samples. This estimates values of missing samples by using surrounding data points to approximate the underlying continuous signal. Groups of missing data longer than 650 samples (~20% of the trial) were not interpolated and were kept as missing data. In the third step, we sampled the data down to 250 Hz, because a resolution of 1000 Hz was not required for our analysis. In addition, it also increased computation speed. In the fourth step, baseline correction was applied by subtracting the baseline of each trial from all samples in that trial (missing data was omitted). This normalizes each trial by removing baseline offsets and low-frequency drift, improving comparability of changes in pupil size across trials. Baselines were calculated as the mean pupil size in the 200 ms time window preceding search-array onset. To avoid using baselines with artifacts during baseline correction, we also calculated standardized baselines for each participant. Trials with an absolute standardized baseline larger than two were excluded (Mathôt & Vilotijević, 2022). Finally, trials with more than 25% of the data missing were rejected. For each participant, the quality of the interpolation and baseline correction was verified using a trial-by-trial plot. Examples of these plots can be found in Appendix A1.

Analysis

All analyses were performed in R (v4.4.1; R Core Team, 2021). Generalized linear mixed models (GLMM) were fitted using glmmTMB (v1.1.14; Brooks et al., 2017) Categorical predictors were effect-coded. Model parameters were estimated using maximum likelihood with the Laplace approximation, and p-values were obtained using a Wald z-test. For all

model estimates and effect sizes, 95% likelihood profile confidence intervals were computed. Random-effects structures were determined by beginning with a maximal random-effects structure, including random intercepts and random slopes for each predictor per participant. When the maximal model failed to converge or produced a singular fit, we iteratively dropped random slopes. Among models that converged and were non-singular, those with the lowest BIC value were selected.

Finally, the fit of the final model was evaluated using the DHARMA package (v0.4.7; Hartig, 2016). DHARMA works by simulating new datasets from the fitted model and comparing them to the observed data. In all simulations, the number of repeats was $n = 1000$. By default, we visually inspected the goodness of fit with the quantile-quantile plot (Q-Q plot) and the scaled residuals vs. predicted values plot (SR-PV plot). The former was used to assess whether the residuals, derived by comparing the observed data to simulated data using from the model, follow the expected uniform distribution. A systematic deviation indicates that the model does not adequately describe the data. The latter was used to assess if the model fitted the data equally well across different values of the dependent variable, or whether systematic patterns of misfit arose. The plot indicates where the median of the simulated residuals should fall across different values of the dependent variable, compared to where the predicted residual medians actually fall. In the SR-PV plot, the residuals and predicted values are scaled between 0 and 1 to better reveal patterns across the entire range of predictions. Depending on the specific model that was being fit, additional checks were performed.

Accuracy

Accuracy (correct vs incorrect) was modelled using a binomial distribution with a logit link function. Fixed effects included reward (high vs. low), frequency (high vs. low), and block (1-

8 as a numerical variable), as well as their three-way interactions (reward $\times$ frequency $\times$ block). To accommodate the expected non-linearity of learning over time and reduce collinearity with other predictors, the block was log-transformed and mean-centered. The random-effects structure allowed the intercept, as well as the effect of reward, frequency, and block, to vary across participants.

Visual inspection of the Q-Q plot and SR-VP plot revealed no violation of the assumptions of the underlying binomial distribution. We further evaluated residual variance across predicted values. Although this is usually evaluated using a dispersion test in DHARMA, this test is less informative for binary outcomes. As an alternative, recommended by the DHARMA developer, we compared residual variance across different predictor levels relying on visual inspection and Levene's tests (Hartig, 2024). Residuals within the levels of all predictors fell within the expected quantiles, and Levene's tests indicated no significant differences in residual variance across different values of reward ($F(1, 29182) = 0.16, p = .6877$), frequency ($F(1, 29182) = 2.03, p = .1545$), and block ($F(7, 29176) = 1.3835, p = .2072$, [treated as categorical for this test]). Plots used for inspecting model fit can be found in Appendix B1.

Response Time

For the analysis of the effects of RL and SL on RT (and pupil size – see next section), only correct trials were included. Correct RTs more directly reflect successful attentional selection guided by RL and SL and therefore provide a higher signal-to-noise ratio as compared to incorrect trials. In addition, incorrect trials were relatively rare, limiting the reliability of any inferences based on them. Also, trials in which an RT of less than 100 ms was recorded were excluded from this analysis. This threshold corresponds to the sensory deadtime – the minimum time required for perceptual processing and response initiation

based on complex visual input (Bompas et al., 2025). This resulted in the exclusion of 1.43% of the trials with a correct response.

The RTs were fit with a gamma distribution with a log link function – a common method for right-skewed RTs (De Boeck & Jeon, 2019; Lo & Andrews, 2015; Palmer et al., 2011). Fixed effects included reward (high - low), frequency (high - low), and block (1-8 as a numerical variable), as well as their three-way interactions (reward $\times$ frequency $\times$ block). Block was again log-transformed and mean-centered. The random-effects structure included a random intercept and a random slope for block per participant.

Model diagnostics based on simulated residuals indicated that the residuals largely followed model expectations, with minor deviations in the lower tail of the RT distribution. This could be attributed to the scarcity of fast responses (< 400 ms), a common issue when modeling RTs (Lo & Andrews, 2015). Importantly, a bootstrap-based outlier test was non-significant, suggesting that the frequency of extreme residuals was consistent with model expectations (expected extreme residuals: 0.0032, 95% CI [0.0011, 0.0069], observed = 0.005, $p = .188$). This implies that the misfit in the tails reflected variability inherent to skewed RT distributions but not a systematic failure of the model to capture the general trends in the data. Consistent with this interpretation, extreme residuals were not clustered within specific participants or experimental conditions. In addition, a non-significant dispersion test (dispersion = 0.90, $p = .488$) indicated that the model accurately captured the residual variance across different predicted values of RT. Finally, predictive checks confirmed that the model reproduced the overall distributional shape of the observed RT data, with only a slight overestimation of fast responses. Plots supporting these diagnostics are provided in Appendix B3.

Pupil Size

Finally, to analyze the pupil dilation in response to the search array, we calculated the mean pupil size within a time window from 750 ms until 1300 ms after search-array onset. This window was selected based on prior literature indicating that pupil modulations associated with covert shifts of attention typically emerge around 750 ms following stimulus onset (Mathôt et al., 2013; Privitera et al., 2010; Stolte et al., 2020). In addition, we performed an exploratory analysis on the pupil size in response to the reward feedback to assess whether participants heeded it (Cole et al., 2022). The baseline period for this analysis started 200 ms before feedback onset. Mean pupil sizes were calculated from 750 ms until 1150 ms after reward-feedback onset (Van Slooten et al., 2018).

For both analyses, mean pupil size values were fit with a t-distribution to account for the heavier tails of mean pupil sizes (Van Rij et al., 2019). Fixed effects included reward (high - low), frequency (high - low), and block (1-8 as a numerical variable), and their three-way interaction effects (reward $\times$ frequency $\times$ block). Block was mean-centered to resolve collinearity issues. It was not log transformed, because we expected no non-linear decrease of pupil size across blocks (for instance, due to fatigue). Random effects consisted of a random intercept and a random slope for the effect of block per participant.

For the analysis of the search-related pupil response, visual inspection of simulated residuals suggested no substantial deviations from model assumptions, although the SR-PV plot indicated outliers (larger-than-expected residuals). Therefore, we performed a bootstrapped outlier test ($n = 1000$), indicating that the number of outliers was not different than expected by the model (expected = 0.003, 95% CI = [0.002, 0.004], observed = 0.002, $p = .100$). In addition, we performed a dispersion test to check that the residual variance did not differ across different values of mean pupil size. The results indicated no difference

between the expected and observed residual variance (dispersion = 1.01, $p = .792$). Finally, a direct comparison of model simulations with the observed distribution of mean pupil sizes confirmed that the t -distribution adequately captured the distribution of mean pupil sizes. Plots used for model validation can be referred to in Appendix B4.

The model for the pupil response to feedback showed similar patterns. The Q-Q plot indicated no substantial deviations from the underlying t -distribution, but the SR-PV plot indicated outliers. A bootstrapped outlier test ($n = 1000$) was not significant (expected: 0.003, 95% CI [0.001, 0.008], observed = 0.004, $p = .256$), and the model showed the expected dispersion (dispersion = 0.99, $p = .968$). Finally, the inspection of simulated values showed good overlap with the true values. Based on these results, we conclude that this model captured the distribution of the mean pupil sizes after reward feedback well. Plots used to evaluate this model can be found in Appendix B5.

Results

Effects of RL and SL on Behavior

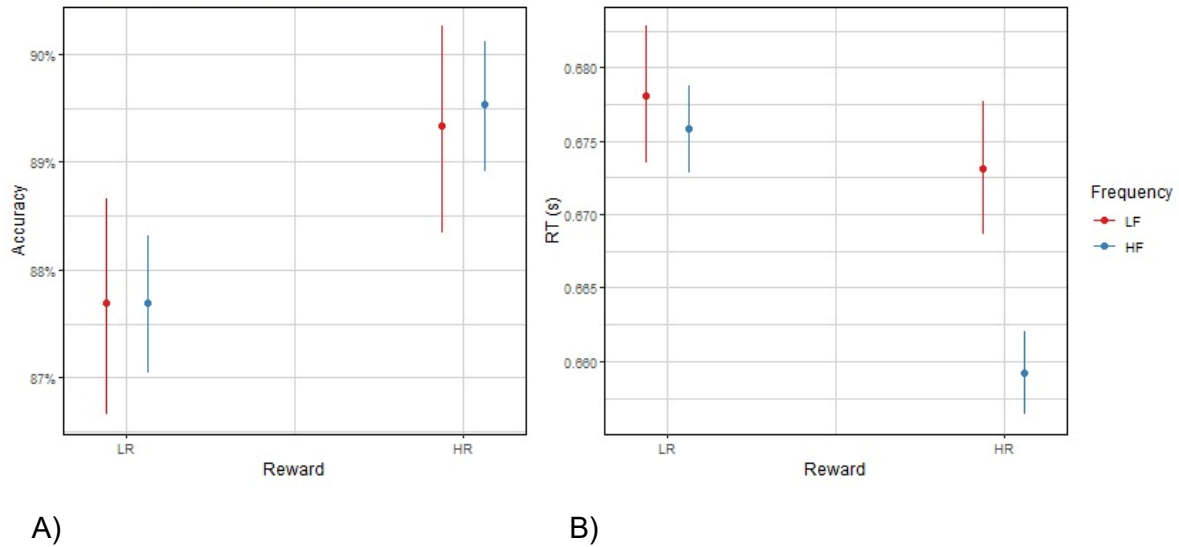
A total of 24 participants participated in the task. Accuracy ($M = 0.88$, $SD = 0.32$) was analyzed using a binomial GLMM, and RTs ($M = 0.675$ s, $SD = 0.32$ s) were analyzed using a gamma GLMM. All random effect estimates can be found in Appendix C1. For accuracy, we found no main effect of RL ($\beta = -0.09$, 95% CI [-0.22, 0.04], $z = -1.39$, OR = 0.91, 95% CI [0.80, 1.04], $p = .164$) or SL ($\beta = -0.01$, 95% CI [-0.08, 0.07], $z = -0.31$, OR = 0.99, 95% CI [0.92, 1.07], $p = .750$). The interaction between RL and SL was also not significant ($\beta = 0.01$, 95% CI [-0.04, 0.05], $z = 0.19$, OR = 1.00, 95% CI [0.96, 1.05], $p = .852$) (Figure 4A). For RTs, we found a main effect of RL such that participants responded faster to target colors associated with high reward compared to a low reward ($\beta = 0.01$, 95% CI [0.01, 0.02],

$z = 5.61$, $OR = 1.01$, 95% CI [1.01, 1.02], $p < .001$). Similarly, there was a main effect for SL, indicating faster responses for high-frequency compared to low-frequency target colors ($\beta = 0.01$, 95% CI [0.01, 0.02], $z = 3.60$, $OR = 1.01$, 95% CI [1.01, 1.02], $p < .001$). Finally, a significant interaction effect between RL and SL revealed that the effect of RL and SL depends on the engagement of the other mechanism ($\beta = -0.003$, 95% CI [-0.01, -0.001], $z = -2.41$, $OR = 0.99$, 95% CI [0.98, 0.99], $p = .015$).

To further examine the interaction between RL and SL, pairwise comparisons of RTs across conditions were conducted using estimated marginal means from the emmeans package (v2.0.2; Lenth & Piaskowski, 2017), with Tukey-adjusted p -values to control for multiple comparisons. The analyses indicated that the HRHF condition yielded the fastest responses. Specifically, RTs in both the HRLF condition (ratio = 1.02, 95% CI [1.02, 1.03], $z = 4.28$, $p < .001$), and the LRHF condition (ratio = 1.02, 95% CI [1.02, 1.03], $z = 7.47$, $p < .001$). In contrast, RTs did not significantly differ between the HRLF and LRHF conditions (ratio = 0.99, 95% CI [0.98, 1], $z = -1.42$, $p = .486$). Furthermore, the LRLF condition did not significantly differ from either the HRLF condition (ratio = 0.99, 95% CI [0.98, 1], $z = -1.42$, $p = .486$) or the LRHF condition (ratio = 1.003, 95% CI [1.00, 1.01], $z = 0.83$, $p = .389$) (Figure 4B).

Figure 4

Behavioral Results



Note: Predictions about task performance depending on which unique combination of reward magnitude and target frequency the target color predicted. Predictions represent task performance in the middle of the experiment. **A)** The probability of a correct response was not significantly influenced by the target color, although there is a tendency to be more correct when a high reward could be obtained. **B)** Only when the target color predicted high reward and high target frequency, did participants respond significantly faster.

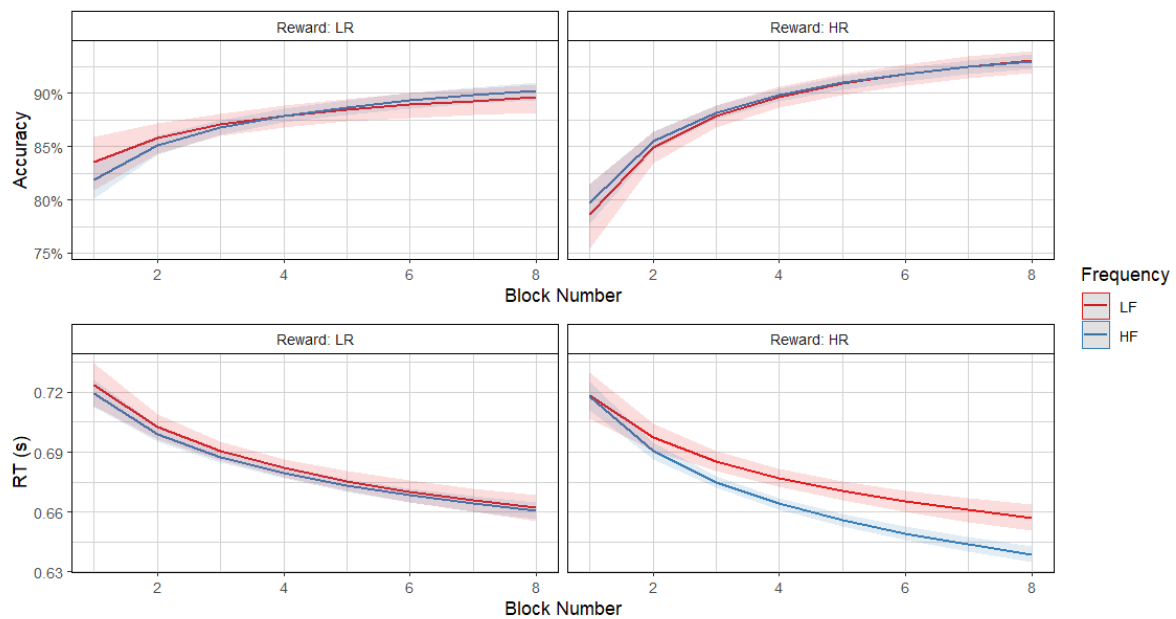
Furthermore, the main effect of block revealed that accuracy improved during the experiment ($\beta = 0.57$, 95% CI [0.24, 0.90], $z = 3.50$, $OR = 1.77$, 95% CI [1.28, 2.45], $p < .001$). This improvement was significantly lower when the target color predicted a low reward ($\beta = -0.08$, 95% CI [-0.15, -0.02], $z = -2.59$, $OR = 0.92$, 95% CI [0.86, 0.98], $p = .009$), whereas no interaction between block and frequency was found ($\beta = -0.002$, 95% CI [-0.07, 0.01], $z = -0.01$, $OR = 1.00$, 95% CI [0.94, 1.06], $p = .940$) (Figure 5A). Similarly, RTs decreased across blocks ($\beta = -0.04$, 95% CI [-0.07, -0.0007], $z = -2.04$, $OR = 0.96$, 95% CI [0.93, 0.99], $p = .041$). This decrease in RT was higher for high frequency target colors ($\beta = 0.004$, 95% CI [0.001, 0.01], $z = 2.04$, $OR = 1.004$, 95% CI [1.001, 1.008], $p = .042$).

Although statistically significant, the effect size for this interaction effect was very small, suggesting limited practical significance (Figure 5B).

Figure 5

Temporal Dynamics

A)



Note: Plots indicate predictions about how behavioral outcomes changed during the experiment. **A)** Accuracy, plotted as the probability of being correct, improved significantly across blocks, with an additional improvement when the target color predicted a high reward. **B)** RTs showed a trend to decrease over time, but this was not statistically significant.

Additional exploratory analysis was conducted to assess whether there was a speed-accuracy trade-off. This was achieved by adding RT as a factor with two levels – fast and slow responses – to the binomial GLMM of accuracy (using the median RT as the cut-off). Overall, fast responses were associated with higher accuracy ($\beta = 0.25$, 95% CI [0.17, 0.33], $z = 5.87$, $OR = 1.28$, 95% CI [1.18, 1.39], $p < .001$). However, in high-reward conditions, the

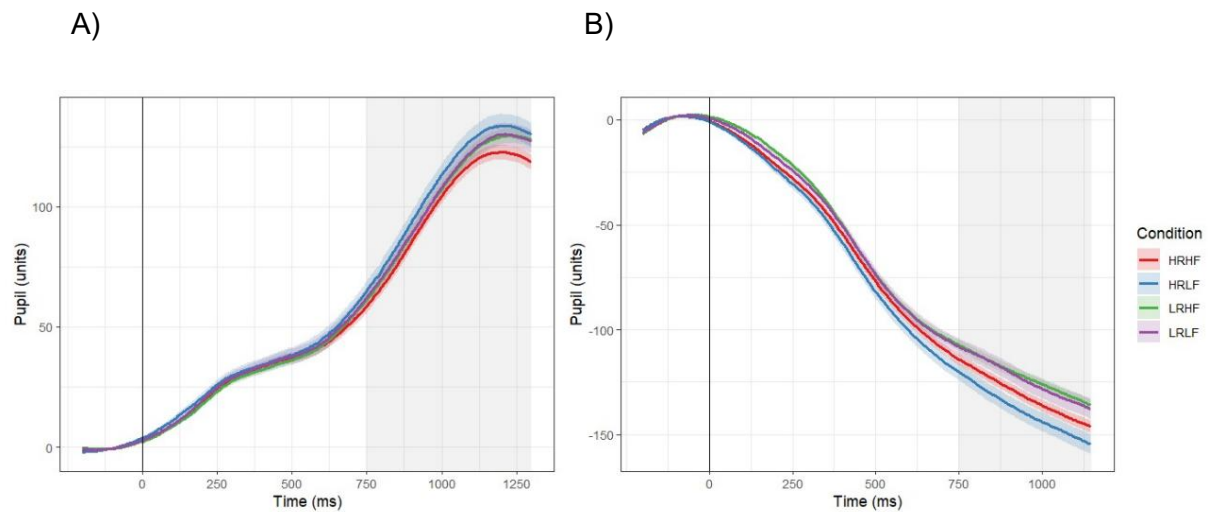
difference in accuracy between slow and fast responses became smaller as participants became more accurate in slower responses. ($\beta = 0.09$, 95% CI [0.01, 0.16], $z = 2.12$, $OR = 1.09$, 95% CI [1.01, 1.18], $p = .034$) (Appendix C2).

Effects of RL and SL on Pupil Size

Besides behavioral indicators of how SL and RL jointly influence AC, we also looked at mean pupil size using a t-distribution to model the distribution of the means. First, we analyzed the mean pupil size in the window between 750 ms and 1300 ms after search array onset. We found that pupil size was not affected by reward ($\beta = 1.00$, 95% CI [-2.06, 4.06], $z = 0.64$, $d = 0.009$, 95% CI [-0.02, 0.04], $p = .521$), nor by frequency ($\beta = 2.39$, 95% CI [-0.66, 5.44], $z = 1.54$, $d = 0.02$, 95% CI [-0.01, 0.05], $p = .125$). The interaction between reward and frequency was also not significant ($\beta = -1.62$, 95% CI [-4.67, 1.44], $z = -1.04$, $d = -0.01$, 95% CI [-0.04, 0.01], $p = .300$) (Figure 6A). Additionally, pupil size did not differ across blocks ($\beta = -2.44$, 95% CI [-7.37, -2.47], $z = -0.99$, $d = -0.01$, 95% CI [-0.04, 0.01], $p = .321$). Secondly, we analyzed the mean pupil size in the window between 750 ms and 1150 ms after reward-feedback onset. Results showed that the mean pupil size after receiving low-reward feedback was higher than after receiving high-reward feedback ($\beta = 3.89$, 95% CI [0.93, 6.85], $z = 2.58$, $d = 0.04$, 95% CI [0.01, 0.06], $p = .001$) (Figure 6B).

Figure 6

Pupil Size



Note: The raw pupil traces, averaged across participants. The gray area is the time window used during the analysis. The colored ribbons represent the standard error. **A)** The search array was presented at time = 0 (black line). The analysis window was between 750 and 1300 ms after search array onset. **B)** The reward feedback was presented at time = 0 ms (black line). The analysis window was between 750 and 1150 ms after reward-feedback onset.

To conclude the results, the awareness check at the end of the experiment indicated that three participants noticed both the reward and the frequency contingency, two noticed only the reward contingency, and one noticed only the frequency contingency. To rule out that this had any effects, we repeated the analysis with awareness as an additional factor (aware vs not aware), but the results remained unchanged.

Discussion

This study investigated how RL and SL jointly influence attentional control when both mechanisms are associated with the same task-irrelevant, non-salient target feature in a visual search task. Participants identified a target based on its orientation, while its color varied in associated reward magnitude and presentation frequency. Through this manipulation, each unique target color represented a factorial combination of RL and SL. We asked whether RL and SL influence AC additively or interactively, and whether one mechanism exerts a stronger influence on AC than the other. Behavioral results showed that both RL and SL produced main effects on RT, with faster responses to high-reward and high-frequency target colors. In addition, a significant interaction between RL and SL revealed that the RT benefit of each mechanism depended on the engagement of the other. Pairwise contrasts qualified this interaction and showed that the RT benefit by one mechanism was only significant when the other was also engaged. Because performance in the two single-mechanism conditions (HRLF and LRHF) did not differ significantly from one another, there is insufficient evidence that either RL or SL exerts a stronger influence on AC, and that they would therefore dominate the other. Furthermore, exploratory pupillometry analyses yielded no significant effects of RL or SL on pupil size, providing no support for the predicted opposing pupil responses associated with each mechanism. Together, these findings suggest that RL and SL both contribute to attentional prioritization, while their combined effects appear to depend on the simultaneous engagement of the other mechanism.

Sensitivity of Behavioral and Physiological Measures to RL and SL Effects

Notably, the effects of RL and SL were not equally detectable across the multiple measures we used. The behavioral effects of RL and SL on AC were mainly reflected by RT, not accuracy. This is not uncommon, as other studies, such as Garner et al. (2021), also reported stronger effects on RT. Importantly, accuracy was high throughout the experiment, and faster responses were generally accompanied by greater accuracy, ruling out a speed–accuracy trade-off as the source of the RT effects. In addition, performance improved across blocks for both RT and accuracy, indicating that participants kept engaging with the task. Therefore, it is presumable that ceiling performance made effects less detectable in the accuracy of participants (Roque et al., 2016). This may indicate that the effects of RL and SL on AC are mainly evident in search efficiency, rather than in performance precision (Zhao et al., 2024).

In addition to accuracy, pupillometry also showed limited sensitivity to possible effects of RL and SL. We specifically failed to observe effects of RL and SL on the search array-related pupil response. Previous work suggests that RL is associated with increased task-evoked pupil dilation, reflecting value-driven mobilization of cognitive resources (Cole et al., 2022), whereas SL is associated with reduced dilation, reflecting prediction-based facilitation (Binda et al., 2025). Because feedback-locked pupil responses were detected, the null results are unlikely to reflect limitations of the eye-tracking setup or analysis pipeline. Instead, pupillometry may simply be less sensitive to the search-related effects of RL and SL under the present task conditions.

A likely explanation for this reduced sensitivity of the pupil measures is that the task itself induced insufficiently distinct cognitive demands across conditions: accuracy was high throughout the experiment, suggesting that RL and SL may not have differentially altered

resource recruitment or facilitated processing to a degree detectable in the pupil signal. The small selection-history-related effects might have been further obscured by other ongoing, arousal-related processes, such as motor preparation, that are also known to modulate the pupil size (Mathôt, 2018; Privitera et al., 2010; Stolte et al., 2020). Even though these additional signatures should be present across all conditions, they might have still increased the overall variability in the pupil size. Importantly, the absence of search array-related pupil effects does not undermine the behavioral evidence that RL and SL influenced attentional prioritization.

Reward and Statistical Learning Influence Attentional Priority

Our results demonstrated main effects of RL and SL on RT, replicating previous findings that RL and SL both influence AC, resulting in faster responses to the target (Stankevich & Geng, 2014; Garner et al., 2021). This indicates that the contributions of both selection history mechanisms contribute to the attentional priority computation (Anderson et al., 2021; Awh et al., 2012). Nevertheless, because both main effects were significant, were comparable in magnitude, and did not differ in their isolated effects (HRLF vs. LRHF effects were comparable), there is no evidence that RL and SL differ in the strength of their influence on AC. Critically, their effects interacted, indicating that both selection history mechanisms exert a mutually dependent influence on AC.

Evidence for an Interactive Effect

The nature of this interaction becomes clearer when examining the pairwise comparisons. These results revealed that the HRHF condition produced the fastest responses, whereas the two single-mechanism conditions (HRLF vs. LRHF) did not differ from each other or from the baseline LRLF condition. In other words, the RT benefit of reward emerged only when

the target color appeared frequently, and the RT benefit of color frequency emerged only when the target color was also related to a high reward. Each mechanism's effect on RT relies on the presence of the other mechanism, rather than producing an additive contribution to performance.

This conditional pattern stands in contrast to several prior findings. Stankevich and Geng (2014), as well as Garner et al. (2021), reported that RL and SL produced additive effects on attentional prioritization of the target. Le Pelley et al. (2022) similarly found that both selection history mechanisms combined additively to bias prioritization of distractors. More recently, Zhao et al. (2024) demonstrated this independence at the neural level, showing that RL and SL modulate distinct cognitive processes using ERPs. RL modulated the N2pc, indicating early attentional capture, whereas SL modulated the PD, associated with proactive suppression, enabled by frequency-based predictions. Importantly, they found no interactions in either behavior or ERPs.

Across these studies, these additive effects were explained by the idea that RL and SL rely on different underlying cognitive processes (e.g., evaluative versus expectancy-based processing; see Failing & Theeuwes, 2018; Wang et al., 2019), resulting in functional differences in how they influence AC. Because they influence AC in different ways, they independently contribute to the same attentional priority map (Anderson, 2024; Awh et al., 2012; Garner et al., 2021). Our finding that RL and SL interact puts this account into question, because we also find evidence that RL and SL are functionally different. This might indicate that functional differences do not necessarily result in additive effects.

Functional Dissociations Between Reward and Statistical Learning

Our Evidence for these dissociations comes from two sources: the pupillary response to reward feedback and behavior. First, despite anticipating dilation in response to high-reward stimuli, we observed a greater dilation in low-reward conditions compared to high-reward conditions. It should be noted that the reward feedback followed the search array rather closely in time. Therefore, the anticipation of the reward-feedback during this window, particularly under varying reward magnitudes, might have influenced the pupil size in a way that we cannot disentangle with the present design (Eayrs et al., 2025; Irons et al., 2017). Therefore, the interpretation of the reward-related pupil response requires the necessary caution. Despite this uncertainty, the effect nevertheless points to reward-related modulation of the pupil size.

Second, in the behavioral data, we found that accuracy improved across blocks, but this improvement was steeper for high rewards. Further, we observed that the speed-accuracy relationship was modulated by reward, such that slower responses were more accurate at higher stakes. However, because these accuracy effects were not accompanied by a significant main effect of reward, they should be interpreted as subtle within-condition indications of reward-related processing rather than evidence of general reward-driven AC. Nevertheless, these findings, both pupillometric and behavioral, provide indications of a functional dissociation between RL and SL.

The increased pupil dilation in response to low-reward feedback might be indicative of how RL and SL establish associations. Reward is delivered as explicit, valenced feedback at the end of each trial, recruiting evaluative processes to establish the stimulus-outcome association (Bachman et al., 2020; Fröber et al., 2020; Van Slooten et al., 2018). Frequency information, in contrast, is not delivered as explicit feedback at all. Instead, it is extracted

implicitly from cumulative exposure to the statistical structure of the environment (Theeuwes et al., 2022). In this respect, the larger dilation in response to low-reward feedback is less surprising: the pupil response likely reflects the magnitude of evaluative engagement rather than reward magnitude per se (Schneider et al., 2018). Less preferred outcomes typically elicit deeper evaluative processing (Cash-Padgett et al., 2018; Nassar et al., 2012).

A parallel interpretation applies to the behavioral asymmetry between reward and frequency-related effects on accuracy. The higher accuracy in slower responses when a high reward could be obtained, could be a subtle indication of enhanced cognitive engagement when the stakes are high. This could be linked to findings that reward-related stimuli are perceived as more salient, causing deeper perceptual processing and richer stimulus representations (Hickey & Peelen, 2015; Hickey & Van Zoest, 2013; S. Wang et al., 2023; Yee & Braver, 2018). The absence of analogous effects for frequency is consistent with the view that SL biases attentional priority through a relatively automatic, expectancy-based process that enhances processing efficiency without recruiting the additional evaluative processes associated with reward (Theeuwes, 2019; Bachman et al., 2020).

Taken together, these results suggest that RL and SL are, at least partially, supported by functionally distinct processes. Despite these differences, the two forms of selection history did not produce independent effects on attentional prioritization in the present task, challenging the account that RL and SL contribute additively to prioritization because they are different associative mechanisms (Anderson, 2024; Awh et al., 2012; Garner et al., 2021). Therefore, to understand what drives this interaction, we consider the role of the task context. Specifically, RL and SL converging on the same target feature in the visual context might be an important contextual mediator to explain the observed interactive effect between RL and SL.

Context-Dependent Integration of Reward and Statistical Learning

We suggest that whether RL and SL combine additively or interactively may depend on whether their associations are tied to the same or to different stimulus features in the visual scene. According to the Attention Priority Map Framework, different forms of learning can shape attentional priority through distinct memory representations of associations (Anderson, 2024; Anderson et al., 2021; Awh et al., 2012). RL biases priority toward features signaling reward, drawing on the perceptual salience enhancement that reward-associated stimuli typically acquire (Anderson et al., 2011b; Grégoire et al., 2022; Zhao et al., 2024). SL biases priority toward features that are predictive of the target through repeated exposure (Turk-Browne et al., 2005; B. Wang & Theeuwes, 2018). Crucially, in most previous paradigms, associations learned through RL and SL were linked to different stimulus features (e.g., Ogden et al., 2023). Under those conditions, each learned representation can bias attentional priority independently, producing additive effects.

In the present study, however, RL and SL were associated with the same target feature. As a result, the same feature became embedded within the representation of both learned associations. This overlap may have allowed the attentional bias generated by one association to amplify the influence of the other (Dolci et al., 2024; Hickey & Peelen, 2015). For instance, the salience of the HR target feature can strengthen the predictive pattern between the color and the target (Hickey et al., 2010). On the other hand, the predictive pattern might facilitate reward processing (Failing et al., 2019). Therefore, the two memory representations both bias attentional priority toward selecting the same color, producing the interactive effect. Returning to the data, when both reward- and frequency contingencies are present, their combined bias is strong enough to dominate selection, producing the substantial advantage observed in the HRHF condition. When only one contingency is

reliably present (HRLF or LRHF), the combined bias is weaker and does not translate into a measurable advantage. This suggests that the integration of RL and SL can occur at the level of the representation of the learned associations, before the priority computation itself.

Critically, this interpretation also addresses a major criticism against interactive effects that has been raised by Garner et al. (2021). Drawing on the Cost-Efficient Incremental Updating Framework (Braver, 2012; Yee & Braver, 2018), Garner et al. (2021) argue that attentional prioritization is metabolically costly, and the visual selection system therefore minimizes computational cost by evaluating the contribution of each source of selection history independently. The result is an additive, sequential updating of attentional priority (Anderson, 2024). Garner et al. (2021) specifically raise this as an argument against the possibility of interactive effects. Interactive effects require an additional, costly computation: the multiplicative integration of RL and SL when they enter the priority computation, which makes integration unlikely.

However, following our proposition, this integration might already happen at the level of the associative representation in which the target feature is encoded (Anderson, 2024; Jeong et al., 2023a). When the LRHF feature representation is activated, it immediately carries the combined influence of both RL and SL associative networks, allowing their effects to enter the priority computation as a single integrated signal, rather than as two independent inputs. This would bypass the need for costly trial-by-trial multiplicative integration at the priority computation stage (Garner et al., 2021).

Implications

The idea that whether RL and SL combine additively or interactively may be context-dependent could have broader theoretical implications for how multiple selection history

mechanisms influence AC. Although RL and SL are functionally dissociable and rely on (partially) distinct neural systems (Bachman et al., 2020; Zhao et al., 2024), the present results show that this dissociation does not guarantee independent contributions to attentional prioritization. Instead, the way in which learned associations are organized within the visual context may determine whether their effects combine additively or interactively. This consideration extends the Attentional Priority Map Framework by specifying a condition that influences how different sources of selection history contribute jointly to attentional prioritization (Anderson, 2024; Anderson et al., 2021; Awh et al., 2012).

Existing formulations of the framework generally assume that different selection history mechanisms contribute independently to the dynamic computation of attentional priority (Anderson, 2024). We suggest that this idea may hold only under specific conditions, particularly when distinct learning mechanisms are associated with different features of the relevant stimulus. When multiple learned contingencies converge on the same feature, their effects may become (mutually) dependent, leading to amplification rather than independent contributions. Consequently, models of attentional prioritization may need to account not only for the source of AC but also for how learned associations are represented within the task environment.

Importantly, this extension of how multiple selection history mechanisms jointly influence AC is not trivial, but has real-world relevance. In natural environments, stimuli are rarely associated with only a single learned regularity (Anderson, 2024; Wolfe & Horowitz, 2004). Instead, objects often simultaneously carry reward value while also being predictable within a given context. By characterizing how multiple co-occurring associations shape AC, the present findings offer a more ecologically valid account of attentional prioritization.

Limitations

Notwithstanding these implications, there are some limitations of the present study that need to be considered. One important limitation applies to our proposed interpretation of how RL and SL might produce interactive effects when converging on the same target feature. By design, our low-frequency conditions involved fewer trials per color than the high-frequency conditions. This affects not only the strength of the SL signal – the intended manipulation – but also, unintentionally, the number of learning opportunities available for the RL association in low-frequency conditions. In HRLF, participants encountered the reward-predicting color less often than in HRHF, suggesting that the underlying stimulus–reward association in HRLF might have been weaker simply because it was acquired over fewer trials (Di Caro & Della Libera, 2021).

However, the comparisons between the LRLF and LRHF argues against this exposure account as a full explanation. This comparison holds the reward constant, but the number of exposures differs. Yet, more exposures did not result in a measurable benefit at low reward. If exposure were the dominant driver of the effects in our study, this comparison could reveal an SL benefit, and it does not. Therefore, differences in learning opportunities might not fully account for the observed pattern whereby RT decreases only when both RL and SL are engaged.

This argument, however, rests on a null result, which is inherently less informative than significant differences. Therefore, we cannot rule out that a more sensitive design or larger sample would reveal smaller exposure-driven effects in the HRLF and LRHF conditions. Our conclusion regarding this first limitation is therefore not that exposure plays no role, but that exposure differences alone cannot account for the patterns observed in our results. Therefore, the benefit of combining RL and SL on the same target feature is well explained

by our proposition that integration happens at the level of overlapping memory representations of the shared feature.

A second limitation is that in the present task, the heterogeneous search array contained colorful fillers, whereas the target feature that was relevant to the reward and frequency contingencies was also color. This overlap between filler characteristics and task-relevant stimulus features could have created unintended side effects, making RL and SL less robust.

First, because the target was explicitly defined by orientation, AC mechanisms may have suppressed color to increase the perceptual dissimilarity between fillers and target (Failing et al., 2019; Kim & Anderson, 2021). That might have rendered the present color-related contingencies less noticeable (Milner et al., 2023). Another related side-effect might have been that participants relied more on top-down search strategies in a heterogeneous search array without perceptually salient stimuli (Adam et al., 2021). This could have diverted attention too much from statistical regularities or reward-related features for robust incidental learning of these regularities to occur (Dolci et al., 2024; D. H. Duncan et al., 2024; Garre-Frutos et al., 2025). Although RL and SL are implicit mechanisms, they still require sufficiently deep engagement with the present contingencies to establish reliable associations (D. H. Duncan et al., 2024; Grüner et al., 2023; Vicente-Conesa et al., 2023).

These side effects might have reduced the effects of RL and SL under the present task conditions, mainly limiting the interpretability of our secondary research objective – whether RL and SL differ in strength when influencing AC. The present paradigm arguably lacks the sensitivity to robustly test this difference. Nevertheless, the paradigm adequately addresses our primary research objective by providing novel insights into the joint effects of RL and SL. This limitation marks a promising avenue for future research.

Future Directions

Future studies could investigate the directionality of the interaction between RL and SL on AC: does predictability of target features enhance reward processing (Hickey et al., 2010), or does reward strengthen the predictability of the target when both converge on the same stimulus feature (Failing et al., 2019)? However, to address this question, the sensitivity of the paradigm should be enhanced. Drawing on features of the learned contingencies known to modulate RL and SL effects on AC (see Section 'What Modulates the Attentional Bias of RL and SL'), we propose three specific adjustments to achieve this.

A first promising adjustment might be to increase the distinctiveness of the learning-relevant feature by using target location rather than stimulus color. Target location provides greater perceptual distinctiveness than color because it more clearly separates the learning-relevant dimension (where) from the task-relevant dimension (what). This allows RL and SL to adopt more qualitatively distinct aspects of the target that might result in stronger selection-history effects (Oor et al., 2025). Alternatively, the target location might also be a more critical stimulus feature to target with the reward and frequency manipulations, because it tends to act as a stimulus dimension that binds other features together during associative learning (Kovacs & Harris, 2019). This could result in potentially stronger associative representations.

Second, the contrast between high- and low-frequency conditions can be increased. The current ratio (35% vs. 15%) was lower than in comparable paradigms. For reference, Ogden et al. (2023) used a ratio of 43.25% vs. 6.25%. Increasing the ratio could make the effect of SL more robust, because the contrast between the conditions becomes more apparent (Di Caro & Della Libera, 2021).

Third, increasing task difficulty, by adding stimuli to the search array, or shortening search array exposure time (Huang & Pashler, 2005), would allow selection-history-driven facilitation to emerge more clearly – perhaps also in accuracy measures and pupillometry (Ivanov et al., 2019). Increasing task difficulty prevents ceiling effects, increasing the reliance on AC. This would leave more room for RL- and SL-driven differences to become apparent.

Besides adjustments to the experimental paradigm, future studies could complement or replace pupillometry with electroencephalography (EEG), particularly ERPs, to further investigate the processes through which RL and SL influence AC. Like pupillometry, ERPs are involuntary measures that can provide insight into attentional processing, and have been used to study both reward- and frequency-related effects on attention (e.g., Bachman et al., 2020; Dolci et al., 2023, 2024; Van Zoest et al., 2021; Zhao et al., 2024). However, unlike the pupil response, unfolding over a period of 1 second or more (O'Bryan & Scolari, 2021), ERPs provide millisecond-level temporal resolution (Zhao et al., 2024). This makes them well-suited to assess different stages of attentional processing. For example, early perceptual suppression of irrelevant information (indexed by the Pd, 100–250 ms), attentional selection (indexed by the N2pc, 180–350 ms), and later evaluative processing and stimulus appraisal (indexed by the P3, 350–550 ms; Bachman et al., 2020; Zhao et al., 2024).

This level of precision offers a potentially valuable method to more directly test our proposal that RL and SL contribute to attentional priority computation with an already integrated priority signal, rather than that their signals converge during online priority computation (Anderson et al., 2021). This could be reflected, for instance, by an interaction at the N2pc, directly showing that the two mechanisms produce a single, integrated bias into attentional selection (Zhao et al., 2024). More broadly, combining the present paradigm with

EEG may clarify when RL and SL produce additive versus interactive effects, moving the field beyond the question of whether these systems jointly bias attention toward a mechanistic account of how and when they do so.

Conclusion

In conclusion, the present study demonstrates that both RL and SL influence attentional control when associated with the same non-salient, task-irrelevant target feature. Behavioral results revealed that both mechanisms facilitated visual search. This effect was mainly reflected by decreased RTs. In contrast to previous work, we found that their combined effects were interactive rather than purely additive. Specifically, attentional benefits emerged most strongly when the target was associated with a high-reward and a high-frequency color. These findings suggest that different forms of selection history do not necessarily contribute independently to attentional prioritization, but may dynamically influence one another depending on how learned contingencies are represented within the task context. Together, the results contribute to a more nuanced understanding of how prior experience shapes attentional selection in complex visual environments.

AI Acknowledgment Section

- I used Claude AI
 - To summarize excerpts from research papers, which made the literature review more practical. By prompting sections of papers, I received overviews of their key points and findings. While these summaries were generally accurate, nuances were occasionally misinterpreted, especially if the summary was generated in an ongoing chat. In such instances, Claude would have the tendency to skip details unrelated to the current chat or reframe content from the paper to align better with previous prompts. Therefore, when a summary highlighted potentially useful findings, I always revisited the paper to ensure the accuracy of the information I extracted from it.
 - To manage the structure of the paper. By prompting intermediate drafts and asking for a summary, I could more easily evaluate which arguments or sections required further elaboration or structural clarification. It also helped me evaluate if the general outline of the paper was in line with the idea that I actually wanted to convey.
 - As a writing assistant, to formulate ideas during writing. Based on drafts I prompted, Claude provided inspiration and advice
 - about connection sentences between paragraphs,
 - for how to rephrase certain details to make them more understandable
 - for how to make paragraphs more concise.
 - for vocabulary (I did not use Claude for this purpose specifically, but it was a side-effect as it suggested alternative phrasings and vocabulary

automatically in its output. Online dictionaries like 'Reverso' were my go-to for translations and synonyms.)

- To proofread the final draft.
 - This was done through an iterative process during which I prompted excerpts of the draft (between 700 and 1000 words) and asked to perform the following check:
 - *I would like you to proofread an academic thesis section. Evaluate the text according to these criteria:*
 - *Transitional flow within paragraphs*
 - *Transitional flow between paragraphs and sections*
 - *Consistency of terminology and abbreviations*
 - *Clarity and simplification of overly complex sentences*
 - *Grammar and tense-use*
 - *For each issue:*
 - *Quote the relevant sentence or short excerpt*
 - *Explain the problem briefly*
 - *Suggest a concrete revision. If extensive revision is required, explain what could be improved, but do not draft a revised text.*
 - This allowed me to evaluate my text very efficiently, while also maintaining a high level of control and authenticity.
- I used Consensus as an assistant during my literature review. It is a tool to search and summarize research papers. It is conveniently question-based, which is a very straightforward way to explore literature. While useful, the number of results after a query was often quite limited, giving me the feeling I was missing out on relevant literature. Moreover, this tool can make research more susceptible to confirmation bias. To minimize this risk, I used neutral prompts and only used Consensus for highly specific queries. Nevertheless, most of my references were acquired via Web

of Science and Google Scholar – using ‘traditional’, keyword-and citation-based search strategies.

- Notebook LM helped me to manage large volumes of literature. Notebook LM is a convenient tool to interact with specific sources (papers, personal notes on papers and summaries). The tool remains very close to the original sources uploaded and you can easily retrieve the exact source of specific information.
- I also used Gemini for Coding in for coding in R
 - I primarily used it to debug errors.
 - To rewrite inefficient code that caused considerable memory-related issues: I was used to the dplyr package in R, but functions from this package appeared to be very memory inefficient for large amounts of data. Therefore, Gemini helped me to rewrite inefficient chunks of code, implementing functions of the data.table package instead – a package that is more memory-efficient.
 - To generate the code for the plots used to inspect whether simulated model predictions matched patterns in the observed data.
 - In other instances, Gemini was used to review existing code or identify functions and packages suited to specific tasks. To familiarize myself with R functions and packages, I relied on a combination of AI, blogs, and CRAN (Comprehensive R Archive Network). However, based on blogs and other documentation alone, I sometimes found it difficult to fully understand how to use certain functions (in combination with other functions/packages) and their arguments. AI was useful for explaining code and provided great help in developing my R skills.

In conclusion, AI has had a large influence on this paper. The tools mentioned above are practical in almost every step of the research process. Nevertheless, I am confident that I can evaluate their flaws. I used AI as a tool to enhance my own work and try to learn from it as much as possible when doing so. I am strongly convinced that AI can be an asset, but its output should not be taken for granted and should be used for specific purposes only. After all, criticism remains one of the most important characteristics of a good researcher.

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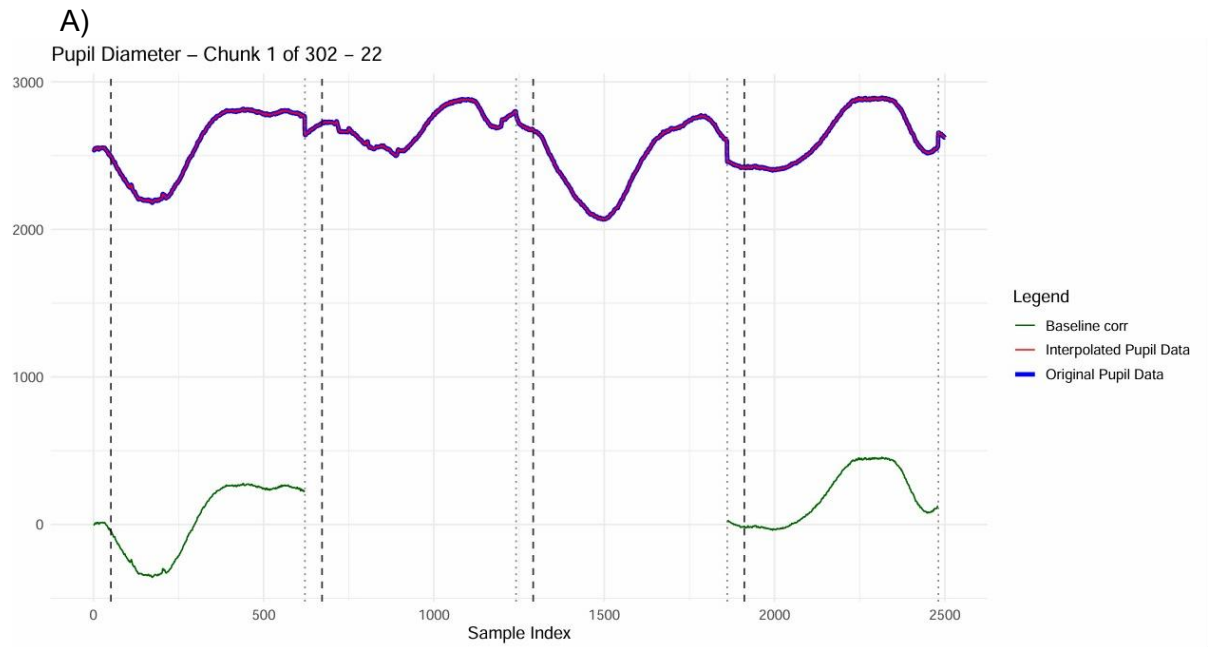
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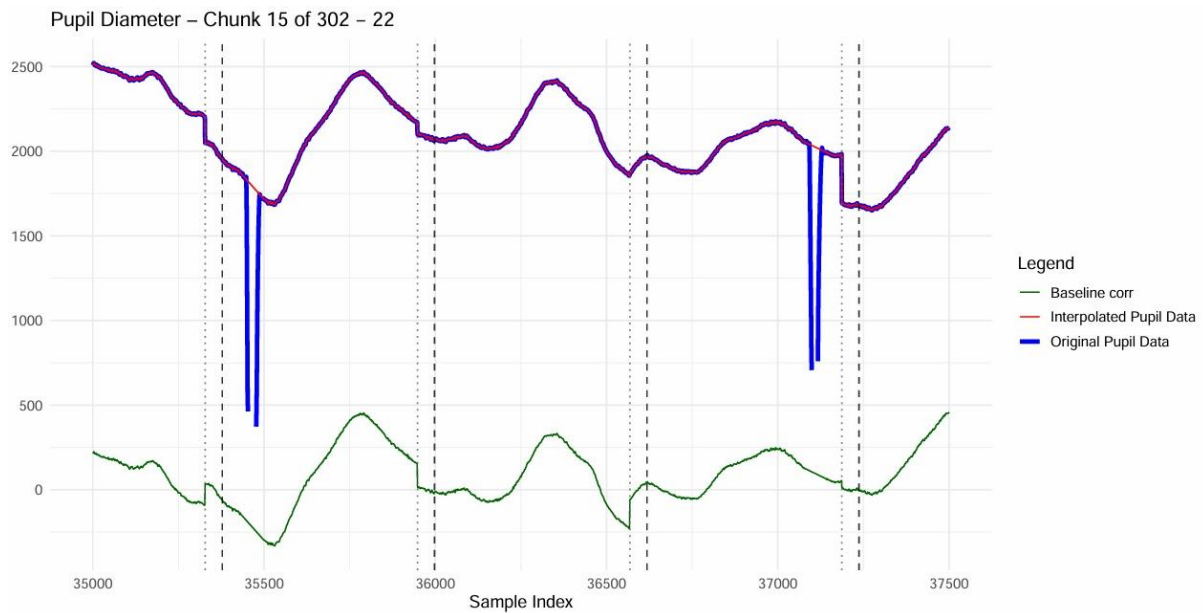
Appendix A

Figure A1

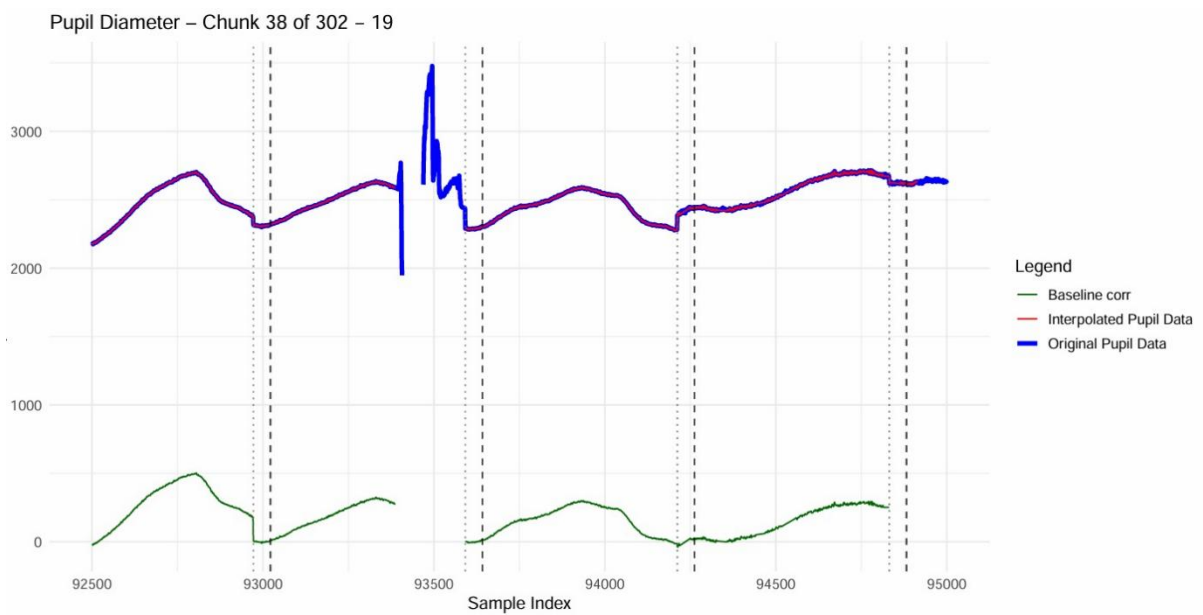
Examples of trial-by-trial plot pupil size



B)



C)



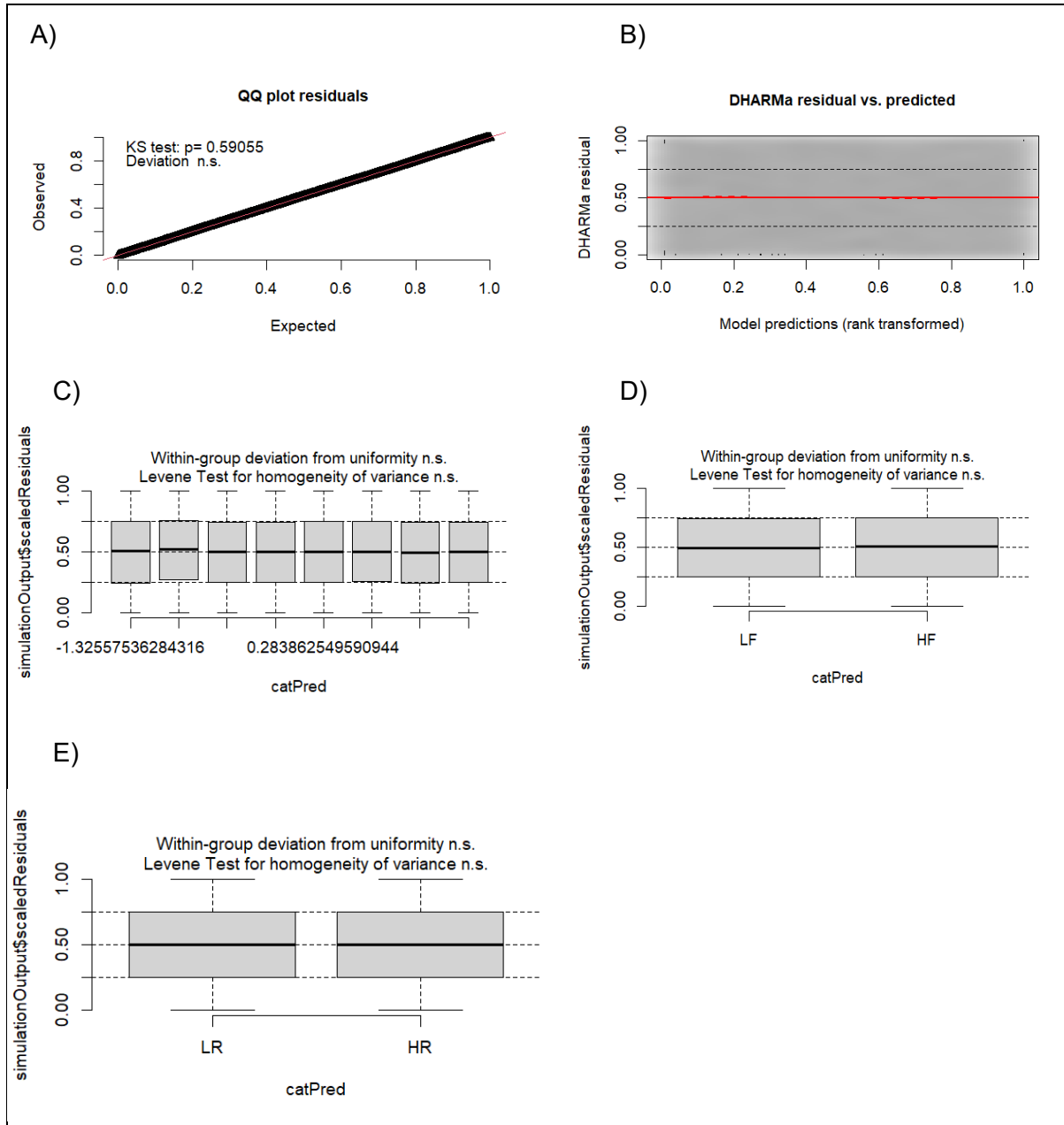
Note. These are examples of the trial-by-trial plots used to check the preprocessing. The Blue line represents the raw signal. The red line is the signal after interpolation. The green line is the baseline-corrected signal that was eventually analyzed. The thin, dotted grey line represents the start of the baseline period that lasts until the

search array onset (dashed grey line). Note that the fixation period is already removed for this plot. **A)** This represents the signal in four trials. The middle two trials were excluded because they had an abnormal baseline. That is, an absolute standardized baseline that was larger than two (see Section 2.6). **B)** An example of two trials containing a blink (the steep decrease and increase in pupil size, with missing data). These blinks were interpolated, recovering the lost signal. **C)** The second trial in this plot likely contains a measurement artifact. The loss of data was too substantial (>650 samples), so the samples in this gap were not interpolated.

Appendix B

Figure B1

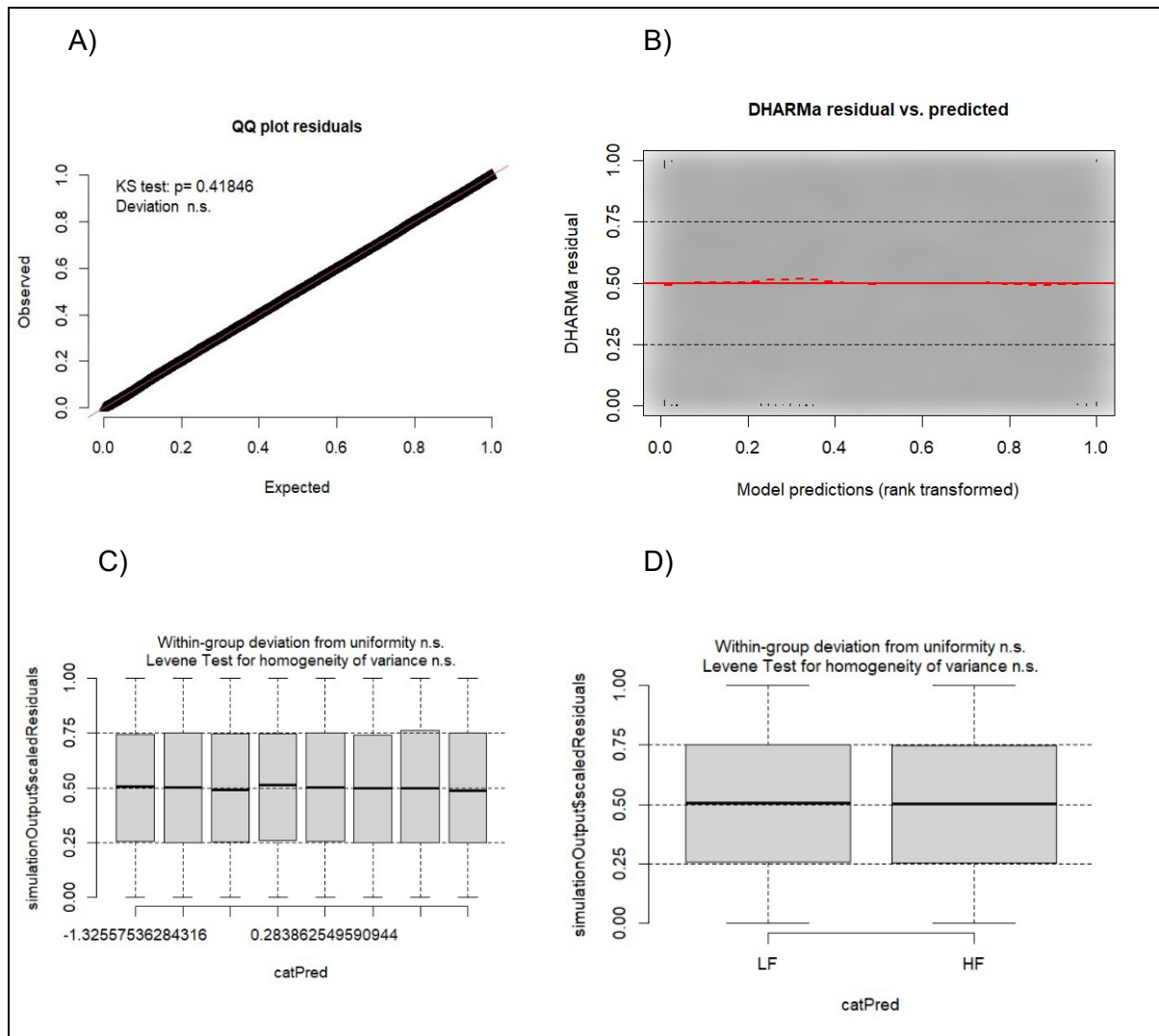
Model Diagnostics Accuracy

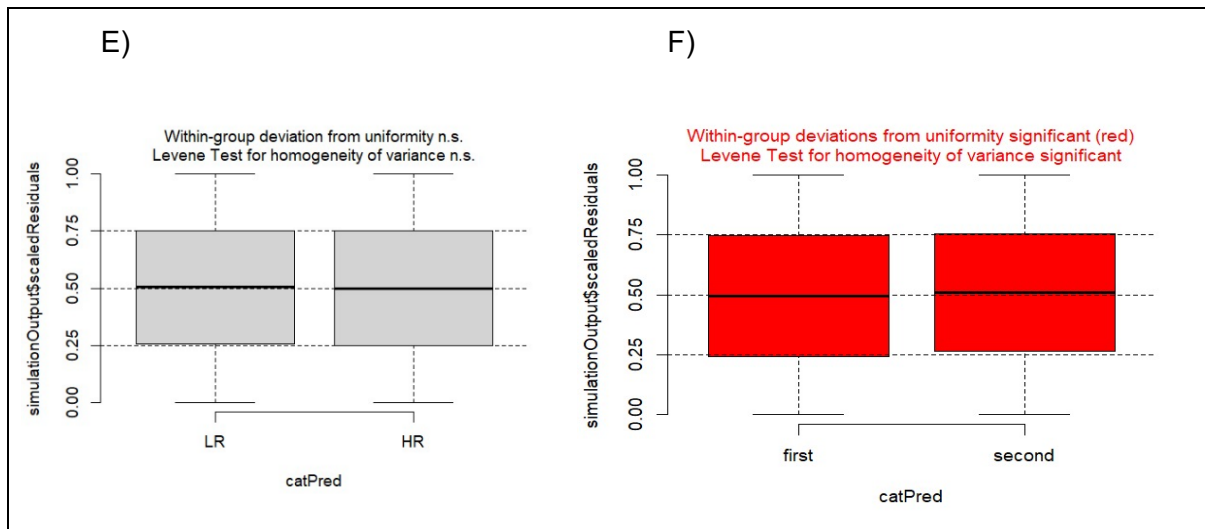


Note. **A)** Quantile-quantile plot (Q-Q plot) of scaled residuals, simulated by DHARMa, against the expected uniform distribution. A model with a good fit should show residuals falling along the diagonal line, indicating that the observed residuals are uniformly distributed. **B)** The scaled residual vs predicted values plot (SR-PV). It displays the scaled residuals (scaled between 0 and 1) against predicted values (also scaled between 0 and 1). The full red line shows the 0.50 quantiles of the simulated residuals under a correctly specified model. The dashed red line shows the 0.50 quantiles of simulated residual quantiles of the fitted model. This dashed line does not deviate systematically from the expected 0.50 quantile across all predicted values, indicating no misfit. **C)** SR-PV displayed as boxplots per level of block (here treated as a categorical variable). The dashed lines indicate the 0.25, 0.50, and 0.75 quantiles of the simulated residuals for the different levels of block under a correctly specified model. The quantiles of the simulated residuals of the fitted model (boxplots) match these quantiles, and the variances of these simulated residuals of the fitted model do not differ between levels of block. **D)** SR-PV displayed as boxplots per level of frequency (high – HF; low – LF). The quantiles of the simulated residuals of the fitted model match these quantiles, and the variance of these simulated residuals of the fitted model do not differ between levels of frequency. **E)** SR-PV displayed as boxplots per level of reward (high – HR; low – LR). The quantiles of the simulated residuals of the fitted model match these quantiles, and the variance of these simulated residuals of the fitted model does not differ between levels of frequency. **E)** Simulated residual variance in the high-and low-reward conditions. There is no difference in predicted residual variance, both within and between the two levels of reward.

Figure B2

Model Diagnostics Accuracy With Speed Factor



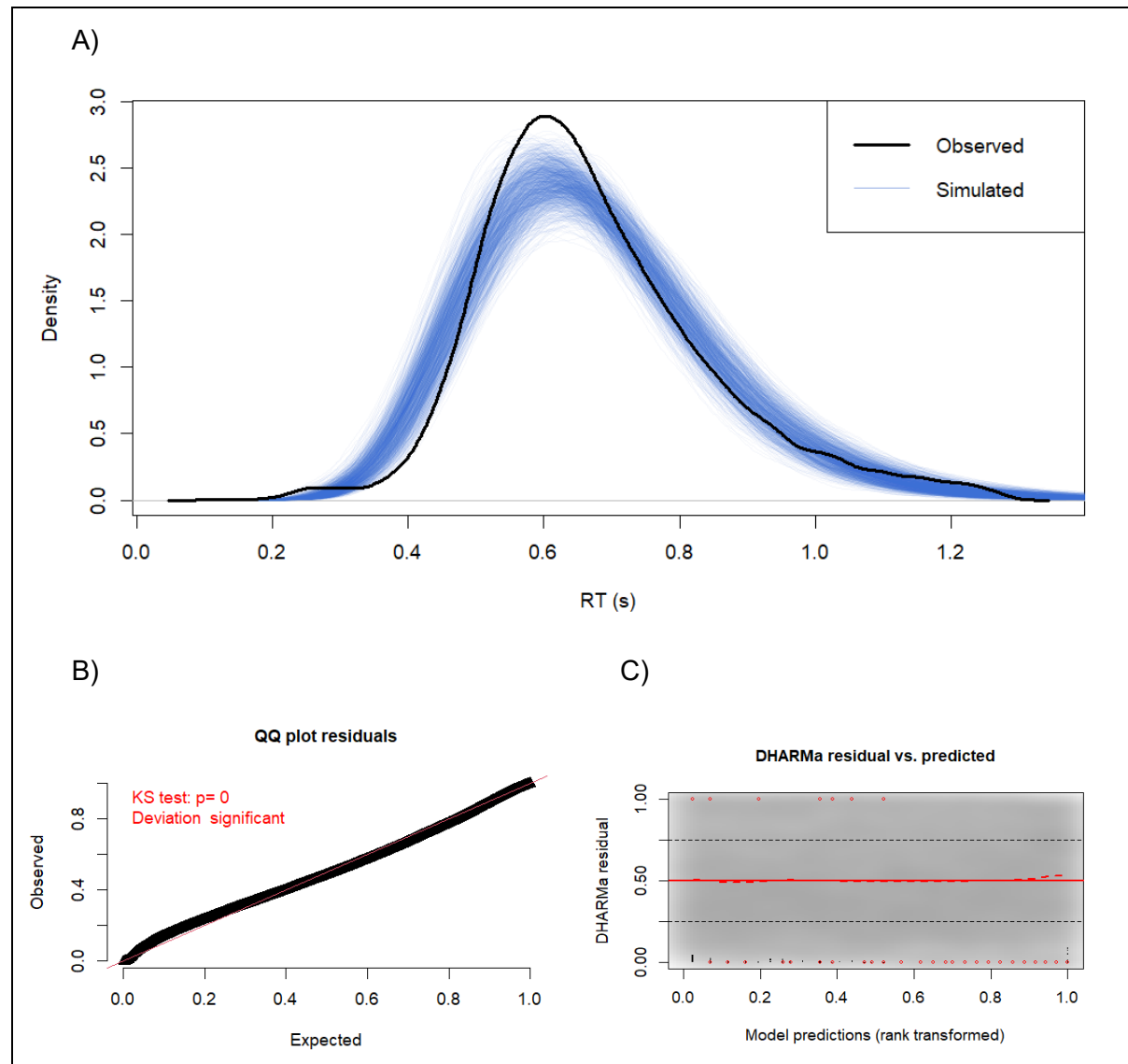


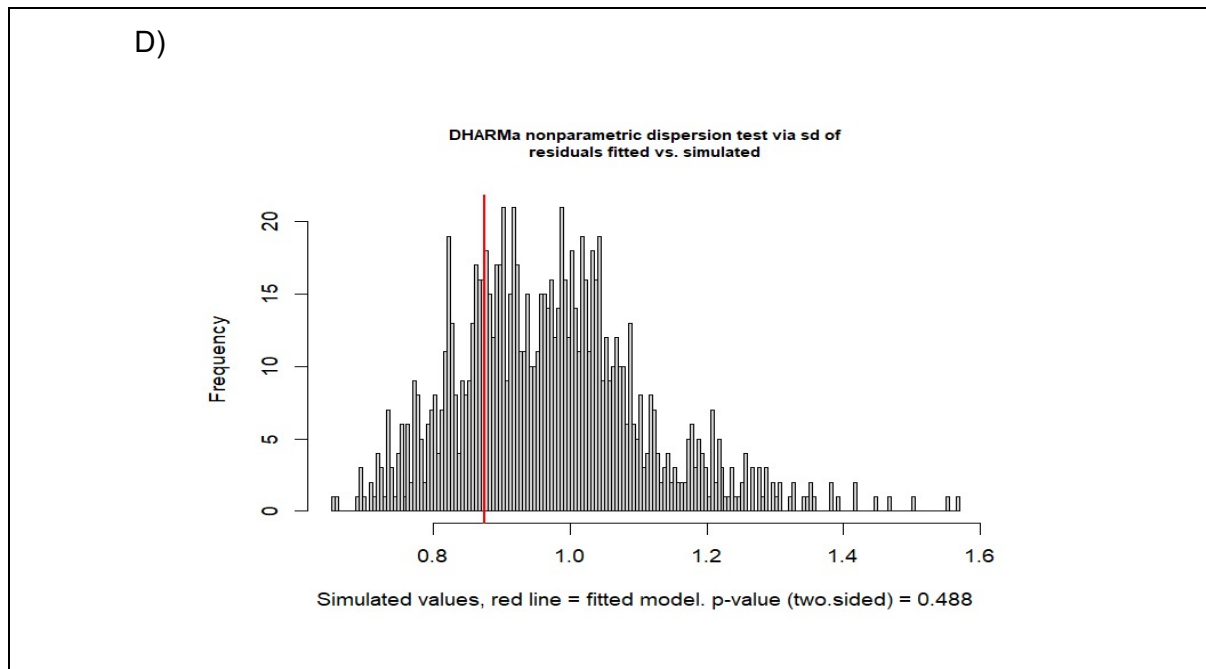
Note. **A)** Quantile-quantile plot (Q-Q plot) of scaled residuals, simulated by DHARMa, against the expected uniform distribution. A model with a good fit should show residuals falling along the diagonal line, indicating that the observed residuals are uniformly distributed. **B)** The scaled residual vs predicted values plot (SR-PV). It displays the scaled residuals (scaled between 0 and 1) against predicted values (also scaled between 0 and 1). The full red line shows the 0.50 quantiles of the simulated residuals under a correctly specified model. The dashed red line shows the 0.50 quantiles of simulated residual quantiles of the fitted model. This dashed line does not deviate systematically from the expected 0.50 quantile across all predicted values, indicating no misfit. **C)** SR-PV displayed as boxplots per level of block (here treated as a categorical variable). The dashed lines indicate the 0.25, 0.50, and 0.75 quantiles of the simulated residuals for the different levels of block under a correctly specified model. The quantiles of the simulated residuals of the fitted model (boxplots) match these quantiles, and the variances of these simulated residuals of the fitted model do not differ between levels of block. **D)** SR-PV displayed as boxplots per level of frequency (high – HF; low – LF). The quantiles of the simulated residuals of the fitted model match these quantiles, and the variance of these simulated residuals of the fitted model do not differ between levels of frequency. **E)** SR-PV displayed as boxplots per level of reward (high – HR; low – LR). The quantiles of the simulated residuals of the fitted model match these quantiles, and the variance of these simulated residuals of the fitted model does not differ between levels of frequency. **F)** SR-PV displayed as boxplots per level of response speed (fast – first; slow – second). The Levene test warns for between-group differences in simulated residual variance ($F[1, 28521] = 17.39, p < .001$), and the Kolmogorov-Smirnov warns for within-group deviations from the theoretical quantiles under a properly defined model (first = $[D = 0.01, p = .012]$,

second = [$D = 0.02$, $p < .001$]). However, with a large number of observations, these tests become highly sensitive (Bilon, 2023). Visual inspection of the plot shows that these violations are minor.

Figure B3

Model Diagnostics Response Times



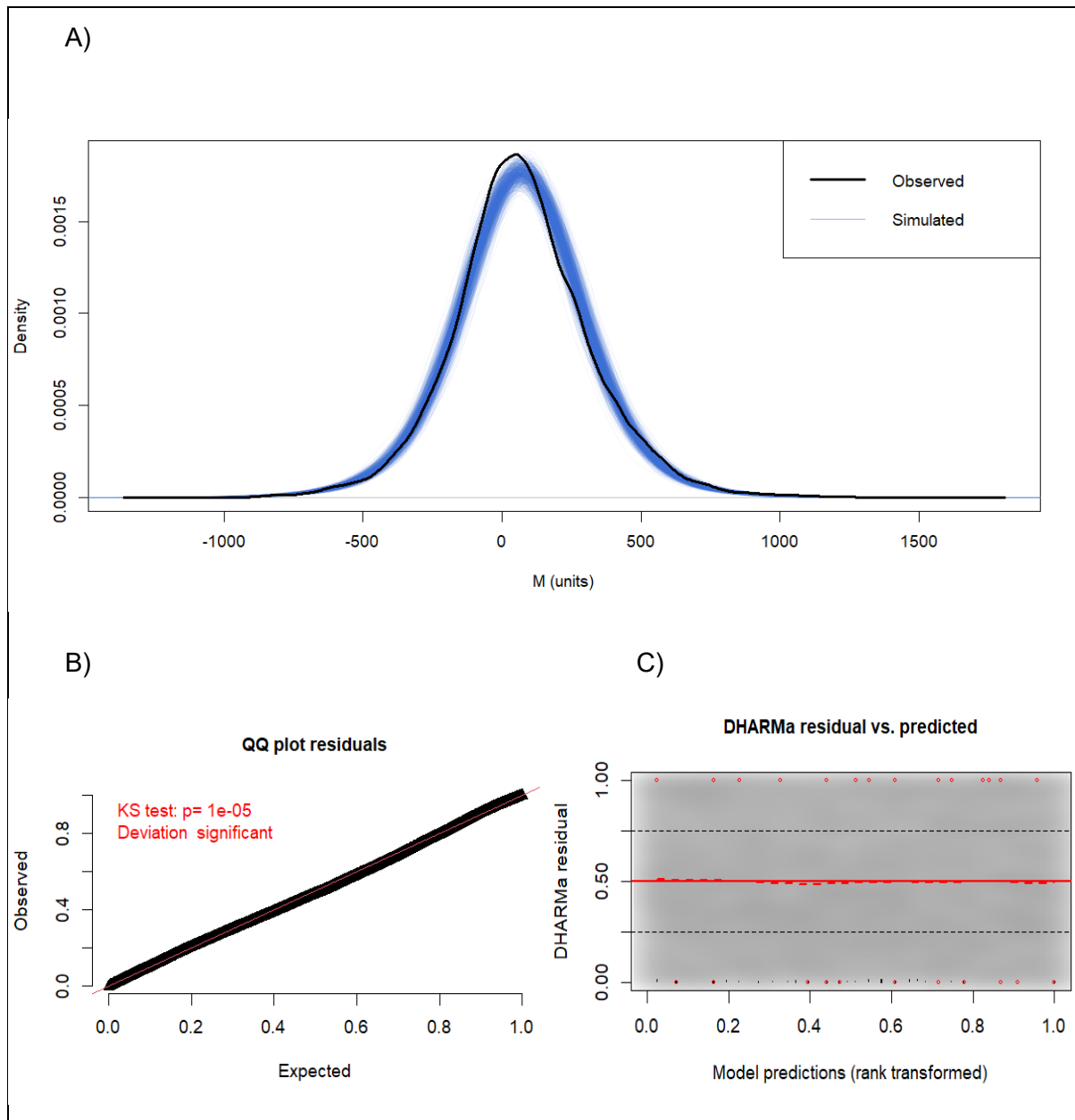


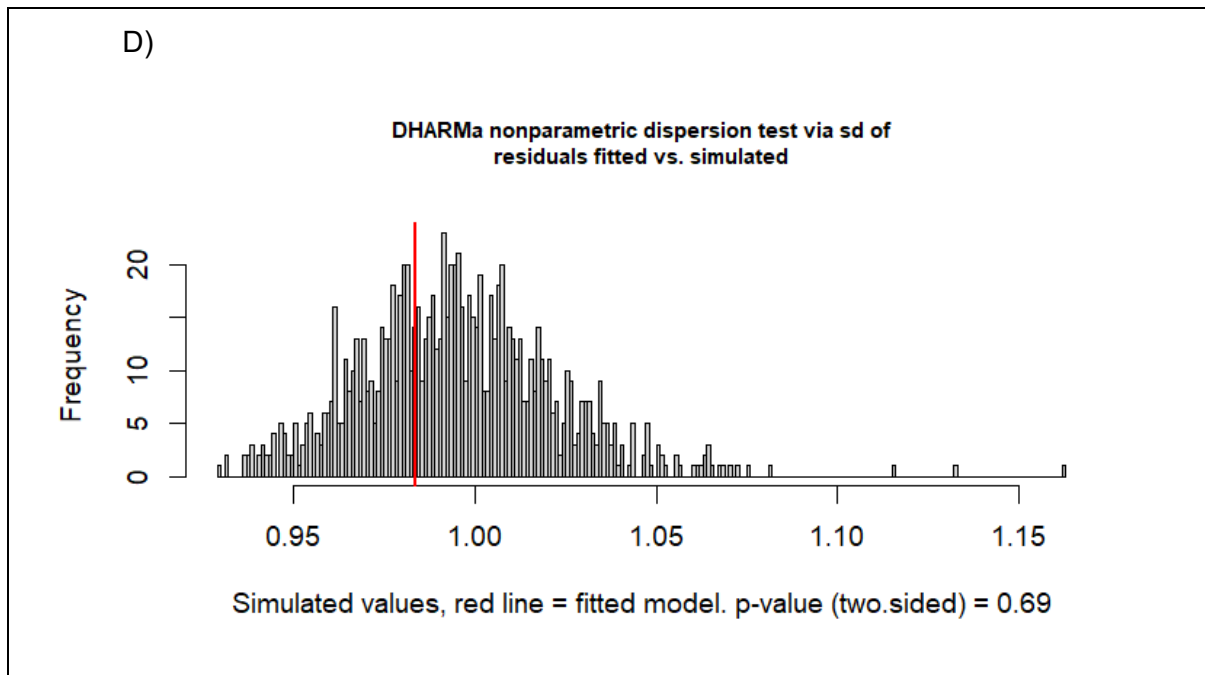
Note. **A)** Simulated RTs (ms) from the fitted gamma GLMM (1000 simulations; blue) compared to observed RTs (black), showing slight overestimation at the lower tail, around 0.4 s. The height of the peak of the observed RTs is underestimated by the model, but it does align well with the expected RTs. Thus, the overall distributional shape of RTs is well captured by the gamma distribution. **B)** Quantile-quantile plot (Q-Q plot) of scaled residuals, simulated by DHARMA, against the expected uniform distribution. A model with a good fit should show residuals falling along the diagonal line, indicating that the observed residuals are uniformly distributed. Although the Kolmogorov–Smirnov test for deviation was significant (red), this is likely due to its sensitivity to minor deviations in large samples (Bilon, 2023). **C)** The scaled residuals vs. predicted values plot (SR-PV plot). It displays the scaled residuals (scaled between 0 and 1) against predicted values (also scaled between 0 and 1). The full red line shows the 0.50 quantiles of the simulated residuals under a correctly specified model. The dashed red line shows the 0.50 quantiles of simulated residual quantiles of the fitted model. This dashed line does not deviate systematically from the expected 0.50 quantile across all predicted values, indicating no misfit. The figure highlights outliers (red dots), representing observations with residuals larger than expected under the fitted model. Although these outliers are present, the overall agreement between simulated and expected 0.50 residual quantiles suggests they have limited influence on model fit. The greater number of negative outliers (brought back to zero 0) indicates a tendency of the model to overpredict RTs. **D)** The gray bars represent the distribution

of dispersion statistics (variance of the residuals) expected under the fitted model, based on simulated data. The red line indicates the observed dispersion in the real data. The plot shows that the observed dispersion is in line with model expectations.

Figure B4

Model Diagnostics Pupil Size After Search Array Onset



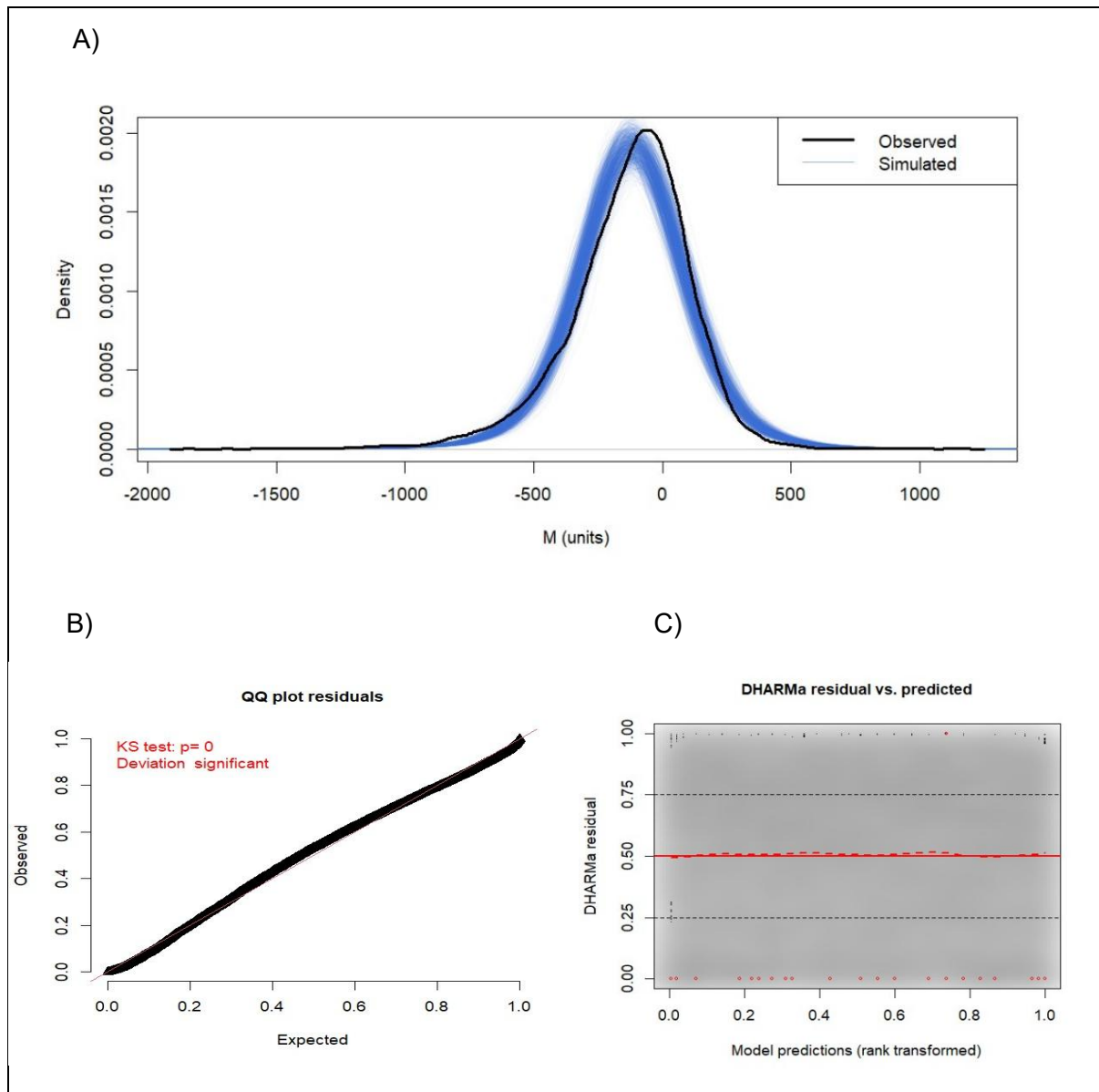


Note. **A)** Simulated mean pupil sizes after the onset of the search array (M; in arbitrary Eyelinker units) from the fitted t-distribution (1000 simulations; blue) compared to observed means (black). Both distributions show large overlap, with a minor shift between the peaks. **B)** Quantile-quantile plot (Q-Q plot) of scaled residuals, simulated by DHARMa, against the expected uniform distribution. A model with a good fit should show residuals falling along the diagonal line, indicating that the observed residuals are uniformly distributed. Although the Kolmogorov–Smirnov test for deviation was significant (red), this is likely due to its sensitivity to minor deviations in large samples (Bilon, 2023). **C)** The scaled residuals vs. predicted values plot (SR-PV plot). It displays the scaled residuals (scaled between 0 and 1) against predicted values (also scaled between 0 and 1). The full red line shows the 0.50 quantiles of the simulated residuals under a correctly specified model. The dashed red line shows the 0.50 quantiles of simulated residual quantiles of the fitted model. This dashed line does not deviate systematically from the expected 0.50 quantile across all predicted values, indicating no misfit. The figure highlights outliers (red dots), representing observations with residuals larger than expected under the fitted model. Although these outliers are present, the overall agreement between simulated and expected 0.50 residual quantiles suggests they have limited influence on model fit. **D)** The gray bars represent the distribution of dispersion statistics (variance of the residuals) expected under the fitted model, based on simulated data. The

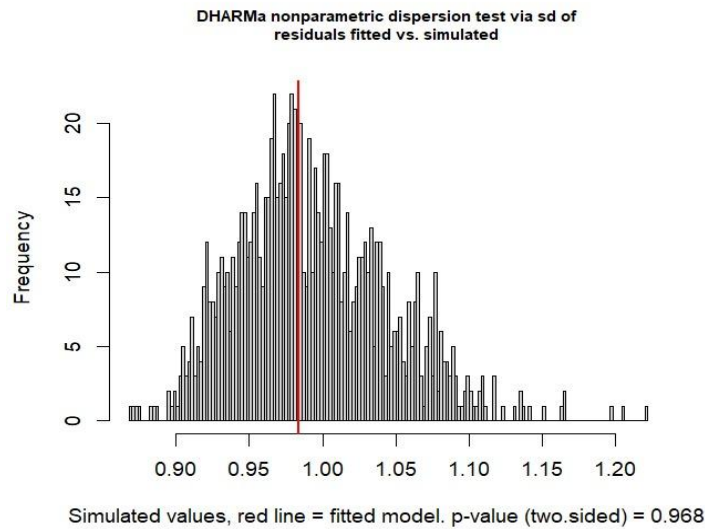
red line indicates the observed dispersion in the real data. The plot shows that the observed dispersion is in line with model expectations.

Figure B5

Model Diagnostics Pupil Size After Reward Feedback



D)



Note: **A)** Simulated mean pupil sizes after the onset of the reward feedback (M; in arbitrary Eyelinker units) from the fitted t-distribution (1000 simulations; blue) compared to observed means (black). Both distributions show large overlap, with a minor shift between the peaks. **B)** Quantile-quantile plot (Q-Q plot) of scaled residuals, simulated by DHARMA, against the expected uniform distribution. A model with good fit should show residuals falling along the diagonal line, indicating that the observed residuals are uniformly distributed. Although the Kolmogorov–Smirnov test for deviation was significant (red), this is likely due to its sensitivity to minor deviations in large samples (Bilon, 2023). **C)** The scaled residuals vs. predicted values plot (SR-PV plot). It displays the scaled residuals (scaled between 0 and 1) against predicted values (also scaled between 0 and 1). The full red line shows the 0.50 quantiles of the simulated residuals under a correctly specified model. The dashed red line shows the 0.50 quantiles of simulated residual quantiles of the fitted model. This dashed line does not deviate systematically from the expected 0.50 quantile across all predicted values, indicating no misfit. The figure highlights outliers (red dots), representing observations with residuals larger than expected under the fitted model. Although these outliers are present, the overall agreement between simulated and expected 0.50 residual quantiles suggests they have limited influence on model fit. **D)** The gray bars represent the distribution of dispersion statistics (variance of the residuals) expected under the fitted model, based on simulated data. The

red line indicates the observed dispersion in the real data. The plot shows that the observed dispersion is in line with model expectations.

Appendix C

Figure C1

Variability in outcome variables by random effects structure

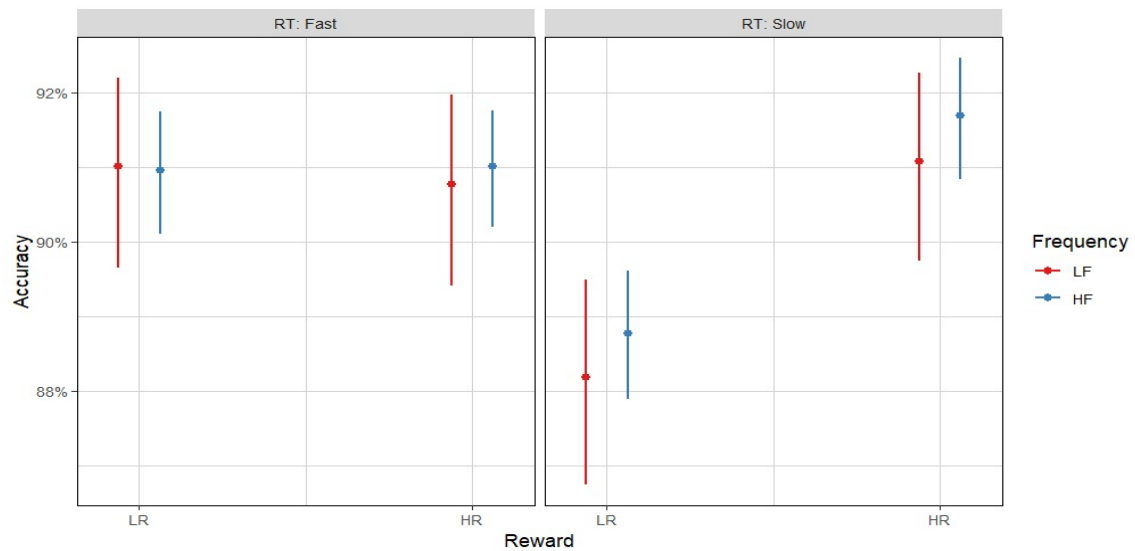
Grouping Factor	Estimate Type	Variable(s)	Estimate
Accuracy			
ID	SD	(Intercept)	0.914
ID	SD	Reward	0.592
ID	SD	Frequency	0.262
ID	SD	Block	0.778
ID	Corr	(Intercept) & Reward	-0.318
ID	Corr	(Intercept) & Frequency	-0.189
ID	Corr	(Intercept) & Block	0.482
ID	Corr	Reward & Frequency	0.294
ID	Corr	Reward & Block	-0.696
ID	Corr	Frequency & Block	-0.017
Response Time			
ID	SD	(Intercept)	0.153
ID	SD	Block	0.085
ID	Corr	(Intercept) & Block	-0.572
Pupil Size (Post Search Array)			
ID	SD	(Intercept)	107.905
ID	SD	Block	11.550
ID	Corr	(Intercept) & Block	-0.118
Pupil Size (Post Feedback)			
ID	SD	(Intercept)	99.492
ID	SD	Block	14.543
ID	Corr	(Intercept) & Block	-0.041

Number of observations: Accuracy N = 29184; Reaction Time N = 25733;
Pupil Size (Post Search Array) N = 20464; Pupil Size (Post Feedback) N = 21831

Note. Random effects table. Random effects (specified under column 'Variables') were calculated for each participant (ID; the grouping factor). For each random effect, we report the standard deviation (SD) and correlation with other random effects (Corr). The number of observations that were included in each analysis are displayed at the bottom of the table.

Figure C2

Predicted Values Speed-Accuracy effect



Note. Predictions about the relation between speed and accuracy grouped per level of response speed (fast vs. slow). Predictions represent task performance in the middle of the experiment. Accuracy was overall lower for slow trials, but reward mediated this effect, showing that accuracy in slow trials was higher for high-reward versus low-reward conditions.