EXAMINING RACIAL BIAS IN EVIDENCE ACCUMULATION: EXPLORING THE IMPACT OF OBJECT SEARCH

By

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ABSTRACT

Prior investigations into racial bias in fatal police shootings have predominantly employed the First-Person Shooter Task (FPST) and the Weapon Identification Task (WIT). These paradigms have revealed consistent patterns of bias, including faster correct decisions to shoot armed Black targets (as shown in the FPST) and a bias towards misidentifying harmless objects as weapons after exposure to Black primes (evidenced in the WIT). While these findings are valuable, they overlook the role of visual search in these high-stakes decision-making processes. The influence of visual search processes and their associated cognitive mechanisms—such as those described by Drift Diffusion Modelling (DDM)—remain relatively unexplored. This dissertation bridged this gap by examining the impact of race on search efficiency within complex visual environments and its reflection in evidence accumulation. Across two studies, I found that race did not significantly impact search efficiency or evidence accumulation. Instead, a consistent target type effect emerged, indicating that searches for guns were more efficient than for other objects, irrespective of racial primes, and this was mirrored in credibly stronger rates of evidence accumulation. This work serves as a first step into understanding the dynamics of racial biases within decision-making processes in high-stakes situations, emphasizing the examination of search behaviors.

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INTRODUCTION

In recent years, the issue of racial bias in police shootings has emerged as a pivotal topic in national conversations, particularly in the context of social justice and law enforcement reform. This issue has been brought into sharp focus by numerous high-profile cases involving unarmed Black Americans who were fatally shot by police officers, often under circumstances that have raised serious questions about the use of lethal force. These tragic incidents have sparked widespread public outcry and underscored the urgent need for a deeper understanding of the underlying factors contributing to these outcomes. In response to this pressing societal issue, social psychologists have investigated the decision-making processes involved in police shootings.

One paradigm that has been used to study shooting decisions is the First-Person Shooter Task (FPST), developed by Correll et al. (2002; see also Figure 1), which was designed to study the role of racial bias in simulated police shooting scenarios. The task attempts to mimic the high-pressure, instantaneous decision-making situations that law enforcement officers may encounter. In this task, participants are first shown a series of images that depict various neighborhood scenes without any people. These scenes serve as the backdrop for the task, creating the context for the presentation of target individuals. After presenting one to four empty scenes, an image of a person is suddenly introduced. This individual is typically a Black or White male and is depicted as holding an object. The object could either be harmless (e.g., a wallet or cellphone) or threatening (e.g., a gun).

Participants are tasked with making a rapid 'shoot' or 'don't shoot' decision based on the perceived threat posed by the target individual within a constrained time window of 630 to 850 milliseconds. This time constraint is designed to simulate the urgency often associated with real-life police shooting incidents. The FPST incorporates a payoff matrix that is structured to encourage shooting, reflecting the potential real-world consequences of failing to respond to a genuine threat. The payoff matrix rewards points for fast and correct decisions and penalizes slow or incorrect ones. The FPST provides a controlled environment for studying the cognitive and social factors influencing decision-making in potentially life-threatening situations, contributing to our understanding of the complex dynamics involved in police shootings (Correll et al., 2002).

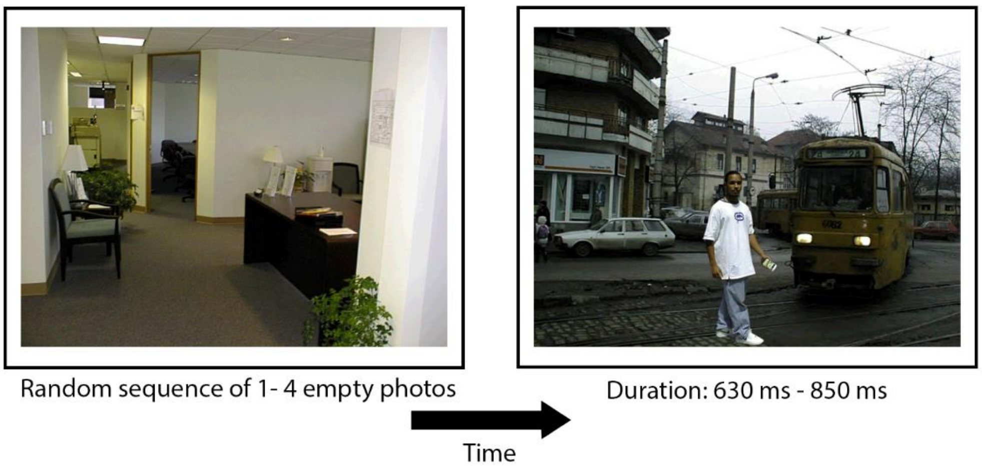

Figure 1: An example of a typical FPST trial.

A separate but related paradigm is the Weapon Identification Task (WIT; Payne, 2001; see Figure 2), which complements the FPST in studying racial bias. The WIT is a sequential priming task designed to assess the speed and accuracy of object identification, with the objects in question being either "weapons" or "tools." A prime face, either Black or White, is presented for 200 milliseconds in a typical WIT trial. This is immediately followed by a target image of either a tool or a gun, also displayed for 200 milliseconds, which is then replaced by a visual mask.

Participants must respond by pressing a key corresponding to either "tool" or "gun" during the presentation of a visual mask. A distinguishing feature of the WIT, as compared to the FPST, is that the prime images are generally headshots, and the target images are displayed against a neutral, empty background. This design feature allows for the isolation of the influence of racial priming on object identification, free from the potential confounding effects of contextual information. The WIT thus provides a valuable tool for investigating the cognitive mechanisms underlying racial bias in object identification and how such bias may influence decision-making in critical situations (Payne, 2001).

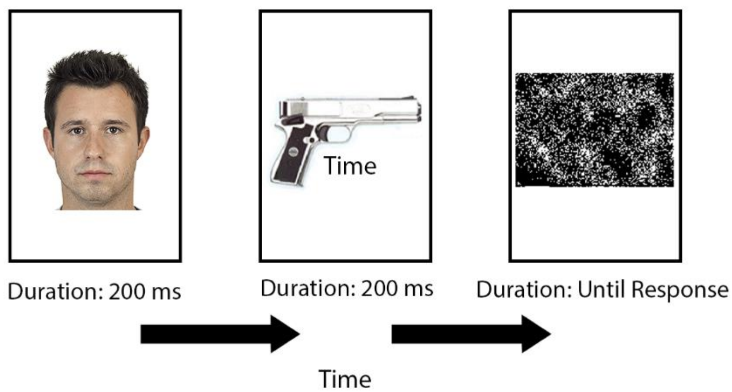

Figure 2: A typical WIT trial.

In both tasks, racial bias is measured based on participants' error rates or response times. For instance, in the FPST, racial bias may manifest as participants being more likely to shoot unarmed Black suspects than unarmed White suspects or responding "shoot" faster to armed Black suspects than armed White suspects (Cesario & Carrillo, 2024; Mekawi & Bresin, 2015). Similarly, racial bias is evident in the WIT when participants are faster or more accurate at identifying guns following Black faces or tools following White faces, compared to the reverse pairings (Rivers, 2017).

A significant focus of these research lines has been on the misidentification of harmless objects. This line of inquiry has been largely driven by real-world incidents where police officers have mistakenly perceived harmless objects (or no objects at all) as weapons, as in the tragic case of Amadou Diallo. However, this research tradition, while valuable, may not fully capture the complexity of decision-making processes in police encounters. An integral aspect of these encounters, often overlooked in research, is the process of not just identifying a target object but also locating it. This process, visual search, is a key component of police academy training. Officers are taught to scan various potential threat locations, such as hands, waists, backpacks, and key locations in the general surroundings. In situations involving multiple officers, roles may be divided, with one officer engaging the suspect while others scan the environment for potential hazards.

Despite its importance in real-world policing, the implications of visual search for decision-making have not been fully appreciated in the existing literature. For example, the WIT is primarily designed to study object identification without search elements. While the FPST incorporates some elements of visual search, it does so in such a way that salience or anchoring may play an important role. That is, the participants view several empty background scenes back-to-back before the rapid presentation of the suspect, which acts as a signal to rapidly guide attention. Consideration of how this may shape search efficiency and object identification is generally not discussed. Given these gaps in the current understanding, this dissertation proposes to investigate the role of visual search in shaping weapon identification.

Visual Search

Visual search is a cognitive process that involves identifying and localizing a target object within a visual field populated with other objects, often referred to as distractors. This process is a fundamental component of many tasks requiring object identification and is typically studied in a controlled laboratory setting. These tasks can vary enormously from searches for a friend in a crowd of people, finding your favorite brand of cereal at the supermarket to scanning for threats in airport baggage. The standard experimental procedure generally involves participants scanning an array of objects for a target object that differs from the distractors by one or more features (Wolfe, 2020; Wolfe & Horowitz, 2017).

The efficiency of visual search, defined as the speed and accuracy with which a target is identified among distractors, can be influenced by various factors. These include the degree of differences between the target and distractors, such as their size, color, and shape (Duncan & Humphreys, 1989). The number of items in the visual field, also known as the set size, can also impact search efficiency, with larger set sizes generally leading to longer search times (Treisman & Gelade, 1980; Wolfe et al., 2010; Wolfe, 2014). Top-down factors such as the goals and expectations of the observer can also play a significant role in visual search efficiency (Wolfe, 1994, 2020). For example, if an observer is actively looking for a specific object, they may be able to identify it more quickly than if they were passively scanning the visual field. When actively searching for their keys on a cluttered desk, an individual quickly zeroes in on specific cues like shape and shine, facilitating rapid identification. In contrast, a casual glance across the same desk, without a specific target in mind, can easily miss the keys among the clutter.

Researchers commonly examine search slopes to assess visual search efficiency, which quantitatively measure how response time increases with the number of items in the search array (Treisman & Gelade, 1980). Search slopes reflect the rate at which response time grows as the set size, or the number of items in the display, increases. A steeper search slope indicates a larger increase in response time per additional item, suggesting a less efficient search process. Conversely, a shallower search slope indicates a smaller increase in response time, indicating a more efficient search process (Wolfe, 1998). That is, search efficiency exists on a continuum. In highly efficient or highly guided search, the target object "pops out" from the display, meaning that it can be quickly and effortlessly detected regardless of the number of distractors present (Egeth et al., 1972). This phenomenon is known as a "pop-out" search, where the target object captures attention automatically and stands out from the distractors.

In pop-out searches, the search slope is nearly flat or absent, indicating that response time remains constant regardless of the set size. For example, a single red apple among a cluster of green apples effortlessly captures attention, showcasing pop-out search through the immediate draw of its distinct color. This contrasts with more demanding or less efficient search tasks, where the search slope is steeper, indicating a longer response time as the set size increases. As an example, imagine performing a search for a green apple among green pears; the task becomes slightly more difficult and involves looking through more of the items. Note, however, that while the use of set size is commonplace in the literature, differences in search efficiency can be reflected in either the search process, the identification process, or some combination of both (Kristjánsson, 2015; Wolfe, 2016).

Guided Search Model 6.0

Determining what guides visual search is a complex task. Wolfe (2021) offers an updated model of visual search, known as Guided Search 6.0 (GS6), which provides a comprehensive framework for understanding this process. The GS6 model assumes that although we can see various items throughout a scene, our capacity for recognizing more than a handful at a time is restricted. To address this limitation, attention is utilized to select items, allowing their features to be "bound" together into recognizable objects.

This attention is not random but "guided," allowing items to be processed in an efficient order. According to the GS6 model, this guidance is derived from five sources of pre-attentive information. These include (1) top-down feature guidance, which refers to the influence of the observer's goals, expectations, and guiding templates; (2) bottom-up feature guidance, which is driven by the salient features of the items in the visual field (Theeuwes 1992); (3) prior history, such as priming effects where previous exposure to an item influences its subsequent recognition; (4) reward, which can bias attention towards items associated with positive outcomes (Anderson et al., 2011; Lee & Shomstein, 2013); and (5) scene syntax and semantics, which refers to the influence of contextual information and the overall meaning of the scene (Boettcher et al. 2018; Henderson & Hayes, 2017).

These sources of guidance are integrated into a spatial "priority map," a dynamic attentional landscape that evolves throughout the search process. This map helps determine the order in which items are attended to and processed, thereby guiding the visual search process. The selected object(s) are compared to target templates in long-term memory. Wolfe (2021) proposes that this process unfolds through an 'asynchronous diffuser.' In essence, the identification of one item can start before the identification of the previous item has been completed. This asynchronous process allows for a more fluid and efficient search. Although many aspects of visual search warrant discussion, I will focus on top-down guidance, priming effects, and the importance of templates. These elements have the potential to be influenced by factors such as race. Understanding how these components function and how racial biases might shape them can provide valuable insights into the broader dynamics of visual search processes and their implications for tasks like the FPST or WIT and, ultimately, police use of force.

Social Information and Search Processes

Top-down feature guidance is a form of attentional guidance that is influenced by an observer's knowledge or expectations about the target's features. Higher cognitive processes drive this form of guidance and direct attention toward specific features of a target that align with the observer's expectations (Eimer, 2014). For instance, if an observer is searching for a green apple among green pears, their knowledge about the shape of an apple would guide their attention toward objects with that shape.

Prior history, including priming effects, significantly impacts attentional guidance, drawing from an observer's past experiences. Priming effects can operate in multiple ways, with the most well-studied including intertrial and cueing. For intertrial priming, if an observer has recently seen a red apple, they are more likely to notice red objects in their visual field in subsequent trials (Kruijne & Meeter, 2015). In cueing, priming of emotional facial cues can facilitate search processes for unrelated target objects (Becker, 2009), and exposure to specific semantic categories prior to the presentation of the visual array can guide attention to semantically similar target objects (Robbins & Hout, 2015, 2020).

An important element to highlight is the role of search templates in this process. Wolfe (2021) posits that two forms of templates significantly contribute to visual search: guiding templates and target templates. Guiding templates are cognitive representations of features that guide attention by highlighting areas in the visual field that match these features (Bravo & Farid, 2009, 2012; Malcolm & Henderson, 2009; Vickery et al., 2005; Wolfe et al., 2004). These templates are flexible and can include multiple features; importantly, there are ongoing debates about the number of templates that can be held in working memory (Bahle et al., 2020; Ort & Olivers, 2020) with clear costs in speed and accuracy for multiple object searches (Menneer et al., 2012; Stroud et al., 2012). On the other hand, target templates are more specific and represent the target the searcher is looking for. They help in identifying targets and rejecting distractors during the search. When an item is selected, it is compared to a target representation, determining whether it is the target or a distractor.

To fully assess the impact of race on visual search, it is crucial to consider the role of guidance, not just identification. Race information may enhance the effectiveness of the search process through the interplay between guiding templates and top-down feature guidance. For example, if a participant is tasked with finding a green apple among green pears, working visual memory may adopt abstract features or attributes of that green apple to facilitate the search. The exact mechanisms of how these representations are developed and utilized are still a subject of ongoing research. However, Yu et al. (2023) proposes that it likely adheres to a "good-enough" principle. This principle suggests that attentional guidance is often based on the simplest, sufficient information that can provide a high-quality estimate of a potential target object's location. Importantly, Yu et al. (2023) highlight that this is context-dependent. For example, in searching for a green apple among green pears, the feature "green" would not be useful, but shape and size might be. In contrast, color would be the useful defining feature if searching for a red apple among green apples.

The contents of this guiding template are influenced by many factors, including the priming of social or categorical information (Yu et al., 2023). Robbins and Hout (2020) demonstrated the influence of scene priming on visual search tasks. Participants were primed with images of scenes contextually related to the target object they were searching for in an array. They found that semantic information activated by the scene guided attention to semantically similar items in the search array, resulting in faster response times following congruent primes. Research using empty backgrounds and classic search arrays has shown that categorical information can influence features in a template. When primed with categorical information, guiding templates can facilitate the search for items, including object features that are typical of a category (Robbins & Hout, 2015) or that are consistent across exemplars of a category (Hout et al., 2017; Yu et al., 2016). Categorical information can also be in the form of social identities; for example, Chiao et al. (2006) primed racial identities and had participants scan a search array for Black or White faces, finding that guidance was faster after congruent priming.

Despite limited research directly exploring the impact of race on visual search, evidence suggests that social and categorical information can influence object search. Given these insights, it is sensible to study both object identification and the potential influence of race on search efficiency. This exploration can be achieved by examining behavioral data such as response times and understanding underlying cognitive processes.

Drift Diffusion Modeling

Researchers have turned to computational models such as the Drift Diffusion Model (DDM) to investigate how race affects decision-making processes. This model offers a comprehensive view of the cognitive processes that drive decision-making and facilitates a nuanced analysis of the effects of racial bias. For example, a review by Johnson et al. (2017) demonstrated that DDM can provide novel insights into the cognitive processes underlying decision tasks like the FPST.

The DDM is a widely used sequential sampling model in cognitive psychology that explains the cognitive processes involved in decision-making tasks (Ratcliff, 1978). It posits that decisions are made by accumulating evidence over time until a decision threshold is reached.

The DDM has been applied to tasks like the FPST and WIT to gain insights into the role of race in decision-making processes (Correll et al., 2015; Harder, 2017, 2020; Johnson et al., 2018; Johnson et al., 2021; Pleskac et al., 2018; Todd et al., 2021).

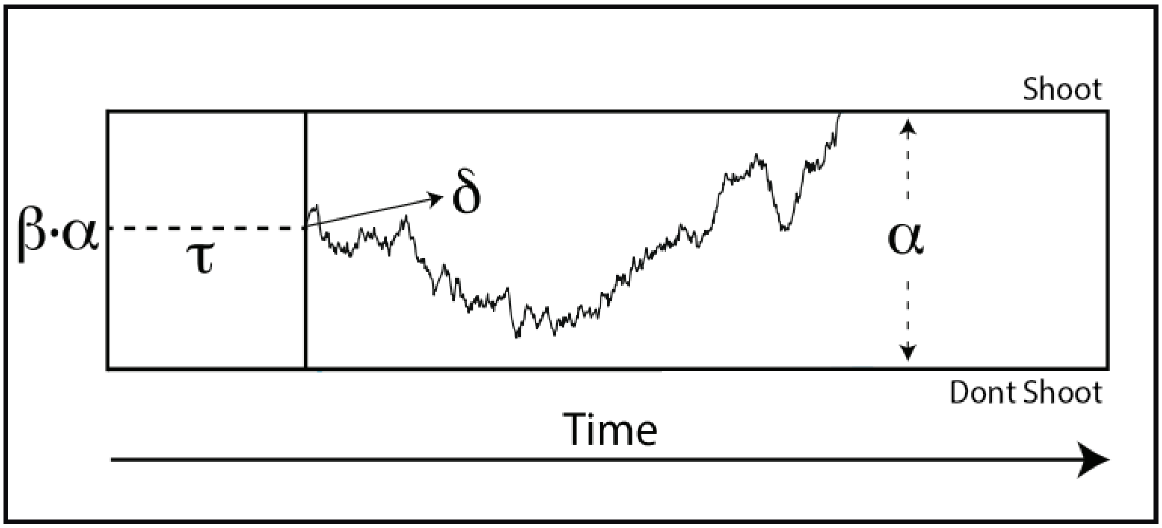

Figure 3: The drift diffusion model.

The DDM consists of four parameters (see Figure 3): Beta (start point), Delta (drift rate), Alpha (evidence threshold), and Tau (non-decision time). Beta, the start point, signifies the initial bias or predisposition before the process of evidence accumulation begins. In the context of the FPST, this could reflect a participant's initial bias towards shooting or not shooting, e.g., being "trigger happy." Delta, or the drift rate, represents the rate of evidence accumulation over time. It mirrors the strength or quality of the evidence being processed during decision-making per unit of time. A steeper drift rate (higher delta) indicates a stronger accumulation of evidence, leading to quicker decisions (all else equal). Conversely, a shallow drift rate (lower delta) suggests weaker evidence accumulation, resulting in slower decisions. Factors such as the clarity of the visual stimuli or prior information can influence this parameter.

Alpha, the evidence threshold, denotes the amount of information or evidence required to make a decision. This parameter is linked to the speed-accuracy trade-off. For example, when response time windows are shorter, evidence thresholds tend to be lower, suggesting a faster but potentially less accurate decision-making process (Pleskac et al., 2018). Lastly, Tau, the non-decision time, accounts for the time taken for processes other than decision-making, such as motor response time. This parameter helps distinguish the cognitive decision-making process from the physical response, thereby providing a more accurate depiction of the cognitive processes involved in tasks like the FPST. The different parameters of the DDM - Beta (start point), Delta (drift rate), Alpha (evidence threshold), and Tau (non-decision time) - work in concert to provide a comprehensive understanding of the decision-making process in tasks like the FPST and WIT.

When applying the DDM to the FPST, significant effects of race on the drift rate or delta are observed. Specifically, evidence is stronger to support a 'shoot' decision when the target is Black rather than White (Correll et al., 2015; Johnson et al., 2018; Pleskac et al., 2018). This suggests that participants gather and process decision-making information more efficiently when the target is Black. In contrast, when applying DDM to the WIT, race generally has no observed effect on the drift rate. This discrepancy could be attributed to a variety of differences between the tasks. However, as this latter WIT finding is based on a single published paper (Todd et al., 2021) and unpublished data from the Cesario lab, it should be interpreted with caution.

In the context of shooting decisions, shifts in these parameters would result in distinct response time and error rate changes (see Figure 4). For instance, if participants receive dispatch information indicating that a suspect at the scene is armed, we might expect the beta parameter to increase or start closer to the shoot threshold. This adjustment would likely result in faster responses when the bias aligns with the correct response. However, this could come at the cost of accuracy if the bias favors an incorrect decision. Additionally, the alpha parameter, or evidence threshold, can be influenced by the allotted response time windows. In shooting decisions, extending the time allowed for a response generally enhances accuracy. A lengthened response time window increases boundary separation, leading to longer response times but typically higher accuracy, as decisions are made with greater certainty.

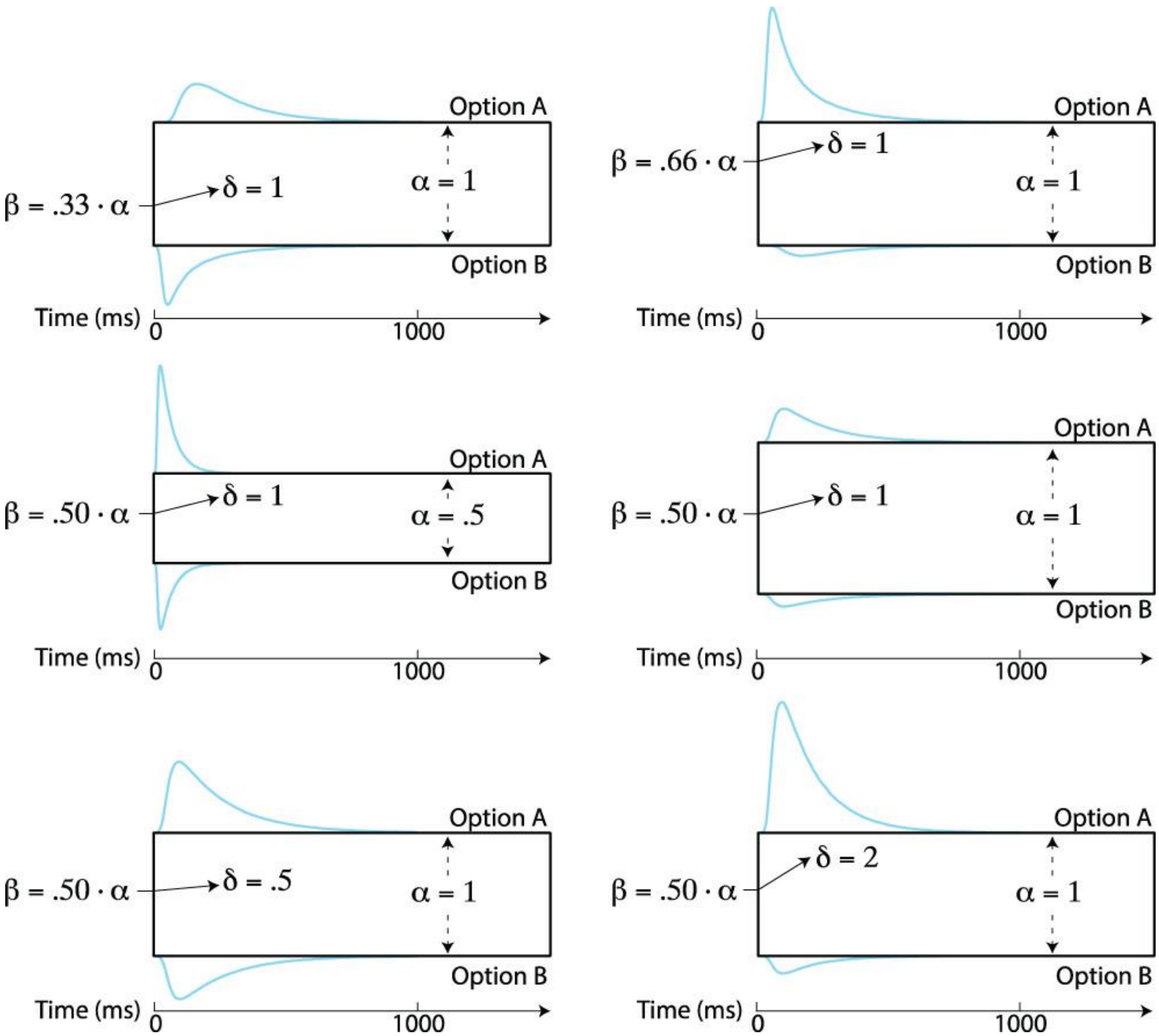

Figure 4: "An illustration of how changing diffusion model parameters impacts decisions and response time distributions (in blue). We assume that evidence is correctly accumulated toward Option A. Top panel: higher relative start point b increases the likelihood and speed of selecting Option A by primarily increasing modal response speed. Middle panel: higher threshold a increases the likelihood of choosing Option A and decreases the speed of choosing both options by shifting the mode and lengthening the tails of responses. Bottom panel: higher drift rate d increases the likelihood and speed of selecting Option A by shortening the tails of the responses. Nondecision time t is not depicted as it simply shifts both distributions by a fixed amount."

Figure 4 (cont'd):
Adapted from "Advancing Research on Cognitive Processes in Social and Personality Psychology: A Hierarchical Drift Diffusion Model Primer," by D. Johnson, C. Hopwood, J. Cesario, & T. Pleskac, 2017, Social Psychological and Personality Science, 8, p. 2. https://doi.org/10.1177/1948550617703174. Reprinted with permission.

The drift rate, can be influenced by the quality or strength of the information presented in the stimuli. For example, a suspect holding a rifle, as opposed to a smaller handgun, provides stronger information, which could increase the drift rate and lead to overall faster decision-making. Finally, the non-decision time (tau) impacts response time but does not directly affect decision accuracy. An increase in tau uniformly extends the response time across all trials, irrespective of the decision difficulty or accuracy.

Visual Search and the DDM

Drift rate, representing the strength of evidence accumulation, is a multifaceted parameter influenced by numerous factors. Yet pinpointing what specifically drives changes in the drift rate can be challenging. Factors such as the clarity of visual stimuli, prior information, or the complexity of the task can all impact the rate at which evidence is accumulated. However, these are just a few examples, and the drift rate can be influenced by many other factors, some of which may not be immediately obvious or easy to measure. One such factor that has been somewhat overlooked is the role of object search. The process of searching for a specific object or feature within a visual scene could potentially influence the drift rate, as it affects how efficiently evidence can be gathered and processed. However, the exact nature of this relationship is not yet fully understood.

One key factor that comes into play is discriminability, which refers to the ability to distinguish between different stimuli. In a study conducted by Pleskac et al. (2018), the FPST was modified by blurring the object held by the target. This manipulation effectively reduced the discriminability of the object, making it harder for participants to identify it. The results showed that this decrease in discriminability led to a slower rate of evidence accumulation, as reflected in a lower drift rate. In other words, when the target object was blurred, participants took longer to gather and process the necessary evidence to make a decision about the object's identity. This study is particularly important as it provides empirical support for interpreting the drift rate (delta) as a measure of evidence strength. It demonstrates that changes in the quality of the visual stimuli, such as a decrease in discriminability, can directly impact the rate at which evidence is accumulated during decision-making tasks.

In a modification of the FPST, Johnson et al. (2018) sought to simulate real-world situations where officers receive dispatch information. They presented participants with race and/or weapon information for 2000 ms, operationalizing the dispatch information typically received by officers. In a within-subjects manipulation where this information was not provided, participants viewed a fixation point for the same duration instead. The findings of Johnson et al. (2018) revealed that providing race information reduced the role of racial bias in evidence accumulation. Interestingly, providing weapon information had a dual effect: it led to stronger drift rates when the weapon information was correct but weaker drift rates when the weapon information was incorrect.

Johnson et al. (2018) hypothesized that these effects could be attributed to differences in search strategies. Specifically, they proposed that participants engage in an exploratory search when no prior information is given (i.e., "What object is being held?"). However, when information is given, participants shift to a confirmatory search (i.e., "Is that person holding a gun?"). This can also be conceptualized in terms of the role of templates in facilitating search and identification. In general, participants are not given information before each trial, resulting in the possibility of broad templates and possible memory searches. However, when participants are informed that the suspect is armed, a template that includes more gun-like features may be used. This shift would result in stronger evidence accumulation when the suspect is armed and substantially weaker evidence accumulation when the suspect is unarmed. However, due to the design of the task, it's challenging to determine whether these effects reflect differences in search or identification processes.

Correll et al. (2015) utilized eye-tracking technology to explore the impact of visual processing on racial bias. They examined participants' eye movements during the FPST and calculated the visual angle between the fixation point and the target object. A larger visual angle suggests a greater deviation between where participants were looking and the target object. The findings revealed that participants had larger visual angles for Black targets than White targets, irrespective of whether the target was armed or unarmed. That is, participants directed their gaze toward areas other than the suspect's hand when the suspect was Black. However, even though participants did not fully fixate on the target item when the suspect was Black, Correll et al. (2015) observed steeper drift rates for guns with Black targets. They concluded that this reflects a stereotype consistency effect, where objects appear more like guns when paired with Black targets.

This could imply that identification was more accurate when stereotypes were congruent, but search efficiency might have been compromised by race. However, it is worth noting that the drift diffusion model employed in their study was overly restrictive due to the absence of hierarchical modeling. Specifically, without the use of hierarchical modeling or Bayesian estimation, the model estimates are generated from a very small number of trials, which constrain the extent to which parameters are allowed to vary (Johnson et al., 2017). This limitation imposed artificial constraints on the model's interpretability. For example, the evidence threshold was not allowed to vary by race. As an alternative account, a lower threshold for Black targets may also work to explain the fact that participants made a decision before full fixation of the target object. In addition, without manipulating search difficulty, strong conclusions about search efficiency cannot be made. While their effort serves as a valuable first attempt, the model constraints limit the insights about visual processes that can be drawn from this study.

The potential influence of visual search processes on the drift rate, or evidence accumulation, is a common thread in the findings discussed. However, direct evidence for such an effect has not been systematically studied. Furthermore, it remains unclear how, or even if, race might influence search efficiency. Thus, a comprehensive understanding on the role of visual search is essential for deciphering the mechanisms underlying racial bias in decision-making tasks.

The Current Research Proposal

There are significant gaps in our understanding of the factors influencing evidence accumulation and decision-making in the decision to shoot. In particular, the influence of object search, an important aspect of visual perception and attention, has been largely overlooked in the existing literature. By investigating the role of race in guiding search efficiency in complex visual environments, this research proposal aimed to fill this gap and provide a more comprehensive understanding of racial bias in deadly force decisions.

Therefore, this research proposal addresses the following research questions: (1) Does race influence search efficiency? (2) Do differences in search efficiency result in distinct patterns in drift rate? This research proposal explored these questions by introducing object search to weapon identification tasks by adding a random search array and manipulating set sizes. A larger set size typically leads to more challenging search tasks, as the target object becomes more difficult to locate among an increased number of distractors. By analyzing participants' search performance across different set sizes, efficiency in finding the target can be evaluated.

In Study 1, the response time window was 10 seconds to ensure that participants could perform the search task accurately. This choice is made for several reasons: first, creating a meaningful time restriction without a baseline is challenging, and second, in studies where set size is manipulated, reaction time is the measure of interest. The reaction time of correct identifications across set sizes is used to calculate the search efficiency or the search slope. A strict deadline without proper consideration may impose artificial limitations on the search slope, such as giving the appearance of a flatter or more efficient slope while ignoring incorrect responses. However, the long response windows limit error rates and thus precluded the use of DDM. Building on the findings of Study 1, Study 2 introduced a response time window informed by the distributions observed in the first study. This introduced errors in the task, allowing for the application of DDM, which gives further insight into the role of race in search.

STUDY 1

While various methods can be used to investigate the impact of race on search efficiency, this study employed a random search array broken into an 8x8 grid with set sizes of 12,16 and 20 (Hout & Goldinger, 2010, 2012, 2015). Race information in the form of a headshot of a Black or White Man and target information in the form of categorical word cues were provided before the presentation of the visual search array. These manipulations were chosen for several reasons. First, using set sizes to understand search efficiency by analyzing the function of the reaction time by set size is a well-established experimental method in the visual search literature (Eckstein, 2011; Treisman & Gelade, 1980; Wolfe, 2021). Second, allowing the target object to appear in any cell mitigates potential contextual cueing effects (Chun, 2000). For example, if a circular array was implemented, participants could adopt a search strategy driven by looking at possible object positions before object presentation, diminishing the role of search. In addition, similar to Hout and Goldinger (2010, 2012, 2015), the grid was broken into four quadrants where 3, 4, or 5 items appear (based on the current set size), which is intended to prevent the effects of object clustering. In general, if each object's position were allowed to vary completely at random, issues with object overlap or tightly clustered items could influence attentional guidance.

Third, using an empty background in the search array allows for careful manipulation of the set size, whereas working with naturalistic scenes requires additional consideration of which elements may draw attention (Henderson & Hayes, 2017). Along the same vein, when using naturalistic scenes, careful consideration must be given to how the scene syntax and semantic meanings guide search (Castelhano & Heaven, 2011; Spotorno et al., 2014).

Fourth, although using categorical word cues is a departure from FPST and WIT type studies, it serves two critical purposes here. It highlights which items should be searched for in each trial, differentiating the targets from distractors. It also works to control the specificity of the categories participants are searching for, which better aligns with the fact that search efficiency is enhanced when more precise information about the target object is provided (Hout & Goldinger, 2015; Maxfield & Zelinsky, 2012; Schmidt & Zelinsky, 2009; Yang & Zelinsky, 2009). For example, in the shooter bias literature, the object to be identified is either a gun or any of many non-gun objects (tools, phones, soda cans, etc.). The notion of a handgun encompasses a more specific category with commonly shared features, whereas the idea of "non-gun objects" is more diffuse, encompassing diverse items possessing distinct characteristics.

Participants performed the visual search task under three conditions: Black prime, White prime, or no prime control. The search slopes were compared between the three conditions to assess the influence of race primes on search efficiency. Three levels of race presentation (Black vs. White vs. No prime) and two levels of target object type (Gun vs. Non-Gun) were manipulated within-subjects. In each condition, three levels of set size (12, 16, 20) were manipulated in equal proportions.

Method

Participants

Student participants were recruited via Michigan State University's Department of Psychology HPR/SONA system to complete an "Attention and Perception" task for a full credit towards the fulfillment of required credit hours in their introductory psychology class. Three hundred and twenty-nine participants were recruited; however, 6 participants who had over 100 errors in the task were excluded. In addition, 7 participants were excluded that did not have a matching Qualtrics survey due to experimenter error in set up. The remaining sample (N = 316;

55 men; 252 women, 9 NA, mean age = 19.75) was primarily White (69%), with marginal representation for Asian (14%), Black (7%), and other/multiracial (10%).

Apparatus

Participants completed the task in PsychoPy (Version 2023.2.1; Peirce et al., 2019) on a 24-in. monitor (20.88 by 10.75 in.). Participants were seated approximately 21 in. (or 55cm) away from the monitor but could adjust this distance. Note that one monitor was 22 in (9.5 x 11.5 in.), all stimuli were scaled appropriately.

Stimuli

Images of real-world objects, such as handguns and hand-held harmless objects, were used as target stimuli. There were 33 items, 17 handguns, and 16 harmless objects. Due to experimenter error, an extra handgun was left in the stimuli set. Non-guns were comprised of the following categories: wallet, hairbrush, cellphone, hammer, flashlight, game controller, stapler, and soda can. Although the harmless objects are made up of multiple categories, participants received specific item information before each trial. Distractor objects were images of real-world objects that are visually and categorically dissimilar from the target objects, such as fruit, bicycles, and barbies (see Table 1 for the full list of distractor objects). Most objects were sourced from the Massive Memory Database (Konkle et al., 2010), with the exception of the wallet and cellphone photos, which were taken from online searches. In the race priming condition, 40 neutral emotion headshot images of Black and White males wearing the same clothing were used as prime stimuli, with 20 images featuring Black males and 20 featuring White males. These images were obtained from the Chicago Face Database (Ma et al., 2015). Each face appeared in each object condition three times and each set size condition four times.

(All stimuli, materials, and data can be found at OSF | Examining Racial Bias in Evidence Accumulation: Exploring the Impact of Object Search)

Search Array Organization

A structured random search array was employed to mimic cluttered environments and facilitate object presentation (see Figure 5). The display was organized as an 8x8 grid, which divides the screen into four equal 4x4 quadrants. However, the four innermost cells were excluded to prevent participants' gaze from falling on items close to the fixation point. Each quadrant contained an equal number of objects, depending on the set size (3, 4, or 5 objects per quadrant). The grid was designed to maintain a visual angle of 2-2.5° for objects and a minimum of 1.5° between adjacent objects and between objects and the screen edges. Visual angles are a measure of the apparent size of an object when perceived from a certain distance. In this context, visual angles allow for precise control of how objects are rendered on a screen using the object's size and the observer's distance.

These visual angles were chosen as an analog to those found in the literature (e.g., Hout & Goldinger, 2015) and ensure a sufficient distance between objects to minimize crowding effects. However, compared to the 6x6 grid employed by Hout and Goldinger (2015) on a 21-inch monitor, the current 8x8 grid is scaled for a 24-inch monitor and maintains the visual angle requirements for the objects and their separation.

To ensure that target positions from the center of the screen are equivalent across conditions, a random assignment method was used to distribute the target objects across the grid cells. Each trial randomly assigned the target objects to these cells. The randomness of this assignment was evaluated and confirmed through a simulation. In this simulation, 360 trials with 300 iterations were conducted, each representing a participant, with varying conditions of race presentation (Black, White, and No Prime), target object type (Gun or Non-gun), and set sizes (12, 16, 20). The average distances from the center for each condition, averaged across all participants, were computed and are presented in Table 2. As indicated by the results, the average distance from the center is approximately equal across all conditions and participants, suggesting that the random assignment method did not introduce a systematic bias in the positioning of the target objects. Appendix A presents a detailed account of the simulation process and the Python script used to generate these values.

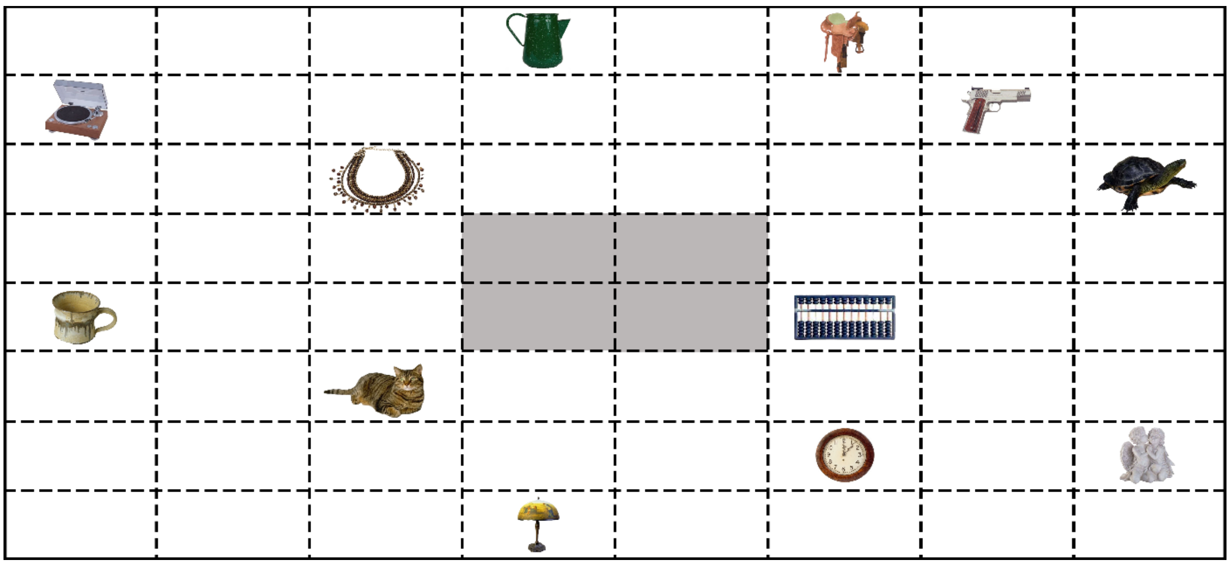

Figure 5: An example of the visual search array. Note that the grid lines and grey boxes will not be shown during the task.

Procedure

Participants' task was to locate and identify the target object among the distractors. Participants were instructed to respond as quickly as possible while remaining accurate. At the beginning of each trial, a fixation cross appeared for 500 ms, followed by word cues of the target items for 1000 ms, followed by the visual search display, which remained until a response was recorded or 10 seconds elapsed. The race stimuli appeared for 500 ms after the word cues in the race priming condition. Participants used a keyboard to make decisions, with "Q" representing "gun" and "P" representing "non-gun." Reaction times were measured from display onset to a button press. In any given trial, only one target object from either of the two categories appeared (See Figure 6 for an example).

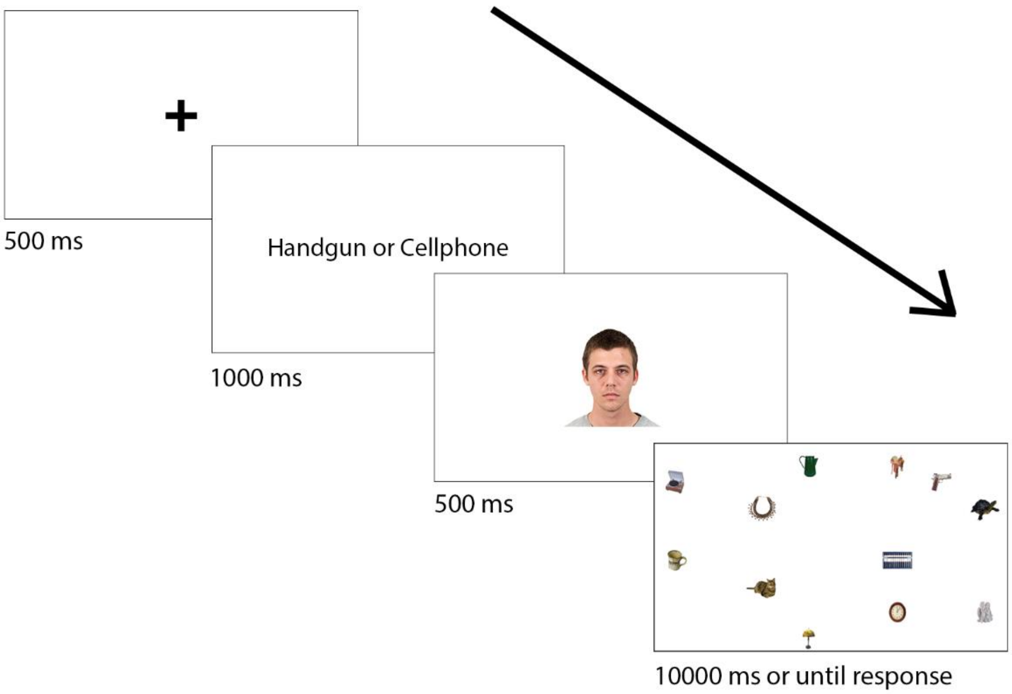

Figure 6: An example of a typical trial. Note that in the no prime condition, an additional fixation point was used in place of the face.

The paired word cues always had a gun as one category and a randomly selected non-gun as the other. To encourage an active search for the target items, an additional manipulation was added to the task. In 36 randomly selected trials, all objects were replaced by a number from 1 to the current number of items in the display (See Figure 7). Using a mouse response, participants then selected the number that replaced the target object. After eight practice trials, 360 experimental trials were presented in 3 blocks of 120. There were 240 trials for the race condition and 120 trials for the no-race condition. Within each block, there were 40 trials in each set size. Within each set size, there were 20 trials for each object type. Across blocks, this resulted in 20 trials per race by object by set size condition. In the race condition blocks, each face was paired with two guns and two non-gun items for a total of six trials per block. Participants were given one minute of rest or longer between blocks. Block order was randomized across participants. Set size, object type, and target location were randomized within blocks.

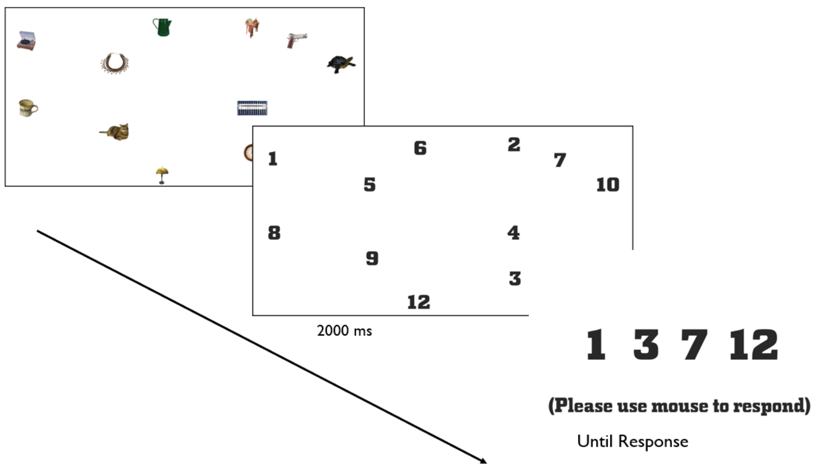

Figure 7: An example of the manipulation check. Once participants made a decision, the objects were replaced with numbers.

Manipulation check

Undergraduate research assistants reported during preliminary trial testing that when they could not rapidly identify a gun on the screen, they would default to choosing the non-gun response. This behavior suggests a search strategy that mirrors a target present versus target absent decision-making process, potentially leading to variations in response times compared to scenarios where participants actively identify an item before responding. An additional manipulation adapted from Hout and Goldinger (2015) was introduced in 36 randomly selected trials to address this. In these trials, upon making a decision, all objects on the screen were replaced with a number ranging from 1 to the total number of items displayed. After a 2-second interval, this screen was replaced by a lineup of four numbers. Participants were then required to select, via mouse response, the number corresponding to the target object. This manipulation, evenly distributed across the various conditions, aimed to encourage active item search by the participants.

Results

Behavioral

The experimental design involves three independent variables: Race condition (Black vs. White vs. No prime), Set size (12 vs. 16 vs. 20), and Object type (Gun vs. Non-Gun). These variables were manipulated within participants, with the order of conditions randomly assigned. The dependent variable is the Response Time (RT) for each trial, representing the time participants take to locate and identify the target object accurately. Incorrect response times and response times below 300 ms and above 10000 ms were removed. See Figure 8 for average response times and error rates.

The data were analyzed using a linear mixed effect model to predict the response time to the target object as a function of the race condition, set size, object type, and their interactions. In additon, a logistic mixed effect model was specified to predict accuracy across conditions. To account for non-independence across participants and targets (Judd et al., 2012), I initially proposed specifying (1) the participant intercept, race condition slope, set size slope, object type slope, and their interactions for participants, (2) the target intercept and set size slope for targets, and (3) the prime intercept and object type slope for primes.. However, this initial model proved too complex for practical specification. Subsequent testing of each model component revealed that a simplified model, which specified only the participant and target intercepts as random effects, was most effective. Including slopes generally leads to convergence issues, while random intercepts for primes introduced singularity effects. The race condition, set size, and object type were effects coded.

The analysis was conducted using the lme4 (Bates et al., 2023), lmerTest (Kuznetsova et al., 2020), and emmeans (Lenth et al., 2024) packages in R.

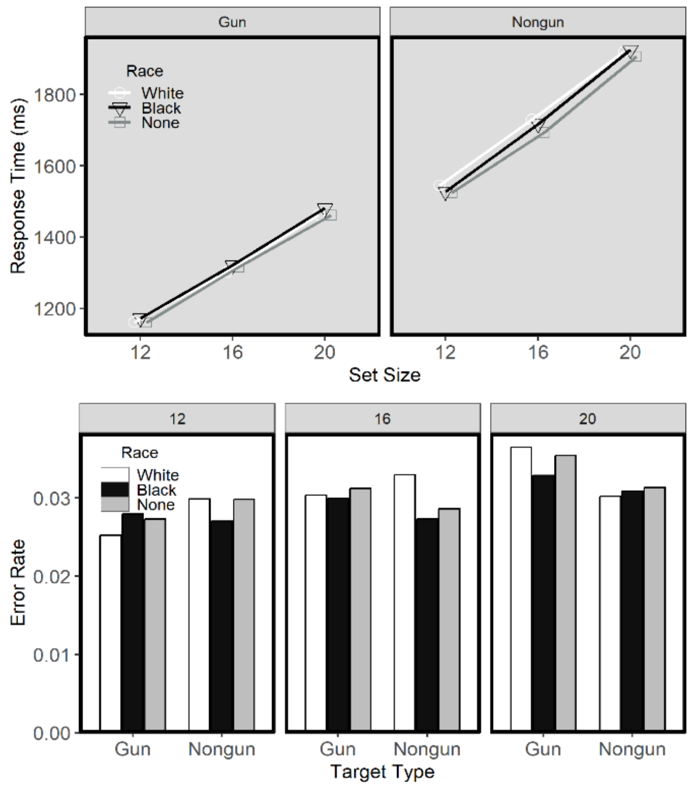

Figure 8: Correct response times (top) and proportion errors (bottom) for all conditions.

Response Time. A multilevel linear regression analysis was conducted to predict response time. The model included fixed effects for race condition, set size, object type, and their interactions. Random effects included random intercepts for participants and targets. In this model, there was a main effect of target type (b = -203.04 ms, 95% CI [-288.14, -117.93]) such that participants responded faster to guns (M = 1316 ms, 95% CI [1193, 1439]) than non-guns (M = 1316 ms, 95% CI [1193, 1439]), b = -406 ms, 95% CI [-17.694, -8.272]). The expected effect of set size was found with faster responses in set 12 (*b* = -169.00 ms, 95% CI [-176.49, -161.51]) and slower responses in set size 20 (*b* = 173.79 ms, 95% CI [166.28, 181.29]).

There was an interaction between race and target type (*b* = -9.22 ms, 95% CI [-16.72, -1.72]) such that participants responses were slower on White non-gun trials (*M* = 1733 ms, 95% CI [1606,1860]) compared to no prime non-gun trials (*M* = 1709 ms, 95% CI [1582,1836], *b* = 24.19, 95% CI [5.82, 42.55]). In addition, participants responded marginally faster to White gun trials (*M* = 1309 ms, 95% CI [1185,1432]) than to Black gun trials (*M* = 1326 ms, 95% CI [1203,1450], *b* = -17.88 ms, 95% CI [-36.23, 0.49]).

An interaction was observed between target type and set sizes 12 (*b* = 18.85 ms, 95% CI[11.36, 26.34]) and 20 (*b* = -21.24 ms, 95% CI [-28.75, -13.74]), indicating that participants responses were faster in gun trials across set sizes compared to non-gun. Table 7 summarizes the mean response times and 95% confidence intervals by set size and target type. A linear contrast test indicated that participants' searches were more efficient when the target item was a gun (*b* = 80.2 ms, 95% CI [54.2, 106.2]). That is, the increase in response times associated with increased set sizes was smaller on gun trials (See Figure 9). No significant interactions were found between race and set size, and the observed two-way interactions did not extend to a three-way interaction. Overall, participants were faster on gun trials than non-gun trials, and the typical race by object interactions were not found.

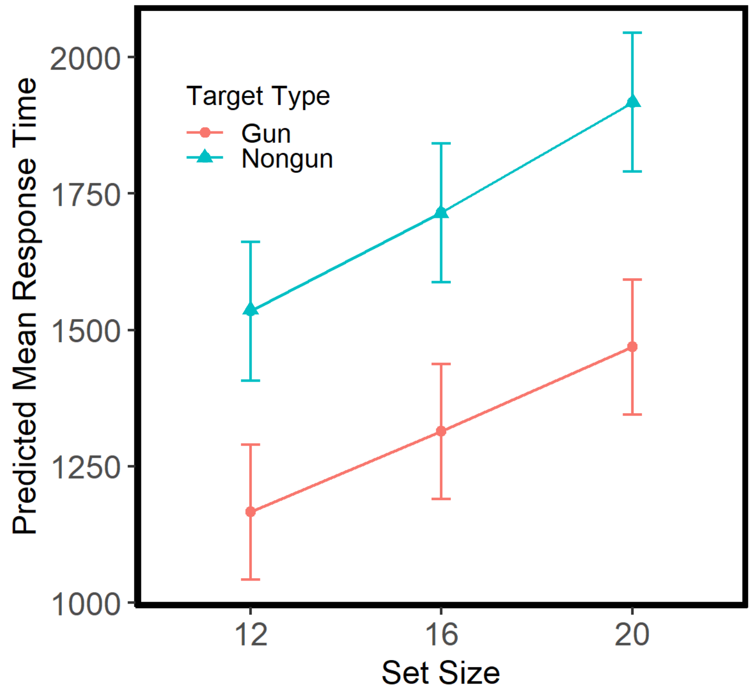

Figure 9: Search slopes by Target Type and Set Size. Bars are 95% CI.

Error Rates. To predict the proportion of correct responses, a multilevel logistic regression was estimated with fixed effects for race condition, set size, object type, and their interactions. Random effects included random intercepts for participants and targets and random slopes for set size for targets. The only effects to emerge were the main effects of set size 12 (*b* = 0.08, 95% CI [0.03, 0.14]) and set size 20 (*b* =-0.09, 95% CI [-0.16, -0.03]) however the differences are small and not particularly informative (12: *M* = 3.83, 95% CI [3.72, 3.95]; 16: *M* = 3.76, 95% CI [3.64, 3.88]; 20: *M* = 3.66, 95% CI [3.55, 3.77]) No other effects were found and thus the exploratory analysis focused on response times.

Exploratory Analysis – Block Order. As part of an exploratory analysis, a noticeable decrease in response times across blocks was observed, suggesting a possible practice effect. To account for this, a multilevel linear regression analysis was conducted to predict response time while controlling for the effect of practice. The model included fixed effects for race condition, set size, object type, and their interactions. Additionally, block order was included as a covariate but not as part of any interaction terms. Random effects included random intercepts for participants' targets. Initial observations indicated an effect of block order, with participants' response times decreasing across blocks (Block 1: M = 1638 ms, 95% CI [1546, 1730]; Block 2: M = 1485 ms, 95% CI [1393, 1576]; Block 3: M = 1435 ms, 95% CI [1343, 1527]). Further analysis using a polynomial contrast test revealed significant linear and quadratic trends, indicating that although participants' responses sped up across blocks (b = -203 ms, 95% CI [-215.9, -190]), this effect plateaued going from block 2 to block 3 (b = 104 ms, 95% CI [81.2, 126]). That is, it appears that participants more or less understood the task by the final block. Despite these trends, the effects related to race condition, set size, and object type remained consistent (See Tables 10-15).

Exploratory Analysis – Manipulation Check. As an additional exploratory analysis, the error rate distributions from the manipulation check were examined by condition and across participants (See Figure 10). The findings show that the majority of participants demonstrated a high degree of accuracy, with 84 percent having fewer than five errors. To investigate if response times differ across participants with higher errors, the manipulation check error rates were mean-centered and added to the multilevel model predicting response times. This model accounted for the original fixed effects and the new interaction between mouse task errors, set size, and target type.

Similar to the inclusion of block order, adding manipulation check error rates to the model did not substantially alter the overall findings (See Tables 16-21). However, for each additional error, response times increased (b = 5.17 ms, 95% CI [0.75, 9.6]). Additionally, an interaction between target type and the manipulation check suggests that participants who performed worse responded faster to non-guns (M = 7.87 ms, 95% CI [3.40, 12.35]) than guns (M = 2.48 ms, 95% CI [-2.0, 6.95]; b = -5.40 ms, 95% CI [-6.786, -4.014]). There was no interaction between set size and manipulation check errors, nor were these effects qualified by the three-way interaction with set size. The longer response times may be attributed to a target present search versus target-absent search such that responses are generally longer in this scenario (Wolfe, 2021), but given the small amount of data, this may be better attributed to noise or inattentiveness.

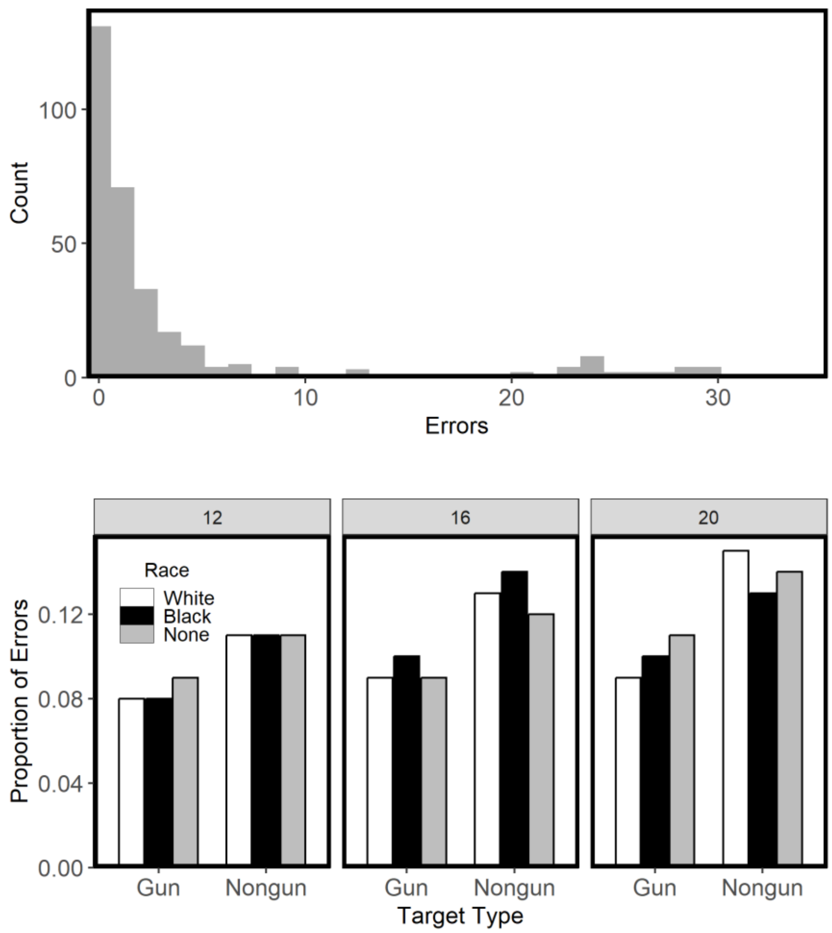

Figure 10: Count of errors by participant (top) and proportion of errors across conditions (bottom).

Process Level

Given that participants were given a large response time window to encourage accurate search, there is not enough error rate data to apply a Drift Diffusion Model.

Discussion

The purpose of Study 1 was twofold: first, to investigate if race would affect search efficiency, and second, to establish a possible response time window for Study 2. Given that there were little to no differences in error rates across different conditions, this discussion will be limited to the analyses of response times. The interactions that would have suggested a search efficiency effect for race would have been found in either the race by set size interactions or the race by set size by target type interaction; however, neither reached significance, indicating that in this task, race did not improve or impair the search process meaningfully. Further, these interactions did not emerge when controlling for block order or the manipulation check.

That being said, an effect of search efficiency did emerge such that participants' searches for gun objects were more efficient than participants' searches for non-gun items. It is not clear what is driving this effect, as it could be the case that participants are attuned to the fact that guns are likely the key item in the task, guns are simply easier to distinguish because of some combination of features, or it could be the case that the diverse item set for non-gun items impaired the search process.

In addition, it is worth noting that the typical race-by-target type interaction was not found. That is, the literature generally supports the idea that gun responses following Black primes are faster and non-gun responses following Black primes are slower. However, this study found that an interaction emerged, such that participants' responses were slower following White and Black primes than those with no primes on the non-gun trial.

STUDY 2

The primary objective of this study was to deepen our understanding of the relationship between race and search efficiency. This was achieved by introducing a time window constraint to induce errors in the search process, thereby allowing for drift-diffusion modeling. However, Study 1 did not find an effect of race on search efficiency; this outcome could have several interpretations. It might suggest that, in this specific task context, race is not a useful source of information, which could be represented in no credible differences between Black and White race primes. Alternatively, counter-stereotypic attitudes could influence the results, leading to findings that diverge from the broader literature on racial biases.

An example of this can be seen in recent work from the Cesario lab on shooter tasks. Participants demonstrated no behavioral differences in response times or error rates, yet DDM results indicated that this was driven by lower starting points and higher evidence thresholds for Black targets. In addition, if the target type search efficiency effect emerges once again, the DDM parameters can be used to infer if these search differences are reflected in evidence accumulation.

The response window was set to capture a range of approximately 70% of the original response times for non-guns in set size 20 (2000 ms) in Study 1. The time window was still relatively long, given that the focus is on search efficiency, and using a constraining time window may undermine the connection to Study 1. By reducing the response window in this way, I expected to maintain the task's sensitivity to our manipulations of interest while ensuring that participants were sufficiently pressured to respond quickly. Three levels of race presentation (Black vs. White vs. No prime) and two levels of target object type (Gun vs. Non-gun) were manipulated within subjects. In each condition, three levels of set size (12, 16, 20) were manipulated in equal proportions.

Method

Participants

Student participants were recruited via Michigan State University's Department of Psychology HPR/SONA system to complete an "Attention and Perception" task for a full credit towards the fulfillment of required credit hours in their introductory psychology class. Three hundred and twenty-two participants were recruited; however, 9 participants who had over 100 errors in the task were excluded. In addition, 6 participants were excluded that did not have a matching Qualtrics survey due to experimenter error in setup. The remaining sample (N = 308; 118 men; 188 women, 2 NA, mean age = 19.5) was primarily White (73%), with marginal representation for Asian (10%), Black (8%), and other/multiracial (9%).

Data collection was paused after 19 participants and 52 participants had completed the task to ensure that the response time window selected was appropriate. This was done by looking at the response times and error rates to determine if the response time window behaved as expected. The first 19 participants had a response window of 2300 ms with an error rate of less than 5% at the highest set size. This was not suitable for DDM entry, so the response window was restricted to 2000 ms. This second session produced an error rate between 5% and 9% from set size 12 to 20. These participants were not included in the final sample.

Apparatus

Participants completed the task in PsychoPy (Version 2023.2.1; Peirce et al., 2019) on a 24-in. monitor (20.88 by 10.75 in.). Participants were seated approximately 21 in. (or 55cm) away from the monitor but could adjust this distance. Note that there was one monitor that was 22 in (9.5 x 11.5 in.), and items were scaled down appropriately.

Stimuli

All stimuli were the same as the stimuli used in Study 1.

Search Array Organization

The specifications of the search array are the same as those listed in Study 1.

Procedure

The procedure is similar to Study 1, with a few exceptions. First, a 2000ms response time window was implemented. Second, if participants responded outside of the window, they were prompted to "Please respond faster."

Manipulation check

Several changes were made to the manipulation check to ensure it only appeared when participants made a correct decision within the response time window. Given that participants were expected to make more errors, the manipulation check only appeared on correct identification trials. Further, performing the manipulation check only if participants were within the response time window aimed to reduce noise from guessing after the items disappeared. Doing it this way, it was not guaranteed that conditions would be evenly split if some participants made more errors for specific combinations of targets and races, but the code was designed to cycle through each combination iteratively and display the manipulation check for the set of conditions with the lowest count value. It only aimed to record 36 trials, 2 per possible condition.

Results

Behavioral

The design of Study 2 closely mirrors that of Study 1. The experimental design remains the same, with three independent variables manipulated within participants: Race Condition (Black vs. White vs. No prime), Set Size (12 vs. 16 vs. 20), and Object Type (Gun vs. Non-gun). The order of conditions continued to be randomly assigned. There are two dependent variables: response time, which represents the time participants take to correctly find and identify the target object, and error rates, which quantify the frequency of incorrect identifications or timeouts across trials. Responses that fell below 300 ms or above 4000 ms were excluded from both the response time and error rate analysis (Ratcliff et al., 2018). Timeouts were not treated as errors, but in the response time analysis only correct response times were used. As in Study 1, MLM was employed. A linear model was used for response times, and a logistic model was used for error rates. See Figure 11 for average response times and error rates.

Response Time. A multilevel linear regression analysis was conducted to predict response time. The model included fixed effects for race condition, set size, object type, and their interactions. Random effects included random intercepts for participants, targets, and prime faces. In this model, there was a main effect of target type (b = -122.88, 95% CI [-166.34, -79.42]) such that gun responses (M = 981 ms, 95% CI [919,1043]) were faster than non-gun responses (M = 1227 ms, 95% CI [1163, 1291]). The expected effect of set size was found with faster responses in set 12 (b = -74.48 ms, 95% CI [-78.02, -70.93]) and slower responses in set size 20 (b = 70.71 ms, 95% CI [67.13, 74.28]).

There was also an interaction between target type and set sizes 12 (b = 5.03 ms, 95% CI [1.49, 8.58]) and 20 (b = -6.50 ms, 95% CI [-10.08, -2.92]), indicating that participants' responses were faster in gun trials across set sizes compared to non-gun. Table 26 summarizes the mean response times and 95% confidence intervals by set size and target type. A linear contrast test indicated that participants' searches were more efficient when the target item was a gun (b = 23.07 ms, 95% CI[10.7, 35.4]). That is, the increase in response times associated with increased set sizes was smaller on gun trials (See Figure 12). No significant interactions were found between race and set size or race and object, and the observed two-way interactions did not extend to a three-way interaction. Overall, the response time findings closely match those of Study 1, with faster response times for guns than non-guns. In addition, the constrained response time window did lead to faster responses in general.

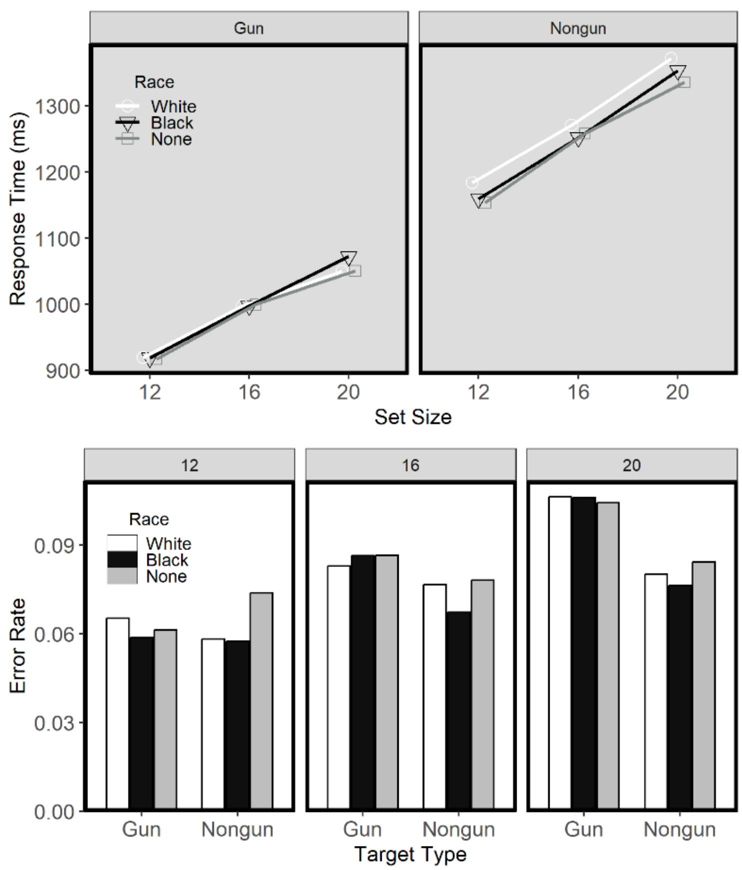

Figure 11: Correct response times (top) and proportion errors (bottom) for all conditions.

Error Rates. To predict the proportion of correct responses, a multilevel logistic regression was estimated with fixed effects for race condition, set size, object type, and their interactions. Random effects included random intercepts for participants and targets. There was a main effect of race for Black (b = 0.05, 95% CI [0.02, 0.08]) such that participants were more accurate following Black primes than no primes (b = 0.10, 95% CI [0.05, 0.16]). There was a main effect for set size 12 (b = 0.24, 95% CI [0.21, 0.27]) and set size 20 (b = -0.20, 95% CI [-0.24, -0.17]) such that as set sizes increased, participants accuracy decreased (12: M = 2.90, 95% CI [2.79, 3.02]; 16: M = 2.63, 95% CI [2.52, 2.74]; 20: M = 2.46, 95% CI [2.35, 2.57]).

There was an interaction between prime race and target type (b = -0.03, 95% CI [-0.07, -1.02e-03]). Participants responses were more accurate on non-gun trials following White (b= 0.11, 95% CI [0.03, 0.19]) and Black (b= 0.18, 95% CI [0.10, 0.26]) primes compared to the no prime condition.

There was also an interaction between set size and target such that as set size increased, participants' accuracy decreased more for guns (12: M = 2.91, 95% CI [2.76, 3.06]; 16: M = 2.56, 95% CI [2.41, 2.70]; 20: M = 2.31, 95% CI [2.16, 2.46]; b = -0.32, 95% CI [-0.43, -0.21]) than non-guns (12: M = 2.89, 95% CI [2.74, 3.05]; 16: M = 2.71 95% CI [2.55, 2.86]; 20: M = 2.61, 95% CI [2.46, 2.76]). A three-way interaction qualified these effects (See Figure 13) such that as set size increased, participants' accuracy decreased more following White primes than no primes in the non-gun condition (b =-0.20, 95% CI [-0.40, -0.002]). However, it's worth noting that although participants' accuracy decreased more following White primes, they also started and ended with overall higher accuracy than the no prime condition. Overall, accuracy decreased as the set size increased, but the most interesting aspect is that participants made more errors on gun-trials than non-gun trials. This particular effect is unexpected and may be better explained by performance in the manipulation check.

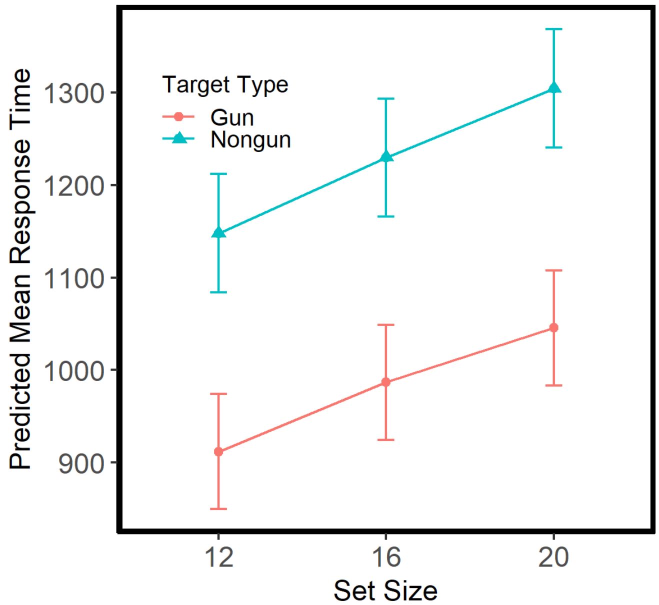

Figure 12: Search slopes by target type and set size. Bars are 95% CI.

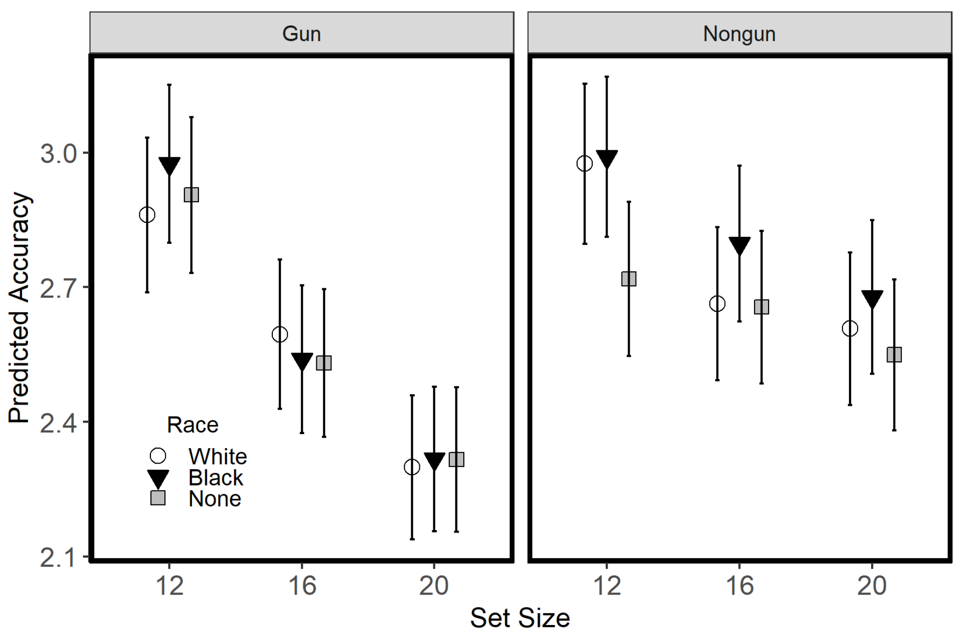

Figure 13: Predicted accuracy (on the logit scale) for race, target type, and set size. Bars are 95% CI.

Exploratory analysis – Block Order. Similar to Study 1, a noticeable decrease in response times across blocks was observed, suggesting a possible practice effect. To account for this, a multilevel linear regression analysis was conducted to predict response time while controlling for the effect of practice. The model included fixed effects for race condition, set size, object type, and their interactions. Additionally, block order was included as a covariate but not as part of any interaction terms. Random effects included random intercepts for participants and targets. The corresponding multilevel logistic model predicting accuracy was specified similarly. Initial observations indicated an effect of block order, with participants' response times decreasing across blocks (Block 1: M = 1168 ms, 95% CI [1123, 1214]; Block 2: M = 1086 ms, 95% CI [1041, 1132]; Block 3: M = 1059 ms, 95% CI [1014, 1105]). A polynomial contrast analysis revealed linear and quadratic trends such that participants responded faster across blocks (b = -109 ms, 95% CI [-115.4, -103.1]). However, this effect was less pronounced in the later block (b = 55.3 ms, 95% CI [44.7, 65.9]).

Not only did participants respond faster, but they also became more accurate across blocks (M = 2.58, 95% CI [2.46, 2.69]) to block 2 (M = 2.71, 95% CI [2.60, 2.83]; b = -0.14, 95% CI [-0.19, -0.08]) but plateaued going to block 3 (M = 2.71, 95% CI [2.59, 2.82]; b = 0.01, 95% CI [0.06, -0.05]).

Interestingly, while the original response time model had no effect on race, when block order was added an effect of race emerged (b = 5.08, 95% CI [0.92, 9.24]) such that participants responses were slower following White primes (M = 1107 ms, 95% CI [1061, 1152], b = 8.37 ms, 95% CI [2.22, 14.52]) and Black primes (M = 1108 ms, 95% CI [1063, 1154], b = 9.95 ms, 95% CI [3.81, 16.09]) compared to no prime (M = 1098 ms, 95% CI [1053, 1144]). An interaction with target type qualified this effect such that participants responses to non-guns were slower for White primes (*M* = 1233 ms, 95% CI [1169, 1297], *b* = 15.70 ms, 95% CI [7.03, 24.37]) and Black primes (*M* = 1231 ms, 95% CI [1168, 1295], *b* = 13.95 ms, 95% CI [5.29, 22.60]) compared to no primes (*M* = 1217 ms, 95% CI [1154, 1281]). All other effects relating to race condition, set size, and object type in the error rate and response time model remained consistent (Tables 33 -47).

Exploratory analysis – Manipulation Check. As an additional exploratory analysis, the error rate distributions from the manipulation check were examined by condition and across participants (See Figure 14). The findings show that the majority of participants demonstrated a high degree of accuracy, with 77 percent having fewer than five errors. Thus, to investigate if response times and error rates differ across participants with worse performance on the manipulation check, the error rates were mean-centered and added to the multilevel models predicting response times and accuracy. This model accounted for the original fixed effects and the new interaction between mouse task errors, set size, and target type.

Adjusting for manipulation check errors in the model, much like controlling for block order, left most results unchanged but revealed a significant effect of race (*b* = 5.08 ms, 95% CI [0.92, 9.24]) such that participants responded slower following White primes (*M* = 1107 ms, 95% CI [1061, 1152], *b* = 8.37 ms, 95% CI [2.22, 14.52]) and Black primes (*M* = 1108 ms, 95% CI [1063, 1154], *b* = 9.95 ms, 95% CI [3.81, 16.09]) compared to no prime (*M* = 1098 ms, 95% CI [1053, 1144]). Alone, the effect of manipulation check errors is statistically non-significant (*b* = -1.270 ms, 95% CI [-2.98, 0.44]). However, there was an effect of target type and the manipulation check such that as participants performed worse on the manipulation check, they responded faster, primarily driven by the gun condition (*b* = -0.713 ms, 95% CI [-1.391, -0.034]; see Table 53). The three-way interaction with set size did not qualify these effects.

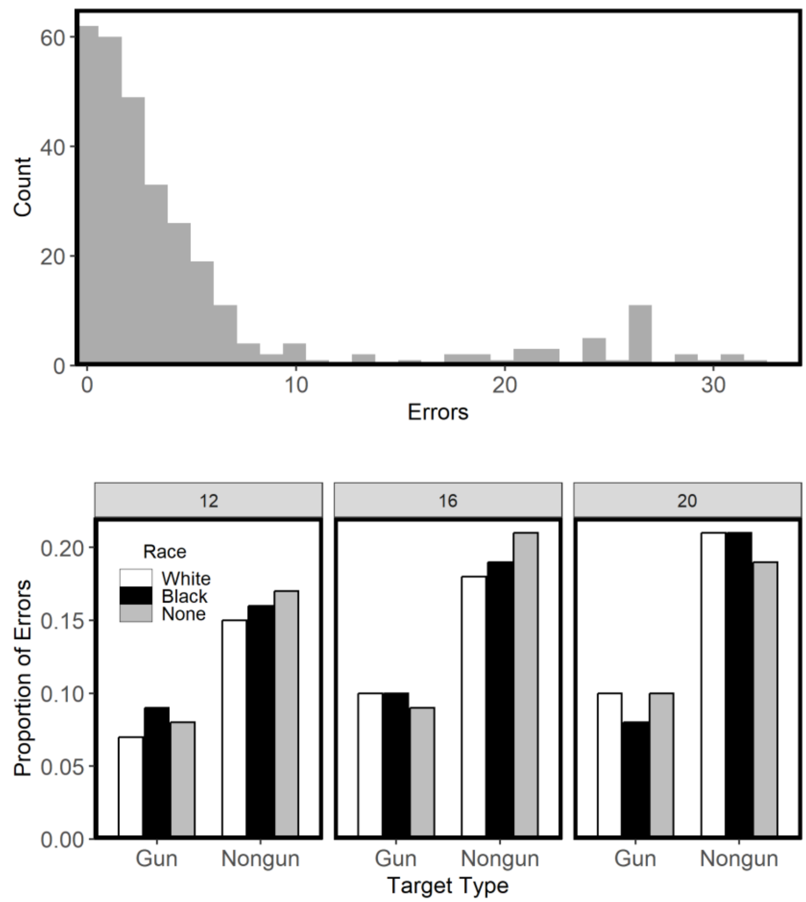

Figure 14: Count of errors by participant (top) and proportion of errors across conditions (bottom).

When manipulation check errors were mean-centered and added to the error rate model, there was a main effect such that overall errors increased for each additional error made in the manipulation check (b = -0.013, 95%CI [-0.021, -0.004]). This was qualified by an interaction with target type such that as participants performed worse in the manipulation check, more errors were made in the gun than non-gun trials (b = -0.030, 95%CI [−0.036,−0.024]). The three-way interaction with set size led to convergence issues and was omitted from the model. Together, the response time and error rate models suggest that participants with worse performance on the manipulation check responded faster, and this was especially noticeable on gun trials. This increase in response time may also explain why more errors were made for gun targets; if participants who generally performed worse or didn't engage in the task as expected to find the gun rapidly, then in larger set sizes, the quitting threshold (Wolfe, 2021) might be smaller leading to more misses for guns. In addition, although they are correctly choosing non-gun when a gun is present, without fixating the target, more errors would be made for non-guns on the manipulation check. As in Study 1, there is less data with poor performance, but this seems to suggest a pattern of differential search strategies.

Summary

The behavioral data show no effect of race on search efficiency in either the two-way or three-way interaction. For race, the drift-diffusion model can highlight how or if race is being used in this task. For example, as in previous work in the lab, we have found the stereotypical response in the race by object drift rates such that participants accumulate stronger evidence when gun is paired with Black than with White, but these effects were masked by participants setting wider thresholds for Black targets such that they needed more evidence to make a decision. So it could be that some similar phenomenon masks race differences between Black and White primes, or perhaps it's the case that, like the behavioral results, no differences emerge between White and Black and instead solely manifest between these two racial categories and the no prime condition.

However, like Study 1, there is a search efficiency effect for guns such that participants' responses are more efficient for gun items than non-gun items. However, this search efficiency effect did not lead to greater accuracy; in fact, it appears that starting at set size 16, participants missed more guns than non-guns. This pattern of results is unexpected. It's possible that this pattern was driven by participants with higher manipulation check errors, such that participants with more errors responded faster and were less accurate at finding guns because of how they engaged in the search process. Thus, it seems possible that participants sometimes rapidly found the gun item they were searching for, and when they did not, they would default to a non-gun response.

This could potentially explain why error rates increased more for guns at the higher set sizes because if participants could not quickly find the gun, an assumption could be made that it was not present. It is not clear how these different results will affect the drift diffusion model parameters, given that the decreased response times for gun items should lead to stronger drift rates or evidence accumulation, but the higher error rate suggests more noise in the evidence accumulation process. Or, in other words, a weaker drift rate. Thus, the drift diffusion model can disentangle what is happening to drive the target type search efficiency effects and the race results.

Process Level

A Hierarchical Bayesian Drift Diffusion Model (HDDM) was implemented with the guidelines outlined by Pleskac et al. (2018). This version of the model allowed the start point to vary according to race prime, the threshold to vary by race prime and set size, and the drift rate and non-decision time to vary according to race of the prime, object type, and set size. Uninformative priors were used for each parameter to let the data have a maximal influence on the posterior estimates. This model was estimated using a Markov Chain Monte Carlo (MCMC) simulation in Just Another Gibbs Sampler (JAGS), as suggested by Plummer (2003), in conjunction with the Wiener module (Wabersich & Vandekerckhove, 2014). The analysis gathered a specified number of samples (10000) with an adaptive phase of (1000) and a burn-in period set at (1000).

Bayesian methods of inference were employed, which provides a distribution of credible values for each parameter. These credible values represent a range of potential values for a parameter that is consistent with the observed data. The most credible value, or the mode of the posterior distribution (i.e., the value with the highest probability), is reported for each parameter. In addition, the Highest Density Interval (HDI) is reported. The HDI, encompassing 95% of the posterior distribution, represents the range of credible values. An effect, such as a race by object interaction on drift rates, is considered credible when the HDI does not contain zero. If the HDI contains zero, this suggests that the null hypothesis is within the range of credible values, lowering confidence that there is a difference between conditions.

Subsequently, given that this is a novel application of the diffusion model, posterior predictive checks were performed for each condition, namely, Black/White/No Prime and Gun/Non-gun across set sizes. These checks analyzed decision probabilities (Gun/Non-gun) and the means and distributions of response latencies. This procedure involves simulating data using the model described above, which is then compared to the original data.

Posterior Predictive Checks revealed systematic discrepancies between observed data and predictions across various conditions. Hit rates are overestimated, and false alarms are slightly underestimated, though the extent of this misestimation is minimal. When examining response times, correct responses to gun stimuli are consistently overestimated, implying the model predicts slower decision times than observed, which in turn explains the overestimated accuracy. In contrast, correct response times for non-gun stimuli align more closely with model predictions, suggesting a more accurate fit. However, both incorrect gun and non-gun responses are underestimated by a large margin, suggesting that model-predicted error responses are faster than observed.

Exploratory analyses revealed that this is likely caused by unaccounted variation in drift rate for different target non-gun items. Specifically, some non-gun items were much harder to identify and create multimodal distributions of response times that were unaccounted for in the current DDM specification. Although gun items were relatively stable, this raises implications for the drift rate such that within non-guns, there is a larger degree of variation in evidence accumulation, which may reflect an overestimation of the true drift rates for non-gun items. Regarding the search efficiency effect between guns and non-guns, the model's ability to capture meaningful differences is not conclusive; thus, the results are speculative, and though the various gun and non-gun effects are reported, they will be discussed within this context. Model fit, diagnostics, and all plots are listed in Appendix D.

Results. DDM results can be seen in Tables 61 to 69 and Figure 15. Contrary to expectations, the hypothesis that Black primes would lead to a higher starting point was not supported. Specifically, there were no credible differences between White primes and no primes (b = -0.001, d = -0.040 [-0.350, 0.260]) or between White and Black primes (b = 0.008, d = 0.280 [-0.030, 0.580]). However, there was a near credible effect such that Black primes had a lower starting point than no primes (b = -0.010, d = -0.310 [-0.610, 0.010]).

Analysis of alpha effects revealed that participants threshold separation was wider for both White primes versus no primes (b = 0.030, d = 0.170 [0.020, 0.320]) and for Black primes versus no primes (b = 0.049, d = 0.260 [0.100, 0.410]). This indicates a preference for speed over accuracy, coinciding with the faster response times found for no primes. There were no credible differences in boundary separation between White and Black primes (b = -0.016, d = -0.090 [-0.240, 0.070]). Additionally, boundary separation was found to increase with set size, demonstrating credible differences between 12 and 16 items (b = -0.049, d = -0.250 [-0.400, -

0.100]), 12 and 20 items (b = -0.100, d = -0.540 [-0.680, -0.370]), and 16 and 20 items (b = -0.055, d = -0.540 [-0.440, -0.140]). These main effects were qualified by an interaction such that participants' boundary separation was wider at set size 12 for White primes compared to no primes (b = 0.055, d = 0.320 [0.030, 0.560]). A similar effect was observed for Black primes (b = 0.082, d = 0.43 [0.15, 0.68]). No other combination of conditions was found to be credibly different (see Table 65 for details).

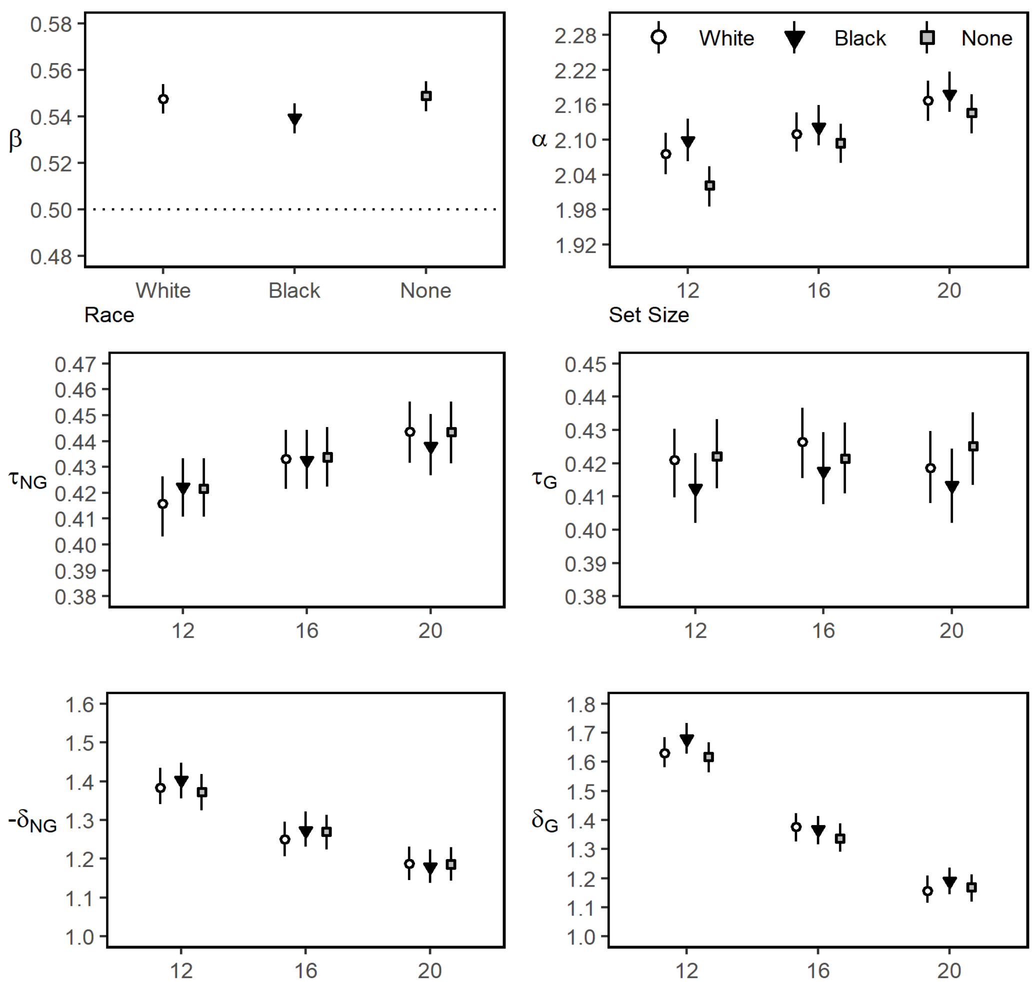

Figure 15: Diffusion model parameters as a function of prime race, set size, and target type for Study 2. Shapes represent modal posterior predictions at the condition level; bars are 95% HDI.

For drift rates, no credible differences were found between White and no primes (*b* = 0.009, *d* = 0.030 [-0.07, 0.13], White and Black primes (*b* = -0.018, *d* = -0.07 [-0.16, 0.04]), or Black and no primes (*b* = 0.022, *d* = 0.08 [-0.01, 0.19]). A credible main effect was observed for target type, with guns showing stronger drift rates than non-guns (*b* = 0.114, *d* = 0.43 [0.33, 0.52]). As predicted, drift rates became weaker as set size increased, with credible differences between 12 and 16 items (*b* = 0.203, *d* = 0.77 [0.66, 0.87]), 12 and 20 items (*b* = 0.337, *d* = 1.26 [1.15, 1.39]), and 16 and 20 items (*b* = 0.136, *d* = 0.50, [0.40, 0.60]). These main effects were not qualified by the anticipated race by object interaction or the race by set size interaction (see Table 67 - 69 for details)

However, a series of credible interactions were observed between target type and set size, such that drift rates were stronger for guns compared to non-guns at set sizes 12 (*b* = 0.259, *d* = 0.98, [0.82, 1.13]) and 16 (*b* = 0.093, *d* = 0.35, [0.20, 0.50]), but not set size 20 (*b* = -0.011, *d* = -0.04, [-0.18, 0.10]). A polynomial contrast test revealed a credible linear trend, with drift rates for guns decreasing more sharply than for non-guns as set size increased (*b* = -0.194, *d* = -0.71 [-0.74, -0.70]), but this effect diminished at the final set size (*b* = 0.012, *d* = 0.04 [0.04, 0.05]). A three-way interaction did not qualify these effects.

Discussion

The purpose of Study 2 was to gain a better understanding of how race is being used in this task, if at all, and to what degree search efficiency can be observed in differences in the drift rate. Regarding race, the only credible difference to emerge was that participants collected more evidence following White and Black primes than they did when there was no prime. Further, there is no conclusive evidence that the null behavioral results between Black and White primes were hiding or masking race-driven differences in evidence accumulation, start point bias, or the evidence threshold.

Next, the behavioral differences in search efficiency for guns over non-guns appear to have been seen in the drift rates such that gun items initially had stronger drift rate values, but the rate of decrease in evidence accumulation was reflected in the higher error rate for gun targets. That is, the model captured a higher rate of decrease in the drift rate of gun items than non-gun items, but it is unclear if this pattern of results would have emerged if the true effects of drift rate were estimated. It is possible that when the full range of variation is modeled, search efficiency effects are limited to specific non-gun conditions such that some drift rates are likely much weaker than other non-gun objects. However, these results are speculative until modifications can be made to the drift diffusion model code to allow intercepts to be created for target objects, similar to how they are implemented in a random effect context where variation due to non-independence is accounted for.

GENERAL DISCUSSION

The current work explored how or if race would affect search efficiency in a visual search task. Further, this work aimed to explore if differences in search efficiency would manifest in evidence accumulation, highlighting a possible unexplored mechanism to explain differences in information processing. Across two studies, race was not found to affect search efficiency in either race by set size interaction or the race by set size by target type interaction. In addition, the application of drift-diffusion modeling did not reveal a pattern of results indicative of the typical racial bias effect. However, a consistent search efficiency effect for target type emerged, such that participants' searches for guns were more efficient than those for non-guns in both Study 1 and Study 2. In Study 2, this effect was seen as stronger drift rates for gun items; however, participants' errors increased, which was then reflected in a large decrease in the strength of evidence accumulation. The strength and direction of these effects are still speculative, given the model misfit highlighted by the posterior predictive checks performed.

Search Efficiency and Modeling

This work was exploratory to test if race would work to guide attention to specific items in the search array. An effect of race on search efficiency was not found in either the two-way or three-way interactions in response time; this could have been due to several reasons. One may be that race is not providing information that is useful or is not meaningfully changing the contents of working memory. However, a more nuanced discussion on the specific effects of race will be discussed later; here, I will focus on elements of search efficiency.

The second major question this dissertation aimed to answer was whether differences in search efficiency would reflect differences in delta or evidence accumulation. It was found that participants' searches for guns were more efficient than those for non-guns, which was reflected in overall stronger drift rates for gun items and weaker drift rates for non-gun items. Notably and contrary to expectations, drift rates decreased far more for guns than non-guns. Note that when this work was first proposed, I anticipated that if there were a three-way interaction between race, target, and set size, this would be reflected such that as set size increased, the rate of decrease for the more efficient searches would be less than the rate of decrease for the less efficient search. That is, I expected differences in search efficiency to emerge not in the overall strength of the evidence accumulation process but in the steps between each set size. This was based on an assumption that equated greater search efficiency with greater accuracy, but that was not the behavioral effect produced.

That is, although the gun searches appear more efficient, this effect was inflated since we are only looking at correct response times, and guns in Study 2 generated more errors than non-guns. Seemingly, gun items were either incredibly fast to spot or were missed in favor of a non-gun response. This effect seems to be driven by participants who made more errors in the manipulation check. If the participants assume that the gun item is consistent in every trial and an initial search doesn't point towards items with gun-like features, then choosing non-gun is an adequate solution. This particular strategy would explain why the greatest amount of errors occurs for guns at the highest set size, where, theoretically, they would be the hardest to find from a brief search. Regardless of the speeded response time, the increase in error rates would result from weaker evidence accumulation across set sizes.

Importantly, however, until the drift diffusion model is refit, we can only speculate on whether the observed differences in evidence accumulation remain in the same direction and magnitude. If we assume that unaccounted variation in delta for target objects is the main driver of misfit, it would be interesting to see what differences emerge among the target object drift rates. The level of specificity of getting a drift rate for either target object or target object categories allows us to explore the possibility that stronger or weaker drift rates can be explained by differences in features of the items (i.e., color, shape, size, sharp or rounded features).

In line with this, some non-gun stimuli seemed harder to find and identify than others, driving multimodal response time distributions. This is not necessarily bad, as real-life items can be varied and introduce these response time differences. Nevertheless, it does have implications for the comparison of search efficiency, such that comparing a static category (gun) where items are more similar in nature and receive more similar responses to a dynamic category (non-gun) with drastic differences in features and in response times may introduce task-specific effects such that search efficiency effects emerge because there is more variation in one group. Or, put another way, if a different set of non-gun stimuli were used that varied in ways that stood out from the search display, would the same gun search efficiency effect be found. Nailing down what possible features of items that impair or enhance the search process for guns could be useful in studying and identifying where police training could be improved.

Individual Differences in Search Process

First, it was not anticipated that participants would approach the task using different search strategies, which is why the manipulation check was used as an attempt to encourage participants to engage in an active search for the target items. The different search strategies could have been prompted by several design choices that diverged from the original Hout and Goldinger (2015) work. For example, participants were always looking for either a gun or some specified non-gun object, hinting that guns are the targets of interest. Effectively, then, if the instruction set is to “answer as quickly as possible while remaining accurate,” participants benefit from using a search strategy that prioritizes guns over non-guns. This would especially be the case when non-gun items are harder to find in the search array.

Although the manipulation check was added, due to the limited number of trials that it appeared in, it is not quite possible to disentangle all possible approaches participants used, but here are some possibilities. Participants actively search for the gun and non-gun objects simultaneously which might reflect in higher accuracy (Cave et al., 2018; Ort & Olivers, 2020; Stroud et al., 2012). Note that the majority of participants in both Studies 1 and 2 had fewer than five manipulation check errors. The second is that participants search for guns and, when not present, default to non-gun without fixation of the target item. Now, this may explain the results of the manipulation check in Study 2. In Study 2, participants with more manipulation check errors were generally faster than participants with lower manipulation check errors, and this is especially noticeable among the gun targets.

When searches are treated as target-present vs. target-absent, target-absent searches are characterized by longer search times as the entire array must be scanned (Wolfe 2021) as seen in study 1, but if a response time window were to make this untenable, then at higher set sizes we might expect more errors or even correct guessing to occur. This might explain a portion of participants whose manipulation check errors were driven by non-gun items and less so by gun items. A third approach is simply inattentiveness; participants either do not engage with the task, do not read the pretrial text cues, or even vary in attention over blocks. This particular approach may be characterized by an overall high manipulation check error rate and task error rate equivalent across conditions. However, there are participants who have high manipulation check error rates and a low overall error rate, which might suggest a strategy that precludes fixation of the target items. For example, it is possible for items to be processed in the field of view surrounding the current point of fixation (Wolfe, 2021). To the extent then that participants see an item in the periphery, they could respond prior to full fixation. It seems likely that participants are approaching the task in varied ways, but the manipulation check fails to meaningfully capture or pinpoint exact differences which should be addressed in any future work.

Race and Priming

Studies 1 and 2 show a distinct deviation from traditional findings in racial bias research using the WIT and FPST. Unlike the expected anti-Black race-by-object interactions typically found in this literature (Cesario and Carrillo, 2024), the results revealed no direct differences in object identification between White and Black primes. Instead, significant differences were observed when comparing conditions with a racial prime (either White or Black) to those without any prime. Further analysis using the DDM indicated that these unexpected findings did not obscure complex race interactions within the model's parameters. The only credible difference was noted in the evidence threshold at set size 12 between the race conditions and the no prime condition, an effect that diminished with increasing set sizes. This pattern suggests that the presence of a racial prime, rather than its specific racial identity, influenced object recognition by slowing responses.

There may be several explanations for why the typical race effects did not emerge; first, it could be that in the last four years since the death of George Floyd, it's plausible that there has been a decrease in anti-Black bias influenced by the broader political and social discourse. Such shifts could reflect how participants respond, potentially leaning towards socially desirable behaviors (Huddy & Feldman, 2009). Second, the study design may not facilitate the use of race as a mental shortcut. Future research should focus on thoroughly examining the mechanisms through which priming may alter search processes.

First, the design of our study, which involved rapid, consecutive trials, may account for the observed tendency of race effects to manifest similarly for both White and Black primes, compared to conditions without a prime. The brief intervals between trials might have led to a compounded racial priming effect, where the priming did not sufficiently decay before the next stimulus was presented. Research on priming decay suggests that longer intervals can reduce residual effects (Neely et al., 2010). To explore this further, one modification could involve adding intervals within the trial design, similar to those used in the FPST. The FPST approach incorporated sequences of empty backgrounds between trials, potentially allowing the initial priming effect to diminish. In this visual search task it may be useful to add buffers between trials of either empty screens or just a fixation cross that is shown for a longer period of time.

Alternatively, adopting a between-subjects design could provide another means to examine these effects. In such a design, participants would be exposed to only one racial category throughout the experiment. This approach would circumvent the need for additional time in the task as only one prime is relevant throughout.

Second, in the current design, the race prime is displayed for 500 milliseconds, which may be sufficiently long to allow participants some control over their responses. For example, when primed with race participants may decide to be more cautious which is reflected by the higher evidence thresholds following the prime. To investigate whether the length of exposure to the prime affects the strength of the priming effect or the participants ability to control their responses a reduced exposure time, perhaps closer to 200 milliseconds as used in the WIT (Payne, 2005). In this way the rapid display of the prime prevents participants from actively changing their search strategies.

Third, we may think that race information may be used in ambiguous situations (Duncan, 1976; Sagar & Schofield, 1980), and in this study, participants receive word cues indicating which items will appear. These text cues might substantially influence cognitive processes more than race cues in low ambiguous situations.

In line with this, Johnson et al. (2018) research into dispatch information found that providing participants with specific information about a target reduced racial biases, evidenced by changes in the drift rate. This indicates that when participants have access to more nuanced information, their reliance on racial stereotypes diminishes, leading to more accurate decision-making processes. In terms of visual search, the content of participants' search templates might be influenced by greater, more specific information given by the pretrial text cues rather than race cues (Yu et al., 2023). One method to test this idea is by designing a follow-up study where participants are tasked with identifying items belonging only to a gun category. Then, participants are given different levels of pretrial information ranging from race information only, text cues, text cues and race information, and specific images of the target items to appear. We would expect that as information gets more specific, attentional guidance would increase leading to faster and more accurate responses. This would allow for additional insights into when and how race information is used. Moreover, this allows for broader insigts into the effectiveness of priming in weapon search tasks.

It is important to consider several factors if the study's focus shifts exclusively to weapon trials. Specifically, simplifying the search task to include only gun items then changes the type of response made to gun present vs gun absent. To maintain an appropriate level of challenge and ensure that the task effectively measures search efficiency, one adjustment could be varying the orientation of the weapon in each trial. By having the gun face left or right randomly, the task would then require participants to determine the direction the gun is pointing. This modification then ensures that the participants are actively searching for the target item and gives specific insights into search efficiency for guns without the obfuscating influence of an additional non-gun target.

While there may be additional aspects of the design that warrant further exploration, these proposed manipulations collectively enable a more comprehensive investigation into the specific conditions under which racial biases might influence search efficiency. Should these manipulations fail to reveal racial bias, it would prompt a reevaluation of whether racial biases are primarily manifested during identification processes rather than during the search processes themselves. This distinction could significantly refine our understanding of the use of race information in deadly force decisions.

Limitations and Future Directions

A notable limitation of this work is that differences in search efficiency alone do not inform us whether these differences emerge from search processes, identification processes, or a combination of both (Kristjánsson, 2015; Wolfe, 2016). Thus, a useful path forward would be to integrate eye-tracking technology in follow-up studies as it can provide additional information above and beyond simple differences in search slopes, such as the point of the first fixation of the target item and the point of identification (Godwin et al., 2021). Additionally, eye-tracking studies will allow researchers to specifically identify how participants are performing the task, such as whether the participant fully fixates the item before the decision is made.

Eye-tracking could also be used to explain why response times and, consequently, evidence thresholds are larger when there is a race prime versus no prime. For example, differences in evidence thresholds are generally found when response times for both correct and incorrect responses shift in one direction (Ratcliff, 1978); if a participant has the time to be more accurate, this is reflected in longer response times for both correct and incorrect decisions and a lower error rate. One explanation may be that this would reflect in longer decision times once participants have fixated the target, but that fails to capture why response time for errors would increase. Thus, a likely explanation could be that when primed, participants spend slightly more time scanning the search array for the target than when they are not primed. Eye tracking could then provide insight into whether this is the case or if a combination of search times and decision times plays a role.

Another limitation is that the design of the tasks may meaningfully shape participants' search strategies. For instance, pretrial text cues consistently highlighted the presence of a gun, potentially biasing participants towards prioritizing guns over non-gun items. It is never the case that the text cues could be two different non-gun items, alerting participants to the fact that the items of central importance are guns and not non-guns. Previous research has indicated that instruction sets can significantly influence performance (Katsimpokis et al., 2020), suggesting that altering task instructions can impact the amount of evidence collected. Further, task-specific instructions (e.g., "gun or no gun" to "shoot or don't shoot" or "threat or non-threat") could modify how information is collected and processed. Importantly, domain-specific experts (i.e., radiologists, TSA) have been found to perform task-specific searches more efficiently than lay people (Papesh et al., 2021). To the extent that the end goal is to understand how police make decisions to shoot, future studies should specifically be designed with this in mind. As an example, deadly force decisions may not always conform to a gun or non-gun decision but rather might be something along threat or non-threat dimension, which can impact search and identification times (Blanchette, 2006; though see Wolfe & Horowitz, 2017).

In this vein, another design limitation concerns the absence of a payoff matrix or reward system to penalize critical errors, such as failing to identify a gun (Correll et al., 2002; Johnson et al., 2018). The lack of negative feedback may lead some participants to prefer a target present versus a target-absent decision-making process, especially under challenging conditions. Such a strategy would explain the observed higher error rates for gun identification at increased set sizes. Taking the feedback as an example, failure to identify a gun is a costly mistake that could result in injury or death of the officer or other civilians. Importantly, this current work does not capture how experiences of threat can shape the search process, which may be an interesting avenue for future work.

CONCLUSION

Despite these limitations, the present study highlighted the use of visual science manipulations as a way of further teasing apart racial bias in weapon identification. The current work did not find racial differences in search efficiency but instead found that searches for guns were more efficient than non-guns. This finding underscores the importance of understanding which features may impair or enhance search efficiency in such decision-making processes. Although it is premature to draw definitive conclusions, there is evidence that search is an important element, but significantly more work is needed to understand how and under what conditions it can interact with race or other social information. For instance, subsequent studies could investigate various search manipulations and modes of presenting racial information to investigate whether racial bias is predominantly a function of identification differences or if it can manifest during the search process itself.

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APPENDIX A: METHOD TABLES AND CODE

Table 1 *List of categories used*

Categories				
abacus	carfront	fish hook	motorcycle	spoon
airplane	cat	flag	mp3player	stamp
apple	ceilingfan	frame	muffins	stool
armyguy	chair	frisbee	mushroom	suit
babushkadolls	cheese	garbagetrash	nailpolish	suitcase
babycarriage	cheesegrater	gift	necklace	tablesmall
backpack	cherubstatue	glove	necktie	tape
bagel	chessboard	goggle	orifan	telescope
ball	christmasstocking	golfball	pants	tennisracquet
balloon	ornamantball	grill	patioloungechair	tent
barbiedoll	cigarette	guitar	pen	toiletseat
baseballcards	clock	handbag	pipe	tongs
basket	coatrack	hanger	pitcher	toothpaste
bathsuit	coffeemug	hat	pizza	toyhorse
beanbagchair	coin	headband	pokercard	toyrabbit
bearteddy	collar	headphone	powerstrip	train
bed	compass	helmet	radio	tree
beermug	computer_key	hourglass	razor	tricycle
bell	cookie	jack-o-lantern	recordplayer	trophy
bench	cookingpan	jacket	ring	trumpet
bike	cookpot	kayak	ringbinder	trunk
bill	crib	key	roadsign	turtle
binoculars	cupsaucer	keyboard	rock	tv
bird	cushion	keychain	rollerskates	vase
bongo	decorativescreen	lamp	rosary	watch
bonzai	desk	lantern	rug	wig
boot	dog	lawnmower	saddle	windchime
bottle	doll	leaves	saltpeppershake	wineglass
bowl	dollhouse	lei	sandwich	
bowtie	domino	licenseplate	scale	
breadloaf	donut	lipstick	scrunchie	
broom	doorknob	lock	seashell	
bucket	dresser	magazinecovers	shoe	
Butterfly	dumbbell	makeupcompact	sippycup	
button	earings	mask	snowglobe	
cake	easteregg_redo	meat	socks	
camcorder	exercise_equip.	microscope	sofa	
camera	fan	microwave	speakers	

Note: There are 17 images per category. All distractor items derived from Massive Memory Database.

Table 2 *Distance from center from screen*

Object	Set Size	Black (Average Distance)	White (Average Distance)	No Prime (Average Distance)
Gun	12	3.20	3.20	3.21
Gun	16	3.21	3.12	3.23
Gun	20	3.17	3.25	3.18
Non-gun	12	3.21	3.20	3.18
Non-gun	16	3.26	3.22	3.19
Non-gun	20	3.19	3.23	3.15

Note: The values are based on the Euclidean distance between the center of a grid item and center of the screen. The Euclidean distance here is expressed as a unitless value because it is a relative measurement used for comparison rather than an absolute distance in physical units like meters or inches.

Chat-GPT 4 generated code to test random assignment. (Verified)

```
import numpy as np
import random

# Define grid size
grid_size = 8

# Define center coordinates
center_x, center_y = 3.5, 3.5

# Create an empty list to store cell coordinates and their distances from the center
cell_distances = []

# Iterate over all cells in the grid
for i in range(grid_size):
    for j in range(grid_size):
        # Exclude the 4 center cells
        if not (3 <= i <= 4 and 3 <= j <= 4):
            # Calculate Euclidean distance from the center
            distance = np.sqrt((i - center_x) ** 2 + (j - center_y) ** 2)
            # Store the cell coordinates and the distance
            cell_distances.append(((i, j), distance))

# Define the conditions and set sizes
race_conditions = ['Black', 'White', 'NoPrime']
object_types = ['Gun', 'Non-gun']
set_sizes = [12, 16, 20]

# Create a list to store the average distances for each participant
all_participants_avg_distances = []

# Repeat the cell assignment and average distance calculation 300 times
for _ in range(300):
    # Shuffle the cell_distances list
    random.shuffle(cell_distances)

    # Split the list into six equal parts, for each combination of race condition and object type
    parts = [cell_distances[i::6] for i in range(6)]

    # Create a dictionary to store the cells for each condition and their average distances
    condition_cells = {}

    # Assign the cells to the conditions
    for i, race_condition in enumerate(race_conditions):
        for j, object_type in enumerate(object_types):
```

```
        # Get the cells for this combination of race condition and object type
        cells = parts[i * len(object_types) + j]

        # Further split the cells into parts for each set size
        set_size_parts = [cells[i::3]  for i in range(3)]

        for k, set_size in enumerate(set_sizes):
            # Get the cells for this set size
            set_size_cells = set_size_parts[k]

            # Calculate the average distance of these cells from the center
            avg_distance = np.mean([dist for _, dist in set_size_cells])

            # Store the cells and their average distance in the dictionary
            condition = (race_condition, object_type, set_size)
            condition_cells[condition] = (set_size_cells,  avg_distance)

    # Store the average distances for this participant
    all_participants_avg_distances.append(condition_cells)

# Create a dictionary to store the total distances for each condition
total_distances = {condition: 0 for condition in condition_cells.keys()}

# Iterate over all participants
for participant in all_participants_avg_distances:
    # Add the average distances of this participant to the total distances
    for condition, (cells, avg_distance) in participant.items():
        total_distances[condition] += avg_distance

# Calculate the average distance for each condition
avg_distances_all_participants = {condition: total / len(all_participants_avg_distances) for
condition, total in total_distances.items()}

# Print the average distances for each condition
for condition, avg_distance in avg_distances_all_participants.items():
    print(f"Condition {condition}: Average Distance = {avg_distance}")
```

APPENDIX B: BEHAVIORAL RESULTS TABLES

Table 3 *Multilevel Linear Regression Predicting Response Time from Race, Target Type, and Set Size in Study 1*

Fixed Effects	*b*	*SE*	*df*	*t*	*p*
Intercept	1519.188	46.759	41.585	32.489	<0.000
Prime RaceW	1.657	3.825	109572.681	0.433	0.665
Prime RaceB	6.368	3.824	109573.024	1.665	0.096
Target Type	-203.035	43.423	31.008	-4.675	<0.000
Set Size12	-168.999	3.822	109572.580	-44.217	<0.000
Set Size20	173.786	3.828	109572.704	45.403	<0.000
Prime RaceW x Target Type	-9.222	3.825	109572.462	-2.411	0.016
Prime RaceB x Target Type	3.942	3.824	109572.464	1.031	0.303
Prime RaceW x Set Size12	1.569	5.406	109572.560	0.290	0.772
Prime RaceB x Set Size12	-2.721	5.405	109572.775	-0.503	0.615
Prime RaceW x Set Size20	-1.389	5.413	109572.580	-0.257	0.797
Prime RaceB x Set Size20	4.233	5.412	109572.575	0.782	0.434
Target Type x Set Size12	18.852	3.822	109572.517	4.932	<0.000
Target Type x Set Size20	-21.244	3.828	109572.696	-5.550	<0.000
Prime RaceW x Target Type x Set Size12	2.503	5.406	109572.589	0.463	0.643
Prime RaceW x Target Type x Set Size20	1.432	5.405	109572.556	0.264	0.791
Prime RaceB x Target Type x Set Size12	1.962	5.413	109572.512	0.362	0.717
Prime RaceB x Target Type x Set Size20	-1.145	5.412	109572.614	-0.211	0.833

Random Effects	*N*	*Variance*
Participant	316	95080
Target	33	61924
Observations	109936	

Note: Race, target type, and set size were effect coded for analysis. "W" represents White primes, and "B" indicates Black primes.

Table 4 *Contrast Tests of Estimated Marginal Means for Response Time Across Prime Race*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
White	1521	1429	1613
Black	1526	1434	1618
None	1511	1419	1603

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
White - Black	-4.711	-17.694	8.272
White - None	9.683	-3.303	22.670
Black - None	14.394	1.413	27.376

Table 5 *Contrast Tests of Estimated Marginal Means for Response Time Across Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
Gun	1316	1193	1439
Nongun	1722	1595	1849

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Gun - Nongun	-406	-17.694	8.272

Table 6 *Contrast Tests of Estimated Marginal Means for Response Time Across Set Size*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12	1350	1258	1442
16	1514	1422	1606
20	1693	1601	1785

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
12 - 20	-343	-355.770	-329.800
12 - 16	-164	-177.185	-151.237
20 - 16	179	165.581	191.567

Table 7 *Contrast Tests of Estimated Marginal Means for Response Time Across Set Size and Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12 Gun	1166	1042	1290
16 Gun	1314	1190	1438
20 Gun	1469	1345	1592
12 Nongun	1534	1407	1662
16 Nongun	1715	1588	1842
20 Nongun	1917	1790	2045
		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Linear Nongun - Gun	32.918	6.971	58.867
Quadratic Nongun - Gun	-127.466	-172.479	-82.454

Table 8 *Contrast Tests of Estimated Marginal Means for Response Time Across Prime Race and Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
White Gun	1309	1185	1432
Black Gun	1326	1203	1450
None Gun	1313	1190	1437
White Nongun	1733	1606	1860
Black Nongun	1725	1597	1852
None Nongun	1709	1582	1836
		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
White - Black Gun	-17.875	-36.234	0.484
White – None Gun	-4.819	-23.182	13.543
Black – None Gun	13.056	-5.305	31.416
White – Black Nongun	8.453	-9.911	26.816
White – None Nongun	24.186	5.819	42.553
Black – None Nongun	15.733	-2.622	34.088

Table 9 *Multilevel Logistic Regression Predicting Correct Decisions from Race, Target Type, and Set Size in Study 1*

Fixed Effects	*b*	*SE*	*z*	*Pr(>|z)*
Intercept	3.751	46.759	73.446	0.000
Prime RaceW	-0.020	3.825	-0.798	0.425
Prime RaceB	0.030	3.824	1.196	0.232
Target Type	-0.012	43.423	-0.477	0.633
Set Size12	0.083	3.822	2.909	0.004
Set Size20	-0.093	3.828	-2.751	0.006
Prime RaceW x Target Type	0.026	3.825	1.052	0.293
Prime RaceB x Target Type	-0.019	3.824	-0.755	0.450
Prime RaceW x Set Size12	0.032	5.406	0.904	0.366
Prime RaceB x Set Size12	-0.018	5.405	-0.521	0.603
Prime RaceW x Set Size20	0.006	5.413	0.182	0.856
Prime RaceB x Set Size20	-0.002	5.412	-0.072	0.943
Target Type x Set Size12	0.053	3.822	1.867	0.062
Target Type x Set Size20	-0.053	3.828	-1.587	0.113
Prime RaceW x Target Type x Set Size12	0.024	5.406	0.672	0.502
Prime RaceW x Target Type x Set Size20	-0.039	5.405	-1.109	0.267
Prime RaceB x Target Type x Set Size12	-0.059	5.413	-1.746	0.081
Prime RaceB x Target Type x Set Size20	0.052	5.412	1.515	0.130

Random Effects	*N*	*Variance*
Participant	316	0.558
Target	33	0.012
Target-Set Size12		0.006
Target-Set Size20		0.018
Observations	113366	

Note: Race, target type, and set size were effect coded for analysis. "W" represents White primes, and "B" indicates Black primes.

Table 10 *Multilevel Linear Regression Predicting Response Time from Race, Target Type, Set Size, and Block Order in Study 1*

Fixed Effects	*b*	*SE*	*df*	*t*	*p*
Intercept	1519.035	46.762	41.572	32.485	<0.000
Prime RaceW	0.553	3.808	109570.682	0.145	0.884
Prime RaceB	5.251	3.806	109571.025	1.380	0.168
Target Type	-203.264	43.428	31.006	-4.681	<0.000
Set Size12	-169.113	3.804	109570.579	-44.454	<0.000
Set Size20	173.793	3.810	109570.702	45.617	<0.000
Block Order1	118.755	3.807	109571.509	31.197	<0.000
Block Order3	-84.222	3.811	109573.399	-22.099	<0.000
Prime RaceW x Target Type	-9.116	3.807	109570.461	-2.394	0.017
Prime RaceB x Target Type	3.969	3.806	109570.463	1.043	0.297
Prime RaceW x Set Size12	1.688	5.381	109570.559	0.314	0.754
Prime RaceB x Set Size12	-2.762	5.380	109570.772	-0.513	0.608
Prime RaceW x Set Size20	-1.431	5.388	109570.579	-0.266	0.791
Prime RaceB x Set Size20	4.353	5.387	109570.574	0.808	0.419
Target Type x Set Size12	18.615	3.804	109570.517	4.893	<0.000
Target Type x Set Size20	-21.155	3.810	109570.694	-5.553	<0.000
Prime RaceW x Target Type x Set Size12	2.616	5.381	109570.588	0.486	0.627
Prime RaceW x Target Type x Set Size20	1.228	5.380	109570.554	0.228	0.819
Prime RaceB x Target Type x Set Size12	2.136	5.388	109570.511	0.396	0.692
Prime RaceB x Target Type x Set Size20	-1.366	5.387	109570.611	-0.254	0.800

Random Effects	*N*	*Variance*
Participant	316	95080
Target	33	61924
Observations	109936	

Note: Race, target type, set size, and block order were effect coded for analysis. "W" represents White primes, and "B" indicates Black primes. Block order 1 and 3 are the first and last blocks.

Table 11 *Contrast Tests of Estimated Marginal Means for Response Time Across Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
Gun	1316	1192	1439
Nongun	1722	1595	1849
		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Gun - Nongun	-406.529	-576.762	-236.296

Table 12 *Contrast Tests of Estimated Marginal Means for Response Time Across Set Size*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12	1350	1258	1442
16	1514	1422	1606
20	1693	1601	1785
		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
12 - 20	-342.907	-355.831	-329.982
12 - 16	-164.434	-177.348	-151.52
20 - 16	178.473	165.54	191.406

Table 13 *Contrast Tests of Estimated Marginal Means for Response Time Across Block Order*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
0	1638	1546	1730
1	1485	1393	1576
2	1435	1343	1527
		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Linear	-153.288	-166.201	-140.375
Quadratic	252.667	230.258	275.077

Table 14 *Contrast Tests of Estimated Marginal Means for Response Time Across Set Size and Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12 Gun	1165	1042	1289
16 Gun	1314	1190	1437
20 Gun	1468	1345	1592
12 Nongun	1535	1407	1662
16 Nongun	1715	1588	1842
20 Nongun	1917	1790	2045

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Linear	-153.288	-166.2009	-140.3751
Quadratic	252.6673	230.2581	275.0766

Table 15 *Contrast Tests of Estimated Marginal Means for Response Time Across Prime Race and Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
White Gun	1307	1183	1431
Black Gun	1325	1201	1449
None Gun	1315	1191	1439
White Nongun	1732	1605	1859
Black Nongun	1724	1596	1851
None Nongun	1711	1584	1839

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
White - Black Gun	-17.783	-36.056	0.491
White – None Gun	-7.905	-26.183	10.374
Black – None Gun	9.878	-8.399	28.154
White – Black Nongun	8.388	-9.89	26.666
White – None Nongun	20.621	2.337	38.904
Black – None Nongun	12.233	-6.039	30.504

Table 16 *Multilevel Linear Regression Predicting Response Time from Race, Target Type, Set Size, and Manipulation Check Errors in Study 1*

Fixed Effects	*b*	*SE*	*df*	*t*	*p*
Intercept	1518.533	46.709	41.439	32.510	0.000
Prime RaceW	1.679	3.824	109567.691	0.439	0.661
Prime RaceB	6.368	3.823	109568.037	1.666	0.096
Target Type	-203.054	43.414	31.006	-4.677	0.000
Set Size12	-168.935	3.821	109567.581	-44.211	0.000
Set Size20	173.675	3.827	109567.698	45.384	0.000
mouseC	5.174	2.257	314.161	2.293	0.023
Prime RaceW x Target Type	-9.222	3.824	109567.467	-2.411	0.016
Prime RaceB x Target Type	3.932	3.823	109567.471	1.029	0.304
Prime RaceW x Set Size12	1.608	5.404	109567.567	0.298	0.766
Prime RaceB x Set Size12	-2.778	5.403	109567.785	-0.514	0.607
Prime RaceW x Set Size20	-1.422	5.412	109567.581	-0.263	0.793
Prime RaceB x Set Size20	4.300	5.411	109567.582	0.795	0.427
Target Type x Set Size12	18.909	3.821	109567.513	4.948	0.000
Target Type x Set Size20	-21.343	3.827	109567.667	-5.577	0.000
Target Type x mouseC	-2.698	0.353	109571.585	-7.633	0.000
Set Size12 x mouseC	0.341	0.499	109567.691	0.439	0.494
Set Size20 x mouseC	-0.760	0.501	109568.014	-1.517	0.129
Prime RaceW x Target Type x Set Size12	2.482	5.404	109567.590	0.459	0.646
Prime RaceW x Target Type x Set Size20	1.431	5.403	109567.550	0.265	0.791
Prime RaceB x Target Type x Set Size12	2.013	5.412	109567.513	0.372	0.710
Prime RaceB x Target Type x Set Size20	-1.156	5.411	109567.606	-0.214	0.831
Target Type x Set Size12 x mouseC	0.310	0.499	109567.784	0.621	0.535
Target Type x Set Size20 x mouseC	-0.465	0.501	109568.016	-0.929	0.353

Random Effects	*N*	*Variance*
Participant	316	93817
Target	33	61900
Observations	109936	

Note: Race, target type, and set size were effect coded for analysis. "W" represents White primes, and "B" indicates Black primes. MouseC is the centered manipulation check errors.

Table 17 *Contrast Tests of Estimated Marginal Means for Response Time Across Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
Gun	1315	1192	1439
Nongun	1722	1595	1848
		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Gun - Nongun	-406.108	-576.289	-235.927

Table 18 *Contrast Tests of Estimated Marginal Means for Response Time Across Set Size*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12	1350	1258	1441
16	1514	1422	1606
20	1692	1600	1784
		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
12 - 16	-164.196	-177.167	-151.225
12 - 20	-342.61	-355.592	-329.629
16 - 20	-178.415	-191.405	-165.424

Table 19 *Contrast Tests of Estimated Marginal Means for Response Time Across Block Order*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
0	1638	1546	1730
1	1485	1393	1576
2	1435	1343	1527
		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Linear	-153.288	-166.201	-140.375
Quadratic	252.667	230.258	275.077

Table 20 *Contrast Tests of Estimated Marginal Means for Response Time Across Set Size and Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12 Gun	1165	1042	1289
16 Gun	1313	1189	1437
20 Gun	1468	1344	1591
12 Nongun	1534	1407	1661
16 Nongun	1714	1587	1842
20 Nongun	1917	1789	2044
		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Linear nongun - gun	80.504	54.54	106.467
Quadratic nongun - gun	14.607	-30.357	59.572

Table 21 *Contrast Tests of Estimated Marginal Means for Response Time Across Manipulation Check Errors and Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
-1SD Gun	1297	1169	1425
0.00 Gun	1315	1192	1439
1 SD Gun	1334	1207	1462
-1SD Nongun	1661	1530	1793
0.00 Nongun	1722	1595	1848
1 SD Nongun	1782	1651	1913
		95% Confidence Limit	
Trends	Estimate	Lower	Upper
Gun	2.48	-2	6.95
Nongun	7.87	3.4	12.35

Table 22 *Multilevel Linear Regression Predicting Response Time from Race, Target Type, and Set Size in Study 2*

Fixed Effects	*b*	*SE*	*df*	*t*	*p*
Intercept	1104.302	23.167	36.893	47.667	<0.000
Prime RaceW	2.309	2.761	6.763	0.837	0.431
Prime RaceB	3.945	2.760	6.753	1.429	0.197
Target Type	-122.881	22.173	31.004	-5.542	<0.000
Set Size12	-74.478	1.808	101207.551	-41.183	<0.000
Set Size20	70.707	1.825	101209.035	38.734	<0.000
Prime RaceW x Target Type	-3.535	1.817	101211.105	-1.945	0.052
Prime RaceB x Target Type	-0.186	1.816	101211.800	-0.103	0.918
Prime RaceW x Set Size12	3.245	2.558	101208.207	1.269	0.205
Prime RaceB x Set Size12	-1.374	2.554	101208.649	-0.538	0.591
Prime RaceW x Set Size20	-1.165	2.582	101209.483	-0.451	0.652
Prime RaceB x Set Size20	2.159	2.580	101209.996	0.837	0.403
Target Type x Set Size12	5.034	1.809	101208.869	2.783	0.005
Target Type x Set Size20	-6.501	1.825	101211.259	-3.561	<0.000
Prime RaceW x Target Type x Set Size12	-2.896	2.558	101209.801	-1.132	0.258
Prime RaceW x Target Type x Set Size20	-0.198	2.554	101208.646	-0.078	0.938
Prime RaceB x Target Type x Set Size12	2.549	2.582	101212.937	0.987	0.323
Prime RaceB x Target Type x Set Size20	-2.170	2.580	101211.647	-0.841	0.400

Random Effects	*N*	*Variance*
Participant	308	12719.43
Prime Face	41	31.09
Target	33	16154.10
Observations	101597	

Note: Race, target type, and set size were effect coded for analysis. "W" represents White primes, and "B" indicates Black primes.

Table 23 *Contrast Tests of Estimated Marginal Means for Response Time Across Prime Race*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
White	1107	1061	1152
Black	1108	1063	1154
None	1098	1051	1145

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
White - Black	-1.635	-8.702	5.432
White - None	8.563	-4.225	21.352
Black - None	10.199	-2.587	22.984

Table 24 *Contrast Tests of Estimated Marginal Means for Response Time Across Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
Gun	981	919	1043
Nongun	1227	1163	1291

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Gun - Nongun	-245.762	-332.676	-158.847

Table 25 *Contrast Tests of Estimated Marginal Means for Response Time Across Set Size*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12	1030	984	1075
16	1108	1063	1154
20	1175	1129	1221

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
12 - 20	-145.185	-151.352	-139.018
12 - 16	-78.25	-84.391	-72.108
20 - 16	66.935	60.736	73.134

Table 26 *Contrast Tests of Estimated Marginal Means for Response Time Across Set Size And Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12 Gun	912	850	974
16 Gun	987	925	1049
20 Gun	1046	984	1108
12 Nongun	1148	1084	1212
16 Nongun	1229	1166	1293
20 Nongun	1304	1241	1368

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Linear Nongun - Gun	23.070	10.734	35.405
Quadratic Nongun - Gun	8.819	-12.560	30.198

Table 27 *Multilevel Logistic Regression Predicting Correct Decisions from Race, Target Type, and Set Size in Study 2*

Fixed Effects	*b*	*SE*	*z*	*Pr(>|z)*
Intercept	2.665	0.056	47.498	<0.000
Prime RaceW	0.002	0.017	0.097	0.923
Prime RaceB	0.051	0.017	3.048	0.002
Target Type	-0.072	0.047	-1.547	0.122
Set Size12	0.239	0.017	13.816	<0.000
Set Size20	-0.204	0.016	-12.868	<0.000
Prime RaceW x Target Type	-0.010	0.017	-0.591	0.554
Prime RaceB x Target Type	-0.034	0.017	-2.021	0.043
Prime RaceW x Set Size12	0.012	0.025	0.499	0.618
Prime RaceB x Set Size12	0.028	0.025	1.111	0.267
Prime RaceW x Set Size20	-0.010	0.022	-0.429	0.668
Prime RaceB x Set Size20	-0.015	0.023	-0.646	0.518
Target Type x Set Size12	0.082	0.017	4.717	<0.000
Target Type x Set Size20	-0.079	0.016	-4.954	<0.000
Prime RaceW x Target Type x Set Size12	-0.057	0.025	-2.325	0.020
Prime RaceW x Target Type x Set Size20	0.016	0.025	0.662	0.508
Prime RaceB x Target Type x Set Size12	0.006	0.022	0.271	0.787
Prime RaceB x Target Type x Set Size20	0.004	0.023	0.156	0.876

Random Effects	*N*	*Variance*
Participant	308	0.293
Target	33	0.067
Observations	109925	

Note: Race, target type, and set size were effect coded for analysis. "W" represents White primes, and "B" indicates Black primes.

Table 28 *Contrast Tests of Estimated Marginal Means for Accuracy Across Prime Race*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
White	2.67	2.55	2.78
Black	2.72	2.6	2.83
None	2.61	2.5	2.73

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
White - Black	-0.049	-0.106	0.007
White - None	0.054	-0.001	0.109
Black - None	0.103	0.047	0.159

Table 29 *Contrast Tests of Estimated Marginal Means for Accuracy Across Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
Gun	2.59	2.45	2.73
Nongun	2.74	2.59	2.88

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Gun - Nongun	-0.144	-0.333	-0.159

Table 30 *Contrast Tests of Estimated Marginal Means for Accuracy Across Set Size*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12	2.9	2.79	3.02
16	2.63	2.52	2.74
20	2.46	2.35	2.57

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
12 - 20	0.274	0.216	0.333
12 - 16	0.443	0.387	0.5
20 - 16	0.169	0.116	0.222

Table 31 *Contrast Tests of Estimated Marginal Means for Accuracy Across Set Size and Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12 Gun	2.91	2.76	3.06
16 Gun	2.56	2.41	2.7
20 Gun	2.31	2.16	2.46
12 Nongun	2.89	2.74	3.05
16 Nongun	2.71	2.55	2.86
20 Nongun	2.61	2.46	2.76

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Linear Nongun - Gun	-0.320	-0.434	-0.207
Quadratic Nongun - Gun	0.018	-0.174	0.211

Table 32 *Contrast Tests of Estimated Marginal Means for Accuracy Across Prime Race, Set Size, and Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
White 12 Gun	2.86	2.69	3.03
Black 12 Gun	2.98	2.8	3.15
None 12 Gun	2.91	2.73	3.08
White 16 Gun	2.6	2.43	2.76
Black 16 Gun	2.54	2.37	2.7
None 16 Gun	2.53	2.37	2.7
White 20 Gun	2.3	2.14	2.46
Black 20 Gun	2.32	2.16	2.48
None 20 Gun	2.32	2.16	2.48
White 12 Nongun	2.98	2.8	3.15
Black 12 Nongun	2.99	2.81	3.17
None 12 Nongun	2.72	2.55	2.89
White 16 Nongun	2.66	2.49	2.83
Black 16 Nongun	2.8	2.62	2.97
None 16 Nongun	2.66	2.49	2.83
White 20 Nongun	2.61	2.44	2.78
Black 20 Nongun	2.68	2.51	2.85
None 20 Nongun	2.55	2.38	2.72

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Linear White-Black Gun	0.096	-0.096	0.288
Quadratic White-Black Gun	-0.244	-0.568	0.08
Linear White-None Gun	0.027	-0.163	0.217
Quadratic White-None Gun	-0.191	-0.514	0.131
Linear Black-None Gun	-0.069	-0.262	0.124
Quadratic Black-None Gun	0.052	-0.27	0.374
Linear White-Black Nongun	-0.056	-0.261	0.15
Quadratic White-Black Nongun	0.182	-0.166	0.529
Linear White-None Nongun	-0.199	-0.397	-0.002
Quadratic White-None Nongun	0.3	-0.036	0.636
Linear Black-None Nongun	-0.143	-0.342	0.055
Quadratic Black-None Nongun	0.118	-0.225	0.462

Table 33 *Multilevel Linear Regression Predicting Response Time from Race, Target Type, Set Size, and Block Order in Study 2*

Fixed Effects	*b*	*SE*	*df*	*t*	*p*
Intercept	1104.548	23.093	36.426	32.485	<0.000
Prime RaceW	2.262	1.807	101241.062	0.145	0.211
Prime RaceB	3.846	1.805	101242.134	1.380	0.033
Target Type	-122.827	22.176	31.004	-4.681	<0.000
Set Size12	-74.603	1.797	101240.555	-44.454	<0.000
Set Size20	70.691	1.814	101241.038	45.617	<0.000
Block Order1	63.825	1.810	101245.755	31.197	<0.000
Block Order3	-45.390	1.806	101244.599	-22.099	<0.000
Prime RaceW x Target Type	-3.555	1.806	101241.110	-2.394	0.049
Prime RaceB x Target Type	-0.219	1.804	101241.144	1.043	0.904
Prime RaceW x Set Size12	3.318	2.541	101240.667	0.314	0.192
Prime RaceB x Set Size12	-1.346	2.538	101240.563	-0.513	0.596
Prime RaceW x Set Size20	-1.252	2.565	101240.813	-0.266	0.625
Prime RaceB x Set Size20	2.147	2.563	101240.930	0.808	0.402
Target Type x Set Size12	4.951	1.797	101240.931	4.893	0.006
Target Type x Set Size20	-6.404	1.814	101241.060	-5.553	<0.000
Prime RaceW x Target Type x Set Size12	-2.757	2.541	101240.352	0.486	0.278
Prime RaceW x Target Type x Set Size20	-0.207	2.538	101240.462	0.228	0.935
Prime RaceB x Target Type x Set Size12	2.616	2.565	101241.123	0.396	0.308
Prime RaceB x Target Type x Set Size20	-2.197	2.563	101240.627	-0.254	0.391

Random Effects	*N*	*Variance*
Participant	308	12774
Target	33	16160
Observations	101597	

Note: Race, target type, set size, and block order were effect coded for analysis. "W" represents White primes, and "B" indicates Black primes. Block order 1 and 3 are the first and last blocks.

Table 34 *Contrast Tests of Estimated Marginal Means for Response Time Across Prime Race*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
White	1107	1061	1152
Black	1108	1063	1154
None	1098	1053	1144

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
White - Black	-1.583	-7.708	4.542
White - None	8.37	2.225	14.516
Black - None	9.954	3.813	16.094

Table 35 *Contrast Tests of Estimated Marginal Means for Response Time Across Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
Gun	982	920	1044
Nongun	1227	1164	1291

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Gun - Nongun	-245.654	-332.584	-158.724

Table 36 *Contrast Tests of Estimated Marginal Means for Response Time Across Set Size*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12	1030	984	1075
16	1108	1063	1154
20	1175	1129	1221

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
12 - 20	-145.294	-151.422	-139.166
12 - 16	-78.516	-84.618	-72.414
20 - 16	66.778	60.619	72.938

Table 37 *Contrast Tests of Estimated Marginal Means for Response Time Across Block Order*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
0	1168	1123	1214
1	1086	1041	1132
2	1059	1014	1105
		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Linear	-109.215	-115.354	-103.076
Quadratic	55.303	44.68	65.927

Table 38 *Contrast Tests of Estimated Marginal Means for Response Time Across Set Size And Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12 Gun	912	850	974
16 Gun	987	925	1049
20 Gun	1046	984	1108
12 Nongun	1148	1084	1212
16 Nongun	1230	1166	1294
20 Nongun	1304	1241	1368
		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Linear Nongun - Gun	22.71	10.455	34.966
Quadratic Nongun - Gun	8.72	-12.522	29.961

Table 39 *Contrast Tests of Estimated Marginal Means for Response Time Across Prime Race and Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
White Gun	980	918	1042
Black Gun	985	923	1047
None Gun	979	917	1041
White Nongun	1233	1169	1297
Black Nongun	1231	1168	1295
None Nongun	1217	1154	1281

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
White - Black Gun	-4.92	-13.607	3.767
White – None Gun	1.042	-7.652	9.735
Black – None Gun	5.961	-2.733	14.655
White – Black Nongun	1.753	-6.884	10.391
White – None Nongun	15.699	7.026	24.372
Black – None Nongun	13.946	5.288	22.603

Table 40 *Multilevel Logistic Regression Predicting Correct Decisions from Race, Target Type, Set Size and Block Order in Study 2*

Fixed Effects	*b*	*SE*	*z*	*Pr(>|z)*
Intercept	2.667	0.056	47.497	<0.000
Prime RaceW	0.001	0.017	0.042	0.967
Prime RaceB	0.050	0.017	2.991	0.003
Target Type	-0.072	0.047	-1.545	0.122
Set Size12	0.239	0.017	13.824	<0.000
Set Size20	-0.204	0.016	-12.874	<0.000
Block Order1	-0.089	0.016	-5.549	<0.000
Block Order3	0.042	0.016	2.532	0.011
Prime RaceW x Target Type	-0.010	0.017	-0.600	0.549
Prime RaceB x Target Type	-0.034	0.017	-2.015	0.044
Prime RaceW x Set Size12	0.012	0.025	0.489	0.625
Prime RaceB x Set Size12	0.028	0.025	1.113	0.266
Prime RaceW x Set Size20	-0.009	0.022	-0.416	0.677
Prime RaceB x Set Size20	-0.015	0.023	-0.649	0.516
Target Type x Set Size12	0.081	0.017	4.702	<0.000
Target Type x Set Size20	-0.078	0.016	-4.946	<0.000
Prime RaceW x Target Type x Set Size12	-0.057	0.025	-2.323	0.020
Prime RaceW x Target Type x Set Size20	0.016	0.025	0.645	0.519
Prime RaceB x Target Type x Set Size12	0.006	0.022	0.289	0.773
Prime RaceB x Target Type x Set Size20	0.003	0.023	0.151	0.880

Random Effects	*N*	*Variance*
Participant	308	0.282
Target	33	0.067
Observations	109925	

Note: Race, target type, set size, and block order were effect coded for analysis. "W" represents White primes, and "B" indicates Black primes. Block order 1 and 3 are the first and last blocks.

Table 41 *Contrast Tests of Estimated Marginal Means for Accuracy Across Prime Race*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
White	2.67	2.55	2.78
Black	2.72	2.6	2.83
None	2.62	2.5	2.73

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
White - Black	-0.049	-0.106	0.007
White - None	0.051	-0.004	0.107
Black - None	0.101	0.045	0.157

Table 42 *Contrast Tests of Estimated Marginal Means for Accuracy Across Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
Gun	2.59	2.45	2.74
Nongun	2.74	2.59	2.88

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Gun - Nongun	-0.144	0.093	-1.545

Table 43 *Contrast Tests of Estimated Marginal Means for Accuracy Across Set Size*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12	2.91	2.79	3.02
16	2.63	2.52	2.75
20	2.46	2.35	2.58

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
12 - 20	0.275	0.216	0.333
12 - 16	0.444	0.387	0.500
20 - 16	0.169	0.116	0.222

Table 44 *Contrast Tests of Estimated Marginal Means for Accuracy Across Block Order*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
0	2.58	2.46	2.69
1	2.71	2.6	2.83
2	2.71	2.59	2.82

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Linear	0.275	0.216	0.333
Quadratic	0.169	0.116	0.222

Note:

Table 45 *Contrast Tests of Estimated Marginal Means for Accuracy Across Set Size and Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12 Gun	2.92	2.76	3.07
16 Gun	2.56	2.41	2.7
20 Gun	2.31	2.17	2.46
12 Nongun	2.9	2.74	3.05
16 Nongun	2.71	2.55	2.86
20 Nongun	2.61	2.46	2.76

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Linear Nongun - Gun	-0.320	-0.434	-0.207
Quadratic Nongun - Gun	0.018	-0.174	0.211

Table 46 *Contrast Tests of Estimated Marginal Means for Accuracy Across Prime Race, Set Size, and Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
White 12 Gun	2.86	2.69	3.03
Black 12 Gun	2.98	2.8	3.15
None 12 Gun	2.91	2.73	3.08
White 16 Gun	2.6	2.43	2.76
Black 16 Gun	2.54	2.37	2.7
None 16 Gun	2.53	2.37	2.7
White 20 Gun	2.3	2.14	2.46
Black 20 Gun	2.32	2.16	2.48
None 20 Gun	2.32	2.16	2.48
White 12 Nongun	2.98	2.8	3.15
Black 12 Nongun	2.99	2.81	3.17
None 12 Nongun	2.72	2.55	2.89
White 16 Nongun	2.66	2.49	2.83
Black 16 Nongun	2.8	2.62	2.97
None 16 Nongun	2.66	2.49	2.83
White 20 Nongun	2.61	2.44	2.78
Black 20 Nongun	2.68	2.51	2.85
None 20 Nongun	2.55	2.38	2.72

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Linear White-Black Gun	0.096	-0.096	0.288
Quadratic White-Black Gun	-0.244	-0.568	0.08
Linear White-None Gun	0.027	-0.163	0.217
Quadratic White-None Gun	-0.191	-0.514	0.131
Linear Black-None Gun	-0.069	-0.262	0.124
Quadratic Black-None Gun	0.052	-0.27	0.374
Linear White-Black Nongun	-0.056	-0.261	0.15
Quadratic White-Black Nongun	0.182	-0.166	0.529
Linear White-None Nongun	-0.199	-0.397	-0.002
Quadratic White-None Nongun	0.3	-0.036	0.636
Linear Black-None Nongun	-0.143	-0.342	0.055
Quadratic Black-None Nongun	0.118	-0.225	0.462

Table 47 *Multilevel Linear Regression Predicting Response Time from Race, Target Type, Set Size, and Manipulation Check Errors in Study 2*

Fixed Effects	*b*	*SE*	*df*	*t*	*p*
Intercept	1104.375	23.080	36.387	47.849	0.000
Prime RaceW	2.299	1.817	101238.078	1.265	0.206
Prime RaceB	3.945	1.816	101239.181	2.173	0.030
Target Type	-122.892	22.171	31.006	-5.543	0.000
Set Size12	-74.441	1.809	101237.591	-41.159	0.000
Set Size20	70.673	1.826	101238.068	38.713	0.000
mouseC	-1.270	0.873	306.185	-1.455	0.147
Prime RaceW x Target Type	-3.538	1.817	101238.143	-1.947	0.052
Prime RaceB x Target Type	-0.183	1.816	101238.176	-0.101	0.920
Prime RaceW x Set Size12	3.254	2.558	101237.703	1.272	0.203
Prime RaceB x Set Size12	-1.366	2.554	101237.584	-0.535	0.593
Prime RaceW x Set Size20	-1.171	2.582	101237.850	-0.454	0.650
Prime RaceB x Set Size20	2.147	2.580	101237.972	0.832	0.405
Target Type x Set Size12	5.062	1.809	101237.951	2.799	0.005
Target Type x Set Size20	-6.530	1.826	101238.108	-3.577	0.000
Target Type x mouseC	-0.364	0.173	101244.165	-2.106	0.035
Set Size12 x mouseC	0.411	0.243	101237.613	1.688	0.091
Set Size20 x mouseC	-0.288	0.246	101237.958	-1.173	0.241
Prime RaceW x Target Type x Set Size12	-2.900	2.558	101237.368	-1.134	0.257
Prime RaceW x Target Type x Set Size20	-0.186	2.554	101237.486	-0.073	0.942
Prime RaceB x Target Type x Set Size12	2.549	2.582	101238.162	0.987	0.323
Prime RaceB x Target Type x Set Size20	-2.185	2.580	101237.660	-0.847	0.397
Target Type x Set Size12 x mouseC	0.454	0.243	101238.261	1.868	0.062
Target Type x Set Size20 x mouseC	-0.390	0.246	101238.300	-1.586	0.113

Random Effects	*N*	*Variance*
Participant	308	12673
Target	33	16151
Observations	101597	

Note: Race, target type, and set size were effect coded for analysis. "W" represents White primes, and "B" indicates Black primes. MouseC is the centered manipulation check errors.

Table 48 *Contrast Tests of Estimated Marginal Means for Response Time Across Prime Race*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
White	1107	1061	1152
Black	1108	1063	1154
None	1098	1051	1144

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
White - Black	-1.646	-7.811	4.519
White - None	8.544	2.370	14.718
Black - None	10.190	4.021	16.359

Table 49 *Contrast Tests of Estimated Marginal Means for Response Time Across Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
Gun	981	920	1043
Nongun	1227	1164	1291

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Gun - Nongun	-245.783	-332.691	-158.876

Table 50 *Contrast Tests of Estimated Marginal Means for Response Time Across Set Size*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12	1030	985	1075
16	1108	1063	1154
20	1175	1130	1220

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
12 - 20	-78.236	-84.378	-72.094
12 - 16	-145.171	-151.339	-139.004
20 - 16	-66.935	-73.134	-60.736

Table 51 *Contrast Tests of Estimated Marginal Means for Response Time Across Prime Race and Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
White Gun	980	918	1042
Black Gun	985	923	1047
None Gun	979	917	1041
White Nongun	1233	1169	1297
Black Nongun	1231	1168	1295
None Nongun	1217	1153	1281
		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
White - Black Gun	-4.979	-13.722	3.764
White – None Gun	1.293	-7.449	10.035
Black – None Gun	6.272	-2.47	15.014
White – Black Nongun	1.71	-6.984	10.403
White – None Nongun	15.805	7.083	24.526
Black – None Nongun	14.095	5.389	22.801

Table 52 *Contrast Tests of Estimated Marginal Means for Response Time Across Set Size And Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12 Gun	912	850	974
16 Gun	987	925	1049
20 Gun	1046	984	1108
12 Nongun	1148	1084	1212
16 Nongun	1230	1166	1293
20 Nongun	1304	1241	1368
		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Linear Nongun - Gun	23.086	10.751	35.421
Quadratic Nongun - Gun	8.836	-12.543	30.215

Table 53 *Contrast Tests of Estimated Marginal Means for Response Time Across Manipulation Check Errors and Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
-1SD Gun	994	930	1057
0.00 Gun	981	920	1043
1 SD Gun	969	906	1033
-1SD Nongun	1234	1169	1299
0.00 Nongun	1227	1164	1291
1 SD Nongun	1221	1156	1285

		95% Confidence Limit	
Trends	Estimate	Lower	Upper
Gun	-1.62	-3.37	0.126
Nongun	-0.907	-2.65	0.836
Gun - Nongun	-0.713	-1.391	-0.034

Table 54 *Multilevel Logistic Regression Predicting Correct Decisions from Race, Target Type, Set Size, and Manipulation Check Errors in Study 2*

Fixed Effects	*b*	*SE*	*z*	*Pr(>|z)*
Intercept	2.670	0.056	47.772	0.000
Prime RaceW	0.002	0.017	0.097	0.922
Prime RaceB	0.051	0.017	3.037	0.002
Target Type	-0.063	0.047	-1.359	0.174
Set Size12	0.240	0.017	13.844	0.000
Set Size20	-0.205	0.016	-12.897	0.000
mouseC	-0.013	0.004	-2.963	0.003
Prime RaceW x Target Type	-0.010	0.017	-0.599	0.549
Prime RaceB x Target Type	-0.034	0.017	-2.022	0.043
Prime RaceW x Set Size12	0.012	0.025	0.497	0.619
Prime RaceB x Set Size12	0.028	0.025	1.113	0.266
Prime RaceW x Set Size20	-0.009	0.022	-0.423	0.672
Prime RaceB x Set Size20	-0.015	0.023	-0.654	0.513
Target Type x Set Size12	0.082	0.017	4.733	0.000
Target Type x Set Size20	-0.079	0.016	-4.980	0.000
Target Type x mouseC	-0.015	0.002	-9.739	0.000
Prime RaceW x Target Type x Set Size12	-0.057	0.025	-2.330	0.020
Prime RaceW x Target Type x Set Size20	0.017	0.025	0.666	0.505
Prime RaceB x Target Type x Set Size12	0.006	0.022	0.269	0.788
Prime RaceB x Target Type x Set Size20	0.004	0.023	0.161	0.872

Random Effects	*N*	*Variance*
Participant	308	0.282
Target	33	0.067
Observations	109925	

Note: Race, target type, and set size were effect coded for analysis. "W" represents White primes, and "B" indicates Black primes. MouseC is the centered manipulation check errors.

Table 55 *Contrast Tests of Estimated Marginal Means for Accuracy Across Prime Race*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
White	2.67	2.56	2.79
Black	2.72	2.61	2.84
None	2.62	2.5	2.73

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
White - Black	-0.049	-0.106	0.008
White - None	0.054	-0.002	0.109
Black - None	0.103	0.047	0.159

Table 56 *Contrast Tests of Estimated Marginal Means for Accuracy Across Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
Gun	2.61	2.47	2.75
Nongun	2.73	2.59	2.88

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Gun - Nongun	-0.127	−0.310	0.056

Table 57 *Contrast Tests of Estimated Marginal Means for Accuracy Across Set Size*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
12	2.91	2.8	3.03
16	2.64	2.52	2.75
20	2.46	2.35	2.58

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
12 - 20	0.274	0.216	0.333
12 - 16	0.443	0.387	0.500
20 - 16	0.169	0.116	0.222

Table 58 *Contrast Tests of Estimated Marginal Means for Accuracy Across Set Size and Target Type*

Effect	Mean	95% Confidence Limit Lower	Upper
12 Gun	2.93	2.78	3.08
16 Gun	2.57	2.42	2.72
20 Gun	2.32	2.17	2.47
12 Nongun	2.89	2.74	3.04
16 Nongun	2.7	2.55	2.85
20 Nongun	2.61	2.46	2.76

Contrasts	Estimate	95% Confidence Limit Lower	Upper
Linear Nongun - Gun	-0.320	-0.434	-0.209
Quadratic Nongun - Gun	0.018	-0.174	0.210

Table 59 *Contrast Tests of Estimated Marginal Means for Response Time Across Manipulation Check Errors and Target Type*

Effect	Mean	95% Confidence Limit Lower	Upper
-1SD Gun	2.82	2.66	2.97
0.00 Gun	2.61	2.47	2.75
1 SD Gun	2.4	2.24	2.55
-1SD Nongun	2.72	2.56	2.88
0.00 Nongun	2.73	2.59	2.88
1 SD Nongun	2.75	2.59	2.91

Trends	Estimate	95% Confidence Limit Lower	Upper
Gun	-0.028	-0.037	-0.019
Nongun	0.002	-0.007	0.011
Gun - Nongun	-0.030	−0.036	-0.024

Table 60 *Contrast Tests of Estimated Marginal Means for Accuracy Across Prime Race, Set Size, and Target Type*

		95% Confidence Limit	
Effect	Mean	Lower	Upper
White 12 Gun	2.88	2.71	3.05
Black 12 Gun	2.99	2.82	3.17
None 12 Gun	2.92	2.75	3.1
White 16 Gun	2.97	2.79	3.15
Black 16 Gun	2.99	2.81	3.17
None 16 Gun	2.71	2.54	2.89
White 20 Gun	2.61	2.44	2.78
Black 20 Gun	2.55	2.39	2.72
None 20 Gun	2.55	2.38	2.71
White 12 Nongun	2.66	2.49	2.83
Black 12 Nongun	2.8	2.62	2.97
None 12 Nongun	2.65	2.48	2.82
White 16 Nongun	2.31	2.15	2.47
Black 16 Nongun	2.33	2.17	2.49
None 16 Nongun	2.33	2.17	2.49
White 20 Nongun	2.6	2.43	2.77
Black 20 Nongun	2.67	2.5	2.85
None 20 Nongun	2.55	2.38	2.71

		95% Confidence Limit	
Contrasts	Estimate	Lower	Upper
Linear White-Black Gun	0.097	-0.095	0.289
Quadratic White-Black Gun	-0.245	-0.569	0.080
Linear White-None Gun	0.028	-0.162	0.218
Quadratic White-None Gun	-0.192	-0.515	0.132
Linear Black-None Gun	-0.069	-0.263	0.125
Quadratic Black-None Gun	0.053	-0.270	0.376
Linear White-Black Nongun	-0.056	-0.261	0.150
Quadratic White-Black Nongun	0.184	-0.164	0.531
Linear White-None Nongun	-0.199	-0.397	-0.002
Quadratic White-None Nongun	0.301	-0.035	0.637
Linear Black-None Nongun	-0.144	-0.343	0.055
Quadratic Black-None Nongun	0.117	-0.226	0.460

APPENDIX C: DDM EFFECTS TABLES

Table 61 *Main effects of Alpha*

		95% HDI		
Condition	Mode	Lower	Upper	ESS
White 12	2.076	2.040	2.112	9371.700
Black 12	2.098	2.063	2.136	9624.300
None 12	2.021	1.985	2.054	9704.000
White 16	2.110	2.080	2.147	10003.000
Black 16	2.121	2.090	2.160	9646.200
None 16	2.094	2.060	2.128	9599.000
White 20	2.167	2.132	2.201	9554.500
Black 20	2.179	2.148	2.217	10003.000
None 20	2.146	2.111	2.178	10003.000

Note: Numbers under factor represent the set size. ESS is the estimated sample size, Kruschke (2014) recommends an ESS of 10000 for stable HDI estimates.

Table 62 *Main effects of Beta*

		95% HDI		
Condition	Mode	Lower	Upper	ESS
White	0.548	0.541	0.554	8364.600
Black	0.539	0.533	0.546	8120.500
None	0.549	0.542	0.555	8425.300

Note: ESS is the estimated sample size, Kruschke (2014) recommends an ESS of 10000 for stable HDI estimates.

Table 63 *Main effects of Tau*

Condition	Mode	95% HDI Lower	95% HDI Upper	ESS
White 12 Gun	0.421	0.410	0.430	8175.700
Black 12 Gun	0.412	0.402	0.423	10003.000
None 12 Gun	0.422	0.413	0.433	10003.000
White 16 Gun	0.426	0.416	0.437	10003.000
Black 16 Gun	0.418	0.408	0.429	9606.400
None 16 Gun	0.421	0.411	0.432	9703.600
White 20 Gun	0.419	0.408	0.430	9314.600
Black 20 Gun	0.413	0.402	0.424	10003.000
None 20 Gun	0.425	0.414	0.435	10003.000
White 12 Nongun	0.416	0.403	0.426	10003.000
Black 12 Nongun	0.422	0.411	0.433	9498.500
None 12 Nongun	0.422	0.411	0.433	10003.000
White 16 Nongun	0.433	0.422	0.444	10003.000
Black 16 Nongun	0.433	0.421	0.444	9322.000
None 16 Nongun	0.434	0.422	0.446	9587.200
White 20 Nongun	0.444	0.432	0.455	9285.200
Black 20 Nongun	0.438	0.427	0.450	10003.000
None 20 Nongun	0.444	0.431	0.455	10003.000

Note: Numbers under condition represent set size. ESS is the estimated sample size, Kruschke (2014) recommends an ESS of 10000 for stable HDI estimates.

Table 64 *Main effects of Delta*

		95% HDI		
Condition	Mode	Lower	Upper	ESS
White 12 Gun	1.630	1.582	1.685	9712.500
Black 12 Gun	1.679	1.629	1.733	9428.500
None 12 Gun	1.618	1.564	1.668	9575.100
White 16 Gun	1.377	1.327	1.424	9609.300
Black 16 Gun	1.368	1.317	1.414	9690.200
None 16 Gun	1.336	1.290	1.389	10003.000
White 20 Gun	1.157	1.115	1.210	10003.000
Black 20 Gun	1.191	1.145	1.237	9617.500
None 20 Gun	1.169	1.120	1.214	9631.700
White 12 Nongun	-1.383	-1.434	-1.341	10138.000
Black 12 Nongun	-1.403	-1.447	-1.356	9809.200
None 12 Nongun	-1.373	-1.419	-1.324	10128.900
White 16 Nongun	-1.250	-1.296	-1.206	10003.000
Black 16 Nongun	-1.273	-1.322	-1.232	10094.600
None 16 Nongun	-1.270	-1.313	-1.224	9694.400
White 20 Nongun	-1.187	-1.231	-1.144	9464.200
Black 20 Nongun	-1.179	-1.223	-1.137	10003.000
None 20 Nongun	-1.186	-1.231	-1.143	10003.000

Note: Numbers under condition represent set size. ESS is the estimated sample size, Kruschke (2014) recommends an ESS of 10000 for stable HDI estimates.

Table 65 *Summary Effects of Alpha*

		95% HDI			95% HDI	
Effect	Mode	Lower	Upper	*d*	Lower	Upper
White - Black	-0.017	-0.044	0.013	-0.090	-0.237	0.067
White - None	0.030	0.004	0.060	0.166	0.020	0.318
Black - None	0.049	0.019	0.075	0.260	0.104	0.406
12 - 16	-0.049	-0.075	-0.018	-0.252	-0.400	-0.097
12 - 20	-0.100	-0.126	-0.070	-0.535	-0.679	-0.373
16 - 20	-0.055	-0.081	-0.026	-0.293	-0.440	-0.144
WB and setSize 12	-0.019	-0.074	0.027	-0.102	-0.401	0.140
WB and setSize 16	-0.013	-0.060	0.036	-0.067	-0.317	0.195
WB and setSize 20	-0.018	-0.062	0.034	-0.095	-0.330	0.186
WN and setSize 12	0.055	0.007	0.106	0.320	0.029	0.558
WN and setSize 16	0.018	-0.032	0.064	0.095	-0.165	0.348
WN and setSize 20	0.017	-0.027	0.069	0.087	-0.145	0.368
BN and setSize 12	0.082	0.028	0.128	0.434	0.151	0.683
BN and setSize 16	0.027	-0.019	0.080	0.144	-0.093	0.435
BN and setSize 20	0.034	-0.013	0.083	0.177	-0.070	0.440

Note: Racial Group Comparisons: WB(White – Black), WN (White – None), BN(Black – None).

Table 66 *Summary Effects of Beta*

		95% HDI			95% HDI	
Effect	Mode	Lower	Upper	*d*	Lower	Upper
White - Black	0.008	0.001	0.017	0.284	-0.027	0.576
White - None	-0.001	-0.011	0.075	-0.044	-0.348	0.260
Black - None	-0.010	-0.018	0.000	-0.310	-0.611	0.006

Table 67 *Summary Effects of Delta Gun-NonGun*

		95% HDI			95% HDI	
Main Effects	Mode	Lower	Upper	*d*	Lower	Upper
setSize 12 - 16	0.204	0.177	0.230	0.772	0.659	0.875
setSize 12 - 20	0.337	0.310	0.363	1.264	1.155	1.386
setSize 16 - 20	0.136	0.108	0.159	0.500	0.405	0.603
White - Black	-0.018	-0.043	0.011	-0.066	-0.160	0.041
White - None	0.009	-0.019	0.036	0.033	-0.072	0.133
Black - None	0.022	-0.004	0.050	0.084	-0.010	0.194
gun -nongun	0.114	0.088	0.139	0.433	0.330	0.523
Interactions						
WB x Object	-0.005	-0.038	0.025	-0.020	-0.145	0.091
WN x Object	0.010	-0.024	0.039	0.029	-0.090	0.147
BN x Object	0.014	-0.019	0.044	0.053	-0.069	0.169
targetType and SetSize 1216	0.081	0.056	0.108	0.303	0.208	0.408
targetType and SetSize 1220	0.135	0.108	0.159	0.505	0.405	0.604
targetType and SetSize 1620	0.053	0.027	0.077	0.202	0.105	0.295
targetType and SetSize 12	0.259	0.218	0.299	0.984	0.816	1.132
targetType and SetSize 16	0.093	0.057	0.135	0.355	0.203	0.496
targetType and SetSize 20	-0.011	-0.048	0.028	-0.041	-0.184	0.100
linear test	-0.194	-0.192	-0.188	-0.714	-0.739	-0.701
quadratic test	0.012	0.011	0.013	0.044	0.037	0.047

Note: Racial Group Comparisons: WB(White – Black), WN (White – None), BN(Black – None). Combined values of set size indicate an interaction between the two.

Table 68 *Summary Effects of Delta Gun*

Interaction	Mode	95% HDI		*d*	95% HDI	
		Lower	Upper		Lower	Upper
RWB-1216	-0.025	-0.077	0.019	-0.098	-0.289	0.072
RWB-1220	-0.011	-0.055	0.039	-0.040	-0.204	0.150
RWB-1620	0.023	-0.027	0.064	0.087	-0.098	0.244
RWN-1216	-0.007	-0.059	0.038	-0.027	-0.220	0.145
RWN-1220	0.012	-0.036	0.058	0.044	-0.137	0.220
RWN-1620	0.019	-0.024	0.066	0.071	-0.089	0.251
RBN-1216	0.016	-0.029	0.067	0.061	-0.111	0.251
RBN-1220	0.018	-0.025	0.069	0.070	-0.096	0.260
RBN-1620	0.001	-0.044	0.048	0.003	-0.176	0.170

Note: Abbreviations used in the 'Interaction' column: RWB: Race White-Black \ RWN: Race White-None \ RBN: Race Black-None. Numbers following the abbreviations represent Set Size interactions.

Table 69 *Summary Effects of Delta Gun*

Interaction	Mode	95% HDI		*d*	95% HDI	
		Lower	Upper		Lower	Upper
RWB-1216	0.008	-0.040	0.047	0.029	-0.153	0.178
RWB-1220	-0.013	-0.052	0.034	-0.048	-0.204	0.119
RWB-1620	-0.016	-0.058	0.026	-0.062	-0.216	0.099
RWN-1216	0.017	-0.028	0.060	0.062	-0.104	0.231
RWN-1220	0.007	-0.036	0.050	0.027	-0.133	0.187
RWN-1620	-0.008	-0.052	0.032	-0.032	-0.190	0.124
RBN-1216	0.016	-0.032	0.057	0.061	-0.118	0.216
RBN-1220	0.018	-0.027	0.060	0.070	-0.096	0.233
RBN-1620	0.009	-0.037	0.048	0.033	-0.139	0.180

Note: Abbreviations used in the 'Interaction' column: RWB: Race White-Black \ RWN: Race White-None \ RBN: Race Black-None. Numbers following the abbreviations represent Set Size interactions.

APPENDIX D: POSTERIOR PREDICTIVE CHECKS

To evaluate the fit of the drift-diffusion model specified, I used JAGS to simulate decision and response time data based on the posterior condition level distributions derived from the DDM. Essentially, the posterior values are used to generate 10,000 sample datasets. This leads to a large amount of data, specifically, 360 trials x 308 participants x 10000 sampled values. This data was then aggregated at the condition level since study analyses were on condition-level estimates. Next, these data were used to summarize the choice probabilities, response times, and response time distributions.

For the choice probabilities, the observed and model-predicted means were plotted for each condition and response type. Hit rates are overestimated, and false alarms are slightly underestimated, though the extent of this misestimation is minimal. That is the model generated data that suggested a higher accuracy than what is found in the observed data. For response times, the observed and model-predicted means were plotted for each condition and response type. These comparisons indicated that predicted means for correct gun responses were overestimated; however, the correct decision times for non-gun were accurate. However, the predicted incorrect gun and non-gun response times were faster than the observed data by a large margin.

Finally, to better evaluate what may be causing these response time differences, the observed and model-predicted response time distributions were plotted for each condition such that the top of the figure indicates correct responses and the bottom of the figure indicates incorrect response for the same condition. In analyzing response time distributions for correct gun trials, the predicted model slightly underestimates the average response time (central tendency) while it tends to overestimate the frequency of longer response times (the right-hand tail of the distribution. In the case of incorrect responses to gun stimuli, the predicted response times exhibit a strong right skew, and notably, the observed data shift towards longer response times (a rightward shift in central tendency) with increasing set sizes.

When examining correct identifications of non-gun objects, the model tends to overestimate the average response time and underestimate the extremities of the response times. For incorrect responses to non-gun stimuli, the shift in observed response times across set sizes is less marked than in the gun conditions, but the rightward shift in central tendency is still observed. Moreover, the observed response time distributions are broader than the predicted, potentially indicating an overestimation of the drift rate.

The fit issues observed cannot be readily attributed to non-decision time (alpha) or threshold (tau) parameters. Typically, discrepancies caused by these parameters would manifest as uniform changes in the shape of response time distributions across both correct and incorrect decisions. However, the analysis shows that correct decisions generally fit the model predictions better than incorrect ones, indicating a different source of error. In addition, it's not likely that the start point (beta) is the cause, given that the starkest differences occur across set sizes in the incorrect decision response time distributions. That is, set size cannot be accurately modeled for the start point parameter since participants have no prior knowledge about the upcoming trial set size. Instead, the differences in model fit might be more closely associated with unaccounted for variations in drift rate (delta).

For example, upon closer inspection of the observed incorrect response time distributions, something that stands out is that there are multiple peaks, suggesting that these distributions may be multimodal. Something that could account for this effect is practice effects. Recall that in Studies 1 and 2, practice effects were found such that participants' responses decreased from block 1 to block 2 but plateaued from block 2 to block 3. As an exploratory analysis, I plotted the observed response time distributions for incorrect non-gun trials across blocks and set sizes to determine if the distribution was moving in a way that would create these multimodal peaks. However, looking at the first and last block, it's not clear that this was the largest contributing factor. Notably, there are instances where the first block has normally distributed response times, but at the final block, two strong peaks emerge. This highlights that there may be more occurring, and one such moderator is the manipulation check.

I figured this manipulation check might be related to different search strategies that participants engage in (i.e., target present/absent decisions versus slower specific target searches). To further extend this work, I looked at the manipulation check and plotted response times for people who were highly accurate (fewer than 1 error (36%) and people with varied errors (greater than 9 errors (14%]) by blocks 1 and 3. While not exact, most of the response time distributions for block 1 are relatively similar, with divergences occurring at the final block. Notice that for the low errors group across set sizes and race, a negatively skewed multi-modal distribution develops, while for the high errors group, there is less consistency in the change of the distribution.

Neither variable may fully explain the multimodal distributions found in the overall response time distribution, given that these peaks are found in both. To address the fact that there are still multi-modal distributions, one possibility is that some of the non-gun items are more difficult to locate, leading to longer incorrect response times. The plots breaking down the response time distributions for correct and incorrect responses at set size 20 for non-gun objects reveals that this is the case. The multimodal peaks found in the data can be best explained by participants struggling with some of the non-gun items. The code for the drift-diffusion model needs modification to include intercepts corresponding to different object categories for the drift rates. This adjustment is essential for optimizing the model's fit to the data.

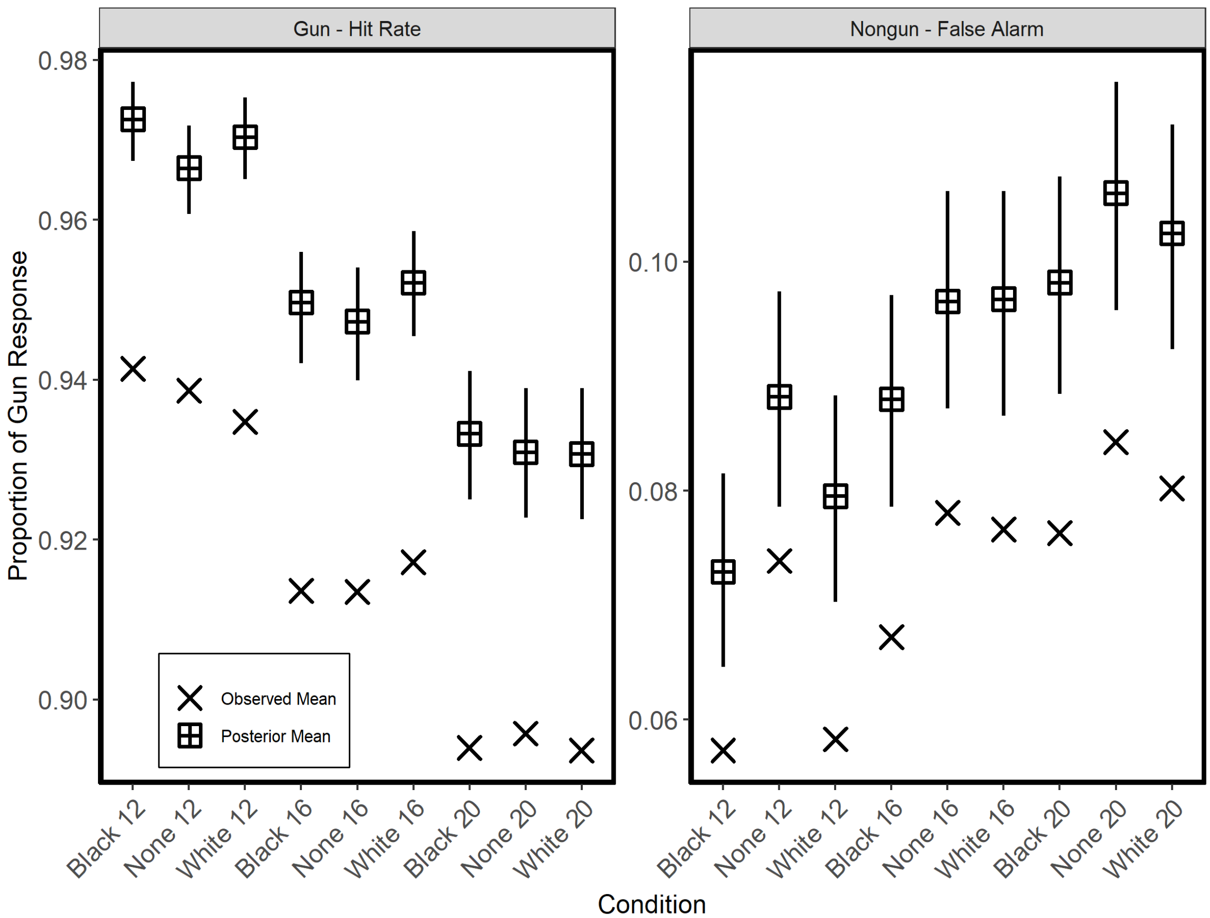

Figure 16: Posterior predictions of hit and false alarm rates for Study 2. X's represent observed condition level choice proportions. Squares represent predicted condition level choice proportions. Bars are the 95% HDI.

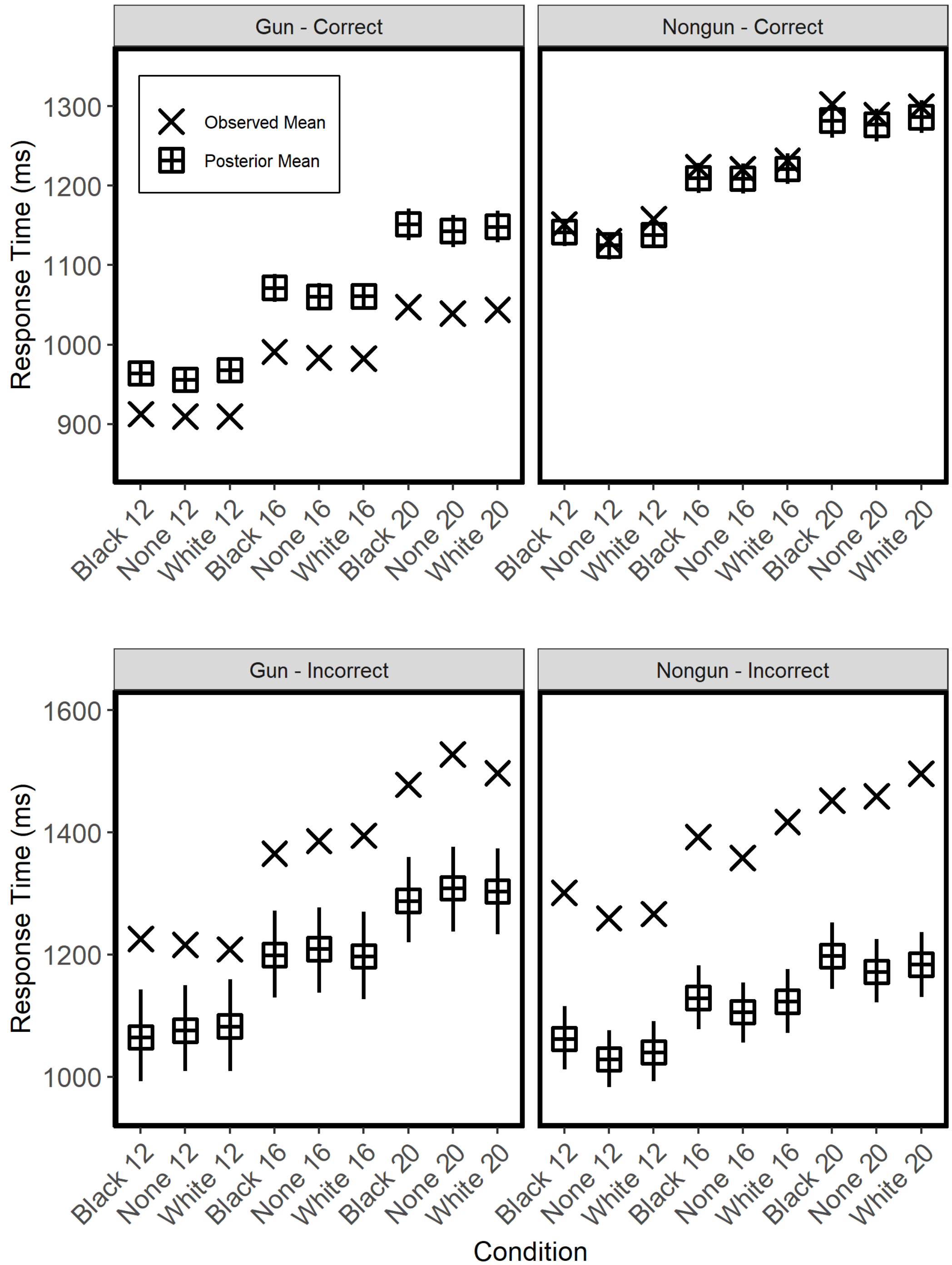

Figure 17: Posterior predictions of response times for Study 2. X's represent observed condition level choice proportions. Squares represent predicted condition level choice proportions. Bars are the 95% HDI.

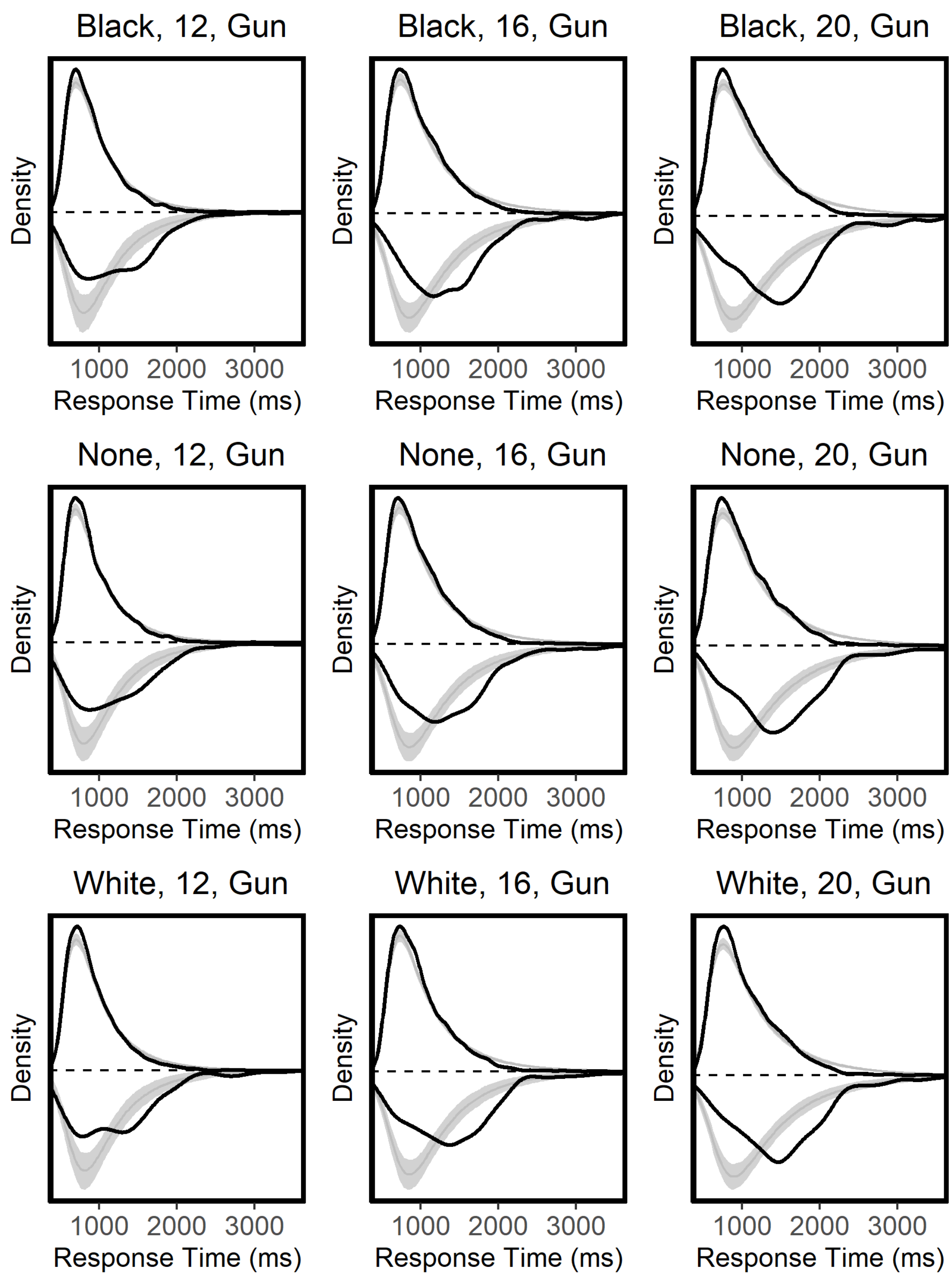

Figure 18: Observed (black) and predicted (gray) response time distributions for each response type at the condition level in Study 2. The top part of the graph is correct responses, and bottom is incorrect.

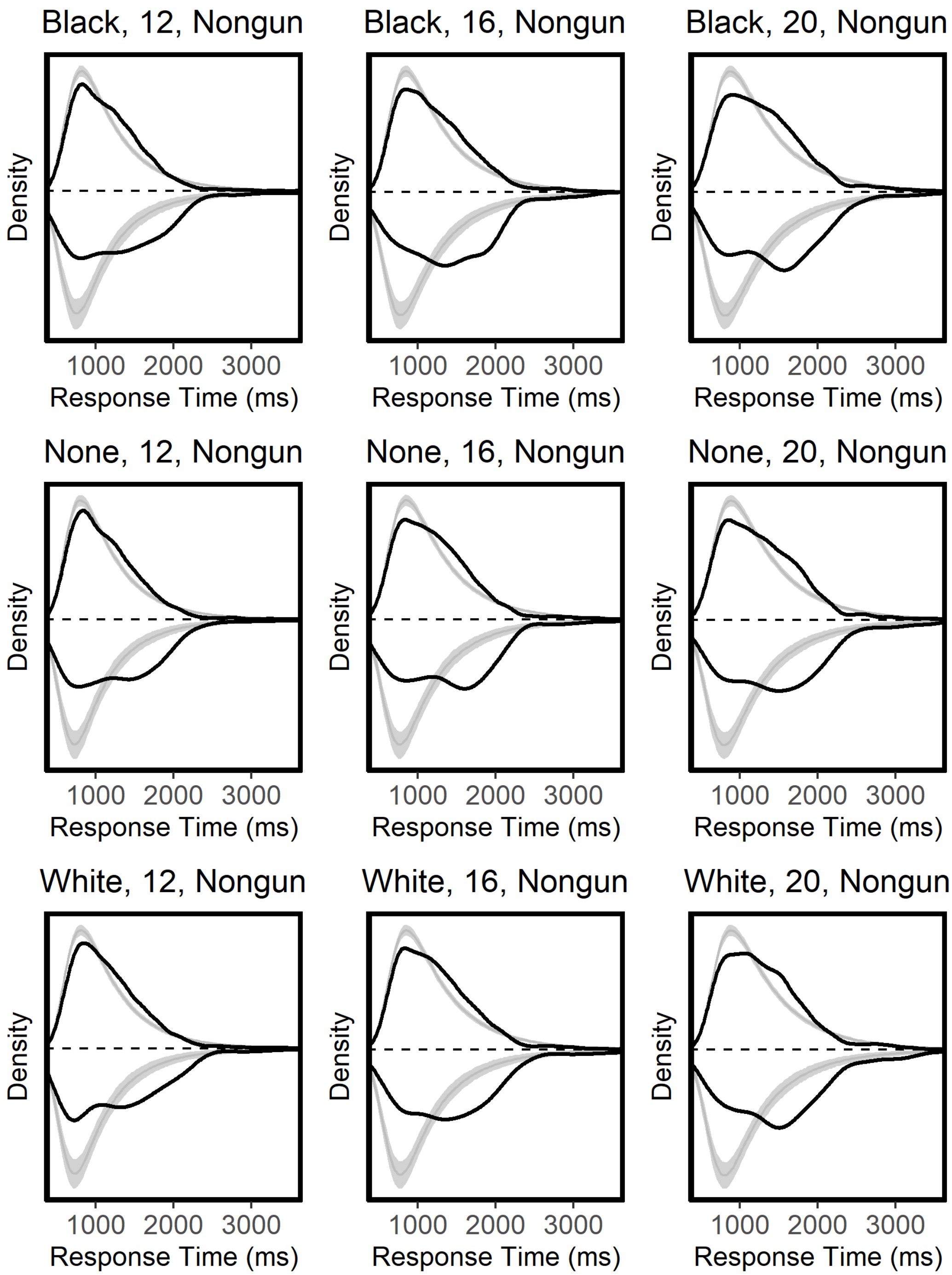

Figure 19: Observed (black) and predicted (gray) response time distributions for each response type at the condition level in Study 2. The top part of the graph is correct responses, and bottom is incorrect.

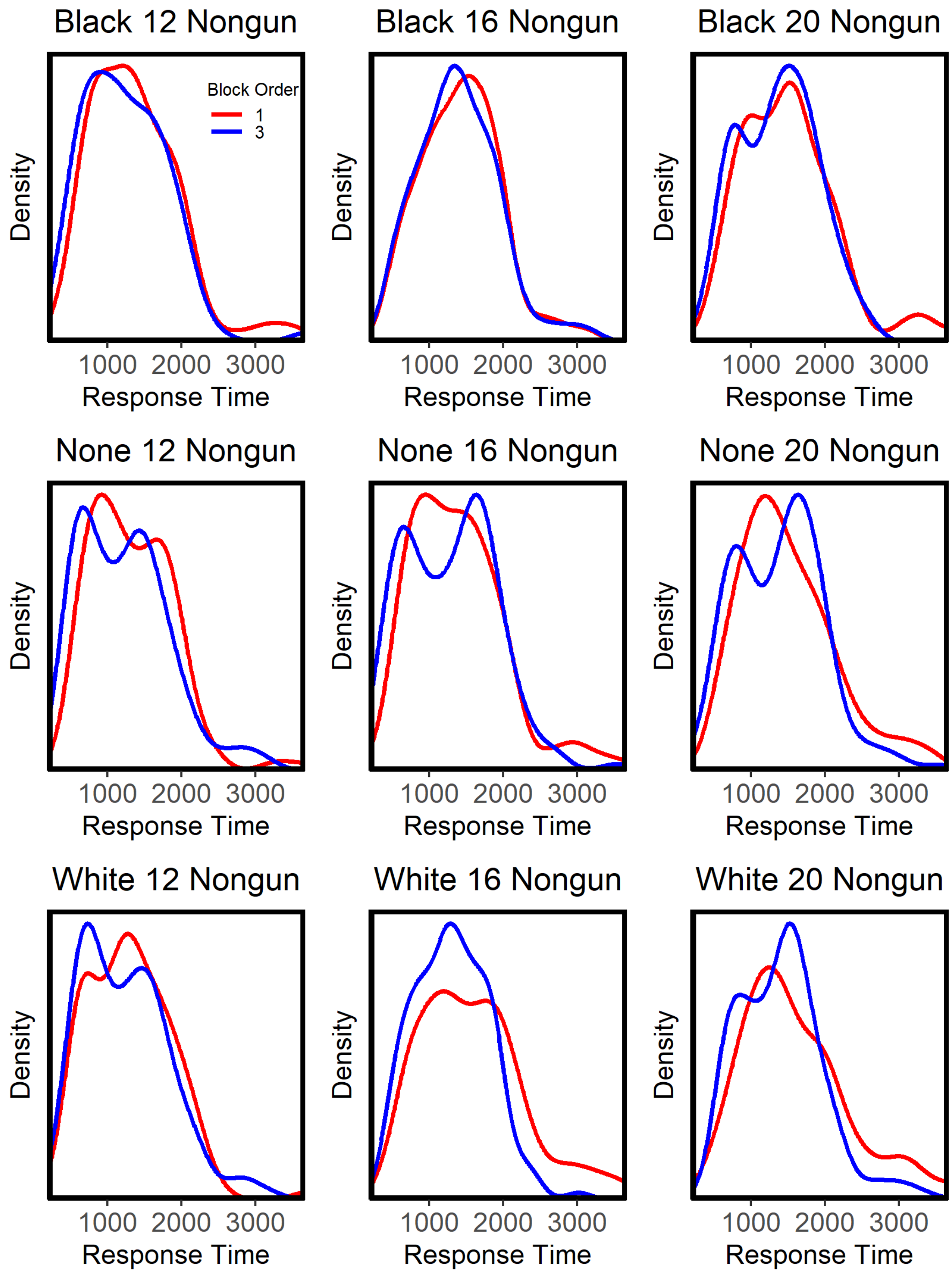

Figure 20: Response time distributions for block 1 (red) and block 3(blue) for incorrect responses in the non-gun conditions.

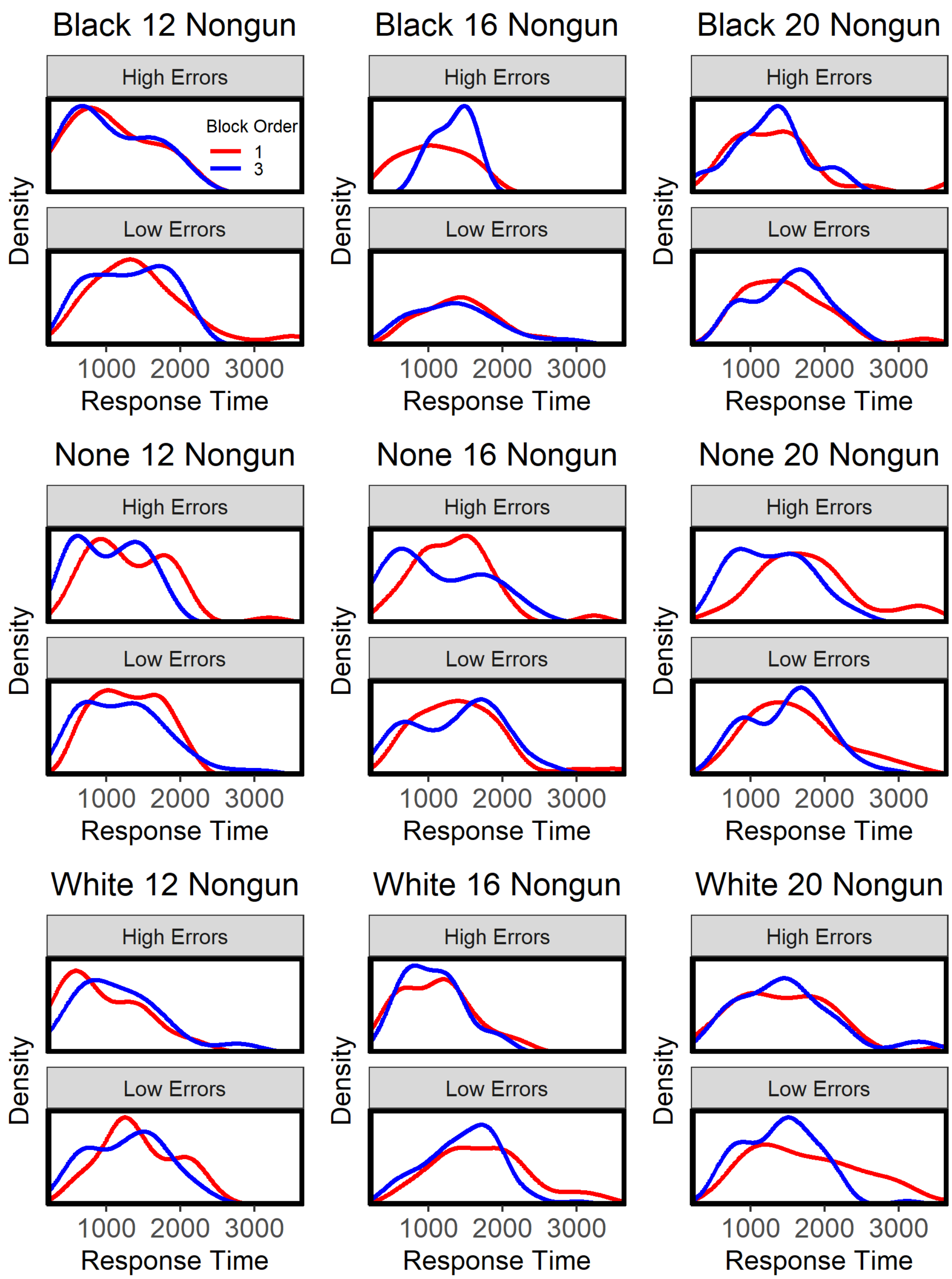

Figure 21: Response time distributions for block 1 (red) and block 3(blue) for incorrect responses in the non-gun conditions in both low and high manipulation check error groups.

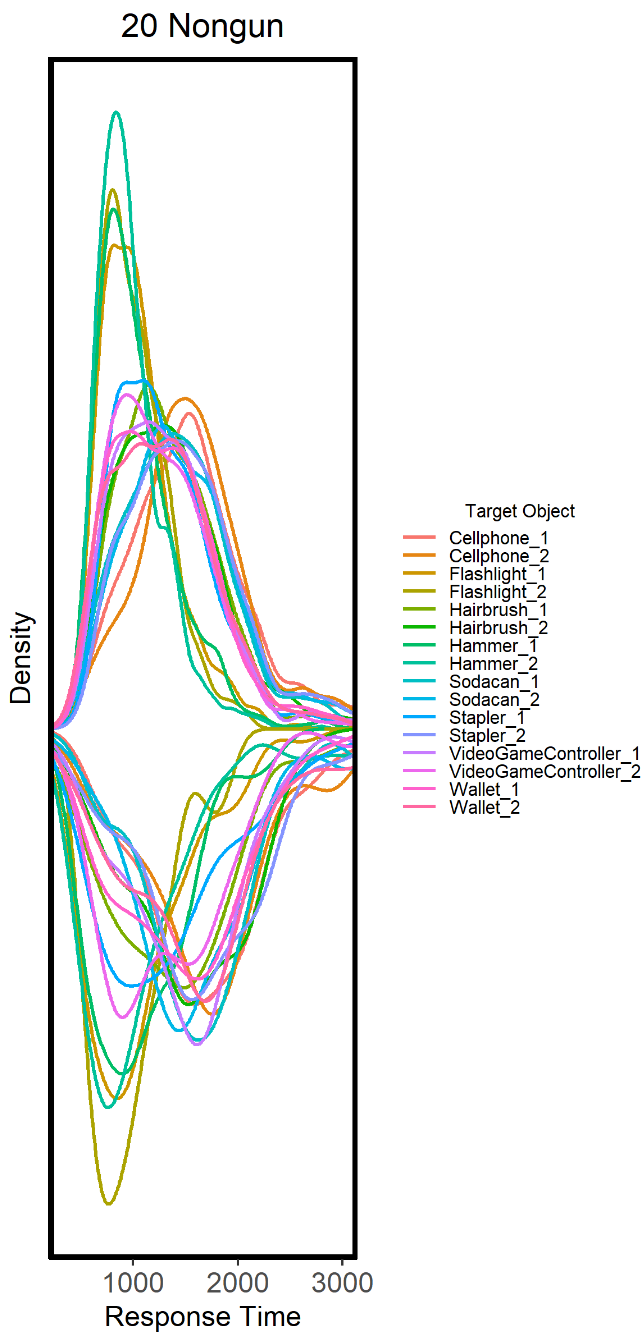

Figure 22: Correct (top) and incorrect (bottom) response time distributions for non-gun objects in set size 20.

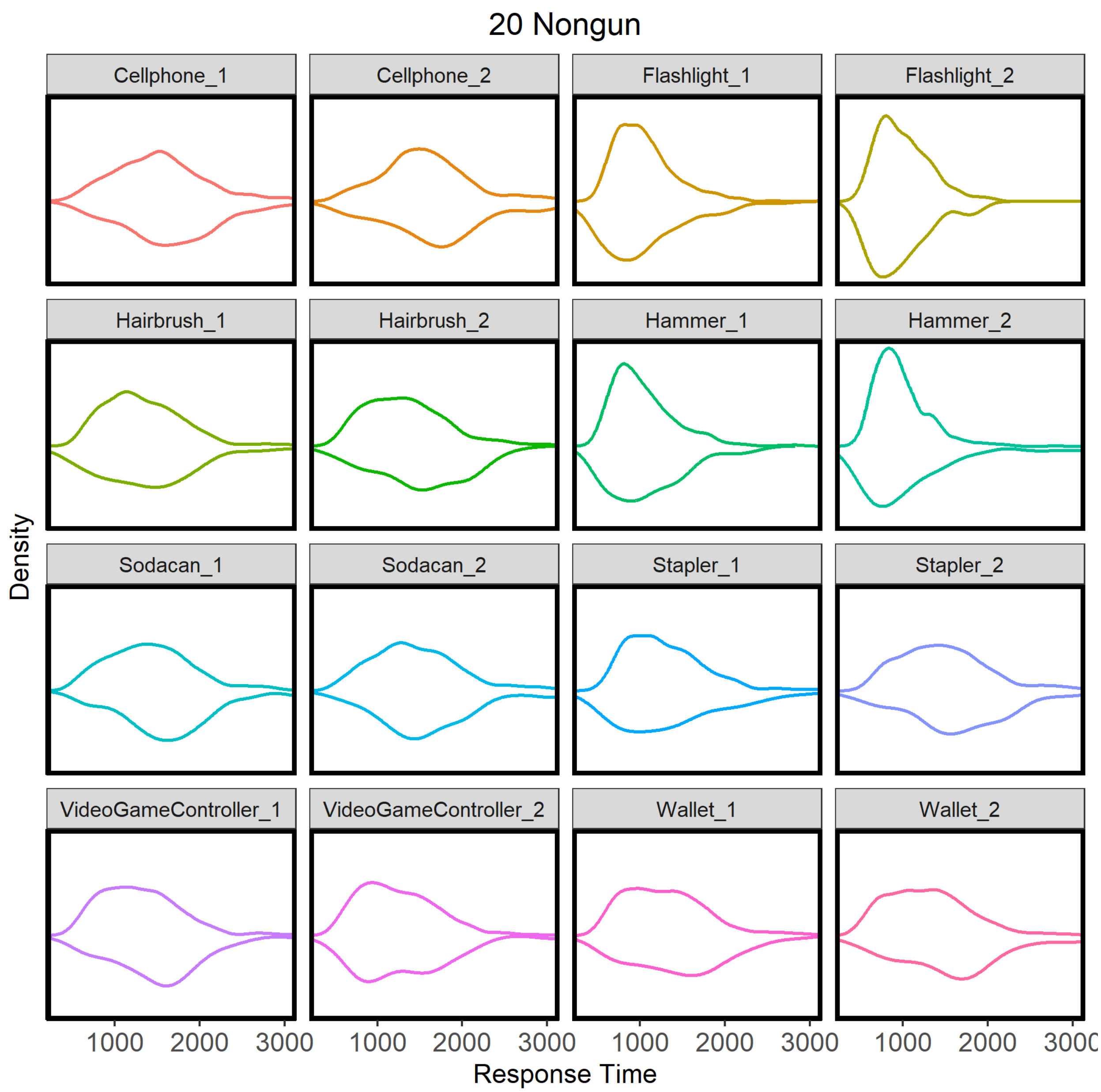

Figure 23: Correct (top) and incorrect (bottom) response time distributions for non-gun objects in set size 20.