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BRIEF REPORT

Integrating body information with faces directs attention away from race, altering racially biased weapon identification

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Abstract

Racially biased weapon identification, wherein guns are identified more easily after seeing Black (vs. White) face primes, is a robust and replicable phenomenon. Mounting evidence suggests that introducing additional facial information (e.g., varying age cues) does not meaningfully alter this racial bias. Only when augmenting its relative salience does the additional, nonrace information appear to mitigate racially biased weapon identification. Even when reducing racial bias by enhancing nonrace facial cues, social information is typically communicated via the face, a context in which race may be particularly salient. Two experiments (N_{total} = 590 participants) using a sequential priming task tested whether broadening the contextual information in primes to include both faces and bodies moderates racially biased weapon identification (gun vs. tool) decisions. Replicating past findings, racial bias was evident when primes cued age and race via facial information only. However, this behavioral effect disappeared when primes included both faces and bodies, providing richer social context. Diffusion decision modeling revealed that race cues shifted the starting point of the decision-making process toward stereotype-consistent responses (e.g., "gun" after Black primes) with face-only primes, but this processing bias disappeared with face-and-body primes. Multinomial processing tree modeling further revealed attenuated attention to race in face-and-body (vs. face-only) primes, whereas attention to age remained intact across conditions. These findings advance theory on the operation of racially biased decision making in richer social contexts.

Keywords Age · Diffusion decision modeling · Multinomial processing tree modeling · Priming · Stereotyping

Introduction

For more than 30 years, social cognition research has documented stereotypes linking Black men with violence-related content (Devine, 1989), with performance indicative of a *Black-gun* association emerging in several laboratory tasks (Payne & Correll, 2020). For example, in the weapon identification task (WIT), participants are often better (i.e., faster, more accurate) at identifying guns and worse at identifying harmless objects (e.g., tools) after seeing Black versus White face primes (Payne, 2001). This racial bias persists with comparable strength even when varying age information in the face primes (e.g., young men vs. young boys, young men vs. older men; Lundberg et al., 2018; Thiem et al., 2019; Todd et al., 2016a, b), despite evidence that available age information modulates racial bias in other contexts (Andreoletti et al., 2015).

One explanation for this effect's persistence entails the salience of (i.e., the attention garnered by; Higgins, 1996) race in a weapon identification context (Petsko et al., 2022). Only after *enhancing* the salience of nonrace facial information beyond its mere availability is the typical pattern of racial bias attenuated. For example, increasing perceivers' prior experience categorizing by nonrace information (e.g., a prior age classification task) or creating contexts designed to highlight nonrace information (e.g., holding race constant but varying age in a block of trials) produces *less* racially

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biased weapon identification (Jones & Fazio, 2010; Todd et al., 2021). Thus, the mere availability of extra nonrace facial information often fails to curb racial bias; additional intervention is typically required.

Racially biased weapon identification may also persist when nonrace information besides age is available. For example, available emotion expressions (e.g., smiles vs. scowls) in the face primes sometimes do (Kubota & Ito, 2014) and sometimes do not (Klein & Todd, 2024) alter weapon identification bias. That is, even inherently salient facial cues that could inform fundamental aspects of sociality (e.g., threat; Todorov et al., 2008) may not reliably mitigate racially biased weapon identification.

Although the mere availability of facial information besides race (e.g., age, emotion expression) frequently fails to modulate racially biased weapon identification, the face is not the only information source that garners attention. People readily use cues from the body (e.g., size, gait) to guide social judgment (Johnson & Hugenberg, 2024), and extracting such information may entail processing cues from the face and body as a holistic unit (Aviezer et al., 2012). Even race categorization via faces is influenced by clothing cues on the body (Freeman et al., 2011; Hester & Hehman, 2023). Ample research attests to the limited efficacy of mitigating racial bias by making nonrace facial information available, but questions remain about whether making information from outside the face available modulates the influence of facial race cues.

We report two experiments that manipulated how age information varied in the primes of the WIT. In one block of trials, age was available alongside race in the faces, as in prior work (e.g., Todd et al., 2016a). In another block of trials, we used face-and-body images (with the bodies clearly differing in size) to convey age information. The experiments were very similar, differing primarily in how the face-and-body images were constructed. In Experiment 1, face images were placed atop silhouetted bodies of men and boys. Experiment 2 aimed to generalize our findings to new images (Wells & Windschitl, 1999) by using face-and-body photos of Black and White men and boys, which we cropped for the face-only block of trials.

Beyond investigating *whether* conveying information besides race via the face or additionally via the body alters racially biased weapon identification, we aimed to understand *how* such an effect emerges with two modeling techniques (Fig. 1A and Fig. 1B). First, we applied the diffusion

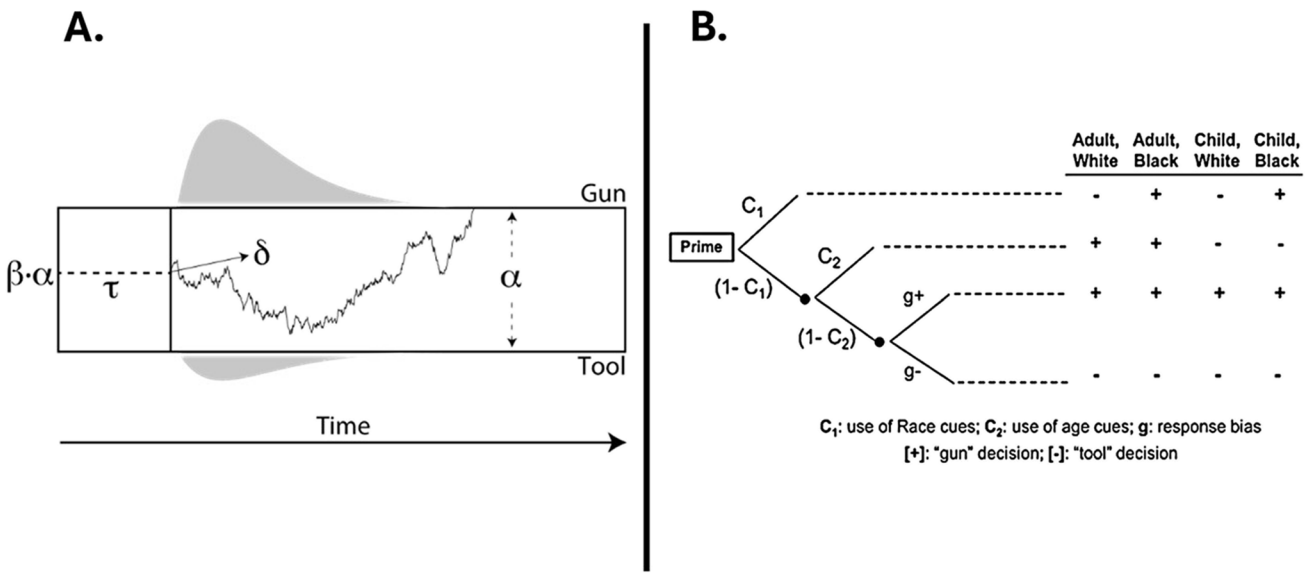

Fig. 1 Illustrations of the diffusion decision model (DDM) and the multi-cue integration (MCI) model. **Panel A** depicts the DDM. The decision process starts with a bias to select gun or tool, as indicated by the relative start point, β. Evidence is then accumulated (as illustrated by the jagged line) for each decision option, with average strength δ. The distance between the thresholds, α, indicates the amount of evidence needed to decide. Finally, the length of nondecision processes is indicated by τ. The hypothetical distributions (in gray) above and below the decision space indicate that the model predicts the distribution of response times for each decision option. **Panel B** depicts the MCI model. Race cues (C_1) are integrated toward racially biased decisions. Age cues are integrated toward age-biased decisions, conditional on race cues not being integrated [$(1 - C_1) \times C_2$]. Finally, a response bias – reflecting a tendency toward "gun" decisions (g) or "tool" decisions (1 – g) – may influence responses, conditional on both cues being insufficient to inform decisions.

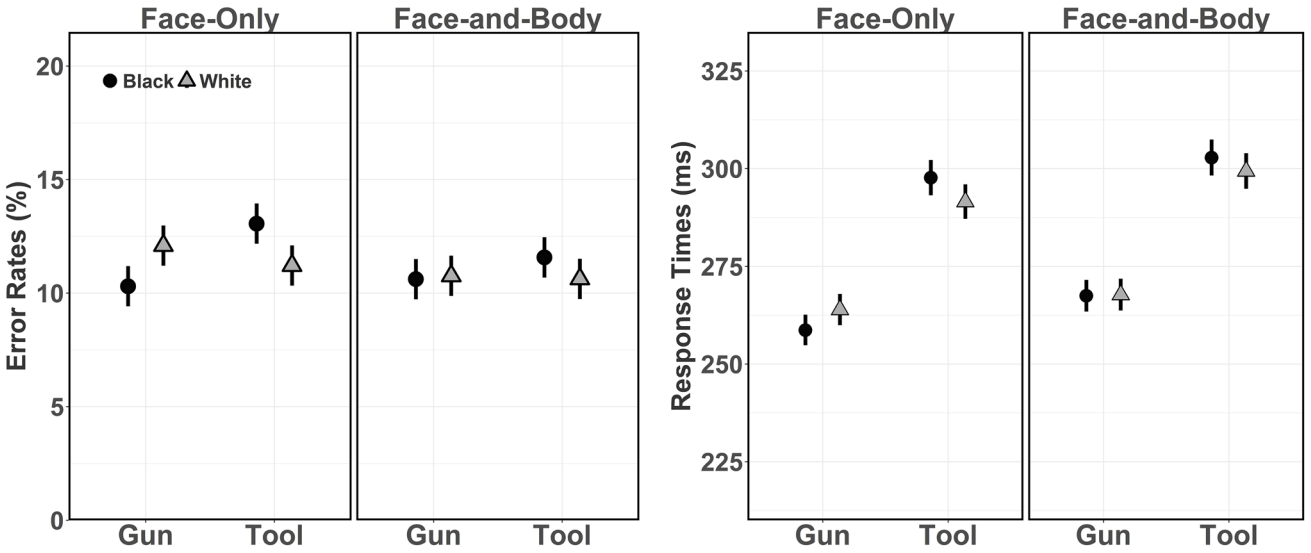

Fig. 2 Error rates and correct response times by race prime and prime format condition. Markers and their error bars reflect the estimated marginal means from the linear mixed-effects model applied in an integrative data analysis. The plot on the left reflects error rates; the plot on the right reflects correct response times. The x-axis displays whether the target object was a gun or tool. Shading and shape of markers reflect whether the target object followed a Black or White prime. Panels vary by prime format, whereby panels on the left within each plot depict face-only primes and panels on the right within each plot depict face-and-body primes.

decision model (DDM; Ratcliff et al., 2016), a four-parameter model that assumes information is sequentially sampled as evidence toward a decision threshold, at which point a decision is made (Table 1). In the WIT, evidence accumulation initiates when the target object appears. The rate of evidence accumulation toward one decision ("gun") over another ("tool") signifies the strength of that evidence for determining the decision and is reflected by the drift rate. If the drift rate explains racial bias, then seeing race cues in the primes should strengthen (weaken) the evidence accumulated for identifying race-stereotypic (non-stereotypic) objects. That is, seeing Black (vs. White) primes should strengthen (weaken) the evidence accumulated toward "gun" ("tool") decisions on gun (tool) trials. On this account, evidence accumulation should be less racially biased when age information is available in the body: a weaker Race Prime ×

Table 1 Parameters of the diffusion decision and multi-cue integration models

Parameter	Interpretation
Relative start point (β)	Initial bias to select *gun* or *tool* at the start of evidence accumulation, with $0 < \beta < 1$. Values >.50 indicate a bias to select *gun*; values <.50 indicate a bias to select *tool*.
Threshold separation (α)	Amount of evidence required to decide, with $0 < \alpha$. Hitting a threshold triggers a decision to select *gun* or *tool*.
Drift rate (δ)	Average quality of information extracted at each unit of time, with $-\infty < \delta < \infty$. Higher absolute values indicate stronger evidence. Positive values indicate evidence to select *gun*; negative values indicate evidence to select *tool*.
Non-decision time (τ)	Length of all response components (encoding time, motor response time, and other unknown contaminants) unrelated to decision making, with $0 < \tau$. Measured in milliseconds.
Race processing (C_1)	Probability of attending to and using race cues for decision making. Values range between 0 and 1; higher values indicate more attention to race.
Age processing (C_2)	Probability of attending to and using age cues for decision making, conditional on race cues not being used. Values range between 0 and 1; higher values indicate more attention to age.
Response bias (g)	A response bias toward "gun" decisions (g) or "tool" decisions (1 – g) when neither race cues nor age cues are used. Values >.50 (<.50) suggest a tendency toward "gun" ("tool") decisions in the absence of using race or age information.

Note. Parameters are sectioned by their respective computational models. Parameters from the diffusion decision model (DDM) appear above the midline. Parameters from the multi-cue integration (MCI) model appear below the midline.

Target Object effect on the drift rate for face-and-body (vs. face-only) primes.

The DDM also captures the starting position of the decision process, which may be closer to one decision threshold or another. Starting closer to one threshold increases the likelihood of crossing it because less evidence needs to be accumulated toward that threshold than toward the alternative threshold.[1] If the relative start point explains racial bias, then seeing Black (vs. White) face primes should shift the starting position of the decision process closer to the "gun" response. On this account, the relative start point should be less racially biased when age information is available in the body: a weaker Race Prime effect on the relative start point for face-and-body (vs. face-only) primes. Shifts in this parameter would reflect changes to the attention to and processing of prime information (i.e., age, race).

Prior DDM analyses of the WIT have consistently supported the initial bias account over the evidence accumulation account (Klein & Todd, 2024; Todd et al., 2021).[2] However, this past work solely manipulated *facial* prime information. It is, therefore, important to determine which process-level account explains how WIT behavior is affected when varying the prime format (face-only vs. face-and-body). Our experiments provide such a test.[3]

If the decision process initiates at a less racially biased position when age cues are available in both the face and body versus just the face, this positional shift is likely driven by a change in the relative salience of age and race (i.e., the relative difference in attention they garner). The availability of different sized bodies could plausibly direct more attention toward age cues, which may compete with race cues to influence decision making. Greater attention to age, therefore, may dampen the impact of race on the starting position of the decision process. However, the same change in relative salience could be explained by a different underlying pattern. Rather than increased attention toward age, the availability of different sized bodies may *decrease* attention toward race cues, producing the same change to their relative salience and subsequent modulation of racially biased starting positions of the decision process.

Whereas the DDM characterizes *when* and *how* information processing unfolds to produce biased behavior in the WIT, it cannot distinguish *what* information is being processed. Consider, for example, the possibility that introducing body information reduces racial bias due to changes in the starting-point parameter (i.e., a change in the use of prime information). In the current context, the DDM cannot distinguish whether this effect is driven by changes in attention to age cues or race cues in the primes, or both. To overcome this limitation, we applied the Multi-Cue Integration (MCI) model (Klein & Sherman, 2024), a multinomial processing tree model that decomposes how much various cues are used in decision making. The MCI model distinguishes the impact of two cues (C_1, C_2; see Fig. S16 in the Online Supplementary Material (OSM)), regardless of *how* and *when* those cues are processed (Table 1). Here, the relevant cues are race (C_1) and age (C_2). Comparing each parameter for face-only versus face-and-body primes can clarify if introducing additional information via the body mitigates racial bias by altering attention to age or race, or both.

Experiments 1 and 2 were highly similar, so we analyzed them together using integrative data analysis (IDA; Curran & Hussong, 2009). We report a single set of *Method* and *Results* sections, noting between-experiment differences. Separate analyses for each experiment appear in the Online Supplementary Material (OSM). Data, code, and model evaluation metrics and visualizations are available at https://osf.io/qzp8x.

Method

Participants

For each experiment, we aimed to collect enough data to ensure 80% power to detect a small-to-medium effect (η_p^2 =.03), settling on a target sample of at least 258 participants (Faul et al., 2007); data were collected until this number was surpassed. In total, 597 undergraduates ($N_{\text{Experiment 1}}$ = 305, $N_{\text{Experiment 2}}$ = 292) participated for course credit. We decided a priori to exclude data for one or both of the following reasons:

(1) Below-chance performance in the WIT or
(2) Completing the other experiment, as the experiments ran concurrently.

Given the multi-level approach to our analyses, we retained data from participants who completed only one of the versions of the WIT. The final sample in both experiments was 290 people each (Experiment 1: 208 women, 76 men, two indicating "other" with no further elaboration, four unreported; 209 White, 17 Latina/o/e/x, 40 Asian, six Black,

[1] In addition, evidence accumulation processes are inherently noisy, so the closer they initiate to a particular threshold, the more likely that a random spike in the process could cross it, activating that decision response.

[2] In DDM analyses of the first-person shooter task (Correll et al., 2002), another weapon-detection task, racially biased decision making is better explained by an evidence accumulation account (Correll et al., 2015; Pleskac et al., 2018), perhaps owing to procedural differences in the tasks (Payne & Correll, 2020).

[3] We did not derive specific predictions about threshold separation and non-decision time, but we report results pertaining to these parameters for completeness.

eight reporting two or more races/ethnicities, three reporting "other" with no further elaboration, seven unreported. Experiment 2: 243 women, 43 men, four unreported; 217 White, 22 Latina/o/e/x, 30 Asian, eight Black, six reporting two or more races/ethnicities, two reporting "other" with no further elaboration, five unreported), for a total of 580 participants.

Materials and procedure

In both experiments, participants arrived at the lab in small groups and were led by an experimenter to an individual computer workstation. There they completed a sequential priming task, the WIT (Payne, 2001), wherein two images appeared in quick succession. Instructions urged participants to ignore the first image (prime; see below for details) and to classify the second image (target object) quickly and accurately via key press ("q" for tool, "p" for gun). The target objects in both experiments were six gun and six tool images (Payne, 2001). All participants completed two variants of a WIT in counter-balanced order. The trial sequence in each variant was as follows: fixation cross (500 ms), prime (200 ms), target object (200 ms), and pattern mask (until participants responded). In Experiment 2, post-trial feedback ("Please respond faster!") appeared for trials on which participants responded slower than 500 ms after target onset. In Experiment 1, no response deadline was imposed.

Experiment 1: Prime stimuli

In the face-and-body condition, the prime images were faces of Black and White men from the Chicago Face Database (Ma et al., 2015) and faces of Black and White boys from the Child Affective Facial Expression set (LoBue & Thrasher, 2015). All images were converted to grayscale, reduced in size, and situated atop grayscale silhouetted men's or boys' bodies. We selected silhouettes of bodies that appeared to be the same ages as the facial images (men: M_{age} = ~25 years; boys: M_{age} = ~5 years). In the face-only condition, the same faces from the face-and-body condition appeared alone. Notably, the display size of faces was held constant across conditions. That is, faces were identically sized regardless of whether they appeared with bodies. In total, there were six face-and-body images and six face-only images of each age/race combination (additional details regarding stimulus generation appear in the OSM).

Experiment 2: Prime stimuli

Face-and-body images of Black and White men and boys (six of each age/race combination) were selected from a larger pool of photos taken from online sources. The people in the selected photos were matched on perceived socioeconomic status and masculinity (see the OSM for details about pilot testing). In the face-only condition, we cropped the face-and-body images below the head.

Analysis plan

Prior to all analyses, we excluded trials with response times (RTs) < 100 ms and > 1,500 ms (Klein & Todd, 2024; Todd et al., 2021), which eliminated 3.5% and 7.3% of the data in Experiments 1 and 2, respectively. Following standard practice with the WIT (Payne, 2001), we also excluded error trials prior to RT analyses. Below, we report analyses pertinent to our focal hypotheses regarding prime format effects on racial bias.

Behavioral data analyses

Both error rates and (correct) RTs were analyzed in a linear mixed-effects modeling (LMEM) framework using the *lmerTest* package (Kuznetsova et al., 2017). Each model contained fixed effects for Prime Format, Race Prime, Age Prime, Target Object, and all identifiable interactions. An additional fixed effect was included for experiment to capture variance associated with experiment membership. The models included a random-effects structure with by-participant and by-stimulus random intercepts. We examined our effect of interest (i.e., the Prime Format × Race Prime × Target Object interaction) via contrasts of the model's Race Prime × Target Object interactions between prime format conditions. A full LMEM table appears in the OSM (Table S3). Results are reported with unstandardized betas.

DDM parameter estimation and analysis

To estimate DDM parameters and analyze their magnitudes between prime format conditions, we mirrored the approach used by Todd et al. (2021): The DDM was estimated using a Markov Chain Monte Carlo (MCMC) sampler in JAGS 4.30 (Plummer, 2003) with the Wiener distribution provided by Wabersich and Vandekerckhove (2014) and an estimation approach to make inferences in this framework (Gelman et al., 2003; Kruschke, 2014). Parameter estimates were averaged across experiments. All parameters were allowed to vary by Race Prime, Age Prime, and Prime Format, and the drift rate and non-decision-time parameters also were allowed to vary by Target Object.[4]

Posterior predictive checks indicate that the model adequately characterizes the data. The representativeness and

[4] As indicated in Table 1, neither the threshold separation nor the relative start-point parameter can be identified across conditions of Target Object (for a detailed explanation, see Klein & Todd, 2024).

accuracy of each model's estimation, which we assessed both visually and numerically (see the OSM), were adequate to rely on the parameter estimates for subsequent process analyses.

To compare parameter estimates across conditions, we computed the 95% highest density interval ($HDI_{95\%}$) of the difference between posterior distributions of each parameter across the relevant conditions. Differences with $HDI_{95\%}$ excluding 0 are considered credible. For each analysis, we report the most credible estimate of the raw difference, a Cohen's *d*, and the $HDI_{95\%}$ around *d*. The effect of Race Prime was compared across Prime Format conditions for all four parameters. For drift rate and non-decision time, contrasts were further computed to assess the effect of Race Prime across the Target Objects. (Fig. 3 displays the relative start point parameter estimates in both experiments; Figs. S4–S7 (OSM) display all other parameter estimates).

MCI model parameter estimation and analysis

Following Klein and Sherman (2024), we fit the MCI model with a hierarchical Bayesian estimation method (*latent-trait* approach; Klauer, 2010) using the *TreeBUGS* package (Heck et al., 2018). Data from Experiments 1 and 2 were integrated and fit to a single MCI model, which included a covariate to account for experiment-level variance. Given the theoretical focus on race in the WIT, we set parameter C_1 to reflect the use of race information and parameter C_2 to reflect the use of age information.[5,6] That is, the MCI model is instantiated to quantify the reliance on race and age cues in the primes, collapsing across gun versus tool trials. This decision is supported by the results of the DDM analyses reported below, which suggest that racial bias varies as a function of information use in the primes, not the target objects (see *DDM*).

Posterior predictive checks were assessed via two fit statistics: T_1, reflecting the model's ability to account for discrepancies between observed and expected responses across all participants (i.e., mean-level fit); and T_2, indicating the model's ability to account for discrepancies between observed and expected covariances (i.e., individual-level fit). The T_1 statistic, defined by a chi-square distribution, is sensitive to large amounts of data. Therefore, we use a descriptive form of the *w* statistic to characterize misfit between the model's expectations and the observed aggregate responses. We use $w < .10$ as a descriptive benchmark for small misfit. The MCI model fit the data well, Median Individual $T_{1\ p\text{-}value} = .894$, Aggregate $T_{1\ p\text{-}value} = .615$, Aggregate $T_{2\ p\text{-}value} < .001$, $w < .01$. Further confidence in the model can be gleaned from visual inspection of the observed and expected frequencies (available at https://osf.io/qzp8x).

To compare MCI model parameters across conditions, we computed differences in their condition-level posterior samples, resulting in a distribution of mean differences. Differences were considered credible if the 95% Bayesian credibility interval ($BCI_{95\%}$) of the differential posterior distribution excluded zero.

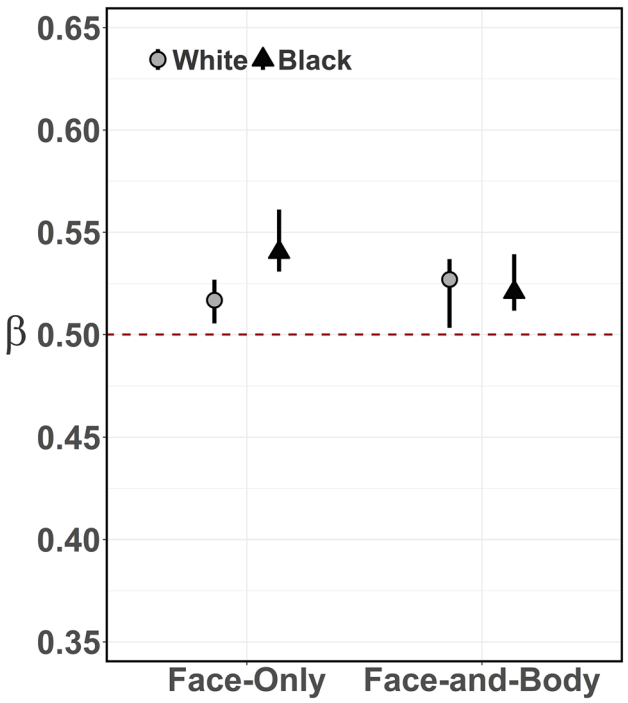

Fig. 3 Relative start point (β) estimates by race prime and prime format conditions. Markers reflect the most credible posterior estimates for Black prime and White prime trials from the diffusion decision model (DDM) applied to the data. Error bars reflect their 95% highest density intervals, respectively. The x-axis displays race prime information. The y-axis reflects the extent of bias toward *gun* (>.50) or *tool* (<.50) decision thresholds. Shading and shape of markers reflect the prime format.

[5] Flipping the parameter mapping does not meaningfully alter the conclusions (see Table S25, OSM).

[6] This is the first application of the MCI model to data whereby both cues assigned to the model are task-irrelevant. Klein and Sherman's (2024) introduction and initial validation of the MCI model relied on data from classification tasks whereby one cue was task-relevant and the other was task-irrelevant. Although the cue-processing parameters of the MCI model are general and do not assume particular cognitive operations (e.g., activation of association, response inhibition), the task-relevance of the cues may alter the cognitive processes determining cue use and, therefore, alter when cues are used and the extent to which the model estimates their use.

Results

Behavioral analyses

Error rates

A significant Prime Format × Race Prime × Target Object interaction, $b = -0.03$, $F(1, 1132.35) = 8.68$, $p = .003$, $R^2 = .01$, revealed substantive variation in racially biased weapon identification based on prime format (Fig. 2, left plot).[7] For face-only primes, the Race Prime × Target Object interaction (i.e., racial bias) was significant, $b = -0.04$, $z = -5.96$, $p < .001$. Guns were misidentified as tools less often ($M_{diff} = -1.9\%$) and tools were misidentified as guns more often ($M_{diff} = 1.8\%$) after Black versus White primes (see Table S6 (OSM) for simple effects). For face-and-body primes, no significant racial bias emerged, $b = -0.01$, $z = -1.80$, $p = .073$ (see Table S8 (OSM) for descriptive statistics). The Race Prime × Target Object effect did not significantly interact with Age Prime, $b = 0.01$, $F(1, 1132.36) = 0.45$, $p = .500$, confirming that the availability of age information often fails to mitigate racially biased weapon identification.

Correct response times

A significant Prime Format × Race Prime × Target Object interaction, $b = -0.03$, $F(1, 1109.80) = 7.84$, $p = .005$, $R^2 = .06$, again revealed substantive variation in racially biased weapon identification based on prime format (Fig. 2, right plot).[8] For face-only primes, racial bias was evident, $b = -0.04$, $z = -5.71$, $p < .001$. Guns were identified faster ($M_{diff} = -3$ ms) and tools were identified slower ($M_{diff} = 3$ ms) after Black versus White primes. For face-and-body primes, no significant racial bias emerged, $b = -0.01$, $z = -1.75$, $p = .080$. The Race Prime × Target Object effect again did not significantly interact with Age Prime, $b = 0.01$, $F(1, 1109.80) = 0.37$, $p = .544$.

Process analyses

DDM

A Prime Format × Race Prime contrast on the relative start point (β) was credible, $\mu_{diff} = -0.01$, $d = -0.22$, $HDI_{95\%}$ [−0.30, −0.14] (Fig. 3). For face-only primes, the decision process began closer to "gun" after seeing Black versus White primes, $\mu_{diff} = -0.03$, $d = -0.50$, $HDI_{95\%}$ [−0.61, −0.37]. For face-and-body primes, no credible racial bias emerged, $\mu_{diff} < 0.01$, $d = -0.06$, $HDI_{95\%}$ [−0.16, 0.07]. No credible effects emerged on the other three parameters.

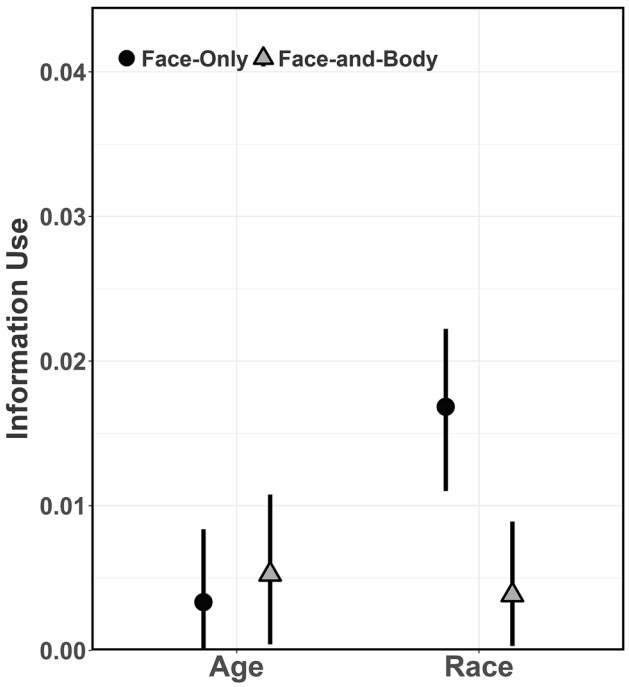

Fig. 4 Reliance on age and race information across prime format conditions. Markers reflect the estimated use of age and race during the weapon identification task (WIT). The x-axis reflects whether the information was age or race. The marker shape reflects whether the information was presented solely in the face (circles) or in both the face and the body (triangles). The y-axis reflects the estimated probability of relying on a particular piece of information. Error bars signify 95% Bayesian credibility intervals around the aggregate-level estimate.

MCI model

Parameter comparisons revealed a credible Prime Format effect on the use of race cues, $\Delta C_1 = .013$, $BCI_{95\%}$ [.005,.020] (Fig. 4). Overall, race was used less (Δ1.3%) when age information was available in both the face and body. No credible Prime Format effect emerged for the use of age cues, $\Delta C_2 = -.002$, $BCI_{95\%}$ [−.009,.005]. That is, the availability of age information via both the face and body did not alter how much age was used to make weapon identifications; it limited how much race was used to make those decisions.

[7] Reported R^2 values are marginal, not conditional, values.

[8] Although the Prime Format × Race Prime × Target Object interaction fell short of significance in Experiment 2 (b = -0.023, p =.098), the underlying simple effects followed the same pattern as in Experiment 1 (see the OSM for detailed reporting of the results per Experiment).

Discussion

Two experiments manipulated the format of the primes – presenting social information either solely via the face or via the face and the body – to test whether and how the availability of additional social information channels dampens racially biased weapon identification. In both behavioral and process analyses, racial bias was weaker when prime information was available in both the face and the body versus solely the face. These results complement well-established findings that the mere availability of age cues in the primes fails to alter racial bias when such information is conveyed solely through the face (Lundberg et al., 2018; Thiem et al., 2019; Todd et al., 2016a, b). Rather, intervention, such as augmenting the salience of age via experimental manipulation (Jones & Fazio, 2010; Todd et al., 2021), is necessary to moderate racially biased WIT behavior. Extending these earlier studies, our results suggest that expanding the number of channels through which additional information is conveyed (e.g., introducing the body alongside the face) can mitigate the biasing impacts of race on decision making.

Modeling-based insights

Applying the DDM clarified the mechanism underlying these findings. Replicating prior work (Klein & Todd, 2024; Todd et al., 2021), we found robust support for an initial bias account of racially biased weapon identification. Specifically, racial bias reflected a shift in the starting position of the decision process toward race-stereotypic responses. Seeing Black face primes pushed the starting position closer to a "gun" response, creating a response bias before the target object was processed. Introducing bodies alongside faces mitigated this initial bias, eliminating its contribution to racially biased decision making. Overall, our findings reinforce the initial bias account. They also support similar, more general accounts of racially biased weapon identification (e.g., the default-interventionist model; Klauer & Voss, 2008; Laukenmann et al., 2023), which assume that early-stage stereotype activation conflicts with later-stage control-oriented processing (see also Amodio et al., 2004).

The DDM clarifies *when* and *how* information processing is altered by available additional information, but it cannot decipher *what* information was responsible for altering racial bias. Introducing the body alongside the face could have increased how often participants attended to age, information that may compete with race to influence weapon identification decisions. Alternatively, the manipulation could have lessened how often participants attended to race, directly mitigating race's impact on decision making. Or maybe both operations – more attention to age and less attention to race – run concurrently. These are just several possible explanations that cannot be clarified by behavioral analyses or by the DDM.

To identify the information responsible for altering racial bias when introducing bodies into the primes, we used the MCI model, which quantifies how much age and race were each used in decision making. The model revealed that introducing different sized bodies into the primes did not increase reliance on age cues; rather, it decreased reliance on race cues. So, the availability of body information appears to limit the salience of race, which may be especially high when only seeing a face, as is common in laboratory tests of racial bias (Cesario, 2022).

Importantly, though, our MCI modeling analyses indicated that the processing of race cues was not at zero when bodies were available in the primes. Future work could introduce social information through additional channels to identify conditions wherein attention to race fully evaporates and no longer informs decision making.

The combined insights of the DDM and MCI model clarify how opening channels to social information outside the face (vs. seeing only the face) affects racial bias. Introducing body information reduces the attention race cues garner, mitigating their impact on decision making. The modeling insights further contrast with alternative possibilities, like age being attended to more or target objects (e.g., guns) being construed differently when bodies appear in the primes.

Limitations and future directions

Race-based attentional shifts may not be the only explanation, however. Racialized facial features (e.g., full lips, broad nose) and skin tone (Maddox, 2004) are often weighted more heavily than age-related features in person perception (Zebrowitz et al., 2010). Importantly, the weight of various features' impact on person perception is malleable (Chua & Freeman, 2021; Hong et al., 2024). Whereas our experiments identified selective shifts in attention to race underlying changes in racial bias, no research has distinguished the weights of race and nonrace information to determine if they, too, explain changes in racial bias in broader social contexts. For example, although age garnered similar attention through faces and through faces and bodies here, age may be weighted more heavily each time it is attended to when bodies are also available in the primes. If so, age would be partially responsible for the altered racial bias, just not through attentional shifts. With recent advances in multinomial processing tree modeling (Klauer et al., 2024), the MCI model could be expanded to integrate response times in a manner that also affords estimates of the strength of evidence (i.e., weight) each cue provides, analogous to isolating a separate drift rate parameter in the DDM for age cues and race cues.

Unlike in the face-only condition, faces were vertically off-center in the face-and-body condition and misaligned with the preceding fixation cross, making it plausible that stimulus positioning contributed to the attentional shift away from race detected by the MCI model. That is, greater difficulty in detecting race during the brief presentation of the prime could weaken its use. Though potentially contributing to our findings, it may not fully explain our results. The automaticity of racial stereotyping is robust, triggered rapidly by minimal or degraded cues (Amodio et al., 2004; Colombatto & McCarthy, 2017) and even when race information is off-center in complex social scenes (Correll et al., 2002). Future work could distinguish the unique contributions of stimulus position (e.g., face primes centered vs. off-centered) and additional social information channels in reducing racial bias. The current research would also benefit from complementary evidence clarifying if bodies themselves are a particularly effective channel of social information to modulate race processing or if *any* additional channels of social information may be equivalent in their modulation of race processing.

The computational modeling used here has value for future research seeking to extend our understanding of cognitive and behavioral biases linking race and weapons. For example, the finding that Black primes cued an expectation for guns (i.e., a relative start-point bias in the DDM) offers a testable hypothesis for how race cues might bias eyewitness memory. By increasing a weapon's expectedness, race cues may lessen the weapon's salience in a scene and thereby alter what is remembered (Pickel & Sneyd, 2018; see also Erikson et al., 2022).

Our experiments examined variability in body size, which presumably cued either *adult* or *child* classifications. Importantly, however, size is only one feature commonly gleaned from body information. Dress features (e.g., clothing, accessories) are also strong cues to various social categories, including age and race (Hester & Hehman, 2023). Although body size mitigated the impact of race here, the availability of other body features (e.g., dress, posture, gait) might cue race more strongly, potentially augmenting racial bias. Future work should move beyond body size to test how other body features affect racially biased decision making.

Conclusion

This research advances our understanding of how the availability of various social information channels moderates racially biased decision making. Whereas prior work manipulated the salience of facial cues, here introducing body information alongside the face fundamentally altered the processing dynamics, shifting the initial positional bias that drives racially biased weapon identification. Furthermore, we clarified the information responsible for this mechanistic shift: Race was attended to less when body information was available, but age was not attended to more. This work provides a new perspective on how the diversity and richness of social information can shape decision-making processes.

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Availability of data and materials Data and code are available at: https://osf.io/qzp8x. Materials will be made available upon request.

Code availability The OSF link included above hosts a page with relevant data and code.

Declarations

Conflicts of interest/Competing interests We report no conflicts of interest in the publishing of this research.

Ethics approval The institutional review board (IRB) at the University of Iowa approved this research and the informed consent process (IRB ID #201507808).

Consent to participate Informed consent was obtained from all participants prior to their participating.

Consent for publication No identifying information is published on the OSF page associated with this article or within the article itself.

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