Response Variability Reveals Hidden Social-Category Effects in Facial-Expression Categorization

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Abstract

The "happy-face advantage" (HFA)—faster categorization of happy vs. fearful expressions—is typically established using mean reaction times (RTs), which obscure the structure of the RT distribution. The present research examined how facial expression and social-category cues influence emotion categorization using ex-Gaussian modelling, decomposing RTs into mean (μ), variability (σ), and slow-tail responding (τ). Ex-Gaussian modelling revealed that expression effects were distributed across distinct components of the RT distribution. Whereas mean RT (μ) replicated the happy-face advantage, σ indexed systematic differences in response consistency and τ captured selective increases in unusually slow responses. These findings demonstrate that social-category influences on emotion categorization are distributed across multiple components of the RT distribution that remain hidden in conventional analyses of mean RT.

Keywords: happy-face advantage; emotion categorization; ex-Gaussian; response variability; face sex; social perception

Humans rapidly extract both emotional and social information from faces. A substantial body of research demonstrates that emotion categorization is systematically shaped by social-category information, including face sex and race (e.g., Bijlstra et al., 2010; Craig & Lipp, 2018; Hugenberg & Sczesny, 2006; Martin et al., 2024, 2026). One robust finding is the happy-face advantage (HFA), whereby happy expressions are categorised more rapidly than negative expressions (Leppänen et al., 2003). Importantly, however, the magnitude of this advantage varies as a function of social-category cues: responses to happy expressions are often faster for female than male faces, especially among female perceivers (Martin et al., 2024; Tipples, 2019, 2022).

Despite theoretical differences among accounts (evaluative congruence, stereotype-based, perceptual structure), most studies share a common assumption: that social-category effects can be adequately characterised using mean RT. However, mean RT collapses across distinct components of the RT distribution and cannot distinguish between qualitatively different forms of processing difficulty. Slower means may reflect uniformly reduced efficiency, increased trial-to-trial instability, occasional extremely slow responses, or some combination.

The ex-Gaussian distribution decomposes RT into three parameters: μ (central tendency), σ (trial-to-trial variability), and τ (slow tail). Effects expressed primarily in σ or τ may remain invisible in conventional mean-based analyses. This distinction may be particularly important for social-category effects: incongruence may not simply slow responses uniformly but instead produce unstable responding across trials by increasing competition between alternative interpretations.

The present study examined whether social-category effects in facial-expression categorization are more strongly expressed in distributional variability than in conventional mean RT. Participants categorised fearful and happy expressions displayed by male and female White and Black faces. Responses were analysed using hierarchical ex-Gaussian mixed-effects models. If social-category influences affect decisional stability or produce occasional unusually slow responses rather than uniform slowing, then key interactions should also emerge in σ and/or τ rather than being confined to μ. Accordingly, we compared models allowing experimental effects on μ alone, on μ and τ, and on all three ex-Gaussian parameters (μ, σ, and τ).

Method

Participants

Ethical approval was obtained from University of Sunderland. Participants were recruited via the Social Psychology Network website (https://www.socialpsychology.org/expts.htm) . The final sample comprised 186 participants (76 male, mean age = 33 years; 110 female, mean age = 27 years). Participants were excluded if their accuracy was below 60% or their mean RT exceeded 1.2 s; one female participant met these exclusion criteria. Twenty-seven non-White participants were excluded to ensure a homogeneous perceiver group for race analyses; all remaining participants identified as White/Caucasian.

Stimuli and Procedure

Face stimuli were selected from the NimStim set (Tottenham et al., 2009): 20 individuals (12 White: 6 male, 6 female; 8 Black: 4 male, 4 female), with four versions per face (mouth open/closed × happy/fearful). Each of the 80 faces was presented once in each of 3 blocks (with a self-paced rest after the second block) and consequently, the total number of trials was 240 (3 repetitions of each face). A new randomized trial order sequence was created for each block, for each participant, based on a computer-generated random seed. Sixteen practice trials preceded the first main block of trials. The faces for the practice trials were not used in the main blocks of trials. The trial sequence was: 1) 1000 milliseconds blank interval 2) 500 milliseconds fixation cross and 3) the face stimulus until either the participant responded, or 3.5 seconds had elapsed. If participants failed to respond within 3.5 seconds, they received the feedback "too slow" for an extra 500 milliseconds. Participants were instructed to respond as quickly and accurately as possible. Participants responded by pressing the F key on their keyboard with their left index finger to indicate a fearful Expression and the H with their right index finger to indicate a happy Expression.

Design

The study employed a fully crossed within-subjects design with the following factors: Expression (happy, fearful) X Face Sex (male, female) X Face Race (Black, White). Participant Sex (male, female) was included as a between-subjects factor. The primary dependent variable was reaction time (RT) for correct responses, analysed at the trial level.

Analysis Plan

Conventional mean-based mixed-effects models (log-transformed RTs, incorrect responses and RTs <200 ms or >2999 ms removed) served as a baseline. Ex-Gaussian models were fitted using GAMLSS (Rigby & Stasinopoulos, 2005) at the trial level, excluding only RTs <150 ms and timeouts (>3499 ms). Three nested models were compared: (1) μ only, (2) μ + τ, (3) full model (μ

+ σ + τ). Models were compared using the Generalised Akaike Information Criterion (GAIC; Rigby & Stasinopoulos, 2005), evaluated using the conventional Akaike penalty (AIC; $k = 2$) and the Bayesian penalty (BIC; $k = \log n$). As with conventional AIC, GAIC values may be negative because they are based on the maximised log-likelihood of the fitted model; only differences between models are meaningful.

Treatment coding was used for all categorical predictors: Expression (0 = fearful, 1 = happy), Face Sex (0 = female, 1 = male), Face Race (0 = White, 1 = Black), and Participant Sex (0 = female, 1 = male). Unlike conventional Gaussian mixed-effects models, which estimate only the conditional mean of the response, the ex-Gaussian distributional model simultaneously estimates the location (μ), variability (σ), and slow-tail (τ) parameters of the RT distribution, with a separate regression equation for each parameter.

Three candidate ex-Gaussian models were compared. To maintain consistency with Table 1 (below), their specifications are presented below as M1, M2, and M3. For clarity, the three candidate models can be represented schematically as follows:

M1 (μ + σ + τ)

μ ~ 1 + Expression × Face Sex × Face Race × Participant Sex + (1 + Expression × Face Sex × Face Race | Participant) + (1 | Face)

σ ~ 1 + Expression × Face Sex × Face Race × Participant Sex + (1 + Expression × Face Sex × Face Race | Participant) + (1 | Face)

τ ~ 1 + Expression × Face Sex × Face Race × Participant Sex + (1 + Expression × Face Sex × Face Race | Participant)

M2 (μ + τ)

μ ~ 1 + Expression × Face Sex × Face Race × Participant Sex + (1 + Expression × Face Sex × Face Race | Participant) + (1 | Face)

σ ~ 1

τ ~ 1 + Expression × Face Sex × Face Race × Participant Sex + (1 + Expression × Face Sex × Face Race | Participant)

M3 (μ only)

μ ~ 1 + Expression × Face Sex × Face Race × Participant Sex + (1 + Expression × Face Sex × Face Race | Participant) + (1 | Face)

$\sigma \sim 1$

$\tau \sim 1$

These formulae provide schematic representations of the fitted GAMLSS models using familiar mixed-effects notation. In the actual implementation, participant-level random effects were estimated using a compound-symmetry covariance structure. In M1, the identical fixed-effects specifications for σ and τ were intentional: the same factorial predictors were allowed to influence both parameters independently. The σ equation additionally included a face-level random intercept.

Results

Conventional Mixed-Effects Model

The conventional analysis revealed: faster responses to happy vs. fearful White female faces (b = −0.062, p < .001); reduced facilitation for male faces (Expression × Face Sex: b = 0.043, p = .001); slower overall RTs for male vs. female participants (b = 0.079, p < .001). The three-way interaction (Expression × Face Sex × Participant Sex) was not significant (b = −0.032, p = .115).

Ex-Gaussian Model Comparison

Table 1 - Model fit indices for the three ex-Gaussian GAMLSS candidate models

Model	df	AIC	BIC
m1 (μ+σ+ τ)	2787	−16022	8064
m2 (μ+ τ)	2453	-15143	6054
m3 (μ only)	22285	−9731	10016

As shown in Table 1, The μ-only model (m3) performed worst under both criteria. AIC strongly favoured the full model (m1; ΔAIC = 879), while BIC favoured m2 (μ+ τ) due to its steep penalty at large *n*. We selected m1 on substantive grounds: constraining σ to an intercept produced systematic distortions. In m2, the critical Expression × Face Sex × Participant Sex interaction on μ was attenuated by ≈30% (b = −0.029 vs. −0.042), a theoretically meaningful interaction on v became non-significant (b = 0.059, p = .234 vs. b = 0.130, p = .007 in m1), and additional effects

emerged on τ. These patterns indicate that variance in σ is misattributed to μ and τ when σ is constrained.

Ex-Gaussian Parameter Estimates

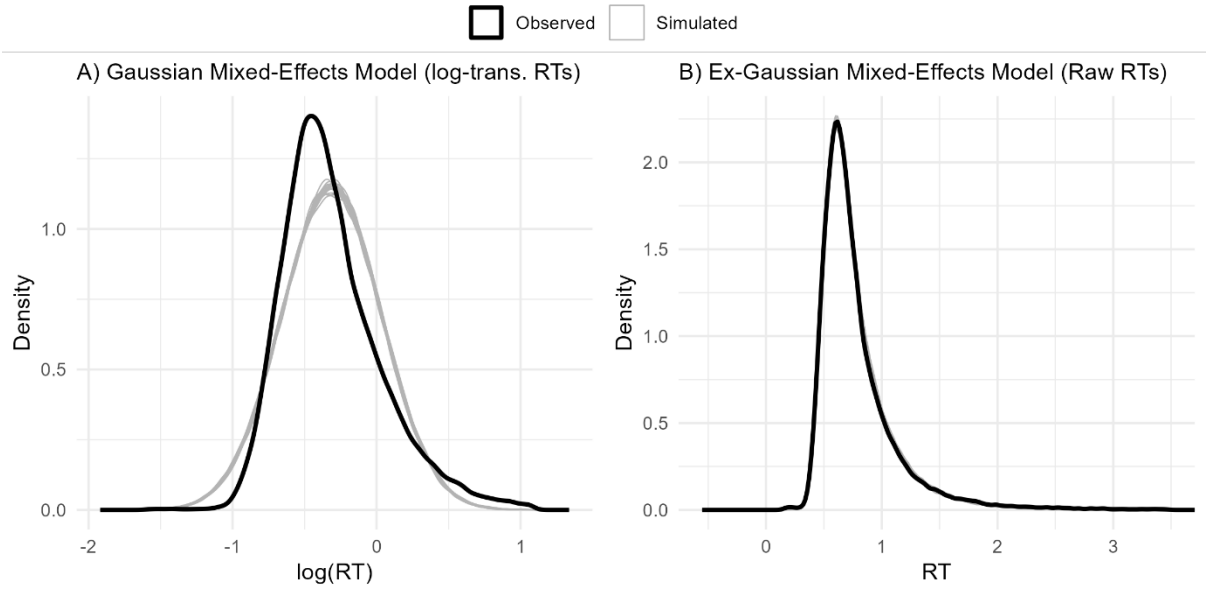

Figure 1. Simulation-based assessment of model fit for the Conventional (Gaussian) Mixed-Effects Model and ex-Gaussian mixed-effects models.

Model fit. To assess the adequacy of the Conventional Mixed-Effects Model described above vs the ex-Gaussian model m1 (μ+σ+ τ), twenty datasets were simulated from the fitted conditional distributions and compared with the observed reaction-time distributions (Figure 1). As shown in Figure 1A, the Gaussian model provided a reasonable approximation to the approximately normal distribution obtained after log transformation. However, this approach necessarily models responses on the transformed scale and provides only a single estimate of residual variability. By contrast, the ex-Gaussian model closely reproduced the characteristic positive skew of the raw RT distribution (Figure 1B) while simultaneously estimating independent parameters describing the distribution's location (μ), variability (σ), and slow tail (τ). The subsequent analyses therefore focused on whether experimentally induced effects were differentially expressed across these distributional components.

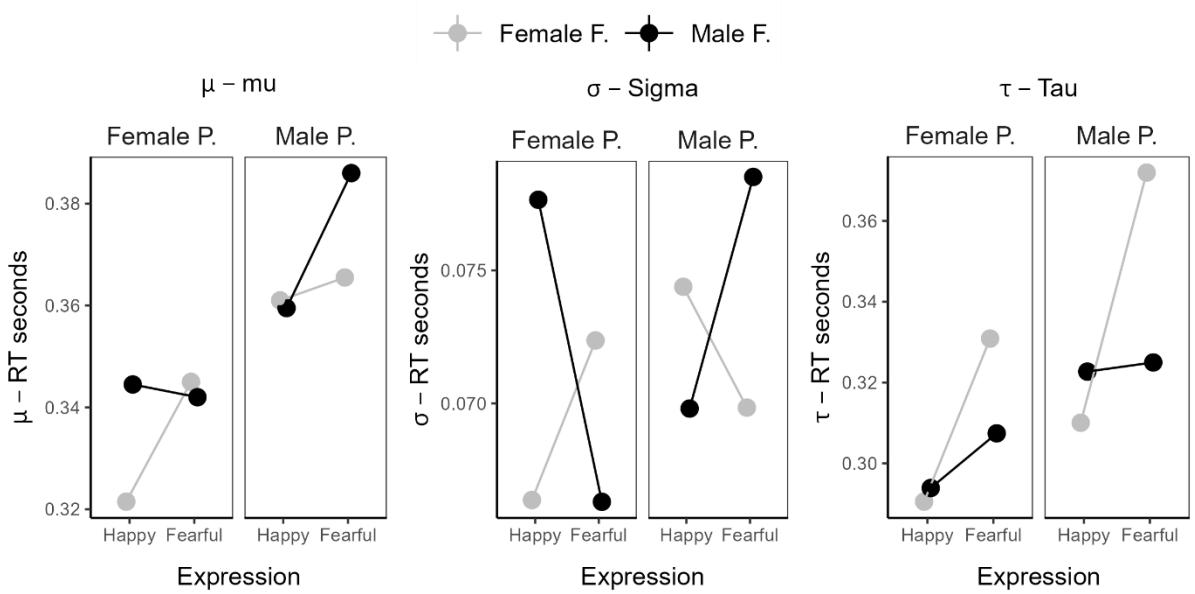

Figure 2. Estimated marginal means from the full ex-Gaussian model (averaged over Face Race) for the μ, σ, and τ parameters as a function of Expression, Face Sex, and Participant Sex. The underlying model included Face Race and all interactions. For all ex-Gaussian parameters Expression effects depended critically on the congruence between Target Sex and Participant Sex but critically, the specific pattern differed between the parameters (see left panel for mu vs middle panel for sigma and right panel for tau).

Mean RT (μ). A significant Expression × Face Sex × Participant Sex interaction (b = −0.042, p < .001) was observed (Figure 2). The estimated marginal means shown in Figure 1 are averaged across Face Race. Representative estimated marginal means for both White and Black faces are provided below to illustrate the interaction. For female participants, happy expressions produced faster responses than fearful expressions for female faces (e.g., Black: 323 vs. 345 ms; White: 322 vs. 347 ms), whereas this facilitation was absent for male faces (Black: 349 vs. 347 ms; White: 342 vs. 339 ms). For male participants, the pattern reversed: female faces showed little expression effect (Black: 366 vs. 360 ms; White: 358 vs. 373 ms), whereas male faces showed substantially slower responses to fearful than happy expressions (Black: 385 vs. 361 ms; White: 389 vs. 360 ms). This double dissociation produced a significant Expression × Face Sex × Participant Sex interaction (b = −0.042, p < .001). Face Race did not significantly modify this overall pattern (b = −0.012, t = −1.23, p = .21). However, a smaller Expression × Face Race × Participant Sex interaction (b = −0.018, t = −2.64, p = .008) indicated that, for male participants, the happy–fear difference was larger for White than Black faces.

RT variability (σ). The Gaussian standard deviation revealed a systematic crossover interaction among Expression, Face Sex, and Participant Sex. For female participants, σ was highest for

happy male faces and decreased for fearful male faces; the reverse pattern was observed for female faces. For male participants, this pattern reversed entirely: σ was lowest for happy male faces and increased for fearful male faces, while female faces remained comparatively stable. This interaction underlies the significant Expression × Face Sex (b = 0.331, p < .001), Face Sex × Participant Sex (b = 0.243, p = .010), and Expression × Face Sex × Participant Sex (b = −0.364, p = .007) effects.

RT tail (τ). A significant Expression × Face Sex × Participant Sex interaction (b = 0.130, p = .007) indicated that the influence of facial expression on the slow tail of the RT distribution depended on both the sex of the face and the participant. For female participants, fearful expressions produced a substantially larger τ than happy expressions for female faces (0.331 vs. 0.291; Δ = 0.040), whereas this difference was markedly smaller for male faces (0.308 vs. 0.294; Δ = 0.014). In contrast, for male participants, the expression effect was largest for female faces (0.372 vs. 0.310; Δ = 0.062) and was virtually absent for male faces (0.325 vs. 0.323; Δ = 0.002). Thus, occasional unusually slow responses to fearful expressions were greatest for female faces, particularly among male participants, whereas expression had little influence on the slow tail for male faces.

Model with Mouth as predictor

To address the reviewers' comments concerning the mouth openness manipulation, the best-fitting ex-Gaussian model (μ + σ + τ) was extended to include Mouth (open vs. closed) as an additional fixed effect. The location (μ), scale (σ), and tail (τ) parameters were each modelled as a function of the fully crossed design: Expression × Face Sex × Participant Sex × Face Race × Mouth. Participant-level random effects were included for each distributional parameter using a compound symmetry covariance structure. Because models including random effects for both participants and face identities did not converge reliably, the final model retained participant-level random effects only. Effect coding (-0.5, +0.5) was used for all categorical predictors, allowing coefficients to be interpreted as ANOVA-like main effects and interactions (DeBruine & Barr, 2021)

Effects of mouth openness

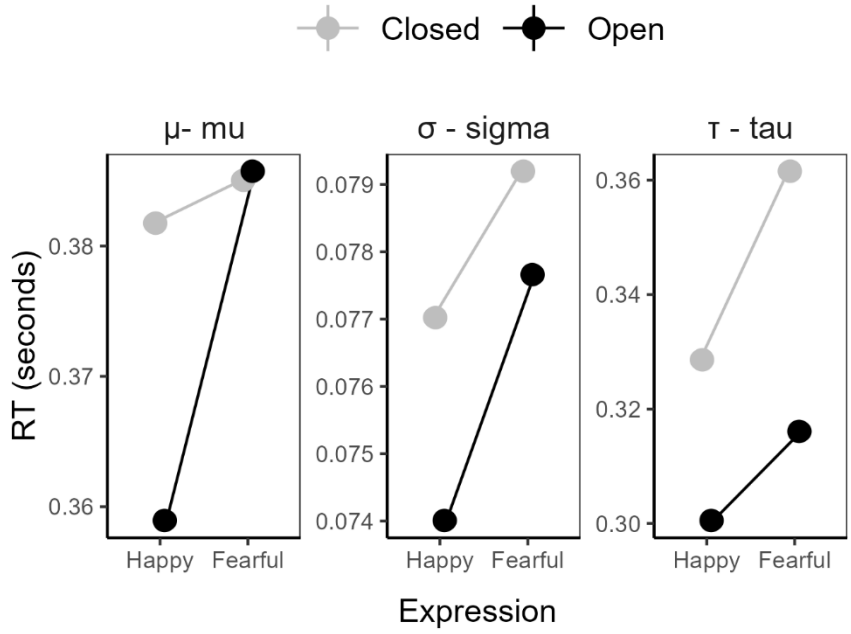

Figure 3. Estimated marginal means from the best-fitting ex-Gaussian model showing the Expression × Mouth interaction for the location (μ), scale (σ), and tail (τ) parameters. Relative to open-mouth faces, closing the mouth increased mean RT (μ), response variability (σ), and the slow-tail parameter (τ), with the largest changes occurring for happy expressions.

As shown in Figure 3, for the parameter mu, closing the mouth increased the mean of the RT distribution (μ; b = 0.011, 95% CI [0.009, 0.013], p < .001), indicating generally slower responses when diagnostic mouth information was unavailable. Importantly, this effect depended on expression, with a robust Expression × Mouth interaction (b = 0.024, 95% CI [0.019, 0.028], p < .001), showing that closing the mouth disproportionately reduced the processing advantage for happy relative to fearful expressions. Several additional higher-order interactions reached conventional levels of statistical significance but were comparatively small in magnitude and, as exploratory findings, are not interpreted further.

For the slow-tail parameter (τ), closing the mouth also produced a substantial increase (b = 0.111, 95% CI [0.091, 0.130], p < .001), indicating a greater proportion of unusually slow responses. This effect was moderated by face race, particularly through a robust Expression × Face Race × Mouth interaction (b = –0.301, 95% CI [–0.380, –0.223], p < .001). The latter interaction reflected a selective increase in the slow tail of the RT distribution for fearful Black faces when the mouth was closed (estimated τ = 0.382) compared with the open-mouth condition (τ = 0.295). In contrast, mouth closure produced only modest changes for happy faces and virtually no change for fearful White faces.

Discussion

The present findings demonstrate that social-category influences on emotion categorization are distributed across multiple components of the reaction-time distribution rather than being confined to overall response speed. Although the mean RT parameter (μ) replicated previously reported interactions between expression, face sex, and participant sex, modelling the full ex-Gaussian distribution revealed additional effects on variability (σ) and the slow tail (τ) that were not apparent from analyses of mean RT alone.

The interaction observed for μ replicated the well-established happy-face advantage while revealing that its magnitude depended jointly on the sex of the face and the observer. Female participants showed the largest happy-face advantage for female faces, whereas male participants showed the converse pattern, exhibiting a larger happy-face advantage for male faces. This crossover is consistent with previous reports of target–perceiver gender congruency in facial emotion perception (Briton & Hall, 1995) but is also compatible with broader accounts of own-gender processing advantages. According to perceptual expertise and social identity accounts (Rehnman & Herlitz, 2006), observers may process own-gender faces more efficiently because of greater perceptual experience, attentional engagement, or motivational relevance. The present findings cannot distinguish between stereotype-based and own-gender explanations, and these mechanisms may operate jointly.

The present findings also extend earlier demonstrations that facial expression and face sex are processed interactively rather than independently. Using both Garner and Simon paradigms, Atkinson et al. (2005) showed that variation in face sex interferes with expression judgements whereas variation in expression has relatively little effect on sex judgements, suggesting asymmetric interactions operating at both perceptual and response-selection stages. The present findings extend this conclusion by showing that these interactions are differentially expressed across distinct components of the RT distribution. Whereas Atkinson et al. inferred these interactions from overall response times, the ex-Gaussian analyses localise them to mean RT (μ), response consistency (σ), and the slow tail (τ).

The σ parameter indexed response consistency rather than average response speed. The crossover interaction indicated that expression and face sex influenced the stability of responding differently for female and male observers. Elevated σ suggests that competing interpretations were resolved less consistently across trials, reflecting greater decisional competition rather than uniformly slower responding. This interpretation is consistent with dynamic models of person perception, in which perceptual cues and social-category

knowledge jointly constrain the evolving decision process (Freeman & Ambady, 2011). Notably, these effects occurred independently of corresponding changes in mean RT.

The τ parameter provided further evidence that distinct processes contribute to emotion categorization. Unlike μ, which reflected average response speed, τ indexed occasional unusually slow responses. Fearful expressions produced a larger slow tail than happy expressions, particularly for female faces, with the strongest effect occurring when female faces were judged by male participants. These findings suggest that the mechanisms responsible for occasional very slow decisions differ from those influencing average performance. One possibility is that fearful female faces occasionally elicited greater decisional uncertainty or prolonged evidence accumulation, producing a small proportion of exceptionally slow responses. Future work combining ex-Gaussian and evidence-accumulation models may help clarify the cognitive processes underlying these dissociations.

The additional analyses incorporating mouth openness further clarified the contributions of perceptual and social factors to emotion categorization. Closing the mouth attenuated the happy-face advantage while increasing both response variability (σ) and the slow-tail parameter (τ). Because the mouth is a highly diagnostic cue for happiness (Bimler & Paramei, 2023), reducing this perceptual information appears to increase decisional uncertainty as well as slowing responses. Nevertheless, interactions involving face sex and participant sex persisted, indicating that social-category influences continued to shape performance despite degraded perceptual evidence. Face race affected different components of the RT distribution. In the principal model, male participants showed a larger happy–fear difference for White than Black faces, whereas in the mouth model, closing the mouth selectively increased the slow tail of responses to fearful Black faces with little effect on fearful White faces. Together, these findings suggest that race and sex influence emotion categorization through partly independent mechanisms expressed in different components of the RT distribution rather than through a single, general social-category bias.

One limitation of the present study is that all participants were White. Although Face Race was explicitly modelled and the principal Expression × Face Sex × Participant Sex interaction remained after accounting for race, the design cannot fully disentangle own-race and own-gender influences because participant race was not manipulated. Future studies employing fully crossed participant- and stimulus-race designs will be needed to determine how these social-category dimensions interact and whether the present effects generalise across observer groups.

More broadly, the present findings illustrate the value of distributional modelling for understanding emotion perception. Conventional Gaussian mixed-effects models estimate only the conditional mean of the RT distribution, whereas ex-Gaussian models separately estimate μ, σ, and τ. Constraining σ redistributed variance to μ and τ, altering parameter estimates and attenuating theoretically important interactions. Conventional analyses are therefore not incorrect but incomplete: distributional modelling reveals complementary aspects of processing that remain hidden when inference is restricted to mean RT.

Declarations

Funding

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Conflicts of interest / Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this article.

Ethics approval

The study received ethical approval from the University of Sunderland Ethics Committee (Reference Number: 024974) and was conducted in accordance with the ethical standards of the 1964 Declaration of Helsinki and its later amendments or comparable ethical standards.

Consent to participate

Informed consent was obtained from all individual participants included in the study. Participants indicated their consent by selecting “yes” to the statement: “I confirm that I have read and understood the information sheet for the above study and understand what is expected of me.”

Consent for publication

Participants provided consent for their anonymised data to be used in academic dissemination. The consent form included the statement: “I agree to the University of Sunderland recording and processing my data, and that these data may be used in academic outputs (e.g., journal articles, conference presentations, or teaching).”

Availability of data and materials

The datasets generated and/or analysed during the current study are available in the Open Science Framework repository: https://osf.io/ngd5f/ . Materials are not publicly available due to copyright restrictions.

Code availability

The code and codebook used for analysis are available in the Open Science Framework repository: https://osf.io/ngd5f/ .

Author contributions

The first author conceived and designed the study, analysed the data, and wrote the manuscript.

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