COGNITION AND EMOTION
2022, VOL. 36, NO. 7, 1440–1447
https://doi.org/10.1080/02699931.2022.2120850

BRIEF ARTICLE

OPEN ACCESS

# No need to collect more data: ex-Gaussian modelling of existing data (Craig & Lipp, 2018) reveals an interactive effect of face race and face sex on speeded expression recognition

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**ABSTRACT**

The results of a previous study (Craig & Lipp, 2018) into the effects of multiple social category cues (face race and face sex) on facial emotion recognition indicate that face sex dominates face race, and moreover, participant sex differences contribute little to the observed effects. Here, I modelled the same dataset (https://osf.io/rsmxb/) using the ex-Gaussian, a distribution that is 1) well suited to RT data and 2) separates slow from relatively fast influences. Corroborating recent results (Tipples, 2022) current results show larger effects of face sex (for the faces of White individuals) for female participants. Further novel interaction effects were revealed. For example, results support a different time course for the influence of face sex on expression for the faces of Black compared to White individuals.

**ARTICLE HISTORY**
Received 11 May 2022
Revised 17 August 2022
Accepted 30 August 2022

**KEYWORDS**
Facial expressions; reaction times; ex-Gaussian; stereotypes and evaluations

The human face is a rich source of information – on seeing a face we form impressions ("he appears trustworthy"), attribute emotional states ("he looks angry") and infer racial and gender identity. Research indicates that social category information influences speeded expression decisions. For example, when asked to judge whether faces appear angry or happy participants are typically faster to categorise happiness (vs anger) and this effect is larger for female faces compared to male faces (Becker et al., 2007; Bijlstra et al., 2010; Hugenberg & Sczesny, 2006). The effect of face sex has been attributed to evaluative associations (Hugenberg & Sczesny, 2006) whereby female faces have stronger positive associations than male faces. Alternative explanations include gender stereotypes (Bijlstra et al., 2010) and an evolutionary-based, perceptual (structural) explanation (Becker et al., 2007).

Researchers have also found that racial identity influences speeded expression decisions – white participants are faster to identify happiness than anger on the faces of white individuals and conversely, faster to identify anger than happiness on the faces of black individuals (Hugenberg, 2005). Finally, researchers (Craig & Lipp, 2018; Smith et al., 2017) have also examined the combined effects of race and face sex. One general conclusion reached in a recent review (Craig & Lee, 2020) is that the happy-face female bias is generally still observed when the faces of black individuals are presented, although overall, the effect is less consistent when additional social dimensions (e.g. race) are included – effects remain unclear.

Here, using existing data (Craig & Lipp, 2018; Experiment 1b), I illustrate a method for increasing clarity – applying the ex-Gaussian model.

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Supplemental data for this article can be accessed online at https://doi.org/10.1080/02699931.2022.2120850.

### *Review of Craig and Lipp (2018; JESP)*

The data used here from the Open Science Framework (https://osf.io/rsmxb/) – came from a series of studies in which the authors examined the effects of multiple social categories on expression decision times. In the experiment (Craig & Lipp, 2018; Experiment 1b), both face race and face sex were included to contrast 3 accounts of the effects of social category information: 1) separate (additive) effects whereby both race and face sex (separately) interact with expression type 2) category dominance account whereby the data is characterised by a face sex X expression type interaction with a larger happy categorisation advantage for female faces for both White and Black targets 3) an interaction model Target race X Target sex X Emotion with, for example, faster RTs for male-angry vs female-angry faces that are, for example, larger in magnitude for the faces of Black individuals.

The authors (Craig & Lipp, 2018) conducted 3 different RT analyses: traditional ANOVA, Bayes Factor Analyses, and a linear mixed-effects model (LME) that included random effects for both participants and stimuli (face identities). The authors had reported larger effects for female participants in 2 laboratory-based studies with 5 male and 30 female participants in 1 study (Experiment 1a) and 11 male and 26 female participants in a further study (Experiment 2). The data analysed here (Experiment 1b) were from a larger ($n = 66$), gender-balanced sample (32 males) that was designed to investigate the influence of participant sex.

For the ANOVA, the authors (Craig & Lipp, 2018) reported Target race × Emotion and Target sex × Emotion interactions (and a non-significant 3-way interaction). In contrast, for the LME, the Target race × Emotion interaction was no longer significant when incorporating both stimuli and participants as random effects, and similarly, Bayes Factor analyses supported the inclusion of the Target sex × Emotion interaction. The Bayes Factor and LME results support the primacy of face sex for the categorisation of facial expressions whereas the ANOVA results support an additive model, whereby evaluations of face sex and race contribute separate additive effects to facial expression categorisation. Finally, the authors concluded that participant sex did not moderate the influence of social category cues on emotion categorisation.

Although the LME used by the authors (Craig & Lipp, 2018) addresses the problem of generalisability across individuals and stimulus identities (see; DeBruine & Barr, 2021) it does not address another salient challenge for RT data namely, the positive skew of the RT distribution. Modelling the mean of a skewed distribution creates a further problem of generalisability – the mean is not representative of the typical, most frequent response. Approaches to address the skew include applying a data transformation. An alternative to such approaches is to use a response distribution suitable for RT data.

An important distinction can be made between distributional approaches that attempt to efficiently describe the data, such as the ex-Gaussian model (Balota & Yap, 2011) and process models, such as the Drift Diffusion Model (Ratcliff, 1978) that go beyond description. The Diffusion Model is preferable to the descriptive approach because it offers greater insight into the basic mechanism(s) responsible for generating the data – one of the key goals of the scientific endeavour. However, fitting the full Diffusion Model to the current dataset will likely be difficult because the number of observations per cell of the design ($n = 16$) is considered too low fit all 4 parameters of the Diffusion Model (see; Lerche et al., 2017). Therefore, this model will not be described further (for an introduction the Diffusion Model see; Forstmann et al., 2016).

The ex-Gaussian (described below) typically provides an excellent fit to RT data (Luce, 1986) even if the processes generating the parameters of the ex-Gaussian remain unclear (Matzke & Wagenmakers, 2009). Furthermore, the ex-Gaussian has been used to reveal patterns of differences that were not found in the analysis of mean RT (Heathcote et al., 1991). Overall, the ex-Gaussian is an excellent descriptive tool and may help yield insights into the effect of face sex and face race on speeded expression recognition that were absent in previous analyses. Finally, there exists variants of the ex-Gaussian implemented in several software packages that can include the random effect terms for both stimuli (e.g. face identities) and persons (e.g. participants) yielding the same advantage of generalisability as LME analyses.

The ex-Gaussian describes the shape of the typical RT distribution as the sum of independent normal and exponential random variables with the Gaussian component captured by the parameters $\mu$ (mu) and $\sigma$ (sigma) and the long tail captured by $\tau$ (tau). In Figure 1, I have illustrated changes in the 3 parameters of the ex-Gaussian. The broken (dashed) lines illustrate (1) a decrease in mu that typifies

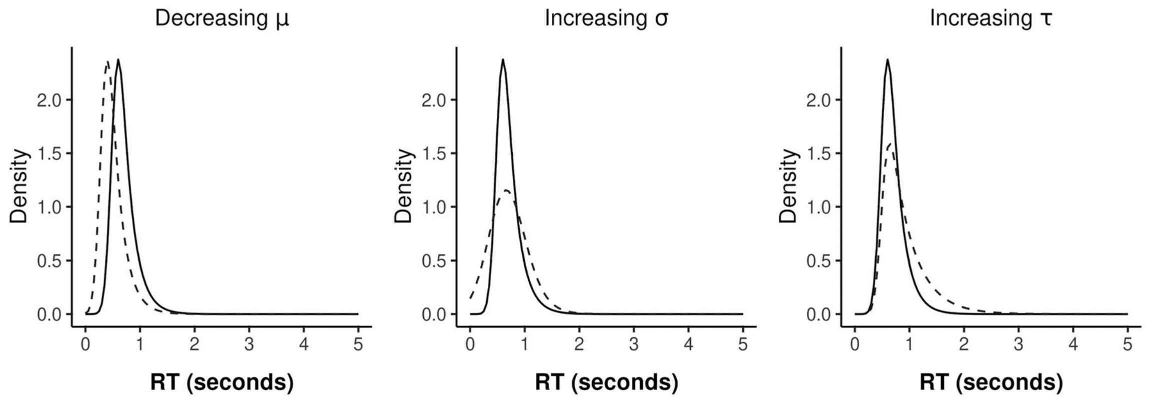


**Figure 1.** An example of changes in the 3 parameters of the ex-Gaussian. Broken (dashed) lines illustrate a decrease (leftward shift) in mu (left), increased sigma (middle) and increased tau, the exponential component (right).

faster RTs (2) increased sigma or more variable RTs (Figure 1, middle), and (3) increased tau, reflecting an increased density of slower RTs (Figure 1, right). Mu reflects RTs that reside in the low to middle percentiles of the RT distribution whereas tau captures RTs in later percentiles. This makes the ex-Gaussian useful for differentiating between effects that occur relatively quickly vs effects that take longer to manifest in RTs.

The results of recent research (Tipples, 2022) illustrate the usefulness of the ex-Gaussian for estimating participant sex differences. Specifically, the study included a multiverse analysis (Steegen et al., 2016) to help establish whether the selection of outlier technique and distribution type might matter for the recording of participant sex differences. The face sex X expression type X participant sex interaction was estimated across 9 outlier removal methods crossed with 5 distribution types. Four of the distribution types (the ex-Wald, ex-Gaussian, shifted Wald, and Wiener/Diffusion) were selected for their suitability for RT analyses. Focusing on multiverse results for the ex-Gaussian, results showed that for the parameter mu, the face sex X expression type interaction was larger in magnitude for female compared to male participants, and moreover, this effect was of similar magnitude across the different outlier removal techniques.

In contrast to the results for the ex-Gaussian, multiverse analyses showed that results of both LME and traditional ANOVA or aggregate RTs were strongly affected by the selection of the RT outlier removal technique. Specifically, when an outlier technique based on the standard deviation was used, the inclusion Bayes Factors for the face sex X expression X participant sex interaction term was inconclusive (BF10 = 0.33–1) – no support for either the model with or the model without the interaction term. However, when one recommended outlier removal approach (Leys et al., 2013) was applied, Bayes Factor indicated "extreme evidence" favouring the inclusion of the same interaction term. In sum, results indicated that testing for the interaction effect of participant sex is best carried out by either applying a suitable response distribution (e.g. the ex-Gaussian) for which outlier removal type is less important or by using one of several recommended outlier removal approaches (Cousineau & Chartier, 2010; Leys et al., 2013; Voss et al., 2015). Here, I choose the former approach (the ex-Gaussian) and used the same outlier approach (correct RTs > 100 ms) adopted previously (Craig & Lipp, 2018).

## Predictions

In previous research (Tipples, 2022), I reported a 3-way expression (happy) X f.sex (male) X p.sex (male) interaction term = -.030, $t = -4.12$, (95% CI[−0.059, −0.015]). The latter, 3-way interaction effect is predicted for the current analyses of existing data. Theoretically, I propose that this is due to the greater activation of evaluative stereotypes ("women are warm and pleasant" and "males are aggressive") for female participants compared to male participants. All other effects (e.g. the 4-way interaction effect, etc.) are exploratory.

### Power and effect size

In terms of statistical power, the value of the t statistic reported previously (Tipples, 2022) for the expression (happy) X f.sex (male) X p.sex (male) interaction for ex-Gaussian analyses was –4.12 and this represents a large between-subjects effect (Cohen's $d = -0.91$) in the difference (between male and female faces) of the differences (between angry and happy expressions). Considering this effect size, power analyses (Faul et al., 2007) indicate that as few as 21 participants for each gender group are required to achieve power .80 with alpha set to .05. In other words, the sample size is sufficient.

### Participants

The participants sampled by the authors (Craig & Lipp, 2018) were 66 Amazon Mechanical Turk workers (32 Males, M = 35.66, SD = 9.74; Experiment 1b). A further 14 participants were not included in analyses because they identified as a member of the racial outgroup.

### Current analytic approach

All code can be found on the Open Science Framework Repository (https://osf.io/ypzuj/?view_only=2ba80e8c80454976a0b381c435bf47cd). I used the same outlier criterion for the ex-Gaussian model reported previously (Craig & Lipp, 2018, p. 30) namely, all correct response times > 100 ms. For the ex-Gaussian analysis, I used the R software package called GAMLSS (Rigby & Stasinopoulos, 2005). GAMLSS permits the inclusion of random effects terms including by-stimulus varying effects. GAMLSS uses maximum likelihood estimation to fit parametric models. Random effects are modelled by applying smoothing to shrink fitted values towards the overall mean (for an introduction see; Mahr, 2021).

For the ex-Gaussian, I regressed the b f.exp (happy) X f.sex(male) X f.race (black) X p. sex (male) interaction term onto mu, sigma, and tau in a single, multilevel regression model. Following past research (Craig & Lipp, 2018), the model included random slopes for all main effects and interactions for participants and both random intercepts and random slopes for emotion effects for the stimuli. In notation used in the popular lme4 R package (Bates et al., 2015):

"RT ~ expression X face sex X face race X participant sex+ (expression X face sex X face race | Participant ID) + (expression | Face ID)"

## Results

Diagnostic plots are provided in the Supplementary Online Material and in Figure 2. The top part of Figure 2 are histograms of empirical RTs overlaid on the ex-Gaussian density curve from fitted parameter values for a participant with a relatively poor model fit (left) and a participant with a relatively good model fit (right). In the lower part of Figure 2, I have plotted RT quantiles for observed data (diamonds) plotted against simulated values (crosses). Simulated RTs ($n = 1000$) were generated from the fitted parameter estimates from the model.

### Preliminary 4-way and 3-way interaction effects

The 4-way, f.sex (male) X f.exp (happy) X f.race (black) X p.sex (male) interaction was significant for mu, $b = 0.067$, 95% CI[0.03, 0.1], $t = 3.90$, $p = .0001$, sigma, $b = 1.24$, 95% CI[1.21, 1.28], $t = 3.43$, $p = .0006$ and tau, $b = -0.48965$, 95% CI[−0.52, −0.46], $t = -2.07$, $p = .03$. For female participants, the 3-way, f. exp (happy) X f.sex (male) X f.race (black) was significant for mu, $b = -0.053$, 95% CI[−0.08, −0.03], $t = -4.38$, $p = .00001$, sigma $b = -1.15$, 95% CI[−1.18, −1.13], $t = -4.57$, $p < .0001$ and tau, $b = 0.4592$, 95% CI[0.44, 0.48], $t = 2.67$, $p = .007$. For male participants, the 3-way, f. exp (happy) X f.sex (male) X f.race (black) interaction was not significant for mu, $b = 0.01464$, 95% CI [−0.01, 0.04], $t = 1.17$, $p = 0.24$, sigma $b = 0.08$, 95% CI [0.06, 0.11], $t = 0.34$, $p = 0.73$ and tau, $b = -0.03044$, 95% CI[−0.05, −0.01], $t = -0.19$, $p = .85$. Considering the non-significant results for male participants (and for the sake of parsimony), I will focus on the results for female participants.

### Two-way interaction and simple effects

The stereotype account compares face sex differences (male vs female) for each emotion separately, whereas the evaluative association account compares expression differences (anger vs happy) for each face sex separately. I report both contrasts following a significant face sex X expression type interaction. In Figure 3 I have plotted the estimated means for female participants for the ex-Gaussian parameters

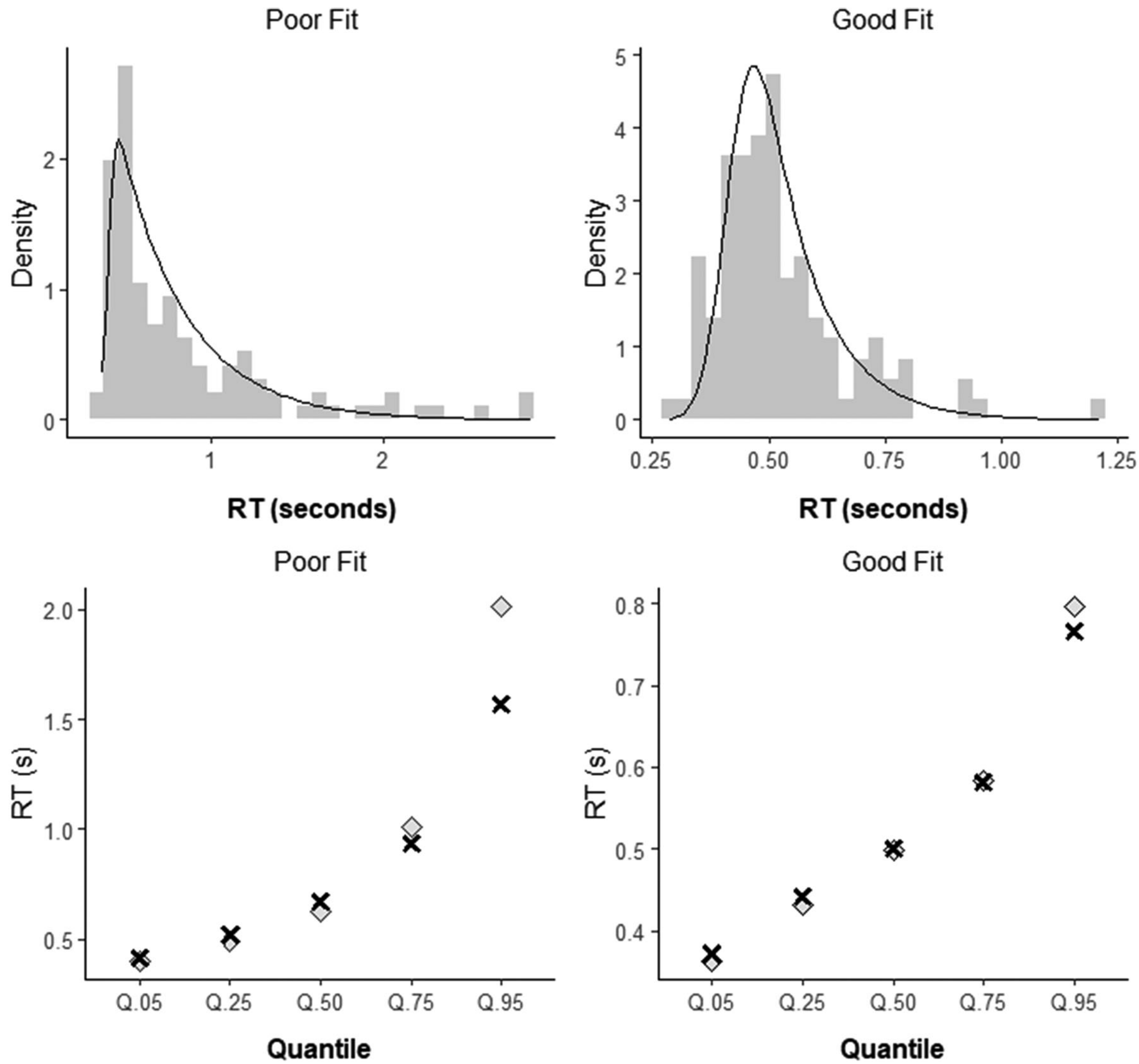


**Figure 2.** Top row – histogram of observed (empirical RTs) and ex-Gaussian density curve (from fitted parameter values) for a participant with a relatively poor model fit (left) and a participant with a relatively good model fit (right). The lower part of the figure shows quantiles for the observed data (diamonds) plotted against simulated values (crosses). Simulated RTs (10,000 iterations per subject and quantile) were generated from the fitted parameter estimates.

mu (a), sigma (b) and tau (c) as a function of expression, face sex and face race.

***Mu - Females (*****Figure 3** ***a).*** For mu, the f. exp (happy) X f.sex (male) interaction was significant for white faces $b = .035$, 95% CI[0.02, 0.05], $t = 4.10$, $p = .00004$ but not black faces, $b = -0.00462$, 95% CI [−0.02, 0.01], $t = -0.5$, $p = .61807$. For white faces, the significant (35 ms) *b* f. exp (happy) X f.sex (male) regression coefficient ($b = 0.0352$, 95% CI[0.02, 0.05], $t = 4.10$, $p = .00004$) showed that the 39 ms facilitation effect for female-happy compared to female-angry expressions ($b = -0.039$, 95% CI[−0.05, −0.03]) was reduced to 4 ms for male faces. Focussing on the face sex difference, results indicate a 19 ms facilitation effect for male-angry compared to female-angry expressions, $b = -0.019$, 95% CI[−0.03, −0.01], $t = -3.30$, $p = .0009$ and reversal of this effect for happy faces, $b = 0.018$, 95% CI[0.008, 0.027], $t = 3.45$, $p = .0001$. For black faces, the face sex difference for angry faces reversed in direction $b = -0.04$, 95% CI [−0.06, −0.03], $t = -5.04$, $p < .0001$ with results indicating slower responses to male-angry compared to female-angry expressions, $b = 0.020$, 95% CI[0.01, 0.03], $t = 3.44$, $p = .0005$. Finally, for black faces, there

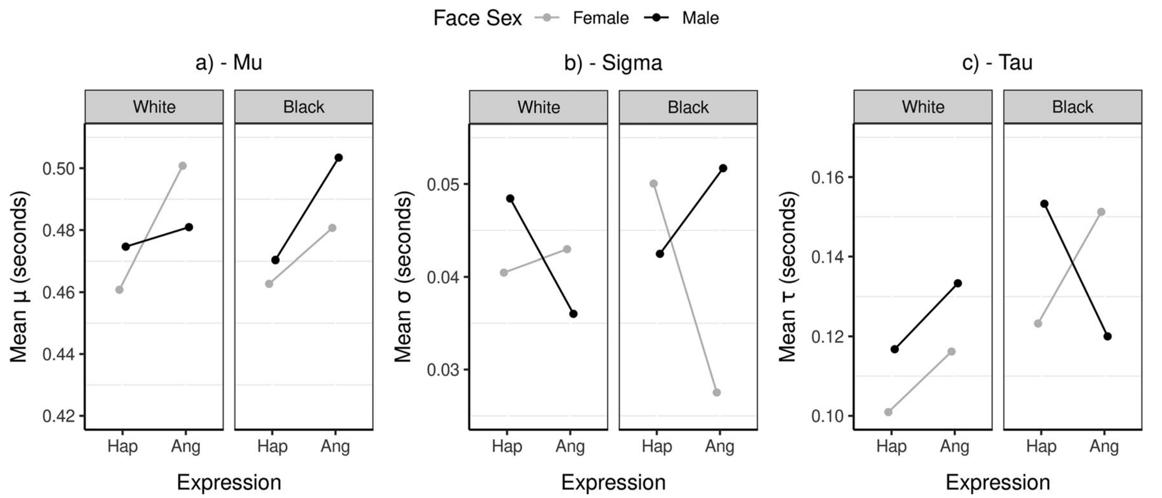


**Figure 3.** The estimated means for female participants for the ex-Gaussian parameters mu (a), sigma (b) and tau (c) as a function of expression, face sex and face race.

was clear happy face facilitation effect for female faces $b = -0.01666$, 95% CI[−0.03, −0.01], $t = -2.88$, $p = 0.004$ which, contrary to the results for white faces, increased (albeit non-significantly) by 4 ms for male faces.

***Sigma - Females* (Figure 3 *b*).** For sigma, the f. exp (happy) X f.sex (male) interaction was significant for both white faces $b = 0.3618$, 95% CI[0.34, 0.38], $t = 2.12$, $p = 0.03$ and black faces $b = -0.59$, 95% CI [−0.62, −0.58], $t = -3.00$ $p = 0.002$. For white faces, simple contrasts were not significant although the pattern of means indicates less variable responses for male-angry compared to female-angry expressions, $b = -0.19$, 95% CI[−0.21, −0.18], $t = -1.57$, $p = 0.11$ and reversal of this pattern for happy faces (e.g. more variable responses to male-happy faces; $b = 0.13$, 95% CI[−0.11, 0.38], $t = 1.08$, $p = 0.27$). For white faces, the significant b f.race (black) = −0.4582, 95% CI[−0.47, −0.45], $t = -3.33$, $p = .0008$ indicated reduced RT variability for female participants responding to black, female-angry faces compared to white, female-angry faces. Focussing on black faces, responses were more variable to female-happy compared female-angry expressions, $b = 0.54487$, 95% CI[0.53, 0.56], $t = 3.73$, $p = .0001$ and this effect was effectively eliminated when the faces were male as indicated by the f. exp (happy) X f.sex (male) interaction reported above. Focussing on face sex differences for black faces, results supported greater variability for responses to male-angry compared to female-angry faces, $b = 0.57$, 95% CI[0.57, 0.59], $t = 3.92$, $p = .00009$.

***Tau – Females* (Figure 3 *c*)** . For the parameter tau, the f. exp (happy) X f.sex (male) interaction was significant for black faces $b = 0.38501$, 95% CI[0.37, 0.4], $t = 3.22$, $p = 0.001$ but not white faces $b = 0.05$, 95% CI [0.04, 0.07], $t = 0.45$, $p = .65$. For female participants, tau was lower for black, female-happy compared to black, female-angry faces $b = -0.20$, 95% CI[−0.21, −0.19], $t = -2.51$, $p = .012$ and this pattern reversed for male faces as indicated by the *b* f. exp (happy) X f.sex (male) = 0.38, 95% CI[0.37, 0.4], $t = 3.22$, $p = .001$. Focussing on face sex differences for female participants responding to black faces, the pattern was reversed to that reported for mu – tau was reduced (indicating a reduction in the slow portion of the RT distribution) for black, male-angry faces relative to black, female-angry faces, $b = -0.20154$, 95% CI [−0.21, −0.19], $t = -2.44$, $p = .014$.

## Discussion

Results highlight the value of considering the distribution of the reaction time data. In contrast to previous LME analyses (Craig & Lipp, 2018) that assumed a Gaussian distribution, interactions between face sex, face race, and participant's sex were recorded when RTs were modelled using an ex-Gaussian distribution. Notably, key effects were larger in magnitude for females compared to males. Basing their conclusions on the same dataset, the authors concluded that the results of their smaller N studies in which they had reported significantly larger effects in female participants (p. 30) "should be interpreted with extreme caution".

The current study shows that this caution is unwarranted. Focussing on mu – ex-Gaussian parameter that relates directly to the results reported in past research where researchers have reported results for mu (the mean) of the normal distribution – results show that effects are larger for female vs male participants. Strikingly, effect sizes (for female participants) are almost identical to those reported in recent research (Tipples, 2022) that reported a 39 ms female-face happy face facilitation effect for female participants that was reduced to 6 ms for male faces. Here, for female participants, the happy face facilitation effect was 39 ms for female faces and 4 ms for male faces. The latter pattern has been interpreted as reflecting stronger positive associations for females relative to males, the "women are wonderful effect" (Hugenberg & Sczesny, 2006). However, for female participants, results for mu also indicate faster responses for stereotype congruent faces relative to stereotype incongruent faces. The latter pattern for angry faces has not always been reported (e.g. Hugenberg & Sczesny, 2006) and can be interpreted as reflecting either activation of a "male-anger" stereotype (Bijlstra et al., 2010; Brooks et al., 2018) or a perceptual process account (Becker et al., 2007) that claims that there exists a physical overlap in the features that define anger and those that define maleness.

All accounts are difficult to apply to the pattern for black faces for female participants. Anger is stereotypically associated with both men (Plant et al., 2000) and Black people (Devine, 1989; table 1) and moreover, from an intergroup perspective, Black men represent a double out-group for white female participants. In other words, evaluative associations for Black, male-angry individuals should be relatively stronger and stereotypes more easily retrieved leading to faster responses to black, male-angry compared Black, female-angry expressions. In contrast, for female participants, for the parameter mu, responses were faster to black, female-angry compared to black, male-angry faces. For the parameter sigma, results indicate the lowest variability for black, female-angry expressions. For the parameter tau (for female participants), a crossover pattern for the face sex X expression was found, with a reduction in the proportion of slow responses for stereotype congruent vs incongruent faces.

Considering the absence of a theoretical account for the pattern of results I will suggest one: The differential effects for white and black faces may reflect an attempt by female participants to inhibit socially undesirable stereotypes of Black individuals. According to this account, inhibition or suppression of stereotypes is successful for most trials as reflected in the pattern for black faces for both mu (e.g. in the form of faster responses to black, female-angry expressions) and sigma (e.g. in the form of reduced variability for stereotype incongruent expressions for sigma). However, on a minority of trials, inhibition will be weak and consequently, stereotypes (e.g. Black males are more likely to display anger) will exert an influence on RTs leading to the same pattern reported for white faces (e.g. faster RTs to male-angry expressions) manifesting in estimates of the parameter tau.

Overall, this analysis breaks new ground and places research on a firm footing to investigate participant sex differences and more specifically, how the influence of face sex on facial expression recognition unfolds across time.

## Disclosure statement

No potential conflict of interest was reported by the author(s).

## Open Science Framework

https://osf.io/ypzuj/?view_only=2ba80e8c80454976a0b381c435bf47cd.

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## References

Balota, D. A., & Yap, M. J. (2011). Moving beyond the mean in studies of mental chronometry. *Current Directions in Psychological Science*, *20*(3), 160–166. https://doi.org/10.1177/0963721411408885

Bates, D., Mächler, M., Bolker, B., & Walker, S. (2015). Fitting linear mixed-effects models using **lme4**. *Journal of Statistical Software*, *67*(1), 1–48. https://doi.org/10.18637/jss.v067.i01

Becker, D. V., Kenrick, D. T., Neuberg, S. L., Blackwell, K. C., & Smith, D. M. (2007). The confounded nature of angry men and happy women. *Journal of Personality and Social Psychology*, *92*(2), 179–190. https://doi.org/10.1037/0022-3514.92.2.179

Bijlstra, G., Holland, R. W., & Wigboldus, D. H. J. (2010). The social face of emotion recognition: Evaluations versus stereotypes.

*Journal of Experimental Social Psychology*, *46*(4), 657–663. https://doi.org/10.1016/j.jesp.2010.03.006

Brooks, J. A., Stolier, R. M., & Freeman, J. B. (2018). Stereotypes bias visual prototypes for sex and emotion categories. *Social Cognition*, *36*(5), 481–493. https://doi.org/10.1521/soco.2018.36.5.481

Cousineau, D., & Chartier, S. (2010). Outliers detection and treatment: A review. *International Journal of Psychological Research*, *3*(1), 58–67. https://doi.org/10.21500/20112084.844

Craig, B. M., & Lee, A. J. (2020). Stereotypes and structure in the interaction between facial emotional expression and Sex characteristics. *Adaptive Human Behavior and Physiology*, *6*(2), 212–235. https://doi.org/10.1007/s40750-020-00141-5

Craig, B. M., & Lipp, O. V. (2018). The influence of multiple social categories on emotion perception. *Journal of Experimental Social Psychology*, *75*, 27–35. https://doi.org/10.1016/j.jesp.2017.11.002

DeBruine, L. M., & Barr, D. J. (2021). Understanding mixed-effects models through data simulation. *Advances in Methods and Practices in Psychological Science*, *4*(1), 251524592096511. https://doi.org/10.1177/2515245920965119

Devine, P. G. (1989). Stereotypes and prejudice: Their automatic and controlled components. *Journal of Personality and Social Psychology*, *56*(1), 5–18. https://doi.org/10.1037/0022-3514.56.1.5

Faul, F., Erdfelder, E., Lang, A.-G., & Buchner, A. (2007). G*power 3: A flexible statistical power analysis program for the social, behavioral, and biomedical sciences. *Behavior Research Methods*, *39*(2), 175–191. https://doi.org/10.3758/BF03193146

Forstmann, B. U., Ratcliff, R., & Wagenmakers, E.-J. (2016). Sequential sampling models in cognitive neuroscience: Advantages, applications, and extensions. *Annual Review of Psychology*, *67*(1), 641–666. https://doi.org/10.1146/annurev-psych-122414-033645

Heathcote, A., Popiel, S. J., & Mewhort, D. J. (1991). Analysis of response time distributions: An example using the stroop task. *Psychological Bulletin*, *109*(2), 340–347. https://doi.org/10.1037/0033-2909.109.2.340

Hugenberg, K. (2005). Social categorization and the perception of facial affect: Target race moderates the response latency advantage for happy faces. *Emotion*, *5*(3), 267–276. https://doi.org/10.1037/1528-3542.5.3.267

Hugenberg, K., & Sczesny, S. (2006). On wonderful women and seeing smiles: Social categorization moderates the happy face response latency advantage. *Social Cognition*, *24*(5), 516–539. https://doi.org/10.1521/soco.2006.24.5.516

Lerche, V., Voss, A., & Nagler, M. (2017). How many trials are required for parameter estimation in diffusion modeling? A comparison of different optimization criteria. *Behavior Research Methods*, *49*(2), 513–537. https://doi.org/10.3758/s13428-016-0740-2

Leys, C., Ley, C., Klein, O., Bernard, P., & Licata, L. (2013). Detecting outliers: Do not use standard deviation around the mean, use absolute deviation around the median. *Journal of Experimental Social Psychology*, *49*(4), 764–766. https://doi.org/10.1016/j.jesp.2013.03.013

Luce, R. D. (1986). *Response times their role in inferring elementary mental organization*. Oxford University Press ; Clarendon Press. http://site.ebrary.com/id/10087174.

Mahr, T. (2021, February 26). *Random effects and penalized splines are the same thing*. Higher-Order Functions. https://tjmahr.github.io/random-effects-penalized-splines-same-thing/.

Matzke, D., & Wagenmakers, E.-J. (2009). Psychological interpretation of the ex-Gaussian and shifted wald parameters: A diffusion model analysis. *Psychonomic Bulletin & Review*, *16*(5), 798–817. https://doi.org/10.3758/PBR.16.5.798

Plant, E. A., Hyde, J. S., Keltner, D., & Devine, P. G. (2000). The gender stereotyping of emotions. *Psychology of Women Quarterly*, *24*(1), 81–92. http://dx.doi.org/10.1111/j.1471-6402.2000.tb01024.x.

Ratcliff, R. (1978). A theory of memory retrieval. *Psychological Review*, *85*(2), 59–108. https://doi.org/10.1037/0033-295X.85.2.59

Rigby, R. A., & Stasinopoulos, D. M. (2005). Generalized additive models for location, scale and shape,(with discussion). *Applied Statistics*, *54*, 507–554.https://doi.org/10.1111/j.1467-9876.2005.00510.x.

Smith, J. S., LaFrance, M., & Dovidio, J. F. (2017). Categorising intersectional targets: An “either/and” approach to race- and gender-emotion congruity. *Cognition and Emotion*, *31*(1), 83–97. https://doi.org/10.1080/02699931.2015.1081875

Steegen, S., Tuerlinckx, F., Gelman, A., & Vanpaemel, W. (2016). Increasing transparency through a multiverse analysis. *Perspectives on Psychological Science*, *11*(5), 702–712. https://doi.org/10.1177/1745691616658637

Tipples, J. (2022). Analyzing facial expression decision times: Reaction time distribution matters. *Emotion*. Advance online publication. https://doi.org/10.1037/emo0001098

Voss, A., Voss, J., & Lerche, V. (2015). Assessing cognitive processes with diffusion model analyses: A tutorial based on fast-dm-30. *Frontiers in Psychology*, *6*, 336. https://doi.org/10.3389/fpsyg.2015.00336.