The Effects of Time Pressure on Temporal Overestimation Due to Threat

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Supplementary Material

Supplementary Material S1

We used a Bayesian multilevel logistic regression model to estimate probable values for the model coefficients – the psychophysical slopes for duration for each condition. Recently, writers have highlighted the benefits of adopting a multilevel approach for the analysis of time perception data (Matthews & Meck, 2014; Moscatelli *et al.*, 2012). In multilevel model estimation fixed effect and individual-level coefficients can mutually influence each other and this means that we can estimate fixed-effect coefficients (often the target for statistical inference) that are not unduly influenced by a single individual's data. The specific benefits of the Bayesian approach are described extensively in other work (Gelman *et al.*, 2014; Kruschke, 2015; McElreath, 2016). For the fitting of psychometric functions the Monte Carlo Markov chain method used in Bayesian estimation has clear computational advantages over estimation approaches as discussed by Kuss and colleagues (Kuss *et al.*, 2005). In summary, the Bayesian multilevel approach has significant appeal for researchers wishing to calculate accurate estimate for coefficients for repeated measures and other multilevel data.

Modelling was carried out in the Stan modelling language (Carpenter *et al.*, 2017) using the brms package (Burkner, 2017) as an interface between Stan and R (R Core Team, 2013). In the Bayesian approach, plausible values of a model parameter (e.g., likely values for the psychophysical slope for duration) are proportional to likelihood of the data (conditioned on the model parameters) multiplied by priors for the parameters. The Bayesian modelling approach uses Markov Chain Monte Carlo (MCMC) sampling to estimate a range of probable values for model parameters. MCMC requires checks for chain convergence.

Priors

We used weakly informative priors for all coefficients. The fixed-effect coefficients for expression and condition (speed, accuracy) and all random effect priors were modelled with priors that were normally distributed with mean 0 and SD 5. The psychometric slope for duration is scaled in milliseconds and therefore, required smaller priors , normally distributed with mean 0.01 and SD 0.01. The fixed-effect intercept is expected to be always negative (on the log odds scale) and was therefore, based on previous research (Tipples, 2015) modelled as normally distributed with mean −5 and SD 5.

Model formulation and selection

The three levels of the multilevel model are trials (Level 1) nested in participants (Level 2) nested in conditions (Level 3). To account for the nesting all models included random intercepts and slopes for expression and duration. For models that included interaction terms we also estimated correlations between random (or varying) slopes and intercepts. This modelling strategy assumes individual differences. Although this may not be warranted for a particular dataset it does provide some continuity with previous research because in previous research (e.g., Tipples, 2011) researchers have routinely calculated indices for each condition nested within each condition before submitting these indices to ANOVA.

In all regression equations both expression (neutral, angry, fearful) and condition (speed, accuracy) were entered as categorical (treatment coded) predictors with the neutral face and accuracy conditions serving as the baseline. Duration was entered as a continuous predictor. Three models were tested. Model 1 was a main-effects model that included expression, duration, and condition as main effects. Model 2 included all possible two-way interactions (and conditional main effects). Model 3 included the three-way interactions: (1) expression (fear vs neutral) × duration (linear) × condition (speed vs accuracy) and (2) expression (angry vs neutral) × duration (linear) × condition (speed vs accuracy) and all conditional interaction and main effect terms. The decision to select the model with three-way interaction terms was based on the theoretical relevance of the three-way interaction terms (they test the central hypothesis that expression moderates the effect of time pressure on the psychophysical slope for duration) and also on statistical criteria, namely, leave-one-out cross-validation (LOO; Vehtari, Gelman, & Gabry, 2017). The model with the smallest LOO value was selected for statistical inference. Model 3 had the smallest LOO value (3322) compared to Model 1 (3323) and Model 2 (3326) and therefore, all statistical inference was carried out on the posterior distribution of the coefficients from Model 3. The estimated regression coefficients (in log units) for the best-fitting model are displayed in Table 1.

Table S1. Group-level posterior estimates (with 95% credibility intervals) for the regression beta coefficients (in log odds) for the best-fitting regression model predicting the probability of responding 'long' as a function of expression (neutral, angry, fearful), duration and condition (speed, accuracy).

Beta coefficient	2.50%	50%	97.50%
Intercept	−8.2365	−7.4274	−6.6851
Expression (angry)	−0.7595	0.0613	0.8899
Expression (fearful)	−0.5725	0.2487	1.0689
Condition (speed, accuracy)	1.2266	2.2361	3.2541
Duration	0.0065	0.0072	0.008
Expression (angry) * Condition	−1.6893	−0.6607	0.341
Expression (fearful) * Condition	−2.1231	−1.1143	−0.1012
Expression (angry) * Duration	−0.0006	0.0002	0.001
Expression (fearful) * Duration	−0.0009	−0.0001	0.0007
Condition*Duration	−0.0025	−0.0014	−0.0004
Expression (angry) * Condition * Duration	−0.0002	0.0008	0.0018
Expression (fearful) * Condition * Duration	0.0003	0.0013	0.0023

Convergence Diagnostics

To assess convergence for the Bayesian hierarchical logistic regression model we calculated the Gelman–Rubin convergence statistic and also carried out visual inspection of three plots of the: (1) trace, (2) autocorrelation and (3) posterior distribution. The Gelman–Rubin statistic requires multiple MCMC runs in order to estimate the ratio of between-chain variance relative to within-chain variance. Chain stability is indicated by values close (+/− 0.01) to 1. Specifically, the Gelman–Rubin statistic was calculated by running two MCMC chains composed of 1000 samples as a burn-in (to increase chain stability) and a subsequent 6000 iterations to estimate the posterior distribution of each parameter. For all models, the Gelman–Rubin statistic was close to 1 (+/– 0.01).

To illustrate convergence for the Bayesian hierarchical logistic regression model, in Figure S1, the trace (top), posterior distribution (middle) and autocorrelation (bottom) for the MCMC chains for (from left to right) the intercept (left), duration and expression*duration*condition interaction fixed-effect coefficients are plotted.

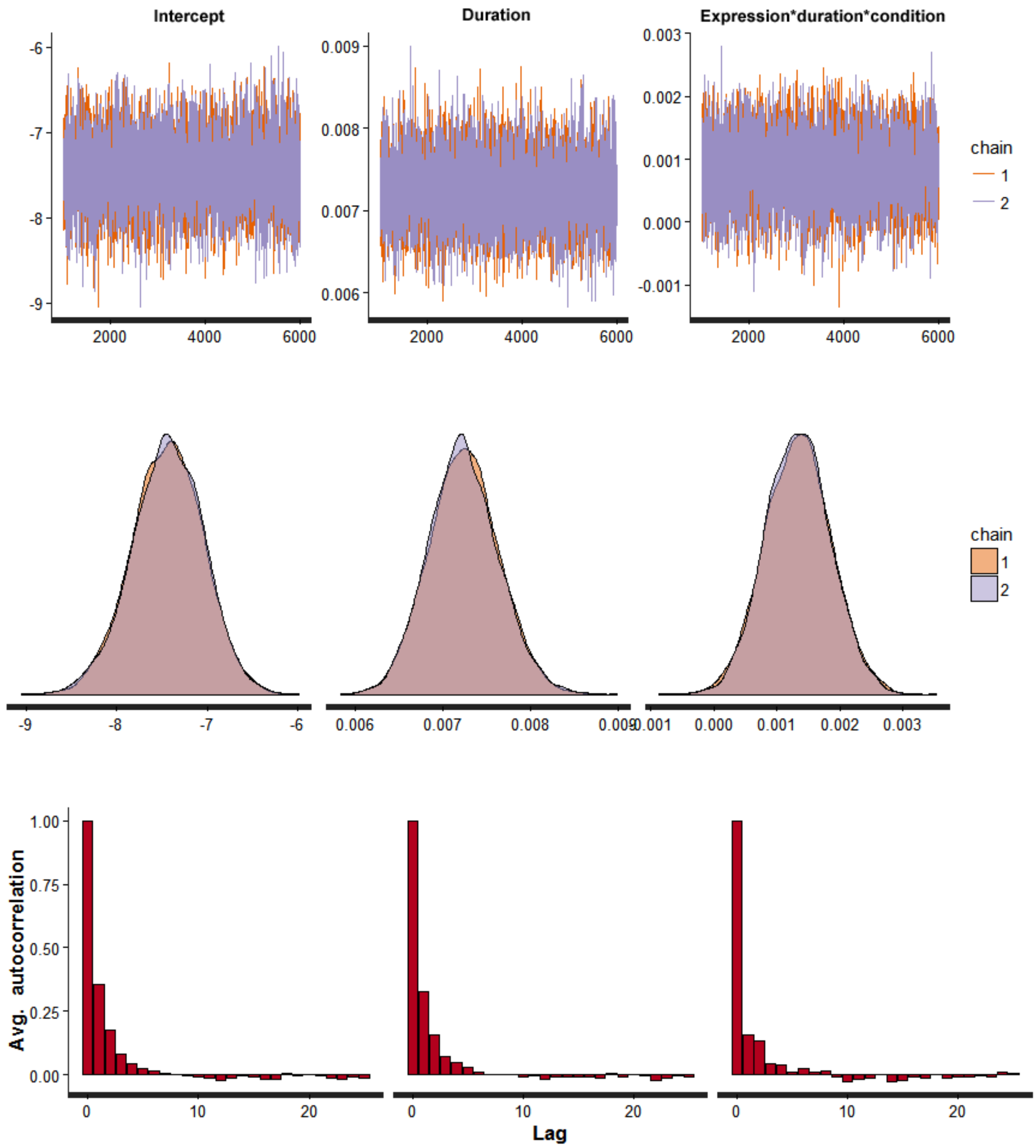

Figure S1. Graphical checks for convergence for the Bayesian Hierarchical Logistic Regression Model. The figure shows the trace (top), posterior distribution (middle) and autocorrelation (bottom) for all two MCMC chains each 6000 iterations long for the intercept (left), duration and expression*duration*condition interaction fixed-effect coefficients.

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Supplementary Material S2

Frequentist Analyses

To permit comparison with previous research that has not used the Bayesian approach we also conducted frequentist (non-Bayesian) analyses. Specifically, we estimated a psychometric curve for each person for each expression and condition, by modelling the number of long responses using a binomial generalized linear model (GLM) with a logistic link function in R (R Core Team, 2018. R: A Language and Environment for Statistical Computing. R Foundation for Statistical Computing, Vienna, Austria. https://cran.r-project.org). Then, the bisection point (BP) and Weber Ratio (WR) were calculated in the same way (described in the text) used to calculate these indices for the Bayesian Model. Both the BPs and WRs were subjected to a mixed ANOVA with expression (angry, fearful, neutral) as the within-subjects variable and condition (accuracy, speed) as the between-subjects variable. The Greenhouse–Geisser correction for sphericity was applied to the degrees of freedom. For the analyses of BPs there was a clear main effect of condition ($F_{1,68} = 182$, $p < 0.001$), reflecting lower BPs for the speed ($M = 877$) compared to the accuracy condition ($M = 1027$). There was also a main effect of expression ($F_{1.92,130.69} = 4.73$, $p = 0.01$), reflecting lower bisection points for angry ($M = 932$) compared to the neutral expression ($M = 973$; $t_{69} = 3.53$, $p = 0.0009$). The contrast between neutral and fearful expressions ($M = 951$) was not significant ($t_{69} = 1.61$, $p = 0.11$). The expression × condition interaction was also not significant for BPs ($F_{1.92,130.69} = 0.65$, $p = 0.51$). For the analyses of WRs, the expression × condition interaction was significant ($F_{1.79,121.45} = 3.65$, $p = 0.03$). There was a simple main effect of expression in the speed condition ($F_{1.61, 54.84} = 5.75$, $p = 0.009$) but not the accuracy condition, $F_{1.82,61.85} = 0.31$, $p = 0.71$. In the speed condition, WRs were lower (indicating higher temporal sensitivity) for fearful ($M = 0.18$) compared neutral expressions (M = 0.23; t_{34} =2.12, p < 0.05). WRs were also lower for angry (M = 0.19) compared to neutral expressions although the effect approached rather than reached significance (t_{34} =1.84, p = 0.07). Overall, the pattern of results matches the Bayesian analyses.