Supplementary Materials for "Scaling Cognitive Modeling to Big Data: A Deep Learning Approach to Studying Individual Differences in Evidence Accumulation Model Parameters"

Mischa von Krause[1] and Stefan T. Radev[2]

[1]Heidelberg University

[2]Rensselaer Polytechnic Institute

Supplementary Materials for "Scaling Cognitive Modeling to Big Data: A Deep Learning Approach to Studying Individual Differences in Evidence Accumulation Model Parameters"

Bayesian Workflow

We present and visualize the details of our Bayesian pipeline, which follows a principled workflow (Schad et al., 2021) and is divided into four key steps. Here we show the results of all four steps for each of the three evidence accumulation models we used for parameter estimation after our model comparison.

Domain Expertise Consistency

Prior predictive checks help evaluate whether a model is consistent with domain expertise. These checks are usually performed in one of two contexts: i) within the prior space, or ii) within the data space. The latter, often called a prior pushforward check, involves drawing a sample from the prior and using it to generate a synthetic dataset based on the sampled parameters. To verify consistency with domain knowledge, we apply the following plausibility assessments and visualizations.

1) For all cognitive models, we used broad, but mildly informative priors based on the EAM literature (Lerche & Voss, 2019; Lerche et al., 2017; Matzke & Wagenmakers, 2009; von Krause et al., 2022; Voss et al., 2013; Wiecki et al., 2013). These priors make no assumptions about differences between experimental conditions (congruent vs. incongruent) or different types of stimuli (words vs. pictures) meaning that any observed differences after estimation will be driven solely by the data. Additionally, the broader prior for non-decision times in incorrect trials, relative to correct trials, reflects the characteristics of the IAT task, as explained in *Cognitive Models* above. There is one dependency between the priors of two parameters: in order to avoid negative non-decision times, the variability in correct non-decision times cannot be larger than two times the (mean) correct non-decision times.

All priors are specified in Table S1. Figures S1, S2, and S3 shows the univariate and

bivariate prior distributions, separately for the $\text{DDM}_{s\tau s\nu}$, the LFM, and the GSR model.

	Prior Distribution
All models	
ν	$Gamma(2.0, 1.0)$
a	$Gamma(6.0, 0.3)$
$\tau_{correct}$	$Gamma(3.0, 0.15)$
τ_{error}	$Gamma(3.0, 0.5)$
$\text{DDM}_{s\tau\nu}$ (and GSR model)	
s_τ	$Uniform(0.0, \tau_{correct} * 2)$
s_ν	$Half - Normal(0.0, 1.0)$
LFM	
α	$Trunc.Normal(1.5, 0.5,\ 1.0\ to\ 2.0)$
GSR model	
γ	$Beta(3.0, 3.0) - 0.5) * 2$

Table S1

Prior distributions of all cognitive model parameters. DDM = diffusion decision model; GSR model = geometric similarity representation model; ν = drift rate for the congruent condition or the incongruent condition (in DDM and LFM); for picture trials or word trials (in GSR model); a = boundary separation for the congruent condition or the incongruent condition; τ = non-decision time for correct or error responses; s = variability in drift rates or correct non-decision times. α = parameter governing the within-trial noise distribution in the LFM (see Cognitive Models); γ = similarity parameter from the GSR model (see the Methods section of the main text). Shared parameters have the same priors across EAMs.

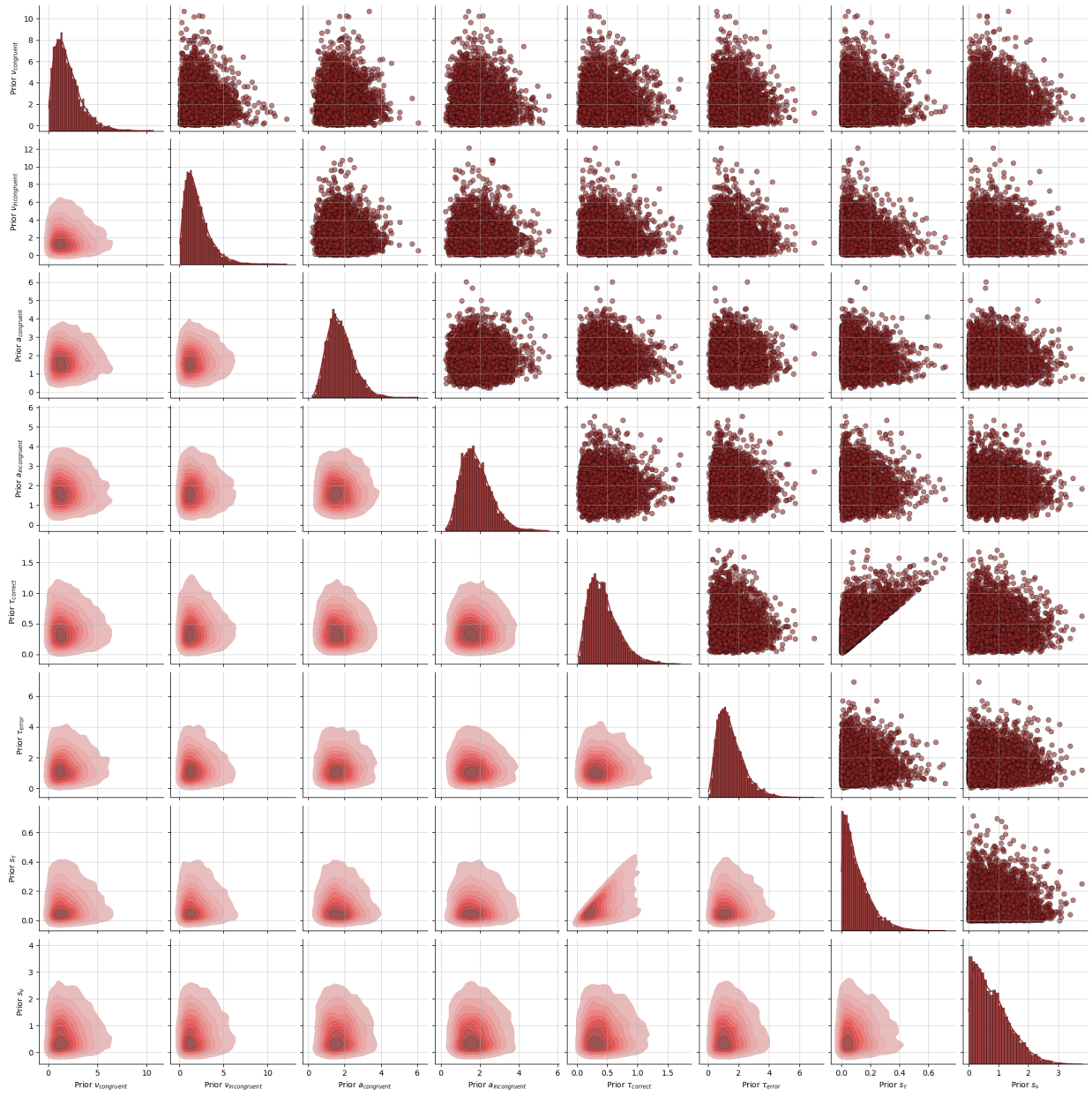


Figure S1

Prior distributions for the $DDM_{s\tau sv}$. 5000 prior samples drawn. The diagonal shows the univariate prior distributions, while the off-diagonal subplots show the bivariate prior distributions (KDE plots on the left, scatter plots on the right side of the diagonal).

2) We used prior pushforward checks in order to ensure that our priors and models generate response time data similar to what is typically found in empirical studies. Figures S4, S5, and S6 show the pushforward densities of mean response times for the three EAMs. The results broadly align with what is typical for the IAT. Error response times are on

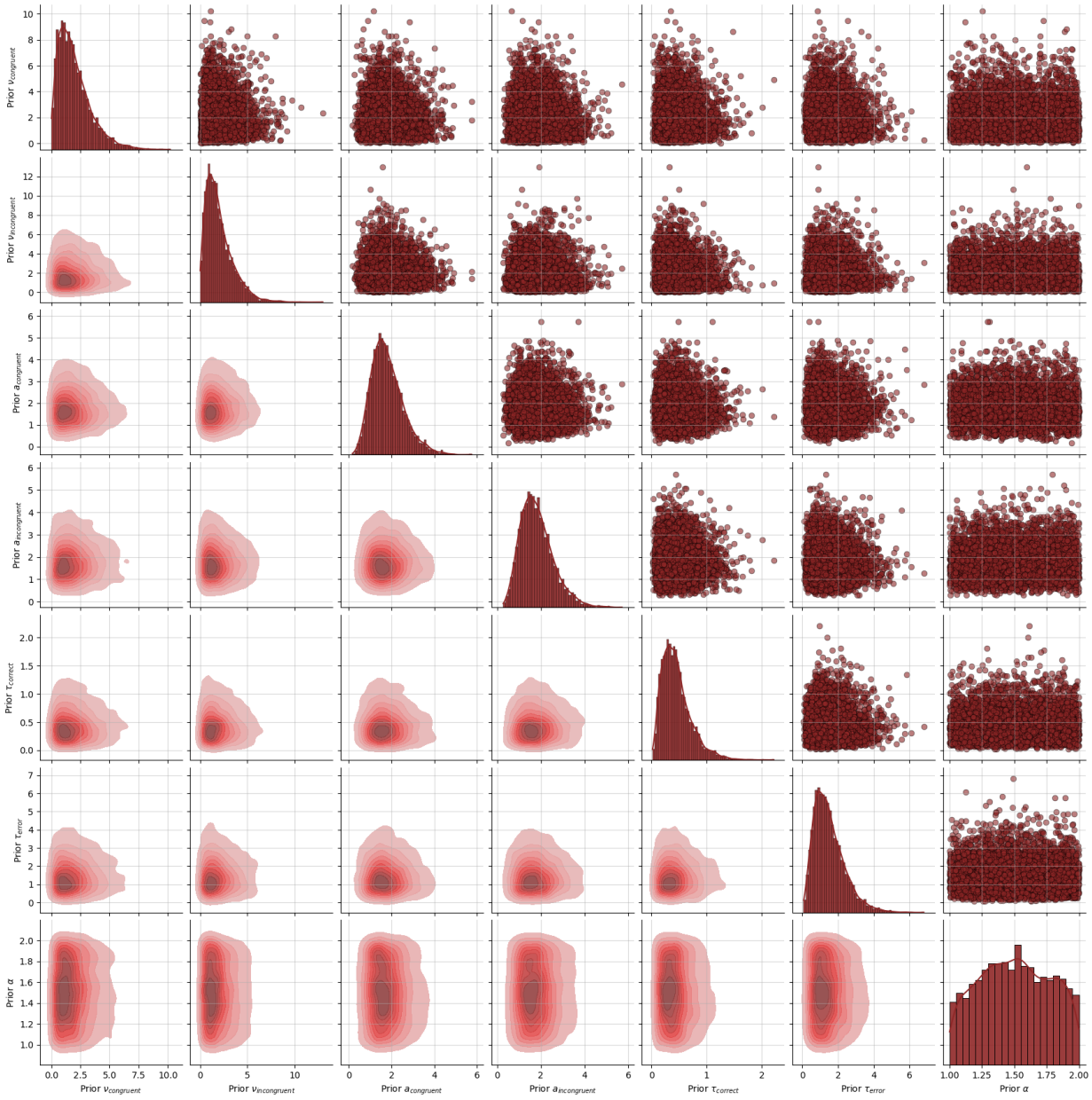


Figure S2

Prior distributions for the LFM. 5000 prior samples drawn. The diagonal shows the univariate prior distributions, while the off-diagonal subplots show the bivariate prior distributions (KDE plots on the left, scatter plots on the right side of the diagonal).

average slower than correct response times, as implied by the experimental setup. There are no noticeable differences between the model-implied mean response times of the three EAMs.

Figures S7, S8, and S9 show the model-implied mean accuracy rates. They are

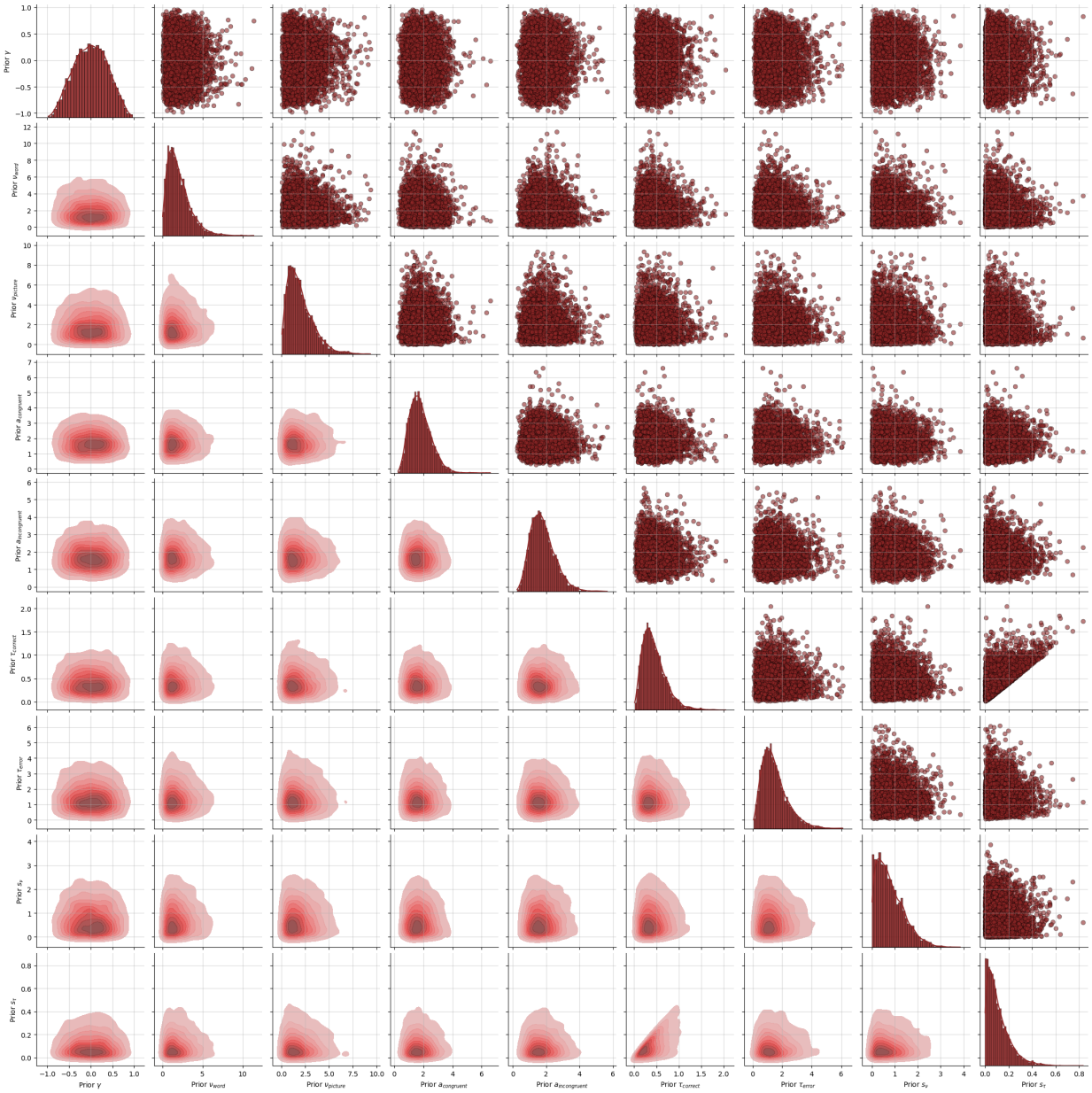


Figure S3

Prior distributions for the GSR model. 5000 prior samples drawn. The diagonal shows the univariate prior distributions, while the off-diagonal subplots show the bivariate prior distributions (KDE plots on the left, scatter plots on the right side of the diagonal).

generally high, as is also the case for the IAT task. It is also evident that the models do not a priori imply differences in accuracy between the two experimental conditions.

Finally, we conduct prior pushforward checks focusing on higher moments of the predicted RT distributions, specifically standard deviations and skewness. The resulting

pushforward distributions are presented in Figures S10, S11, and S12 for standard deviations; Figures S13, S14, and S15 show the results for skewness. Our prior selection suggests a reasonable level of variability in individual RTs, with sufficient breadth to account for participants exhibiting considerable response time variability. Additionally, higher variability is anticipated in incorrect responses. As expected, we generally observe a positive skewness in the response time distributions, aligning with trends found in numerous empirical RT studies. For error response times, the skewness is slightly lower due to the large influence of error non-decision times.

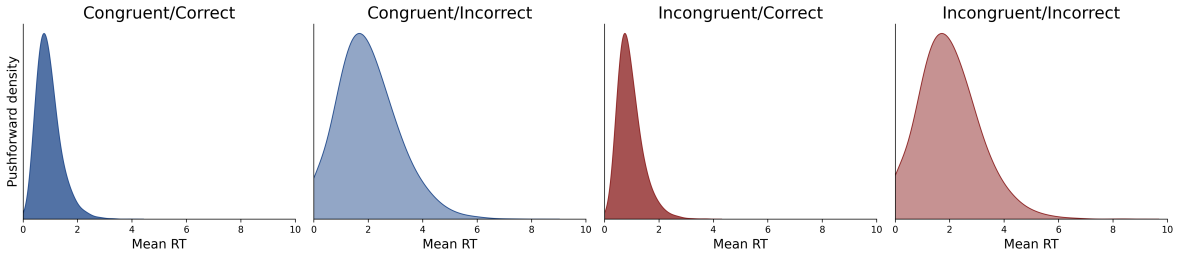


Figure S4

Mean response times from 10,000 simulations generated based on the prior distributions for the $DDM_{s\tau sv}$. Data are split by experimental condition (congruent/incongruent) and accuracy. Smoothed density functions plotted.

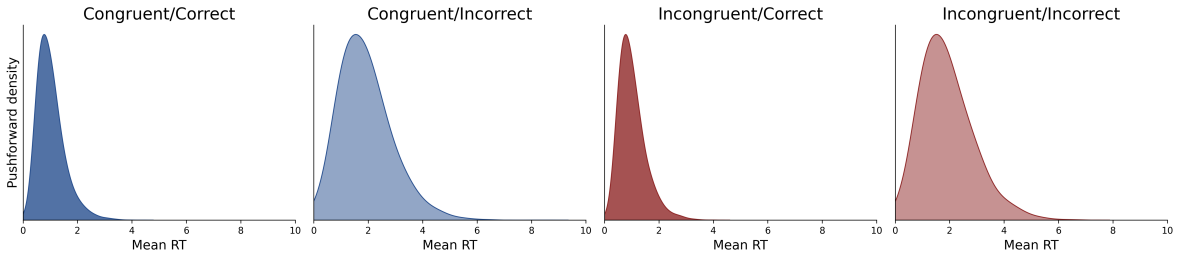


Figure S5

Mean response times from 10,000 simulations generated based on the prior distributions for the LFM. Data are split by experimental condition (congruent/incongruent) and accuracy. Smoothed density functions plotted.

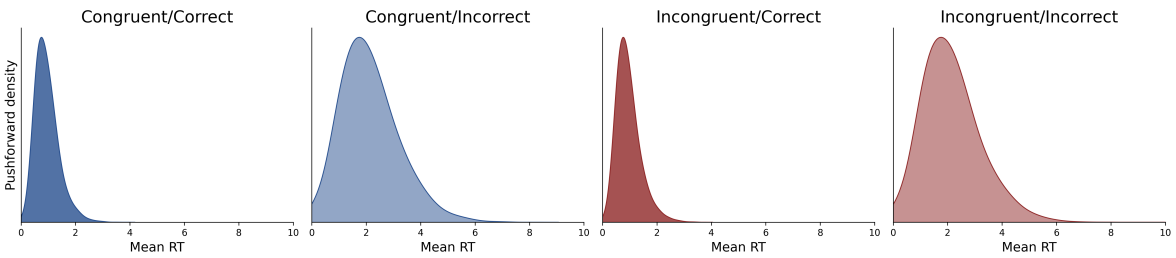


Figure S6

Mean response times from 10,000 simulations generated based on the prior distributions for the GSR model. Data are split by experimental condition (congruent/incongruent) and accuracy. Smoothed density functions plotted.

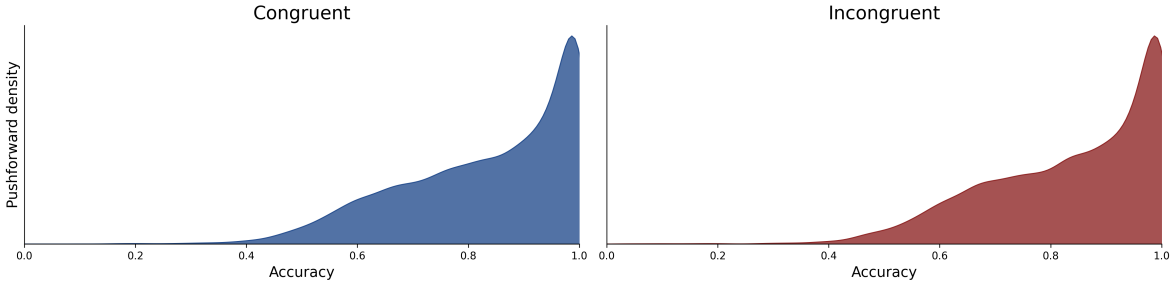


Figure S7

Mean accuracy from 10,000 simulations generated based on the prior distributions for the $DDM_{s\tau sv}$. Data are split by experimental condition (congruent/incongruent). Smoothed density functions plotted.

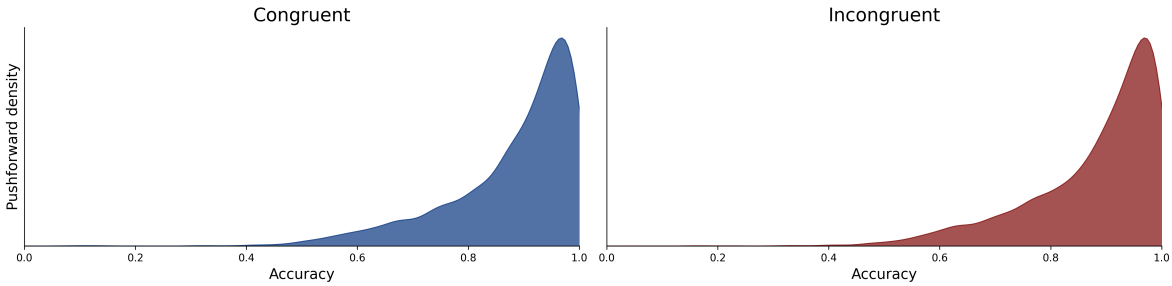


Figure S8

Mean accuracy from 10,000 simulations generated based on the prior distributions for the LFM. Data are split by experimental condition (congruent/incongruent). Smoothed density functions plotted.

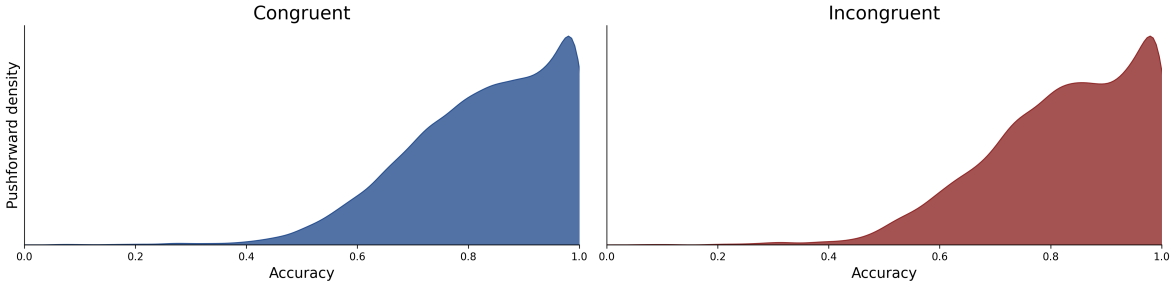


Figure S9

Mean accuracy from 10,000 simulations generated based on the prior distributions for the GSR model. Data are split by experimental condition (congruent/incongruent). Smoothed density functions plotted.

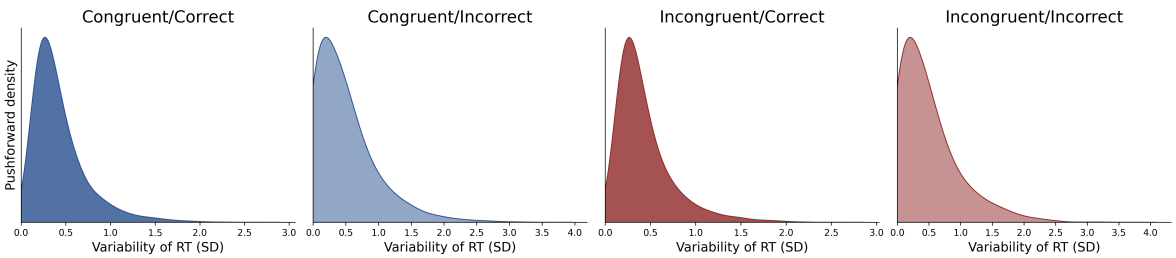


Figure S10

Standard deviations in response times from 10,000 simulations generated based on the prior distributions for the $DDM_{s\tau sv}$. Data are split by experimental condition (congruent/incongruent) and accuracy. Smoothed density functions plotted.

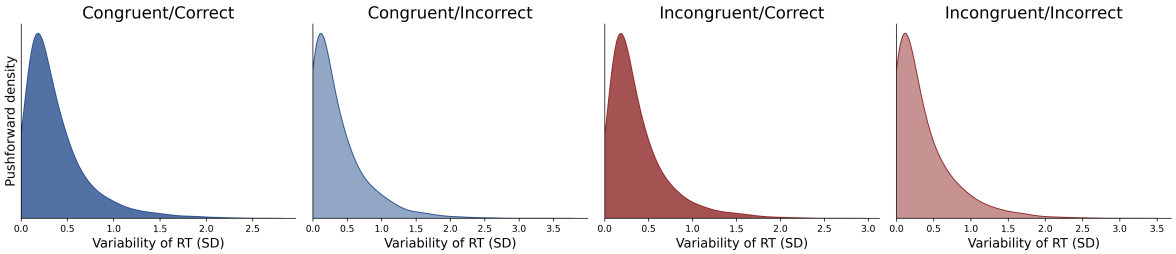


Figure S11

Standard deviations in response times from 10,000 simulations generated based on the prior distributions for the LFM. Data are split by experimental condition (congruent/incongruent) and accuracy. Smoothed density functions plotted.

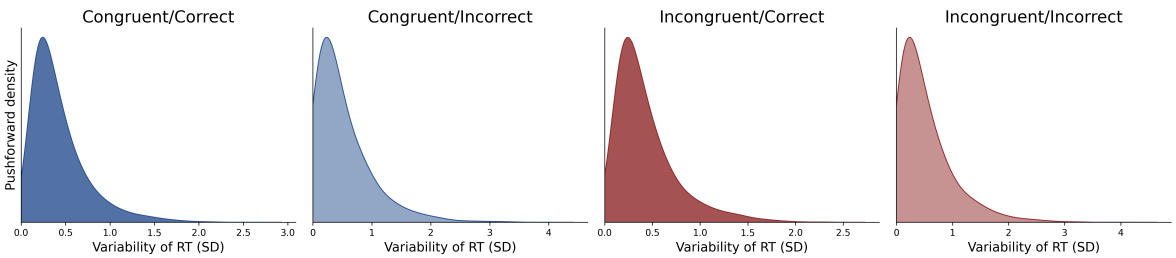


Figure S12

Standard deviations in response times from 10,000 simulations generated based on the prior distributions for the GSR model. Data are split by experimental condition (congruent/incongruent) and accuracy. Smoothed density functions plotted.

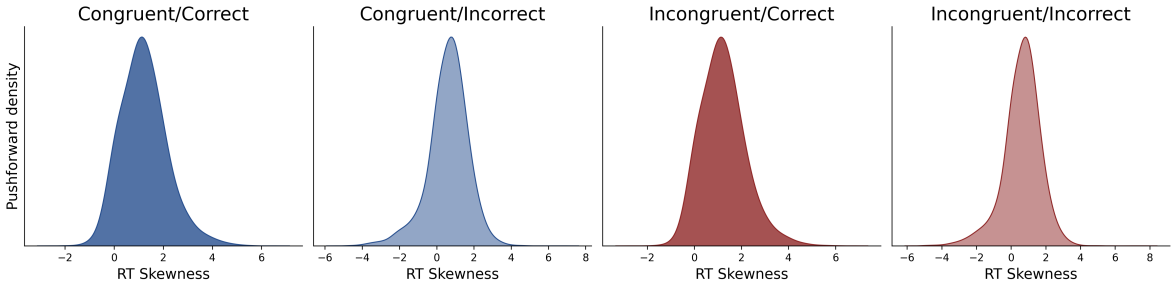


Figure S13

Skew in response times from 10,000 simulations generated based on the prior distributions for the $DDM_{s\tau sv}$. Data are split by experimental condition (congruent/incongruent) and accuracy. Smoothed density functions plotted.

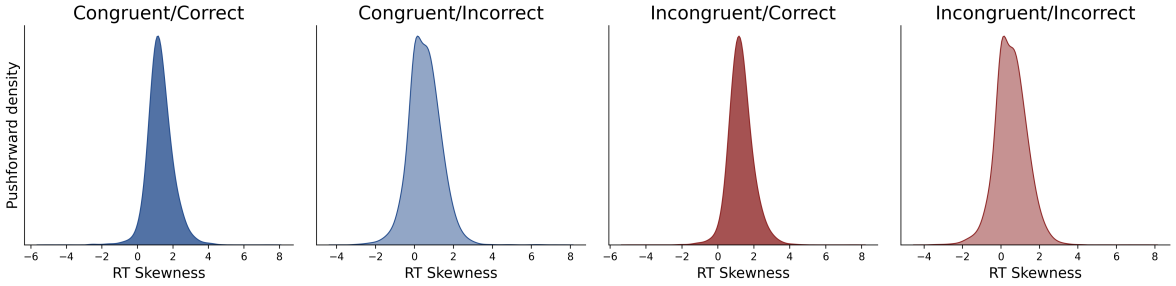


Figure S14

Skew in response times from 10,000 simulations generated based on the prior distributions for the LFM. Data are split by experimental condition (congruent/incongruent) and accuracy. Smoothed density functions plotted.

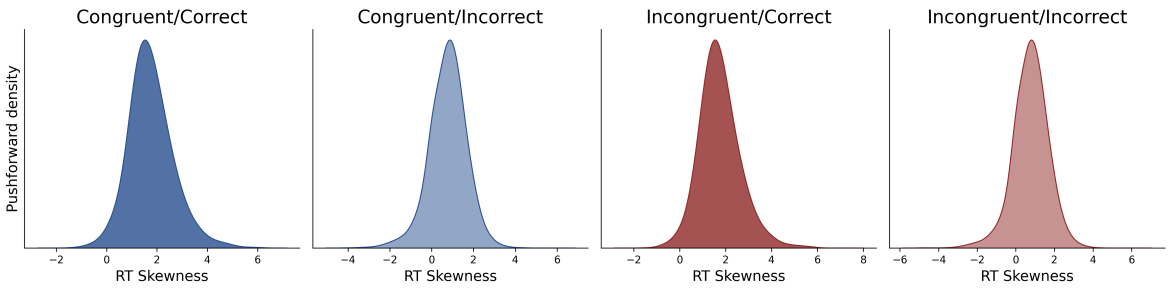


Figure S15

Skew in response times from 10,000 simulations generated based on the prior distributions for the GSR model. Data are split by experimental condition (congruent/incongruent) and accuracy. Smoothed density functions plotted.

Computational faithfulness

Computational faithfulness refers to a Bayesian method's ability to accurately recover the true target posterior in a given modeling scenario. BayesFlow supports fully amortized inference, enabling efficient simulation-based calibration (SBS; Säilynoja et al., 2022; Talts et al., 2020), a technique that helps identify potential biases in posterior estimation. After training the neural networks, we performed 500 simulations using the respective EAM and collected 3000 posterior samples for each simulated dataset. As we were primarily interested in the person-specific posterior medians of cognitive model parameters which tend to stabilize under relatively low numbers of samples for approximately Gaussian posteriors, more posterior samples would not have provided any substantial benefits. In addition, ABI evades potential chain convergence issues, as it provides independent draws from the approximate posterior. The ECDF plots of the resulting rank statistics, shown in Figures S16, S17, and S18 reveal no noticeable global biases in either posterior location or dispersion, as the rank ECDF plots always remain within the 95% confidence bands. This suggests that posterior credibility intervals are well-calibrated.

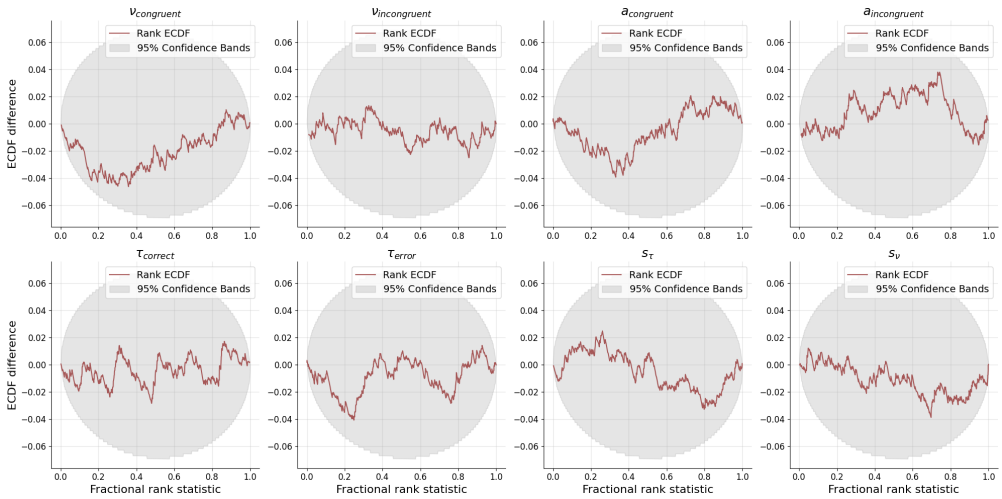


Figure S16

Rank ECDF (empirical cumulative distribution function) plots for the $DDM_{s\tau sv}$. Red lines staying within the gray area indicate good calibration for all parameters.

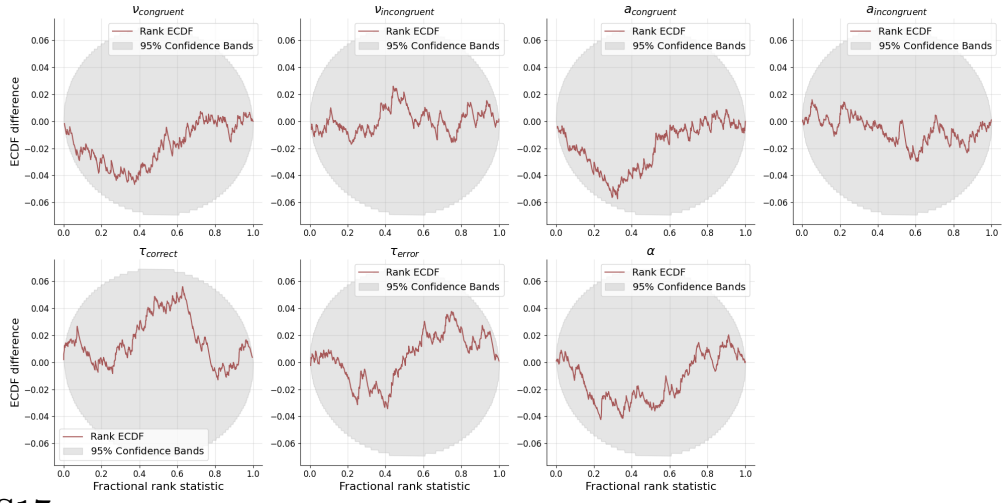


Figure S17

Rank ECDF (empirical cumulative distribution function) plots for the LFM. Red lines staying within the gray area indicate good calibration for all parameters.

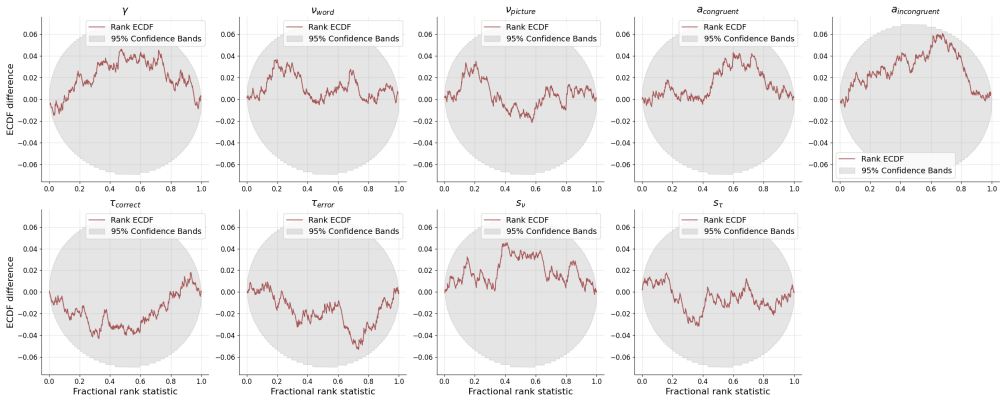


Figure S18

Rank ECDF (empirical cumulative distribution function) plots for the GSR model. Red lines staying within the gray area indicate good calibration for all parameters.

Model Adequacy/Sensitivity

To ensure that the trained networks can estimate the parameters of all models with sufficient accuracy *in silico*, we inspect and quantify the relationships between ground-truth parameter values and posterior summaries (e.g., posterior means) on a set of 500 test simulations. Parameter recovery was generally very good, with most correlations between *true* and *estimated* parameters $r > .90$. Some τ_{error} values could not be recovered as the simulated data contained no error trials. Parameter recovery was not ideal for the α parameter from the LFM and for the inter-trial variability parameters, particularly s_ν. This is to be expected, as these parameters generally require a larger number of experimental trials per person to be estimated with greater precision, regardless of the parameter estimation method (Lerche et al., 2017; Ratcliff & Rouder, 1998; Voss et al., 2019). Figures S19, S20, and S21 show parameter recoveries for the three EAMs.

We also inspected the posterior contraction plots, which depict the posterior z-scores along the contraction of the marginal posterior distributions relative to the prior distributions. The plots thus reveal the degree to which the marginal distributions envelop the ground-truth parameter values. Posterior contraction was generally high, with the exception of α and the variability parameters, which can only be estimated more precisely with a larger number of experimental trials. Figures S22, S23, and S24 show the posterior

contractions across the three EAMs.

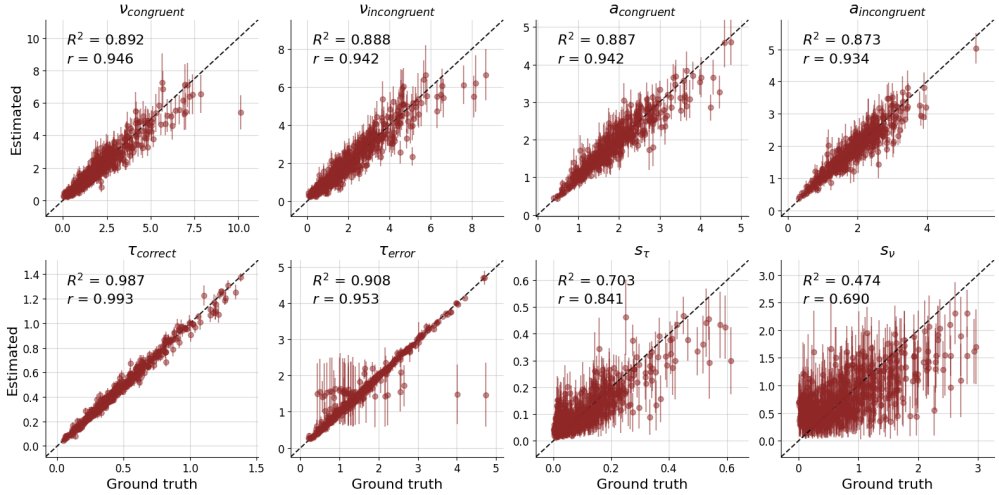


Figure S19

Recovery plot for the $DDM_{s\tau sv}$. Scatter plot showing the ground truth vs. estimated parameters. Dots index the posterior means, bars the posterior standard deviations of individual parameter estimates.

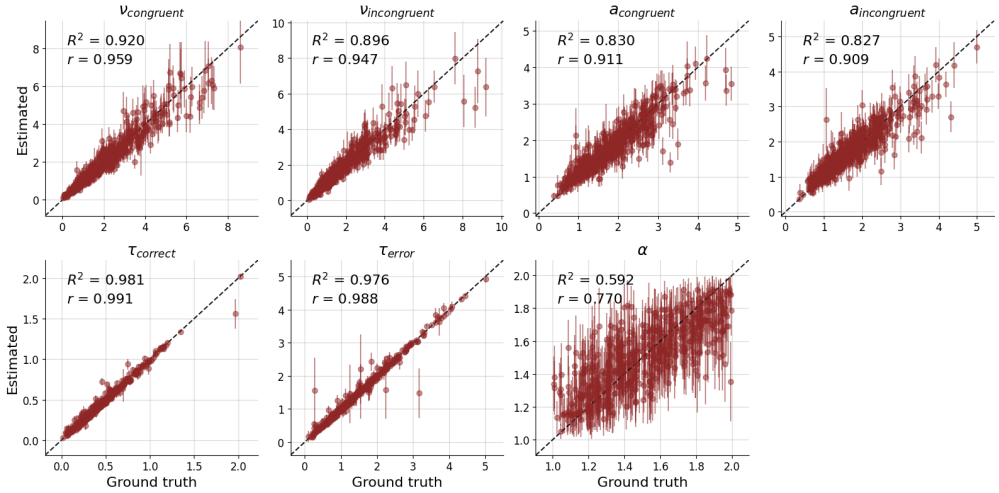


Figure S20

Recovery plot for the LFM. Scatter plot showing the ground truth vs. estimated parameters. Dots index the posterior means, bars the posterior standard deviations of individual parameter estimates.

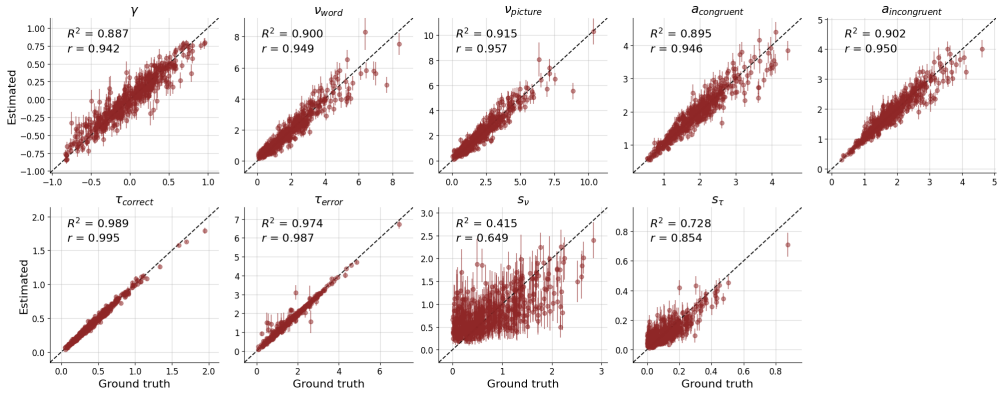


Figure S21

Recovery plot for the GSR model. Scatter plot showing the ground truth vs. estimated parameters. Dots index the posterior means, bars the posterior standard deviations of individual parameter estimates.

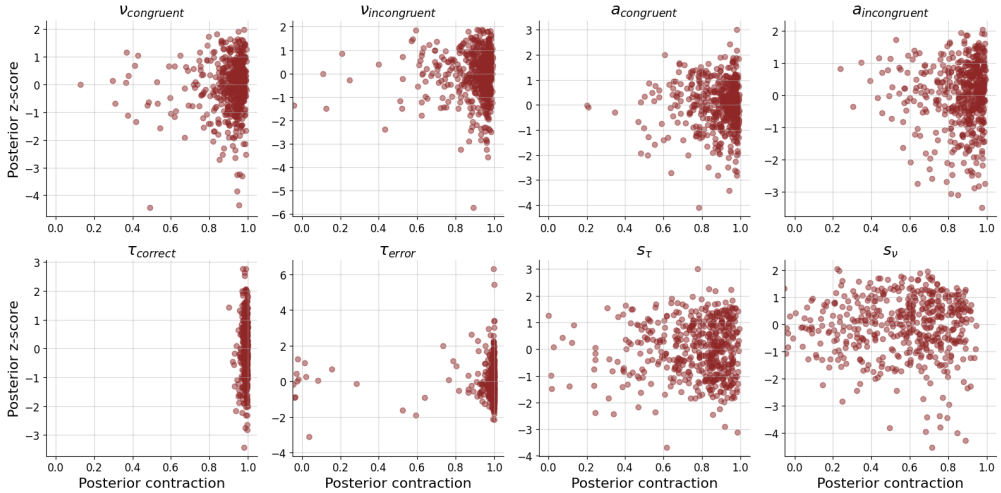


Figure S22

Posterior contraction plot for the $DDM_{s\tau sv}$. Dots toward the left side of the subplots indicate little posterior contraction compared to the priors, where the networks are not able to extract information on the parameter values from the data. This is, for example, the case for error non-decision times in data sets that contain little to no error responses.

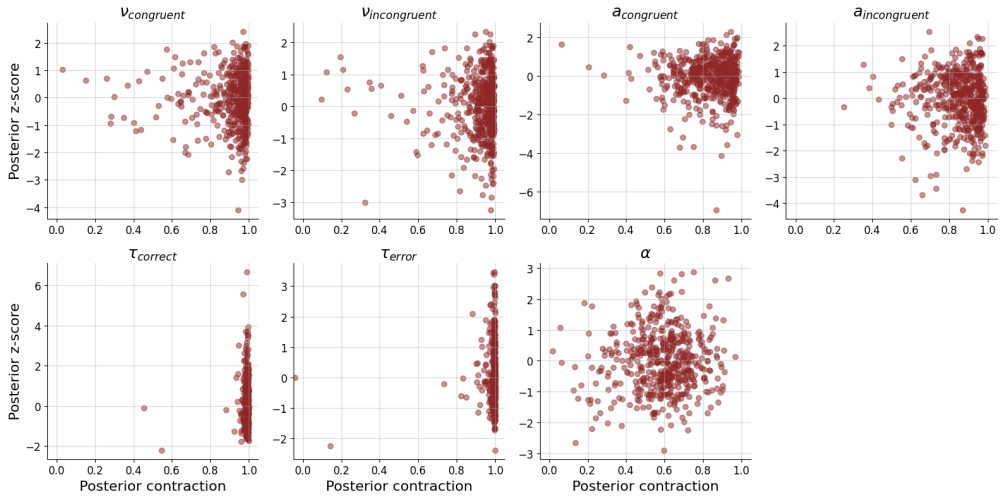


Figure S23

Posterior contraction plot for the LFM. Dots toward the left side of the subplots indicate little posterior contraction compared to the priors, where the networks are not able to extract information on the parameter values from the data. This is, for example, the case for error non-decision times in data sets that contain little to no error responses.

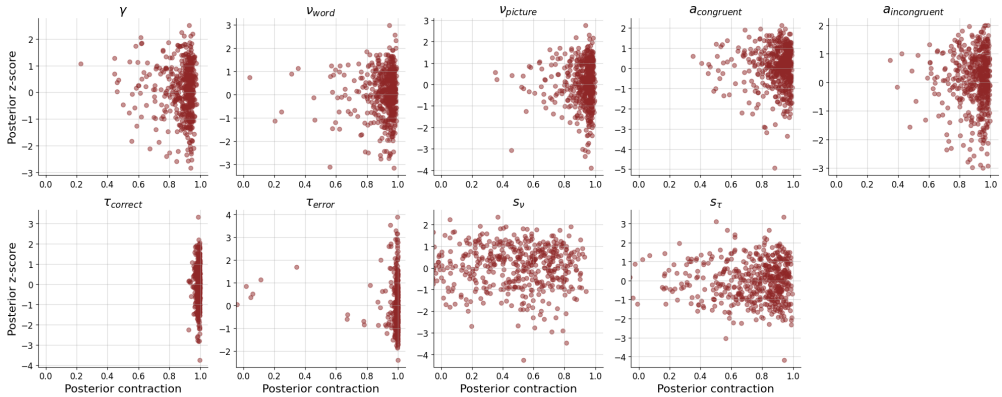


Figure S24

Posterior contraction plot for the GSR model. Dots towards the left side of the subplots indicate little posterior contraction compared to the priors, where the networks are not able to extract information on the parameter values from the data. This is, for example, the case for error non-decision times in same data sets that contain little to no error responses.

Neural network sensitivity analysis. To safeguard against the possibility that our parameter estimates might be specific to the neural network trained, we used the same simulations to train two different neural networks independently. We then used both neural networks to obtain parameter estimates for one randomly chosen actual IAT dataset file (11, 893 participants). Figures S25, S26, and S27 show the scatter-plots of posterior means for all parameters from the three EAMs. Across-network agreement is generally very high, with the more slightly noisy scatter-plots for the τ_{error}, s_v and α parameters explainable through their lower recoverability.

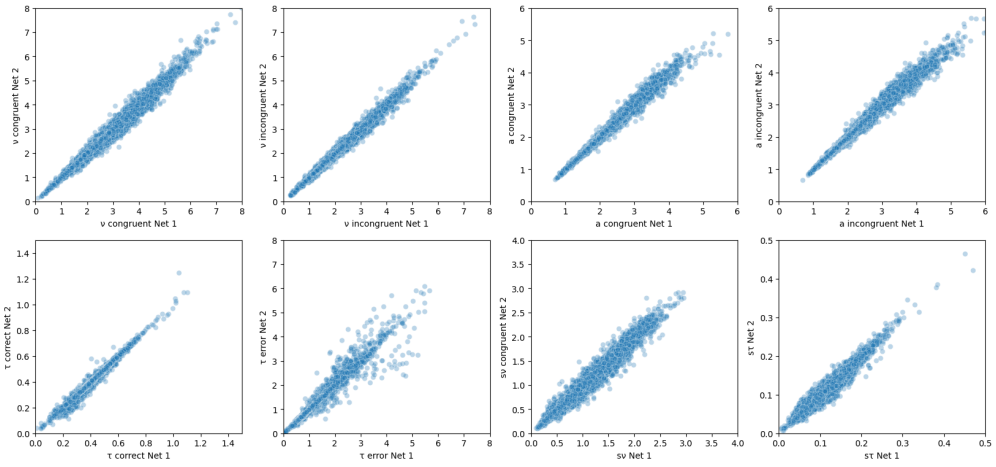


Figure S25
Ensemble agreement plot for the $DDM_{s\tau sv}$.

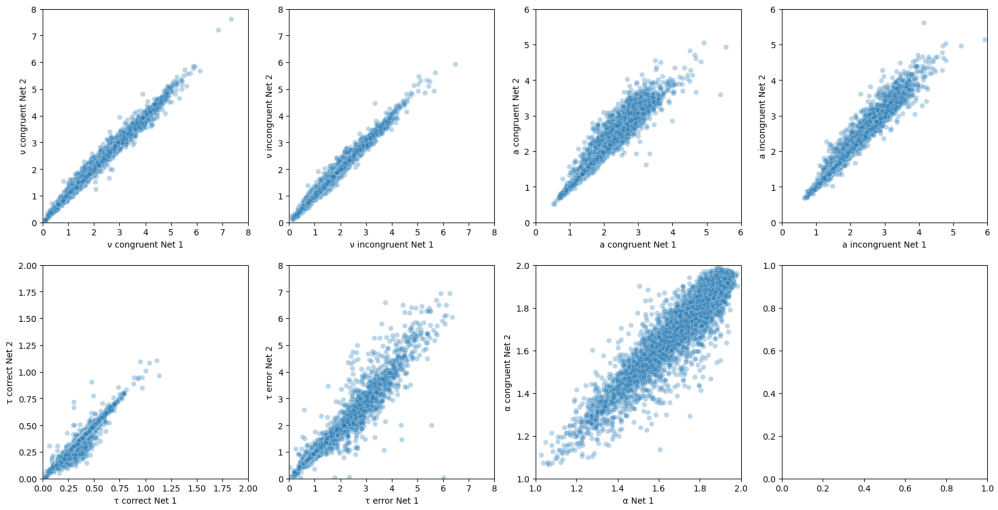


Figure S26
Ensemble agreement plot for the LFM.

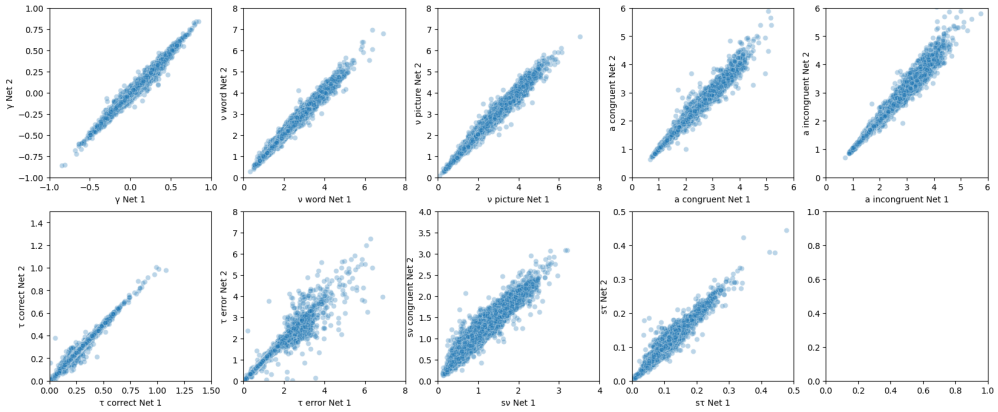


Figure S27
Ensemble agreement plot for the GSR model.

Retrodictive performance/Model fit

Finally, we performed posterior "retrodictive checks" for accuracy and RT across the three EAMs. These checks assess the ability of our models to fit and reproduce the empirical data. To this end, we chose, for each of the the EAMs, $10,000$ random cases from the actual empirical IAT data. For these cases, we took the estimated EAM parameters and used these to generate new, synthetic response time datasets. We then compared the empirical response time quartiles for correct and error responses, as well as the accuracy rates, with those obtained from the simulated data. We did this separately for the congruent and incongruent experimental condition, and also separately for trials with picture stimuli and word stimuli.

Figures S28, S29, and S30 show the model-implied vs. the empirical correct response times. Note that plot opacity is high to account for the large number of cases plotted (10,000). In all three EAMs, the response time quartiles from simulated data closely map those of the empirical data in the overwhelming majority of cases. Figures S31, S32, and S33 show the model-implied vs. the empirical error response times. While the retrodictive performance of our models is also good for error response times, there are also some cases where the empirical response times quartiles could not be recovered. This is to be expected due to low average number of errors in the data, with sometimes only one or two errors per person. In these cases, both the empirical and simulated error response time quartiles are unstable. Finally, figures S34, S35, and S36 show the model-implied vs. the empirical accuracy rates. As already noted, accuracy was generally high, in most cases $> 90\%$. The EAMs were able to reproduce the empirical accuracy rates neatly, with most points being close to the main diagonal of the plot. It is interesting to note that the $\text{DDM}_{s\tau s\nu}$ and LFM could recover the accuracy rates in the congruent and incongruent condition slightly better, while the GSR could recover the accuracy rates specific to word and picture trials slightly better. This reflects the fact that the models contain different types of drift rates relating to these respective conditions.

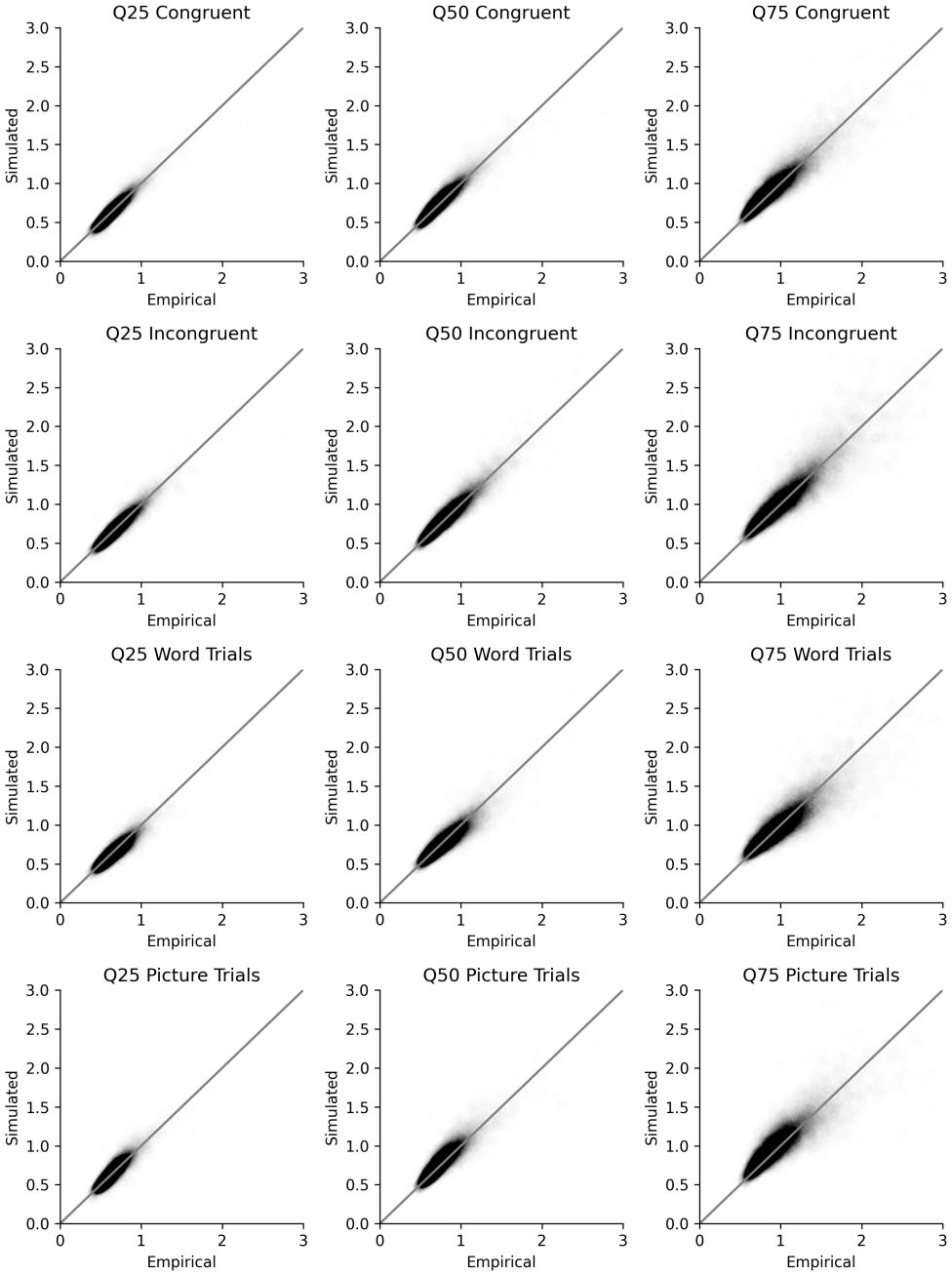


Figure S28

Predictive performance plot for correct response time quartiles for the $DDM_{s\tau s\nu}$. Subplots show the RTs split up by experimental condition (congruent/incongruent) and by stimulus type (word/picture). 25th, 50th, and 75th RT percentiles in empirical vs. re-simulated data shown. Opacity is lowered due to the very high number of points plotted.

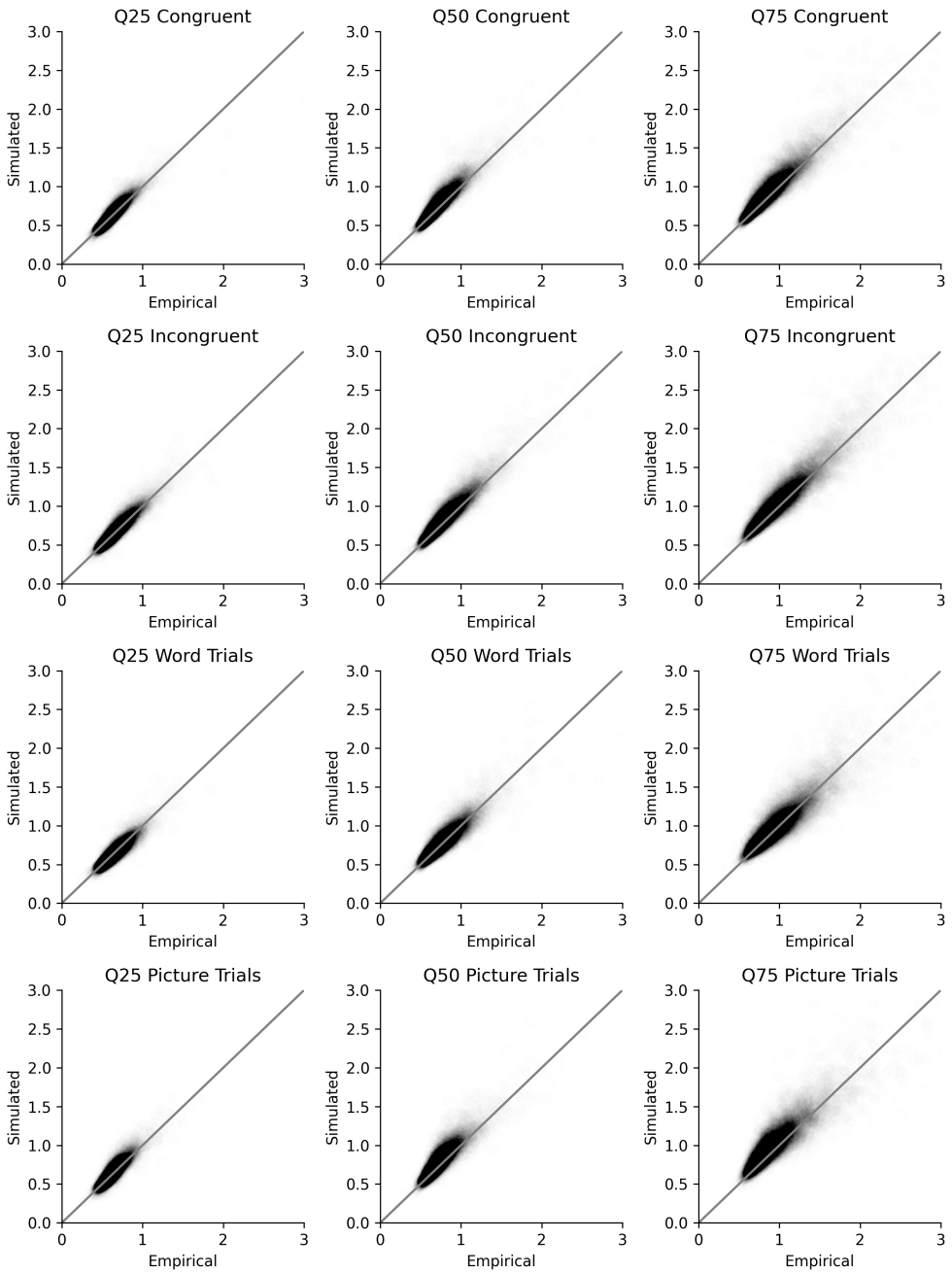


Figure S29

Predictive performance plot for correct response time quartiles for the LFM. Subplots show the RTs split up by experimental condition (congruent/incongruent) and by stimulus type (word/picture). 25th, 50th, and 75th RT percentiles in empirical vs. re-simulated data shown. Opacity is lowered due to the very high number of points plotted.

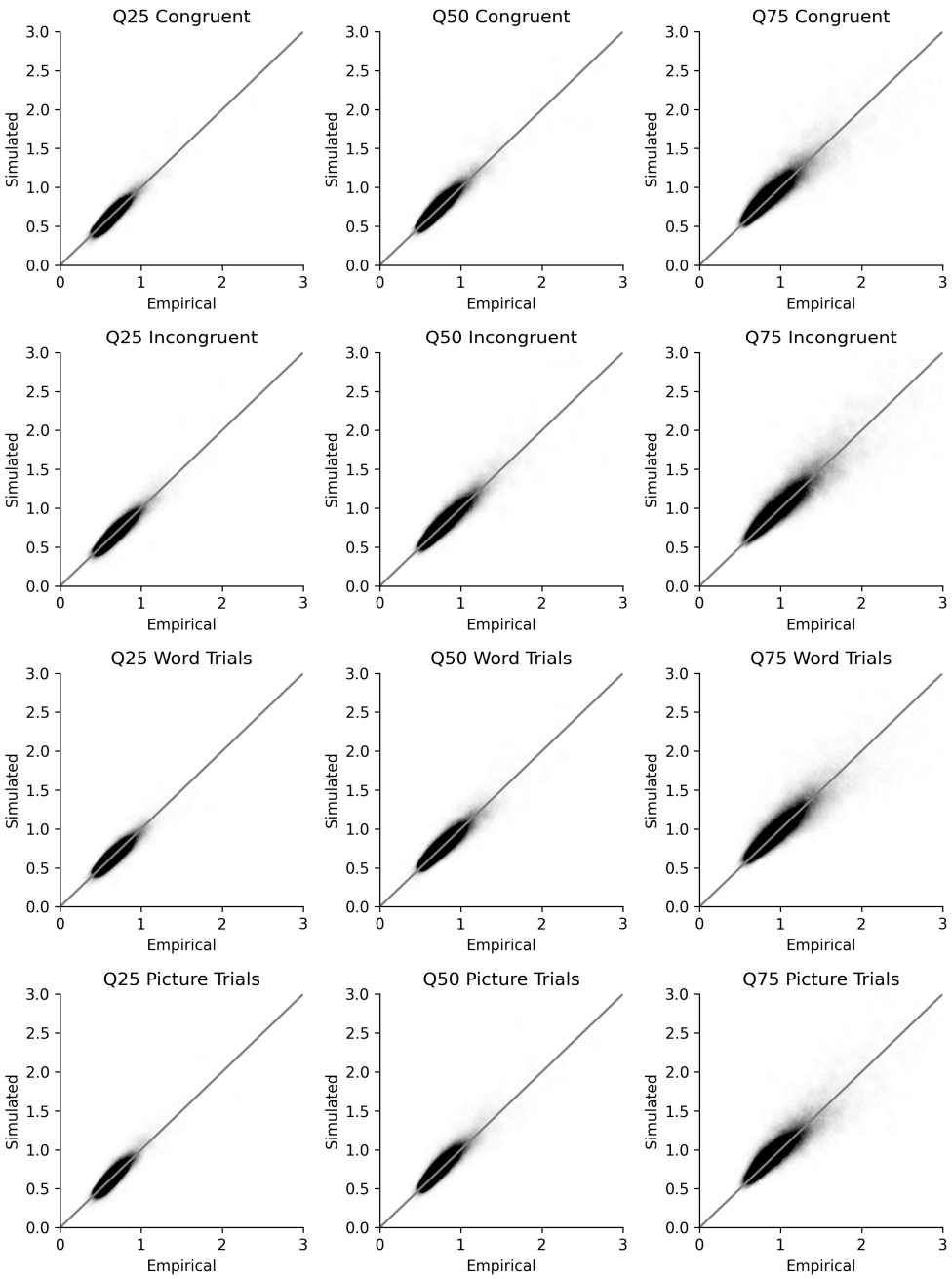


Figure S30

Predictive performance plot for correct response time quartiles for the GSR model. Subplots show the RTs split up by experimental condition (congruent/incongruent) and by stimulus type (word/picture). 25th, 50th, and 75th RT percentiles in empirical vs. re-simulated data shown. Opacity is lowered due to the very high number of points plotted.

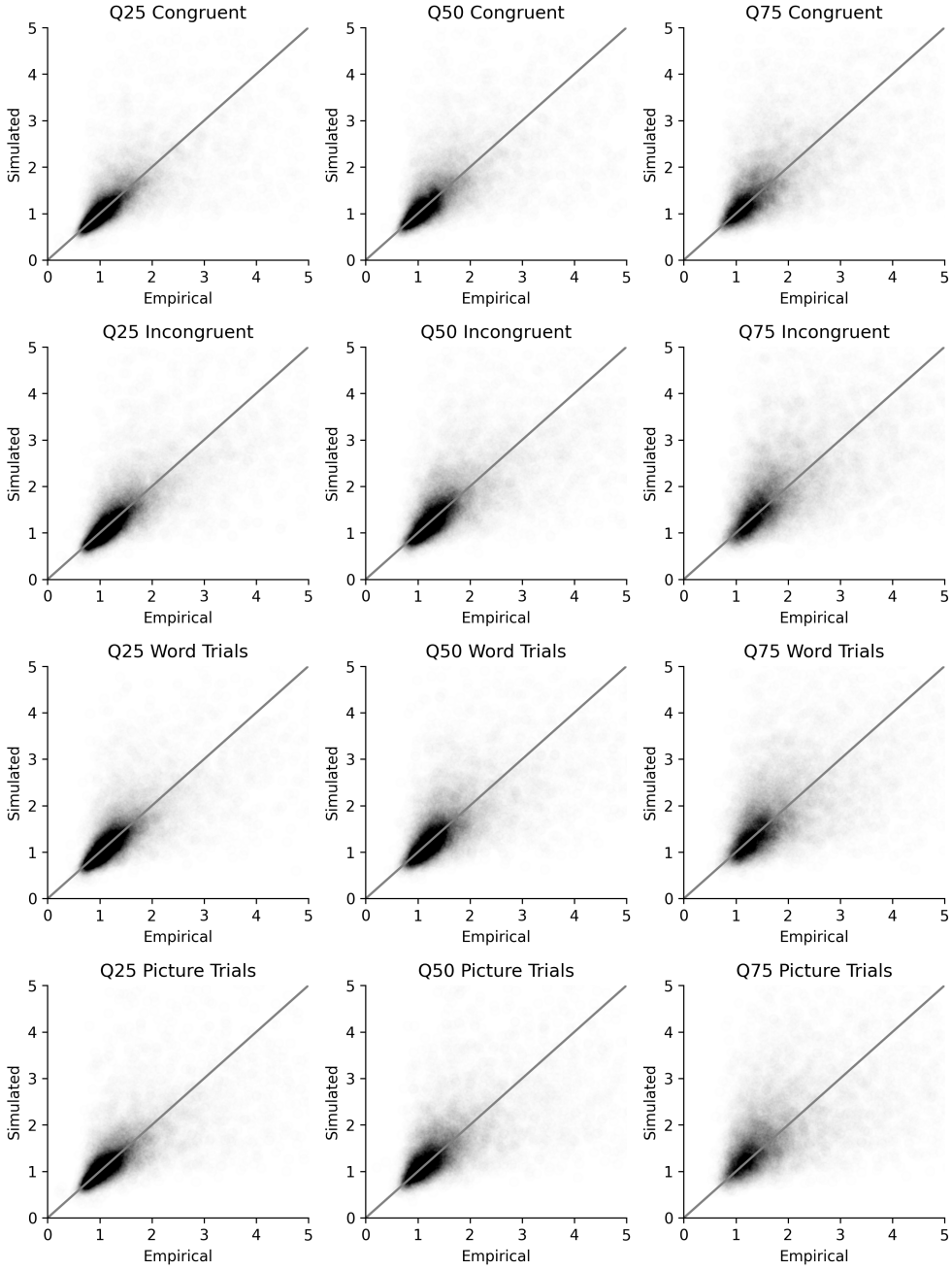


Figure S31

Predictive performance plot for error response time quartiles for the $DDM_{s\tau s\nu}$. Subplots show the RTs split up by experimental condition (congruent/incongruent) and by stimulus type (word/picture). 25th, 50th, and 75th RT percentiles in empirical vs. re-simulated data shown. Opacity is lowered due to the very high number of points plotted.

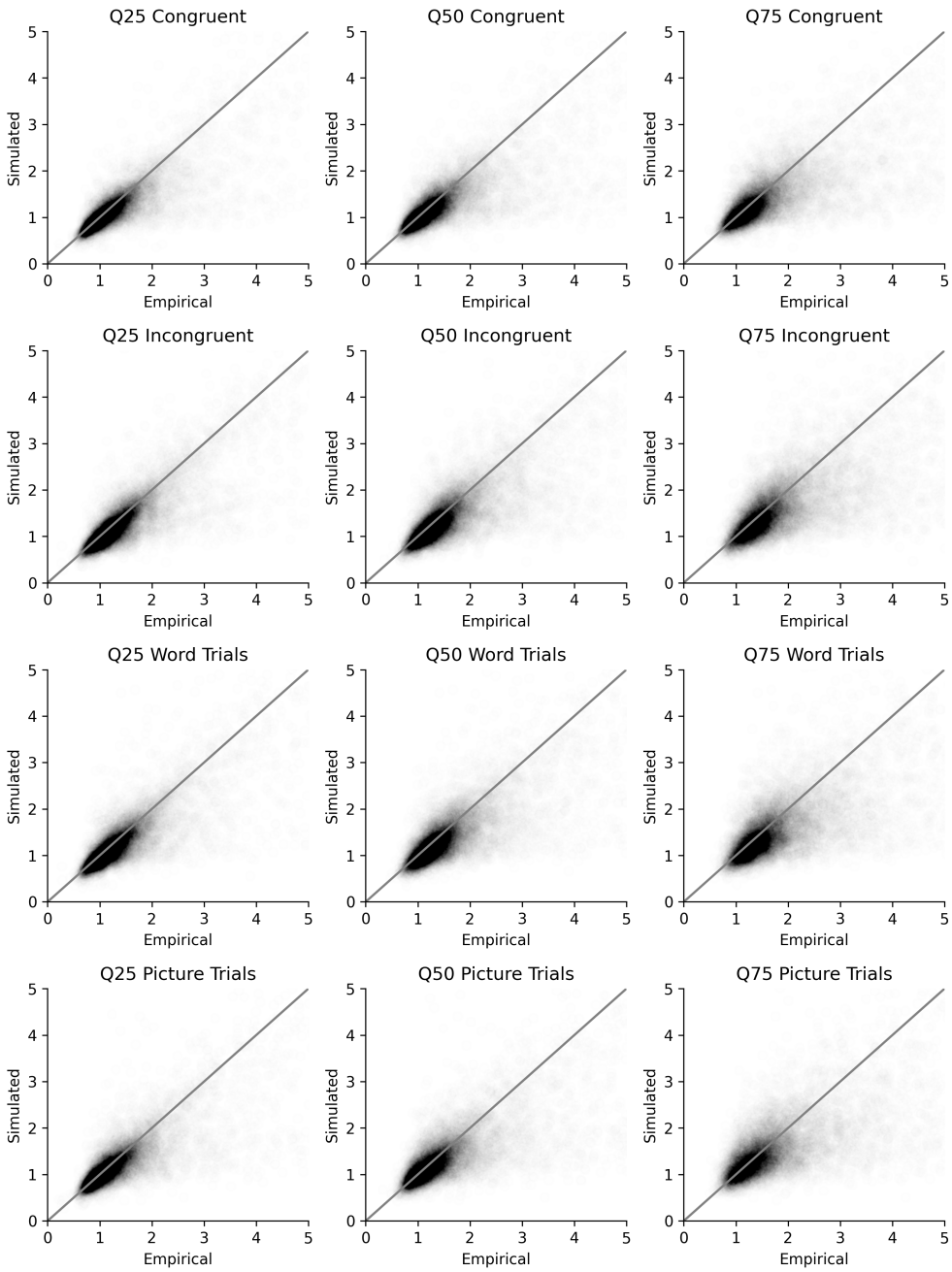


Figure S32

Predictive performance plot for error response time quartiles for the LFM. Subplots show the RTs split up by experimental condition (congruent/incongruent) and by stimulus type (word/picture). 25th, 50th, and 75th RT percentiles in empirical vs. re-simulated data shown. Opacity is lowered due to the very high number of points plotted.

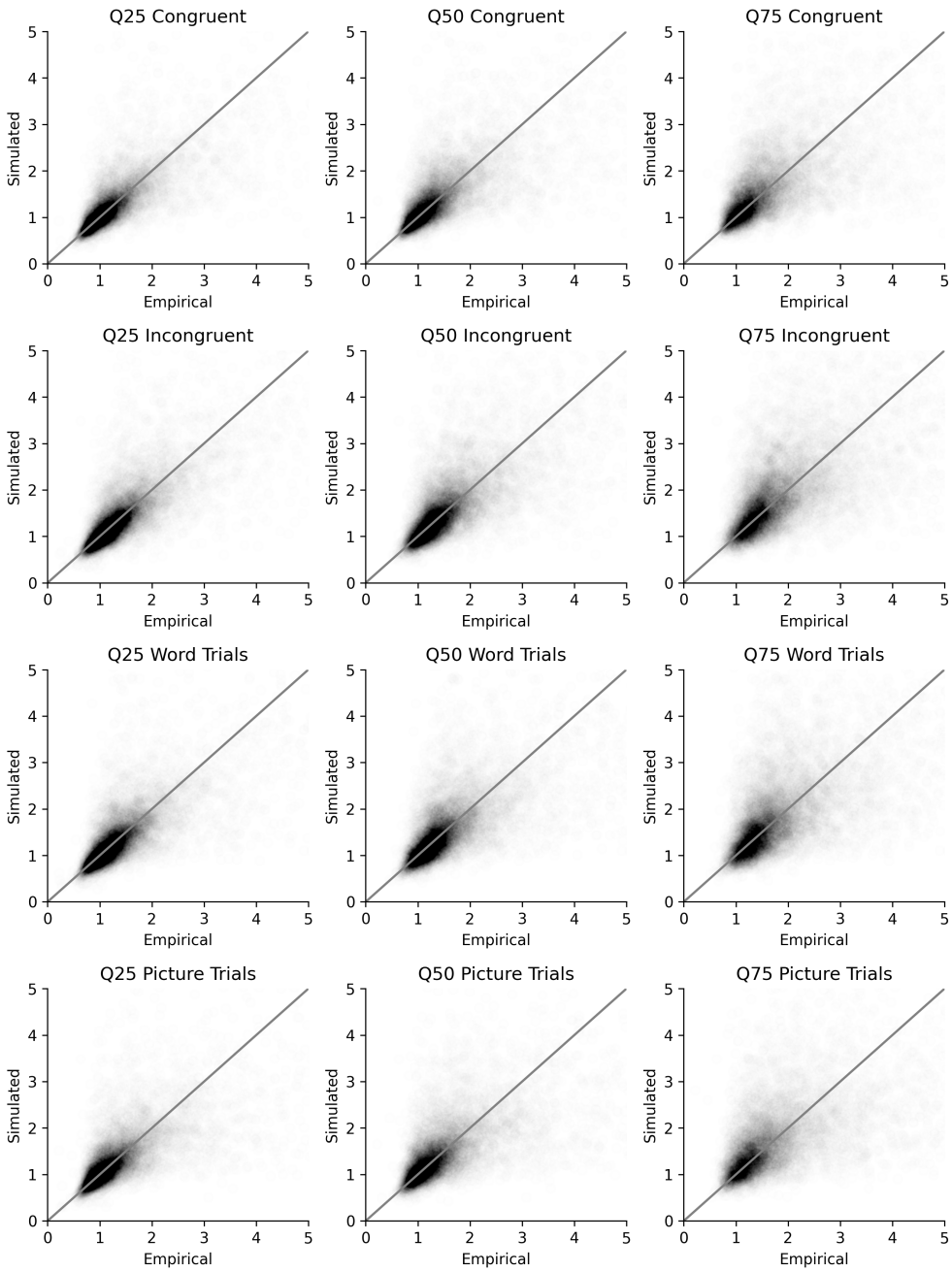


Figure S33

Predictive performance plot for error response time quartiles for the GSR model. Subplots show the RTs split up by experimental condition (congruent/incongruent) and by stimulus type (word/picture). 25th, 50th, and 75th RT percentiles in empirical vs. re-simulated data shown. Opacity is lowered due to the very high number of points plotted.

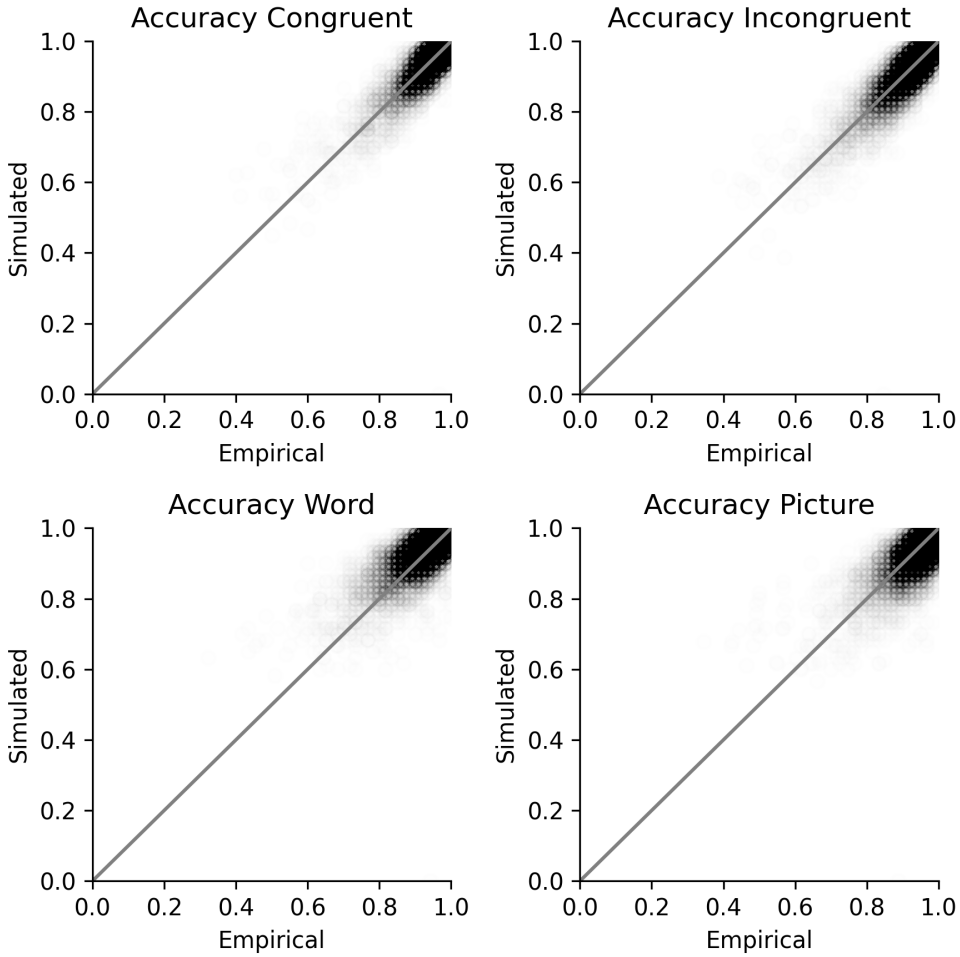


Figure S34

Predictive performance plot for accuracy rates for the $DDM_{s\tau s\nu}$. Subplots show the proportions of correct answers split up by experimental condition (congruent/incongruent) and by stimulus type (word/picture). Opacity is lowered due to the very high number of points plotted.

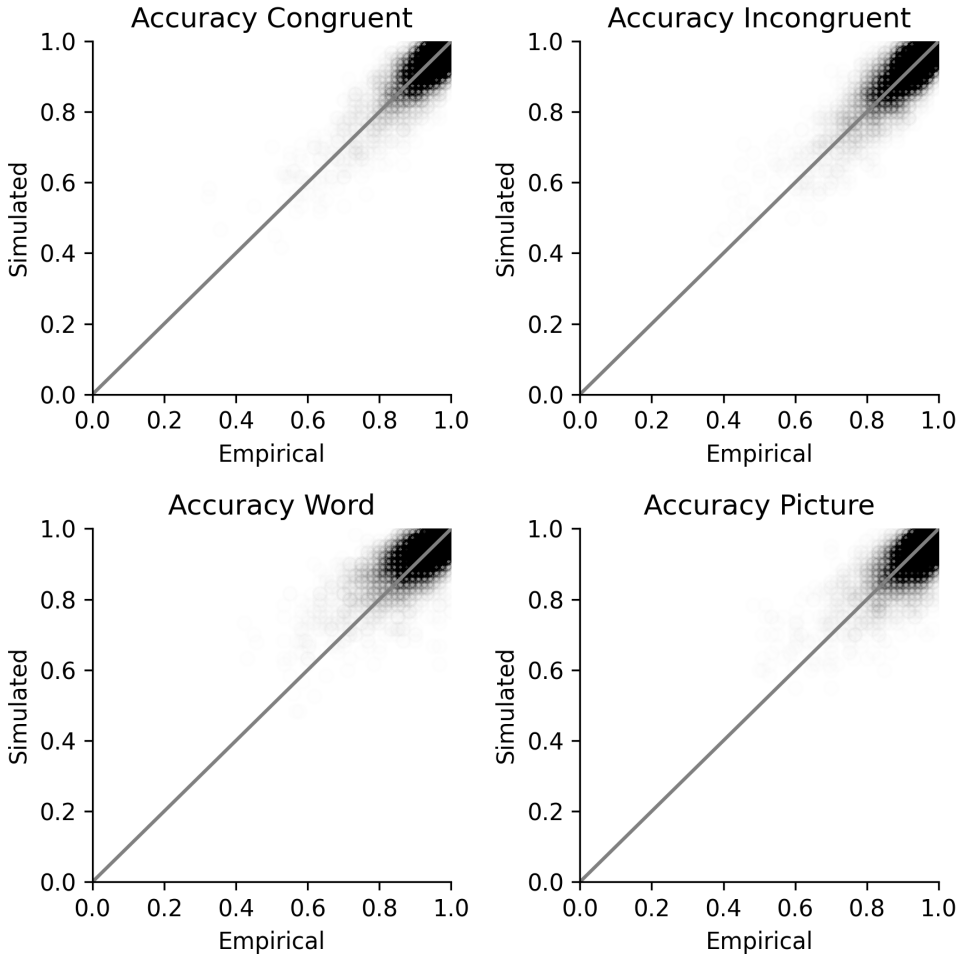


Figure S35

Predictive performance plot for accuracy rates for the LFM. Subplots show the proportions of correct answers split up by experimental condition (congruent/incongruent) and by stimulus type (word/picture). Opacity is lowered due to the very high number of points plotted.

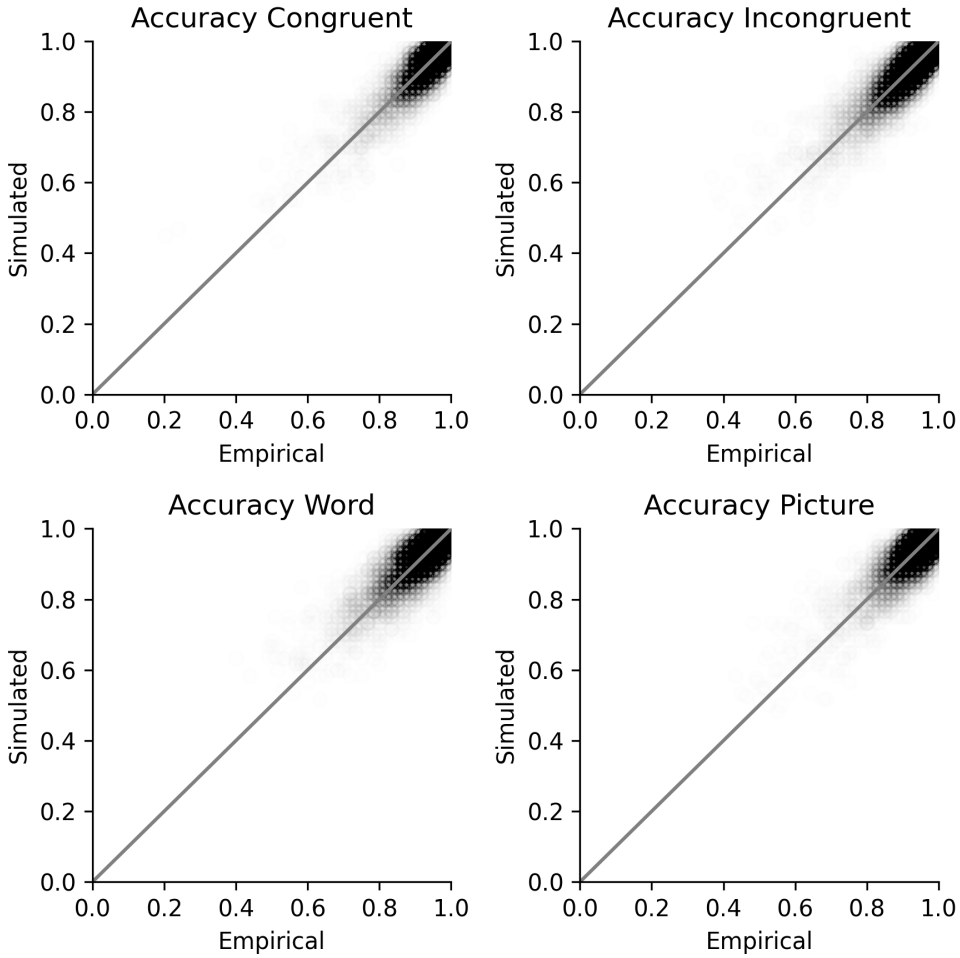


Figure S36

Predictive performance plot for accuracy rates for the GSR model. Subplots show the proportions of correct answers split up by experimental condition (congruent/incongruent) and by stimulus type (word/picture). Opacity is lowered due to the very high number of points plotted.

Model comparison diagnostics

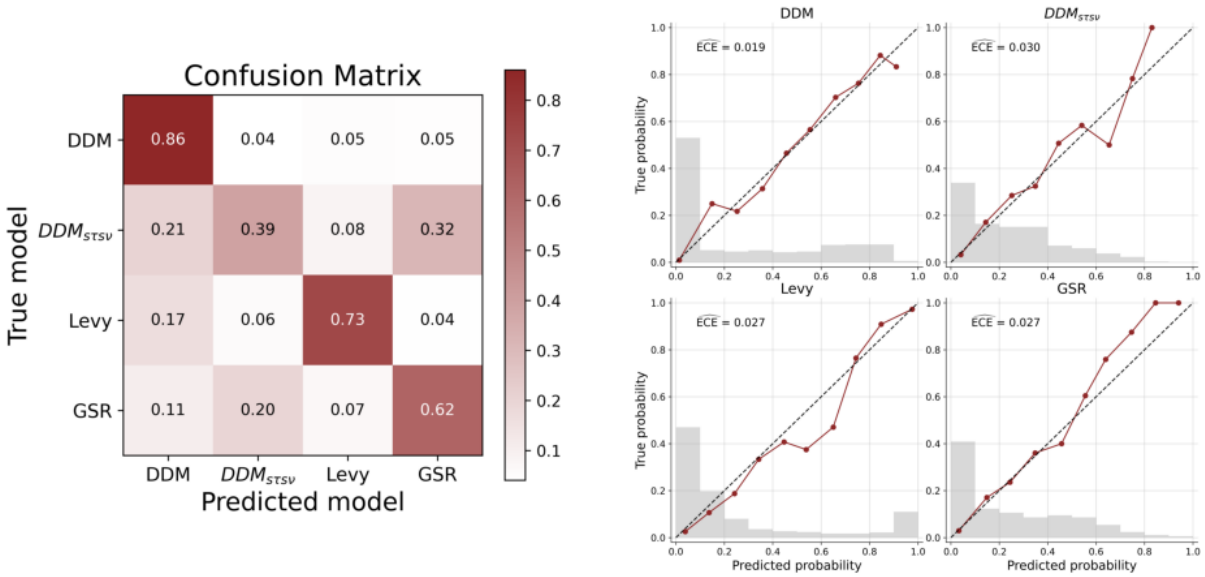


Figure S37

Confusion matrix (left) and calibration plots (right) of the model comparison procedure. ECE = Expected Calibration Error. The confusion matrix show the proportions of predicted models given a (known) true data generating model in simulated data. Perfect classification would imply 1.0 *on the diagonal and* 0 *in all other cells. Perfect calibration would imply the red line aligning with the diagonal in the calibration plots on the right.*

Additional results

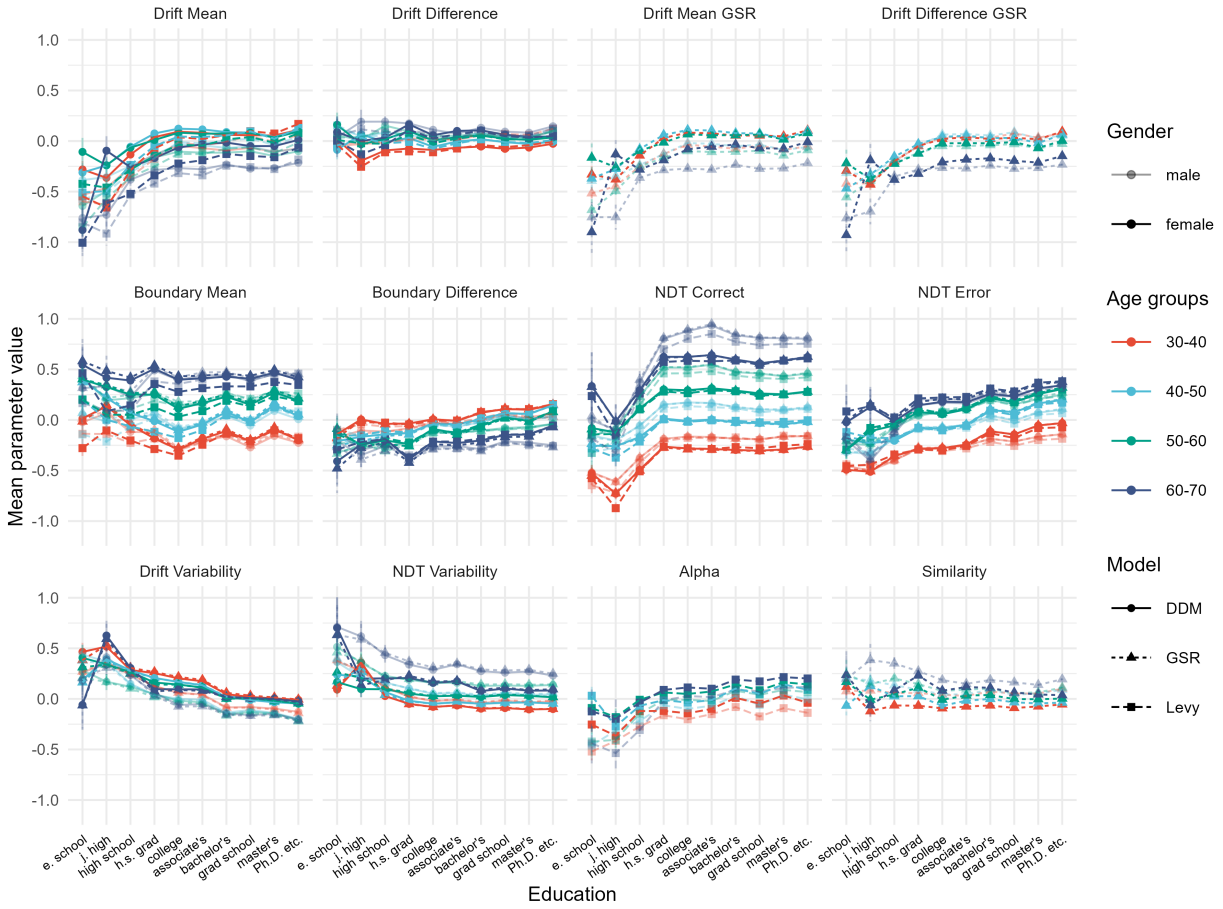


Figure S38

Mean standardized cognitive model parameters by educational attainment and mean/difference scores for drift rates and boundary separations. For the DDM and LFM, drift mean and difference scores relate to the congruent/incongruent conditions, for the GSR they relate to word/picture trials. Educational categories: Elementary school, junior high, some high school, high school graduate, some college, associate's degree, bachelor's degree, some graduate school, master's degree, other higher degree (Ph.D., J.D., M.D., M.B.A). See the Methods section of the main text for model details and explanations of all parameters. $N = 1,808,884$.

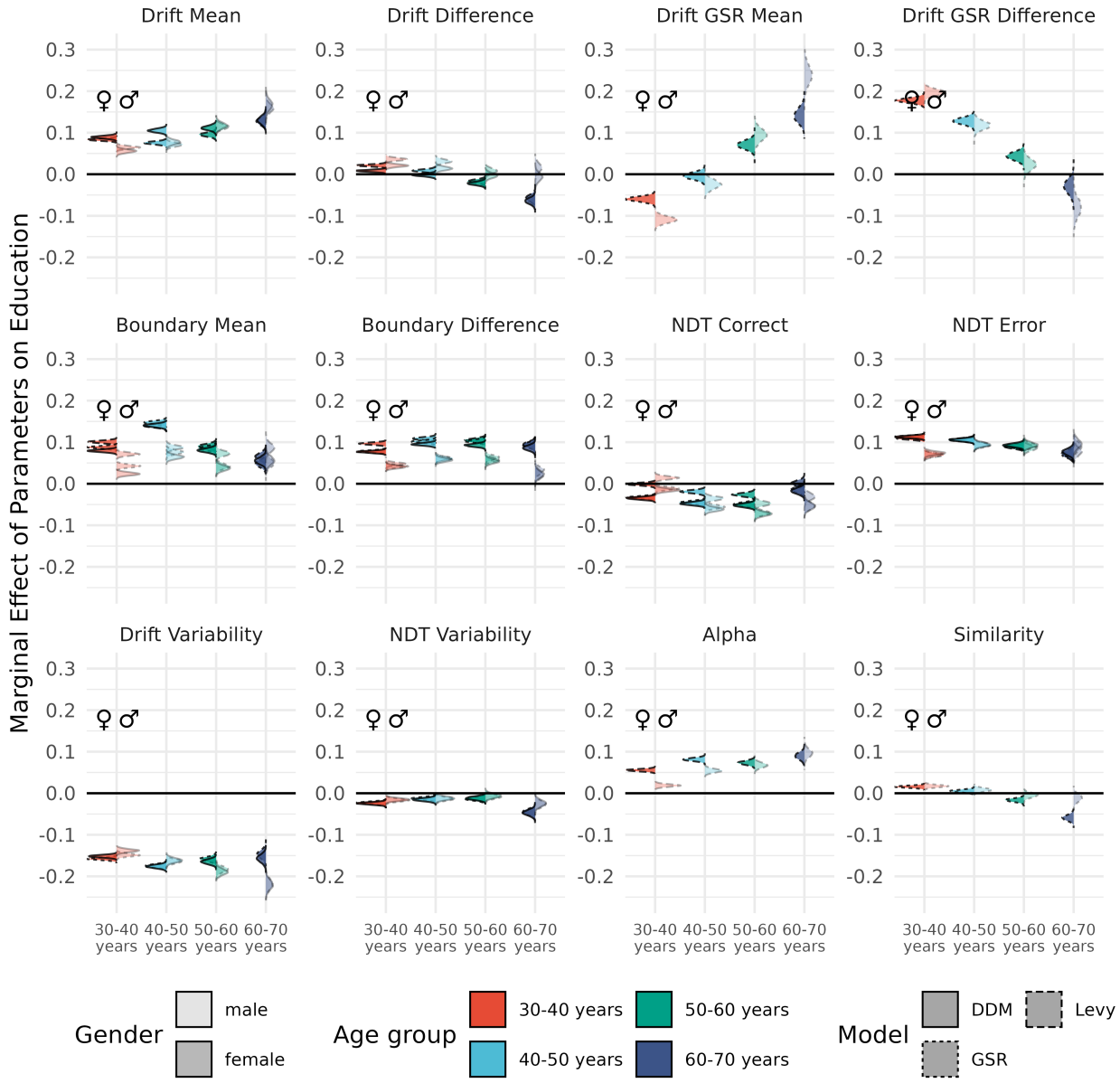


Figure S39

Results of the regression analysis with educational attainment as the (ordinal) outcome variable and mean/difference scores for drift rates and boundary separations. For the DDM and LFM, drift mean and difference scores relate to the congruent/incongruent conditions, for the GSR they relate to word/picture trials. All cognitive model parameters were standardized, thus the effects indicate the shift in the (standard normal) latent education variable for a 1 standard deviation change in the predictor variables. See the Methods section of the main text for model details and explanations of all parameters.
$N = 1,808,884$.

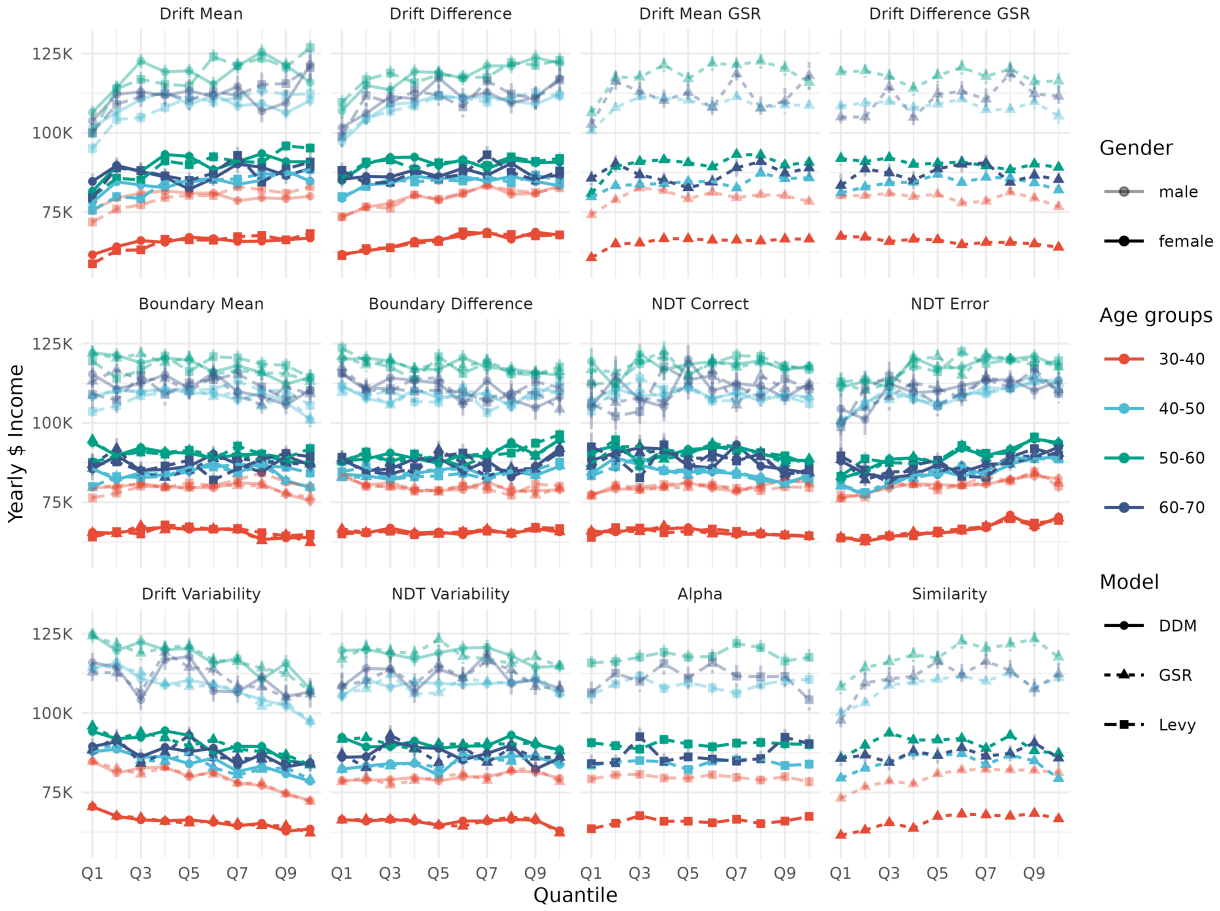


Figure S40

Mean self-reported yearly $ income by cognitive parameter quantiles and mean/difference scores for drift rates and boundary separations. For the DDM and LFM, drift mean and difference scores relate to the congruent/incongruent conditions, for the GSR they relate to word/picture trials. See the Methods section of the main text for model details and explanations of all parameters. $N = 92,047$.

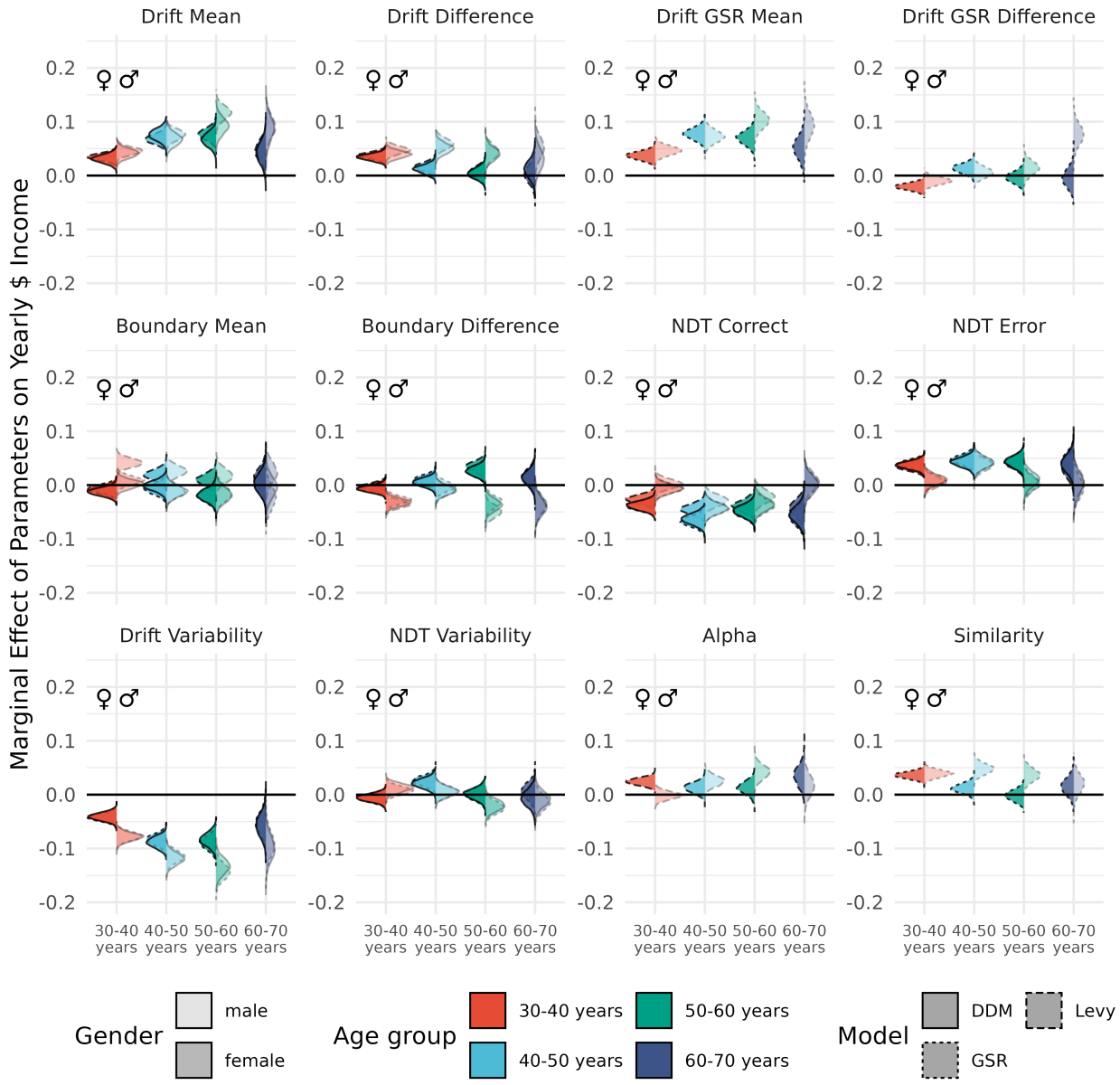


Figure S41

Results of the regression analysis with yearly dollar ($) amount of income as the outcome variable and mean/difference scores for drift rates and boundary separations. For the DDM and LFM, drift mean and difference scores relate to the congruent/incongruent conditions, for the GSR they relate to word/picture trials. See the Methods section of the main text for model details and explanations of all parameters. $N = 92,047$.

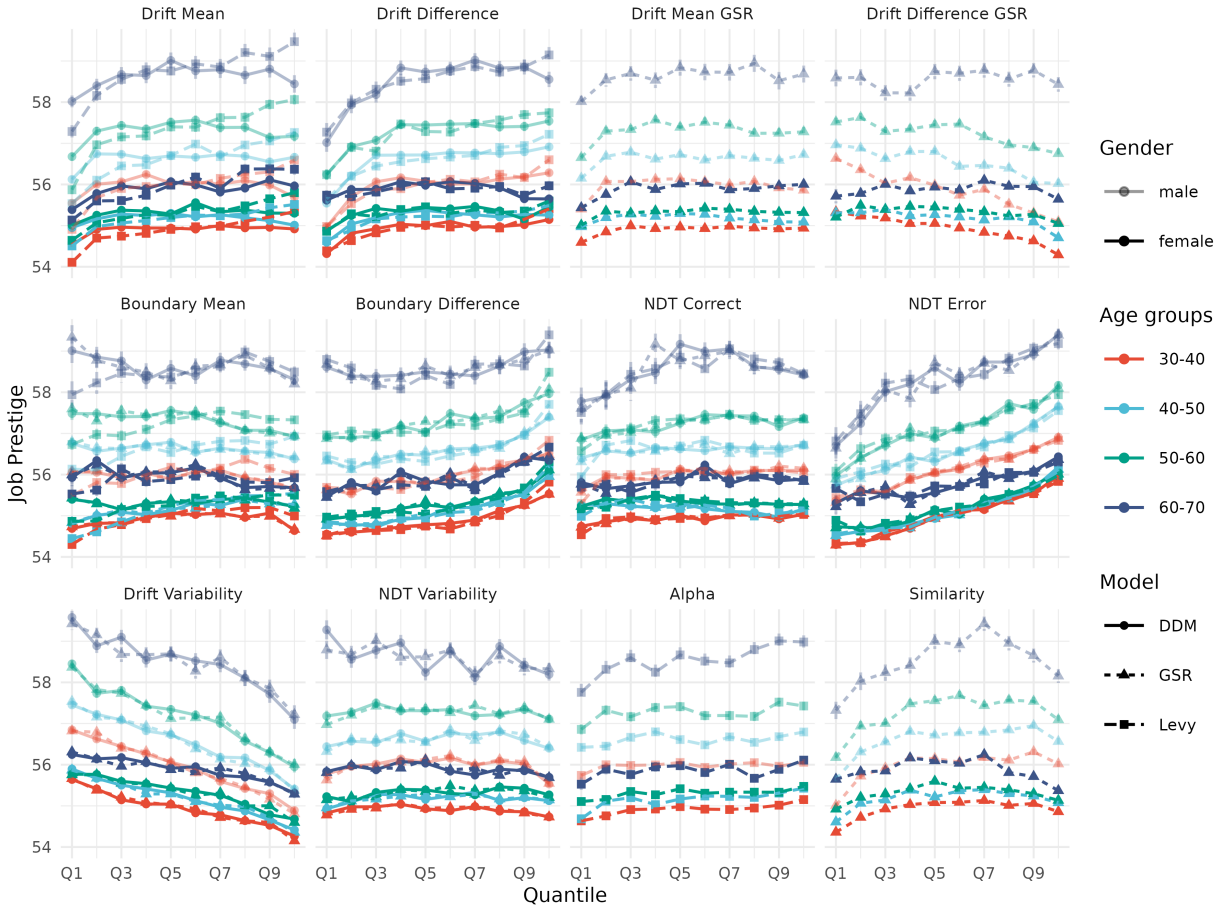


Figure S42

Mean job prestige by cognitive parameter quantiles and mean/difference scores for drift rates and boundary separations. For the DDM and LFM, drift mean and difference scores relate to the congruent/incongruent conditions, for the GSR they relate to word/picture trials. See the Methods section of the main text for model details and explanations of all parameters. $N = 1,145,584$.

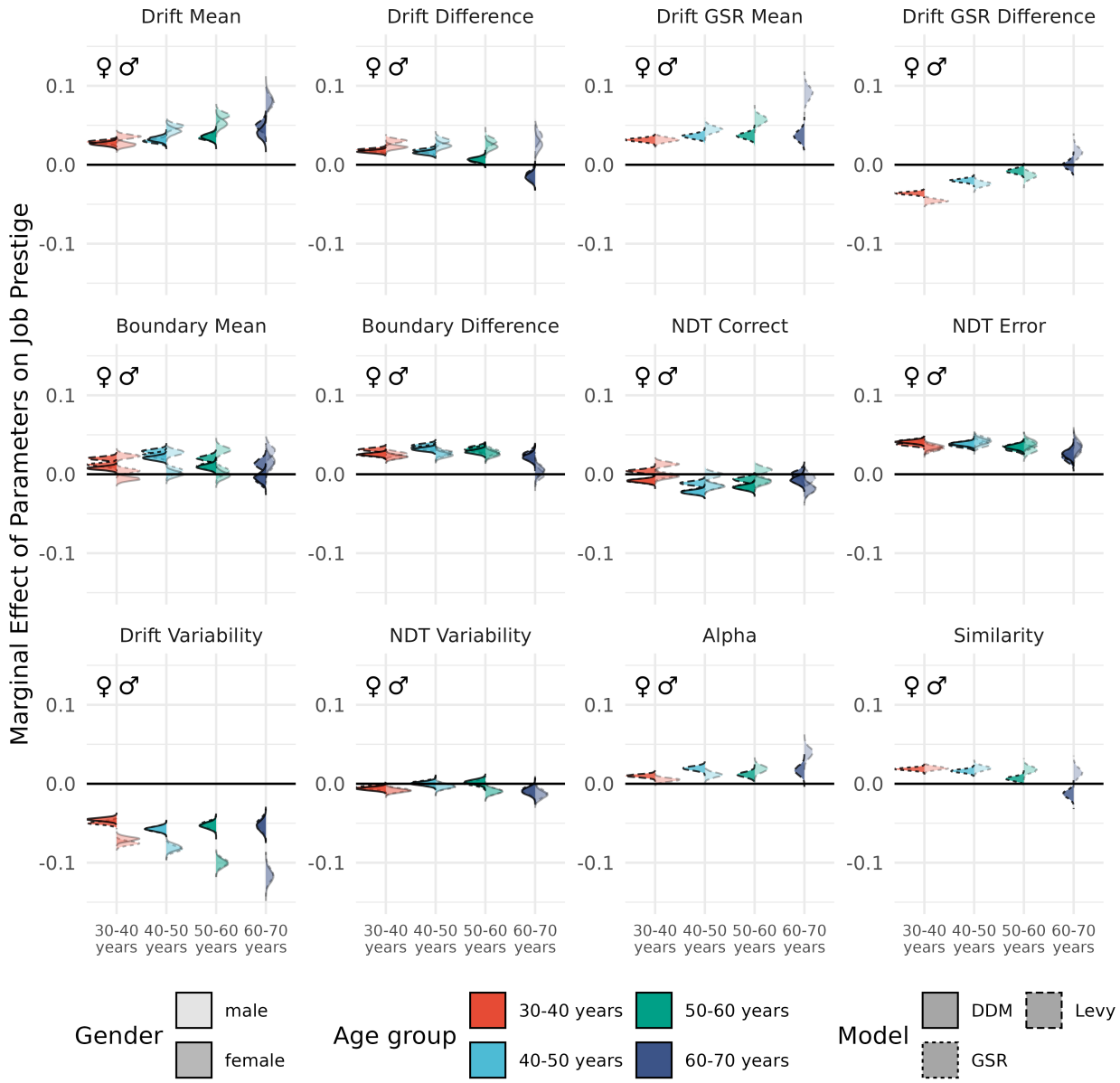


Figure S43

Results of the regression analysis with job prestige as the outcome variable and mean/difference scores for drift rates and boundary separations. For the DDM and LFM, drift mean and difference scores relate to the congruent/incongruent conditions, for the GSR they relate to word/picture trials. See the Methods section of the main text for model details and explanations of all parameters. $N = 1,145,584$.

EAM parameter correlations

	$\nu_{congruent}$	$\nu_{incongruent}$	$a_{congruent}$	$a_{incongruent}$	$\tau_{correct}$	τ_{error}	s_τ	s_ν
s_ν	0.36	0.47	-0.01	0.03	-0.13	-0.23	-0.14	1.00
s_τ	-0.22	-0.20	0.09	0.07	0.22	0.03	1.00	
τ_{error}	-0.02	0.02	0.23	0.20	0.27	1.00		
$\tau_{correct}$	0.10	0.05	-0.14	-0.08	1.00			
$a_{incongruent}$	-0.31	-0.19	0.50	1.00				
$a_{congruent}$	-0.24	-0.16	1.00					
$\nu_{incongruent}$	0.40	1.00						
$\nu_{congruent}$	1.00							

Table S2

Correlation table for $DDM_{s\tau s\nu}$ parameters. Bayesian across-person correlations (posterior medians). $N = 2,012,936$.

	$\nu_{congruent}$	$\nu_{incongruent}$	$a_{congruent}$	$a_{incongruent}$	$\tau_{correct}$	τ_{error}	α
α	-0.20	-0.13	0.17	0.23	0.23	0.27	1.00
τ_{error}	-0.02	0.03	0.32	0.37	0.26	1.00	
$\tau_{correct}$	0.11	0.07	-0.12	-0.04	1.00		
$a_{incongruent}$	-0.35	-0.18	0.47	1.00			
$a_{congruent}$	-0.10	-0.17	1.00				
$\nu_{incongruent}$	0.33	1.00					
$\nu_{congruent}$	1.00						

Table S3

Correlation table for LFM parameters. Bayesian across-person correlations (posterior medians). $N = 2,026,630$.

	γ	$\nu_{picture}$	ν_{word}	$a_{congruent}$	$a_{incongruent}$	$\tau_{correct}$	τ_{error}	s_τ	s_ν
s_ν	-0.08	0.41	0.44	-0.00	0.02	-0.14	-0.25	-0.18	1.00
s_τ	0.01	-0.25	-0.22	0.08	0.06	0.21	0.02	1.00	
τ_{error}	-0.05	-0.07	-0.00	0.23	0.22	0.28	1.00		
$\tau_{correct}$	0.07	0.08	0.10	-0.13	-0.08	1.00			
$a_{incongruent}$	-0.07	-0.38	-0.24	0.48	1.00				
$a_{congruent}$	-0.11	-0.27	-0.19	1.00					
ν_{word}	0.04	0.63	1.00						
$\nu_{picture}$	0.03	1.00							
γ	1.00								

Table S4

Correlation table for GSR model parameters. Bayesian across-person correlations (posterior medians). $N = 1,993,411$.

Regression tables

Parameter	Beta	95% Credible Interval
(Intercept)[1]	-7.5	[-7.5, -7.4]
(Intercept)[2]	-6.4	[-6.4, -6.3]
(Intercept)[3]	-4.8	[-4.9, -4.8]
(Intercept)[4]	-3.1	[-3.1, -3.0]
(Intercept)[5]	-1.3	[-1.3, -1.3]
(Intercept)[6]	-0.85	[-0.86, -0.85]
(Intercept)[7]	0.18	[0.17, 0.18]
(Intercept)[8]	0.51	[0.50, 0.52]
(Intercept)[9]	1.8	[1.8, 1.8]
s_ν	-0.14	[-0.15, -0.13]
$\nu_{congruent}$	0.06	[0.05, 0.06]
$\nu_{incongruent}$	0.01	[0.01, 0.02]
$a_{congruent}$	0.05	[0.04, 0.06]
$a_{incongruent}$	-0.03	[-0.04, -0.02]
$\tau_{correct}$	-0.02	[-0.02, -0.01]
s_τ	-0.02	[-0.02, 0.01]
τ_{error}	0.07	[0.07, 0.08]
Female	-0.02	[-0.03, -0.01]
Age 40-50	0.21	[0.20, 0.22]
Age 50-60	0.41	[0.40, 0.42]
Age 60-70	0.79	[0.76, 0.81]
s_ν:Female	-0.01	[-0.02, 0.00]
$\nu_{congruent}$:Female	0.01	[0.00, 0.02]
$\nu_{incongruent}$:Female	0.03	[0.02, 0.04]
$a_{congruent}$:Female	0.06	[0.05, 0.07]
$a_{incongruent}$:Female	0.00	[-0.01, 0.01]
$\tau_{correct}$:Female	-0.02	[-0.03, 0.01]
s_τ:Female	-0.01	[-0.02, 0.00]
τ_{error}:Female	0.04	[0.03, 0.05]
s_ν:Age 40-50	-0.02	[-0.04, -0.01]
s_ν:Age 50-60	-0.05	[-0.07, -0.04]
s_ν:Age 60-70	-0.08	[-0.11, -0.06]
$\nu_{congruent}$:Age 40-50	0.01	[0.00, 0.02]
$\nu_{congruent}$:Age 50-60	0.02	[0.00, 0.03]
$\nu_{congruent}$:Age 60-70	0.05	[0.02, 0.07]
$\nu_{incongruent}$:Age 40-50	0.02	[0.00, 0.03]
$\nu_{incongruent}$:Age 50-60	0.05	[0.04, 0.07]
$\nu_{incongruent}$:Age 60-70	0.09	[0.06, 0.11]
$a_{congruent}$:Age 40-50	0.04	[0.03, 0.05]
$a_{congruent}$:Age 50-60	0.02	[0.01, 0.03]
$a_{congruent}$:Age 60-70	0.00	[-0.02, 0.02]
$a_{incongruent}$:Age 40-50	0.01	[-0.01, 0.02]
$a_{incongruent}$:Age 50-60	-0.01	[-0.02, 0.01]
$a_{incongruent}$:Age 60-70	0.04	[0.02, 0.06]
$\tau_{correct}$:Age 40-50	-0.05	[-0.06, -0.03]
$\tau_{correct}$:Age 50-60	-0.06	[-0.07, -0.04]
$\tau_{correct}$:Age 60-70	-0.04	[-0.06, -0.02]
s_τ:Age 40-50	0.00	[-0.01, 0.01]
s_τ:Age 50-60	0.01	[0.00, 0.02]
s_τ:Age 60-70	-0.01	[-0.03, 0.01]
τ_{error}:Age 40-50	0.02	[0.01, 0.03]
τ_{error}:Age 50-60	0.02	[0.01, 0.03]
τ_{error}:Age 60-70	0.02	[0.00, 0.04]
Female:Age 40-50	-0.09	[-0.10, -0.07]
Female:Age 50-60	-0.18	[-0.20, -0.16]
Female:Age 60-70	-0.34	[-0.37, -0.31]
s_ν:Female:Age 40-50	0.00	[-0.02, 0.02]
s_ν:Female:Age 50-60	0.04	[0.02, 0.06]
s_ν:Female:Age 60-70	0.08	[0.05, 0.11]
$\nu_{congruent}$:Female:Age 40-50	-0.01	[-0.02, 0.01]
$\nu_{congruent}$:Female:Age 50-60	-0.03	[-0.05, -0.01]
$\nu_{congruent}$:Female:Age 60-70	-0.09	[-0.12, -0.06]
$\nu_{incongruent}$:Female:Age 40-50	0.00	[-0.02, 0.02]
$\nu_{incongruent}$:Female:Age 50-60	-0.02	[-0.04, 0.00]
$\nu_{incongruent}$:Female:Age 60-70	0.00	[-0.03, 0.03]
$a_{congruent}$:Female:Age 40-50	0.01	[0.00, 0.03]
$a_{congruent}$:Female:Age 50-60	0.00	[-0.02, 0.01]
$a_{congruent}$:Female:Age 60-70	0.00	[-0.03, 0.02]
$a_{incongruent}$:Female:Age 40-50	0.01	[-0.01, 0.03]
$a_{incongruent}$:Female:Age 50-60	-0.01	[-0.03, 0.01]
$a_{incongruent}$:Female:Age 60-70	-0.06	[-0.09, -0.04]
$\tau_{correct}$:Female:Age 40-50	0.03	[0.02, 0.05]
$\tau_{correct}$:Female:Age 50-60	0.04	[0.02, 0.06]
$\tau_{correct}$:Female:Age 60-70	0.06	[0.03, 0.08]
s_τ:Female:Age 40-50	0.01	[-0.01, 0.02]
s_τ:Female:Age 50-60	0.00	[-0.01, 0.02]
s_τ:Female:Age 60-70	-0.01	[-0.04, 0.01]
τ_{error}:Female:Age 40-50	-0.03	[-0.04, -0.01]
τ_{error}:Female:Age 50-60	-0.04	[-0.06, -0.02]
τ_{error}:Female:Age 60-70	-0.06	[-0.09, -0.03]

Table S5

Regression results for education with $DDM_{s\nu s\tau}$ parameters as predictors.

Parameter	Beta	95% Credible Interval
(Intercept)[1]	-7.5	[-7.6, -7.4]
(Intercept)[2]	-6.4	[-6.4, -6.4]
(Intercept)[3]	4.9	[-4.9, -4.8]
(Intercept)[4]	-3.1	[-3.1, -3.1]
(Intercept)[5]	-1.3	[-1.3, -1.3]
(Intercept)[6]	-0.87	[-0.88, -0.86]
(Intercept)[7]	0.16	[0.15, 0.17]
(Intercept)[8]	0.49	[0.48, 0.50]
(Intercept)[9]	1.8	[1.8, 1.8]
α	0.02	[0.01, 0.03]
$\nu_{congruent}$	0.08	[0.07, 0.09]
$\nu_{incongruent}$	0.01	[0.00, 0.01]
$a_{congruent}$	0.09	[0.08, 0.09]
$a_{incongruent}$	0.00	[-0.01, 0.00]
$\tau_{correct}$	0.01	[0.01, 0.02]
τ_{error}	0.07	[0.06, 0.08]
Female	-0.03	[-0.03, -0.02]
Age 40-50	0.20	[0.19, 0.21]
Age 50-60	0.39	[0.37, 0.40]
Age 60-70	0.75	[0.73, 0.78]
α:Female	0.04	[0.03, 0.05]
$\nu_{congruent}$:Female	0.00	[-0.01, 0.01]
$\nu_{incongruent}$:Female	0.02	[0.01, 0.03]
$a_{congruent}$:Female	0.06	[0.05, 0.07]
$a_{incongruent}$:Female	-0.03	[-0.04, -0.02]
$\tau_{correct}$:Female	-0.02	[-0.02, -0.01]
τ_{error}:Female	0.04	[0.03, 0.05]
α:Age 40-50	0.04	[0.02, 0.05]
α:Age 50-60	0.05	[0.04, 0.06]
α:Age 60-70	0.08	[0.06, 0.10]
$\nu_{congruent}$:Age 40-50	0.00	[-0.01, 0.01]
$\nu_{congruent}$:Age 50-60	0.01	[-0.01, 0.02]
$\nu_{congruent}$:Age 60-70	0.04	[0.02, 0.07]
$\nu_{incongruent}$:Age 40-50	0.01	[0.00, 0.02]
$\nu_{incongruent}$:Age 50-60	0.05	[0.03, 0.06]
$\nu_{incongruent}$:Age 60-70	0.07	[0.04, 0.09]
$a_{congruent}$:Age 40-50	0.02	[0.01, 0.03]
$a_{congruent}$:Age 50-60	0.01	[0.00, 0.02]
$a_{congruent}$:Age 60-70	-0.02	[-0.04, 0.01]
$a_{incongruent}$:Age 40-50	0.00	[-0.02, 0.01]
$a_{incongruent}$:Age 50-60	-0.01	[-0.02, 0.01]
$a_{incongruent}$:Age 60-70	0.04	[0.02, 0.06]
$\tau_{correct}$:Age 40-50	-0.05	[-0.06, -0.04]
$\tau_{correct}$:Age 50-60	-0.06	[-0.08, -0.05]
$\tau_{correct}$:Age 60-70	-0.05	[-0.06, -0.03]
τ_{error}:Age 40-50	0.03	[0.01, 0.04]
τ_{error}:Age 50-60	0.02	[0.00, 0.03]
τ_{error}:Age 60-70	0.01	[-0.01, 0.03]
Female:Age 40-50	-0.09	[-0.10, -0.07]
Female:Age 50-60	-0.18	[-0.20, -0.16]
Female:Age 60-70	-0.34	[-0.37, -0.31]
α:Female:Age 40-50	-0.01	[-0.02, 0.00]
α:Female:Age 50-60	-0.03	[-0.05, -0.01]
α:Female:Age 60-70	-0.04	[-0.07, -0.02]
$\nu_{congruent}$:Female:Age 40-50	-0.02	[-0.03, 0.00]
$\nu_{congruent}$:Female:Age 50-60	-0.04	[-0.05, -0.02]
$\nu_{congruent}$:Female:Age 60-70	-0.09	[-0.12, -0.06]
$\nu_{incongruent}$:Female:Age 40-50	0.00	[-0.02, 0.01]
$\nu_{incongruent}$:Female:Age 50-60	-0.01	[-0.03, 0.00]
$\nu_{incongruent}$:Female:Age 60-70	0.02	[-0.01, 0.04]
$a_{congruent}$:Female:Age 40-50	0.01	[0.00, 0.03]
$a_{congruent}$:Female:Age 50-60	-0.01	[-0.02, 0.01]
$a_{congruent}$:Female:Age 60-70	-0.01	[-0.03, 0.02]
$a_{incongruent}$:Female:Age 40-50	0.01	[0.00, 0.03]
$a_{incongruent}$:Female:Age 50-60	-0.01	[-0.02, 0.01]
$a_{incongruent}$:Female:Age 60-70	-0.06	[-0.08, -0.03]
$\tau_{correct}$:Female:Age 40-50	0.03	[0.02, 0.05]
$\tau_{correct}$:Female:Age 50-60	0.04	[0.02, 0.05]
$\tau_{correct}$:Female:Age 60-70	0.05	[0.02, 0.07]
τ_{error}:Female:Age 40-50	-0.03	[-0.04, -0.01]
τ_{error}:Female:Age 50-60	-0.04	[-0.06, -0.02]
τ_{error}:Female:Age 60-70	-0.05	[-0.07, -0.02]

Table S6

Regression results for education with LFM parameters as predictors.

Parameter	Beta	95% Credible Interval
(Intercept)[1]	-7.5	[-7.5, -7.4]
(Intercept)[2]	-6.4	[-6.4, -6.3]
(Intercept)[3]	-4.8	[-4.8, -4.8]
(Intercept)[4]	-3.0	[-3.0, -3.0]
(Intercept)[5]	-1.3	[-1.3, -1.3]
(Intercept)[6]	-0.84	[-0.84, -0.83]
(Intercept)[7]	0.20	[0.19, 0.20]
(Intercept)[8]	0.53	[0.52, 0.53]
(Intercept)[9]	1.8	[1.8, 1.8]
s_ν	-0.15	[-0.16, -0.14]
$\nu_{picture}$	0.13	[0.13, 0.14]
ν_{word}	-0.06	[-0.07, -0.05]
$a_{congruent}$	0.06	[0.06, 0.07]
$a_{incongruent}$	-0.02	[-0.03, 0.01]
$\tau_{correct}$	-0.01	[-0.02, 0.00]
γ	0.02	[0.01, 0.02]
s_τ	-0.02	[-0.02, -0.01]
τ_{error}	0.07	[0.06, 0.08]
Female	0.01	[0.00, 0.02]
Age 40-50	0.21	[0.20, 0.22]
Age 50-60	0.42	[0.41, 0.44]
Age 60-70	0.81	[0.78, 0.83]
s_ν:Female	-0.01	[-0.02, 0.00]
$\nu_{picture}$:Female	0.01	[0.00, 0.02]
ν_{word}:Female	0.03	[0.02, 0.04]
$a_{congruent}$:Female	0.06	[0.05, 0.07]
$a_{incongruent}$:Female	-0.01	[-0.02, 0.00]
$\tau_{correct}$:Female	-0.02	[-0.03, -0.01]
γ:Female	0.00	[-0.01, 0.01]
s_τ:Female	-0.01	[-0.01, 0.00]
τ_{error}:Female	0.04	[0.03, 0.05]
s_ν:Age 40-50	-0.01	[-0.03, 0.00]
s_ν:Age 50-60	-0.03	[-0.05, -0.02]
s_ν:Age 60-70	-0.07	[-0.10, -0.04]
$\nu_{picture}$:Age 40-50	-0.03	[-0.04, -0.02]
$\nu_{picture}$:Age 50-60	-0.06	[-0.07, -0.04]
$\nu_{picture}$:Age 60-70	-0.08	[-0.11, -0.05]
ν_{word}:Age 40-50	0.05	[0.03, 0.06]
ν_{word}:Age 50-60	0.11	[0.09, 0.13]
ν_{word}:Age 60-70	0.19	[0.16, 0.21]
$a_{congruent}$:Age 40-50	0.04	[0.02, 0.05]
$a_{congruent}$:Age 50-60	0.02	[0.01, 0.03]
$a_{congruent}$:Age 60-70	-0.01	[-0.03, 0.02]
$a_{incongruent}$:Age 40-50	0.00	[-0.01, 0.01]
$a_{incongruent}$:Age 50-60	-0.02	[-0.04, -0.01]
$a_{incongruent}$:Age 60-70	0.02	[-0.01, 0.04]
$\tau_{correct}$:Age 40-50	-0.04	[-0.06, -0.03]
$\tau_{correct}$:Age 50-60	-0.06	[-0.07, -0.05]
$\tau_{correct}$:Age 60-70	-0.04	[-0.06, -0.02]
γ:Age 40-50	-0.01	[-0.02, 0.00]
γ:Age 50-60	-0.02	[-0.03, -0.01]
γ:Age 60-70	-0.03	[-0.05, -0.01]
s_τ:Age 40-50	0.00	[-0.01, 0.01]
s_τ:Age 50-60	0.01	[0.00, 0.02]
s_τ:Age 60-70	-0.01	[-0.03, 0.01]
τ_{error}:Age 40-50	0.02	[0.01, 0.04]
τ_{error}:Age 50-60	0.02	[0.01, 0.04]
τ_{error}:Age 60-70	0.02	[0.00, 0.04]
Female:Age 40-50	-0.09	[-0.11, -0.08]
Female:Age 50-60	-0.20	[-0.22, -0.18]
Female:Age 60-70	-0.37	[-0.40, -0.34]
s_ν:Female:Age 40-50	0.00	[-0.02, 0.01]
s_ν:Female:Age 50-60	0.03	[0.01, 0.05]
s_ν:Female:Age 60-70	0.08	[0.05, 0.11]
$\nu_{picture}$:Female:Age 40-50	0.01	[-0.01, 0.03]
$\nu_{picture}$:Female:Age 50-60	0.00	[-0.02, 0.02]
$\nu_{picture}$:Female:Age 60-70	-0.01	[-0.05, 0.02]
ν_{word}:Female:Age 40-50	-0.02	[-0.03, 0.00]
ν_{word}:Female:Age 50-60	-0.04	[-0.06, -0.02]
ν_{word}:Female:Age 60-70	-0.08	[-0.11, -0.05]
$a_{congruent}$:Female:Age 40-50	0.02	[0.00, 0.03]
$a_{congruent}$:Female:Age 50-60	0.00	[-0.02, 0.02]
$a_{congruent}$:Female:Age 60-70	0.00	[-0.03, 0.02]
$a_{incongruent}$:Female:Age 40-50	0.01	[-0.01, 0.03]
$a_{incongruent}$:Female:Age 50-60	0.00	[-0.02, 0.01]
$a_{incongruent}$:Female:Age 60-70	-0.06	[-0.08, -0.03]
$\tau_{correct}$:Female:Age 40-50	0.03	[0.02, 0.05]
$\tau_{correct}$:Female:Age 50-60	0.04	[0.03, 0.06]
$\tau_{correct}$:Female:Age 60-70	0.06	[0.04, 0.08]
γ:Female:Age 40-50	0.00	[-0.01, 0.01]
γ:Female:Age 50-60	0.00	[-0.03, 0.01]
γ:Female:Age 60-70	-0.05	[-0.07, -0.02]
s_τ:Female:Age 40-50	0.01	[-0.01, 0.02]
s_τ:Female:Age 50-60	0.00	[-0.01, 0.02]
s_τ:Female:Age 60-70	-0.01	[-0.03, 0.01]
τ_{error}:Female:Age 40-50	-0.03	[-0.05, -0.02]
τ_{error}:Female:Age 50-60	-0.04	[-0.06, -0.03]
τ_{error}:Female:Age 60-70	-0.06	[-0.09, -0.03]

Table S7

Regression results for education with GSR model parameters as predictors.

Parameter	Beta	95% Credible Interval
s_ν	-0.08	[-0.09, -0.06]
$\nu_{congruent}$	0.06	[0.05, 0.08]
$\nu_{incongruent}$	-0.01	[-0.03, 0.01]
$a_{congruent}$	-0.03	[-0.05, -0.01]
$a_{incongruent}$	0.03	[0.02, 0.06]
$\tau_{correct}$	-0.01	[-0.02, 0.01]
s_τ	0.02	[0.01, 0.03]
τ_{error}	0.01	[-0.01, 0.03]
female	-0.27	[-0.28, -0.25]
Age 40-50	0.54	[0.51, 0.56]
Age 50-60	0.73	[0.70, 0.76]
Age 60-70	0.59	[0.54, 0.64]
s_ν * female	0.04	[0.02, 0.06]
$\nu_{congruent}$ * female	-0.01	[-0.03, 0.01]
$\nu_{incongruent}$ * female	0.00	[-0.02, 0.02]
$a_{congruent}$ * female	0.01	[-0.01, 0.04]
$a_{incongruent}$ * female	-0.03	[-0.06, -0.01]
$\tau_{correct}$ * female	-0.03	[-0.05, 0.01]
s_τ * female	-0.02	[-0.04, 0.00]
τ_{error} * female	0.03	[0.00, 0.05]
s_ν * Age 40-50	-0.04	[-0.07, -0.01]
s_ν * Age 50-60	-0.06	[-0.09, -0.02]
s_ν * Age 60-70	-0.02	[-0.07, 0.03]
$\nu_{congruent}$ * Age 40-50	0.03	[0.00, 0.05]
$\nu_{congruent}$ * Age 50-60	0.03	[0.00, 0.07]
$\nu_{congruent}$ * Age 60-70	0.02	[-0.02, 0.07]
$\nu_{incongruent}$ * Age 40-50	0.01	[-0.02, 0.03]
$\nu_{incongruent}$ * Age 50-60	0.03	[0.01, 0.06]
$\nu_{incongruent}$ * Age 60-70	0.03	[-0.01, 0.08]
$a_{congruent}$ * Age 40-50	0.01	[-0.01, 0.04]
$a_{congruent}$ * Age 50-60	-0.02	[-0.05, 0.02]
$a_{congruent}$ * Age 60-70	-0.01	[-0.05, 0.03]
$a_{incongruent}$ * Age 40-50	-0.03	[-0.06, 0.00]
$a_{incongruent}$ * Age 50-60	-0.01	[-0.04, 0.03]
$a_{incongruent}$ * Age 60-70	0.01	[-0.03, 0.04]
$\tau_{correct}$ * Age 40-50	-0.04	[-0.06, -0.01]
$\tau_{correct}$ * Age 50-60	-0.03	[-0.06, 0.00]
$\tau_{correct}$ * Age 60-70	0.01	[-0.03, 0.05]
s_τ * Age 40-50	0.01	[-0.03, 0.02]
s_τ * Age 50-60	-0.03	[-0.06, -0.01]
s_τ * Age 60-70	-0.02	[-0.05, 0.01]
τ_{error} * Age 40-50	0.03	[0.00, 0.06]
τ_{error} * Age 50-60	0.00	[-0.03, 0.03]
τ_{error} * Age 60-70	-0.01	[-0.05, 0.04]
female * Age 40-50	-0.19	[-0.22, -0.16]
female * Age 50-60	-0.26	[-0.29, -0.22]
female * Age 60-70	-0.16	[-0.22, -0.09]
s_ν * female * Age 40-50	-0.01	[-0.04, 0.03]
s_ν * female * Age 50-60	0.01	[-0.03, 0.06]
s_ν * female * Age 60-70	0.01	[-0.06, 0.07]
$\nu_{congruent}$ * female * Age 40-50	-0.02	[-0.06, 0.01]
$\nu_{congruent}$ * female * Age 50-60	-0.04	[-0.08, 0.00]
$\nu_{congruent}$ * female * Age 60-70	-0.04	[-0.10, 0.02]
$\nu_{incongruent}$ * female * Age 40-50	0.04	[0.00, 0.07]
$\nu_{incongruent}$ * female * Age 50-60	0.02	[-0.02, 0.06]
$\nu_{incongruent}$ * female * Age 60-70	-0.01	[-0.07, 0.05]
$a_{congruent}$ * female * Age 40-50	0.00	[-0.03, 0.04]
$a_{congruent}$ * female * Age 50-60	0.04	[0.00, 0.08]
$a_{congruent}$ * female * Age 60-70	0.04	[-0.02, 0.09]
$a_{incongruent}$ * female * Age 40-50	0.02	[-0.01, 0.06]
$a_{incongruent}$ * female * Age 50-60	-0.03	[-0.07, 0.01]
$a_{incongruent}$ * female * Age 60-70	-0.02	[-0.08, 0.04]
$\tau_{correct}$ * female * Age 40-50	0.01	[-0.02, 0.05]
$\tau_{correct}$ * female * Age 50-60	0.02	[-0.02, 0.06]
$\tau_{correct}$ * female * Age 60-70	-0.03	[-0.08, 0.03]
s_τ * female * Age 40-50	0.03	[0.00, 0.07]
s_τ * female * Age 50-60	0.04	[0.00, 0.08]
s_τ * female * Age 60-70	0.02	[-0.02, 0.07]
τ_{error} * female * Age 40-50	-0.02	[-0.06, 0.01]
τ_{error} * female * Age 50-60	0.01	[-0.03, 0.05]
τ_{error} * female * Age 60-70	0.01	[-0.04, 0.07]

Table S8

Regression results for income with $DDM_{s\nu s\tau}$ model parameters as predictors.

Parameter	Beta	**95% Credible Interval
α	0.00	[-0.02, 0.01]
$\nu_{congruent}$	0.08	[0.06, 0.09]
$\nu_{incongruent}$	-0.01	[-0.02, 0.00]
$a_{congruent}$	-0.01	[-0.03, 0.01]
$a_{incongruent}$	0.06	[0.04, 0.08]
$\tau_{correct}$	0.00	[-0.01, 0.02]
τ_{error}	0.01	[-0.01, 0.03]
female	-0.27	[-0.29, -0.25]
Age 40-50	0.53	[0.51, 0.56]
Age 50-60	0.72	[0.69, 0.74]
Age 60-70	0.57	[0.53, 0.62]
α * female	0.03	[0.01, 0.04]
$\nu_{congruent}$ * female	-0.02	[-0.04, 0.00]
$\nu_{incongruent}$ * female	0.00	[-0.02, 0.02]
$a_{congruent}$ * female	0.00	[-0.02, 0.02]
$a_{incongruent}$ * female	-0.06	[-0.08, -0.04]
$\tau_{correct}$ * female	-0.03	[-0.05, -0.01]
τ_{error} * female	0.03	[0.00, 0.05]
α * Age 40-50	0.03	[0.00, 0.05]
α * Age 50-60	0.04	[0.02, 0.07]
α * Age 60-70	0.02	[-0.02, 0.06]
$\nu_{congruent}$ * Age 40-50	0.03	[0.01, 0.06]
$\nu_{congruent}$ * Age 50-60	0.04	[0.01, 0.07]
$\nu_{congruent}$ * Age 60-70	0.04	[-0.01, 0.08]
$\nu_{incongruent}$ * Age 40-50	0.01	[-0.02, 0.03]
$\nu_{incongruent}$ * Age 50-60	0.04	[0.01, 0.07]
$\nu_{incongruent}$ * Age 60-70	0.02	[-0.02, 0.06]
$a_{congruent}$ * Age 40-50	0.01	[-0.01, 0.04]
$a_{congruent}$ * Age 50-60	-0.03	[-0.06, 0.00]
$a_{congruent}$ * Age 60-70	-0.01	[-0.05, 0.03]
$a_{incongruent}$ * Age 40-50	-0.03	[-0.06, -0.01]
$a_{incongruent}$ * Age 50-60	0.00	[-0.03, 0.03]
$a_{incongruent}$ * Age 60-70	-0.01	[-0.05, 0.03]
$\tau_{correct}$ * Age 40-50	-0.03	[-0.06, 0.00]
$\tau_{correct}$ * Age 50-60	-0.02	[-0.05, 0.00]
$\tau_{correct}$ * Age 60-70	0.00	[-0.03, 0.04]
τ_{error} * Age 40-50	0.03	[0.00, 0.06]
τ_{error} * Age 50-60	0.00	[-0.03, 0.03]
τ_{error} * Age 60-70	0.00	[-0.04, 0.04]
female * Age 40-50	-0.19	[-0.22, -0.16]
female * Age 50-60	-0.25	[-0.29, -0.22]
female * Age 60-70	-0.16	[-0.22, -0.10]
α * female * Age 40-50	-0.04	[-0.07, -0.01]
α * female * Age 50-60	-0.05	[-0.09, -0.02]
α * female * Age 60-70	-0.01	[-0.06, 0.05]
$\nu_{congruent}$ * female * Age 40-50	-0.03	[-0.06, 0.01]
$\nu_{congruent}$ * female * Age 50-60	-0.05	[-0.08, -0.01]
$\nu_{congruent}$ * female * Age 60-70	-0.06	[-0.12, 0.00]
$\nu_{incongruent}$ * female * Age 40-50	0.03	[-0.01, 0.06]
$\nu_{incongruent}$ * female * Age 50-60	0.01	[-0.03, 0.04]
$\nu_{incongruent}$ * female * Age 60-70	0.01	[-0.05, 0.07]
$a_{congruent}$ * female * Age 40-50	0.01	[-0.02, 0.05]
$a_{congruent}$ * female * Age 50-60	0.07	[0.03, 0.11]
$a_{congruent}$ * female * Age 60-70	0.04	[-0.02, 0.10]
$a_{incongruent}$ * female * Age 40-50	0.04	[0.00, 0.08]
$a_{incongruent}$ * female * Age 50-60	-0.03	[-0.07, 0.02]
$a_{incongruent}$ * female * Age 60-70	0.00	[-0.05, 0.06]
$\tau_{correct}$ * female * Age 40-50	0.01	[-0.02, 0.05]
$\tau_{correct}$ * female * Age 50-60	0.01	[-0.03, 0.05]
$\tau_{correct}$ * female * Age 60-70	-0.02	[-0.07, 0.03]
τ_{error} * female * Age 40-50	-0.02	[-0.06, 0.01]
τ_{error} * female * Age 50-60	0.01	[-0.03, 0.05]
τ_{error} * female * Age 60-70	0.00	[-0.06, 0.05]

Table S9

Regression results for income with LFM parameters as predictors.

Parameter	Beta	95% Credible Interval
s_ν	-0.08	[-0.09, -0.06]
$\nu_{picture}$	0.04	[0.02, 0.06]
ν_{word}	0.01	[0.00, 0.03]
$a_{congruent}$	-0.02	[-0.04, 0.00]
$a_{incongruent}$	0.03	[0.02, 0.05]
$\tau_{correct}$	-0.01	[-0.02, 0.01]
γ	0.04	[0.03, 0.05]
s_τ	0.01	[-0.01, 0.02]
τ_{error}	0.01	[-0.01, 0.03]
female	-0.26	[-0.28, -0.24]
Age 40-50	0.54	[0.51, 0.56]
Age 50-60	0.73	[0.70, 0.76]
Age 60-70	0.59	[0.55, 0.64]
s_ν * Gender		
s_ν * female	0.03	[0.01, 0.06]
$\nu_{picture}$ * female	0.01	[-0.02, 0.03]
ν_{word} * female	-0.02	[-0.04, 0.01]
$a_{congruent}$ * female	0.01	[-0.01, 0.03]
$a_{incongruent}$ * female	-0.03	[-0.05, -0.01]
$\tau_{correct}$ * female	-0.03	[-0.06, -0.01]
γ * female	0.00	[-0.02, 0.02]
s_τ * female	-0.01	[-0.03, 0.01]
τ_{error} * female	0.03	[0.01, 0.05]
s_ν * Age 40-50	-0.04	[-0.06, -0.01]
s_ν * Age 50-60	-0.07	[-0.10, -0.03]
s_ν * Age 60-70	-0.02	[-0.07, 0.03]
$\nu_{picture}$ * Age 40-50	0.00	[-0.03, 0.03]
$\nu_{picture}$ * Age 50-60	0.00	[-0.03, 0.04]
$\nu_{picture}$ * Age 60-70	-0.08	[-0.13, -0.02]
ν_{word} * Age 40-50	0.03	[0.00, 0.06]
ν_{word} * Age 50-60	0.06	[0.02, 0.09]
ν_{word} * Age 60-70	0.12	[0.06, 0.17]
$a_{congruent}$ * Age 40-50	0.01	[-0.01, 0.04]
$a_{congruent}$ * Age 50-60	-0.02	[-0.05, 0.01]
$a_{congruent}$ * Age 60-70	-0.03	[-0.07, 0.02]
$a_{incongruent}$ * Age 40-50	-0.04	[-0.07, -0.01]
$a_{incongruent}$ * Age 50-60	-0.01	[-0.04, 0.02]
$a_{incongruent}$ * Age 60-70	-0.01	[-0.05, 0.03]
$\tau_{correct}$ * Age 40-50	-0.04	[-0.06, -0.01]
$\tau_{correct}$ * Age 50-60	-0.03	[-0.06, 0.00]
$\tau_{correct}$ * Age 60-70	0.01	[-0.03, 0.05]
γ * Age 40-50	0.01	[-0.01, 0.03]
γ * Age 50-60	0.00	[-0.03, 0.03]
γ * Age 60-70	-0.02	[-0.06, 0.02]
s_τ * Age 40-50	0.00	[-0.03, 0.02]
s_τ * Age 50-60	-0.03	[-0.06, -0.01]
s_τ * Age 60-70	-0.02	[-0.05, 0.01]
τ_{error} * Age 40-50	0.03	[0.01, 0.06]
τ_{error} * Age 50-60	0.00	[-0.04, 0.03]
τ_{error} * Age 60-70	-0.01	[-0.06, 0.03]
female * Age 40-50	-0.20	[-0.23, -0.17]
female * Age 50-60	-0.26	[-0.30, -0.23]
female * Age 60-70	-0.16	[-0.23, -0.10]
s_ν * female * Age 40-50	0.00	[-0.04, 0.03]
s_ν * female * Age 50-60	0.02	[-0.02, 0.06]
s_ν * female * Age 60-70	0.00	[-0.06, 0.07]
$\nu_{picture}$ * female * Age 40-50	-0.01	[-0.05, 0.03]
$\nu_{picture}$ * female * Age 50-60	0.00	[-0.05, 0.04]
$\nu_{picture}$ * female * Age 60-70	0.06	[-0.01, 0.13]
ν_{word} * female * Age 40-50	0.03	[-0.01, 0.07]
ν_{word} * female * Age 50-60	-0.02	[-0.07, 0.03]
ν_{word} * female * Age 60-70	-0.09	[-0.16, -0.02]
$a_{congruent}$ * female * Age 40-50	0.00	[-0.03, 0.04]
$a_{congruent}$ * female * Age 50-60	0.04	[0.00, 0.08]
$a_{congruent}$ * female * Age 60-70	0.05	[0.00, 0.11]
$a_{incongruent}$ * female * Age 40-50	0.02	[-0.01, 0.06]
$a_{incongruent}$ * female * Age 50-60	-0.03	[-0.07, 0.01]
$a_{incongruent}$ * female * Age 60-70	0.00	[-0.06, 0.05]
$\tau_{correct}$ * female * Age 40-50	0.01	[-0.03, 0.04]
$\tau_{correct}$ * female * Age 50-60	0.02	[-0.02, 0.06]
$\tau_{correct}$ * female * Age 60-70	-0.03	[-0.08, 0.02]
γ * female * Age 40-50	-0.03	[-0.06, 0.00]
γ * female * Age 50-60	-0.04	[-0.07, 0.00]
γ * female * Age 60-70	0.00	[-0.05, 0.05]
s_τ * female * Age 40-50	0.03	[0.00, 0.07]
s_τ * female * Age 50-60	0.04	[0.00, 0.08]
s_τ * female * Age 60-70	0.03	[-0.01, 0.08]
τ_{error} * female * Age 40-50	-0.03	[-0.06, 0.01]
τ_{error} * female * Age 50-60	0.01	[-0.03, 0.05]
τ_{error} * female * Age 60-70	0.02	[-0.04, 0.07]

Table S10

Regression results for income with GSR parameters as predictors.

Parameter	Beta	95% Credible Interval
s_ν	-0.07	[-0.08, -0.06]
$\nu_{congruent}$	0.04	[0.03, 0.04]
$\nu_{incongruent}$	0.00	[-0.01, 0.00]
$a_{congruent}$	0.02	[0.01, 0.02]
$a_{incongruent}$	-0.03	[-0.03, -0.02]
$\tau_{correct}$	0.00	[-0.01, 0.00]
s_τ	-0.01	[-0.01, 0.00]
τ_{error}	0.04	[0.03, 0.04]
female	-0.12	[-0.12, -0.11]
Age 40-50	0.06	[0.06, 0.07]
Age 50-60	0.14	[0.13, 0.15]
Age 60-70	0.29	[0.28, 0.31]
s_ν * female	0.02	[0.02, 0.03]
$\nu_{congruent}$ * female	0.00	[-0.01, 0.00]
$\nu_{incongruent}$ * female	0.01	[0.00, 0.01]
$a_{congruent}$ * female	0.01	[0.00, 0.02]
$a_{incongruent}$ * female	0.00	[0.00, 0.01]
$\tau_{correct}$ * female	-0.01	[-0.01, 0.00]
s_τ * female	0.00	[0.00, 0.01]
τ_{error} * female	0.01	[0.00, 0.01]
s_ν * Age 40-50	-0.01	[-0.02, 0.00]
s_ν * Age 50-60	-0.03	[-0.04, -0.02]
s_ν * Age 60-70	-0.05	[-0.06, -0.03]
$\nu_{congruent}$ * Age 40-50	0.01	[0.00, 0.02]
$\nu_{congruent}$ * Age 50-60	0.02	[0.01, 0.03]
$\nu_{congruent}$ * Age 60-70	0.04	[0.02, 0.05]
$\nu_{incongruent}$ * Age 40-50	0.01	[0.00, 0.02]
$\nu_{incongruent}$ * Age 50-60	0.01	[0.00, 0.03]
$\nu_{incongruent}$ * Age 60-70	0.03	[0.01, 0.05]
$a_{congruent}$ * Age 40-50	0.01	[0.00, 0.01]
$a_{congruent}$ * Age 50-60	0.01	[0.00, 0.02]
$a_{congruent}$ * Age 60-70	0.00	[-0.02, 0.01]
$a_{incongruent}$ * Age 40-50	0.00	[-0.01, 0.01]
$a_{incongruent}$ * Age 50-60	0.00	[-0.01, 0.01]
$a_{incongruent}$ * Age 60-70	0.03	[0.02, 0.04]
$\tau_{correct}$ * Age 40-50	-0.01	[-0.02, 0.00]
$\tau_{correct}$ * Age 50-60	-0.01	[-0.02, 0.00]
$\tau_{correct}$ * Age 60-70	-0.02	[-0.03, 0.00]
s_τ * Age 40-50	0.01	[0.00, 0.01]
s_τ * Age 50-60	0.00	[-0.01, 0.01]
s_τ * Age 60-70	-0.01	[-0.02, 0.01]
τ_{error} * Age 40-50	0.01	[0.00, 0.02]
τ_{error} * Age 50-60	0.00	[-0.01, 0.01]
τ_{error} * Age 60-70	0.00	[-0.01, 0.02]
female * Age 40-50	-0.05	[-0.05, -0.04]
female * Age 50-60	-0.10	[-0.11, -0.09]
female * Age 60-70	-0.18	[-0.20, -0.16]
s_ν * female * Age 40-50	0.00	[-0.01, 0.01]
s_ν * female * Age 50-60	0.02	[0.01, 0.04]
s_ν * female * Age 60-70	0.04	[0.02, 0.06]
$\nu_{congruent}$ * female * Age 40-50	-0.01	[-0.02, 0.00]
$\nu_{congruent}$ * female * Age 50-60	-0.02	[-0.03, -0.01]
$\nu_{congruent}$ * female * Age 60-70	-0.06	[-0.08, -0.04]
$\nu_{incongruent}$ * female * Age 40-50	0.00	[-0.01, 0.01]
$\nu_{incongruent}$ * female * Age 50-60	0.00	[-0.01, 0.01]
$\nu_{incongruent}$ * female * Age 60-70	0.01	[-0.02, 0.03]
$a_{congruent}$ * female * Age 40-50	0.01	[0.00, 0.02]
$a_{congruent}$ * female * Age 50-60	0.00	[-0.01, 0.01]
$a_{congruent}$ * female * Age 60-70	-0.01	[-0.03, 0.01]
$a_{incongruent}$ * female * Age 40-50	0.00	[-0.01, 0.01]
$a_{incongruent}$ * female * Age 50-60	0.00	[-0.01, 0.01]
$a_{incongruent}$ * female * Age 60-70	-0.03	[-0.05, -0.02]
$\tau_{correct}$ * female * Age 40-50	0.00	[-0.01, 0.01]
$\tau_{correct}$ * female * Age 50-60	0.00	[-0.01, 0.01]
$\tau_{correct}$ * female * Age 60-70	0.02	[0.00, 0.03]
s_τ * female * Age 40-50	0.00	[-0.01, 0.01]
s_τ * female * Age 50-60	0.01	[0.00, 0.02]
s_τ * female * Age 60-70	0.00	[-0.01, 0.02]
τ_{error} * female * Age 40-50	-0.01	[-0.02, 0.00]
τ_{error} * female * Age 50-60	-0.01	[-0.02, 0.00]
τ_{error} * female * Age 60-70	-0.02	[-0.03, 0.00]

Table S11

Regression results for prestige with $DDM_{s\nu s\tau}$ model parameters as predictors.

Parameter	Beta	95% Credible Interval
α	0.00	[0.00, 0.01]
$\nu_{congruent}$	0.05	[0.05, 0.06]
$\nu_{incongruent}$	0.00	[-0.01, 0.00]
$a_{congruent}$	0.04	[0.03, 0.04]
$a_{incongruent}$	-0.01	[-0.02, -0.01]
$\tau_{correct}$	0.01	[0.01, 0.02]
τ_{error}	0.03	[0.03, 0.04]
female	-0.12	[-0.13, -0.12]
Age 40-50	0.06	[0.05, 0.06]
Age 50-60	0.12	[0.11, 0.13]
Age 60-70	0.27	[0.26, 0.29]
α * female	0.01	[0.00, 0.01]
$\nu_{congruent}$ * female	-0.02	[-0.02, -0.01]
$\nu_{incongruent}$ * female	0.00	[0.00, 0.01]
$a_{congruent}$ * female	0.00	[0.00, 0.01]
$a_{incongruent}$ * female	-0.01	[-0.01, 0.00]
$\tau_{correct}$ * female	-0.01	[-0.02, 0.00]
τ_{error} * female	0.01	[0.00, 0.01]
α * Age 40-50	0.01	[0.00, 0.01]
α * Age 50-60	0.01	[0.00, 0.02]
α * Age 60-70	0.03	[0.02, 0.05]
$\nu_{congruent}$ * Age 40-50	0.01	[0.00, 0.02]
$\nu_{congruent}$ * Age 50-60	0.02	[0.01, 0.03]
$\nu_{congruent}$ * Age 60-70	0.04	[0.02, 0.05]
$\nu_{incongruent}$ * Age 40-50	0.01	[0.00, 0.01]
$\nu_{incongruent}$ * Age 50-60	0.01	[0.01, 0.02]
$\nu_{incongruent}$ * Age 60-70	0.02	[0.00, 0.03]
$a_{congruent}$ * Age 40-50	0.00	[0.00, 0.01]
$a_{congruent}$ * Age 50-60	0.00	[-0.01, 0.01]
$a_{congruent}$ * Age 60-70	-0.02	[-0.04, -0.01]
$a_{incongruent}$ * Age 40-50	0.00	[-0.01, 0.01]
$a_{incongruent}$ * Age 50-60	0.00	[-0.01, 0.01]
$a_{incongruent}$ * Age 60-70	0.03	[0.02, 0.04]
$\tau_{correct}$ * Age 40-50	-0.01	[-0.02, -0.01]
$\tau_{correct}$ * Age 50-60	-0.01	[-0.02, 0.00]
$\tau_{correct}$ * Age 60-70	-0.02	[-0.03, -0.01]
τ_{error} * Age 40-50	0.01	[0.00, 0.01]
τ_{error} * Age 50-60	0.00	[-0.01, 0.01]
τ_{error} * Age 60-70	0.00	[-0.01, 0.01]
female * Age 40-50	-0.04	[-0.05, -0.03]
female * Age 50-60	-0.10	[-0.11, -0.08]
female * Age 60-70	-0.17	[-0.19, -0.15]
α * female * Age 40-50	0.00	[-0.01, 0.01]
α * female * Age 50-60	-0.01	[-0.02, 0.00]
α * female * Age 60-70	-0.03	[-0.05, -0.01]
$\nu_{congruent}$ * female * Age 40-50	-0.01	[-0.02, 0.00]
$\nu_{congruent}$ * female * Age 50-60	-0.03	[-0.04, -0.01]
$\nu_{congruent}$ * female * Age 60-70	-0.05	[-0.07, -0.03]
$\nu_{incongruent}$ * female * Age 40-50	-0.01	[-0.02, 0.00]
$\nu_{incongruent}$ * female * Age 50-60	0.00	[-0.01, 0.01]
$\nu_{incongruent}$ * female * Age 60-70	0.02	[0.00, 0.03]
$a_{congruent}$ * female * Age 40-50	0.01	[0.00, 0.02]
$a_{congruent}$ * female * Age 50-60	0.00	[-0.02, 0.01]
$a_{congruent}$ * female * Age 60-70	0.01	[-0.01, 0.03]
$a_{incongruent}$ * female * Age 40-50	0.00	[-0.01, 0.01]
$a_{incongruent}$ * female * Age 50-60	-0.01	[-0.02, 0.01]
$a_{incongruent}$ * female * Age 60-70	-0.03	[-0.05, -0.01]
$\tau_{correct}$ * female * Age 40-50	0.00	[-0.01, 0.01]
$\tau_{correct}$ * female * Age 50-60	0.00	[-0.01, 0.01]
$\tau_{correct}$ * female * Age 60-70	0.01	[0.00, 0.03]
τ_{error} * female * Age 40-50	-0.01	[-0.02, 0.00]
τ_{error} * female * Age 50-60	0.00	[-0.02, 0.01]
τ_{error} * female * Age 60-70	-0.02	[-0.03, 0.00]

Table S12

Regression results for prestige with LFM parameters as predictors.

Parameter	Beta	95% Credible Interval
s_ν	-0.08	[-0.08, -0.07]
$\nu_{picture}$	0.07	[0.07, 0.08]
ν_{word}	-0.03	[-0.04, -0.03]
$a_{congruent}$	0.02	[0.02, 0.03]
$a_{incongruent}$	-0.02	[-0.03, -0.01]
$\tau_{correct}$	0.00	[-0.01, 0.00]
γ	0.02	[0.02, 0.02]
s_τ	-0.01	[-0.01, 0.00]
τ_{error}	0.03	[0.03, 0.04]
female	-0.10	[-0.11, -0.10]
Age 40-50	0.07	[0.06, 0.07]
Age 50-60	0.14	[0.13, 0.15]
Age 60-70	0.30	[0.29, 0.32]
s_ν * female	0.03	[0.02, 0.03]
$\nu_{picture}$ * female	-0.01	[-0.02, 0.00]
ν_{word} * female	0.01	[0.00, 0.02]
$a_{congruent}$ * female	0.01	[0.00, 0.01]
$a_{incongruent}$ * female	0.00	[0.00, 0.01]
$\tau_{correct}$ * female	-0.01	[-0.01, 0.00]
γ * female	0.00	[-0.01, 0.00]
s_τ * female	0.00	[0.00, 0.01]
τ_{error} * female	0.01	[0.00, 0.01]
s_ν * Age 40-50	-0.01	[-0.02, 0.00]
s_ν * Age 50-60	-0.02	[-0.03, -0.01]
s_ν * Age 60-70	-0.04	[-0.06, -0.02]
$\nu_{picture}$ * Age 40-50	-0.02	[-0.03, -0.01]
$\nu_{picture}$ * Age 50-60	-0.02	[-0.04, -0.01]
$\nu_{picture}$ * Age 60-70	-0.04	[-0.06, -0.02]
ν_{word} * Age 40-50	0.03	[0.02, 0.04]
ν_{word} * Age 50-60	0.05	[0.04, 0.06]
ν_{word} * Age 60-70	0.10	[0.08, 0.12]
$a_{congruent}$ * Age 40-50	0.00	[-0.01, 0.01]
$a_{congruent}$ * Age 50-60	0.01	[0.00, 0.02]
$a_{congruent}$ * Age 60-70	-0.01	[-0.02, 0.00]
$a_{incongruent}$ * Age 40-50	0.00	[-0.01, 0.01]
$a_{incongruent}$ * Age 50-60	-0.01	[-0.02, 0.00]
$a_{incongruent}$ * Age 60-70	0.02	[0.01, 0.04]
$\tau_{correct}$ * Age 40-50	-0.01	[-0.02, -0.01]
$\tau_{correct}$ * Age 50-60	-0.01	[-0.02, 0.00]
$\tau_{correct}$ * Age 60-70	-0.02	[-0.03, -0.01]
γ * Age 40-50	0.00	[-0.01, 0.01]
γ * Age 50-60	0.00	[-0.01, 0.01]
γ * Age 60-70	-0.01	[-0.02, 0.01]
s_τ * Age 40-50	0.00	[0.00, 0.01]
s_τ * Age 50-60	0.00	[-0.01, 0.01]
s_τ * Age 60-70	0.00	[-0.01, 0.01]
τ_{error} * Age 40-50	0.01	[0.00, 0.02]
τ_{error} * Age 50-60	0.00	[-0.01, 0.01]
τ_{error} * Age 60-70	0.00	[-0.01, 0.01]
female * Age 40-50	-0.05	[-0.06, -0.04]
female * Age 50-60	-0.11	[-0.12, -0.10]
female * Age 60-70	-0.20	[-0.22, -0.17]
s_ν * female * Age 40-50	0.00	[-0.01, 0.01]
s_ν * female * Age 50-60	0.02	[0.01, 0.04]
s_ν * female * Age 60-70	0.04	[0.02, 0.06]
$\nu_{picture}$ * female * Age 40-50	0.00	[-0.01, 0.01]
$\nu_{picture}$ * female * Age 50-60	-0.01	[-0.02, 0.01]
$\nu_{picture}$ * female * Age 60-70	0.00	[-0.02, 0.02]
ν_{word} * female * Age 40-50	-0.01	[-0.02, 0.00]
ν_{word} * female * Age 50-60	-0.02	[-0.03, 0.00]
ν_{word} * female * Age 60-70	-0.06	[-0.08, -0.04]
$a_{congruent}$ * female * Age 40-50	0.01	[0.00, 0.02]
$a_{congruent}$ * female * Age 50-60	0.00	[-0.01, 0.01]
$a_{congruent}$ * female * Age 60-70	0.00	[-0.02, 0.02]
$a_{incongruent}$ * female * Age 40-50	0.00	[-0.01, 0.01]
$a_{incongruent}$ * female * Age 50-60	0.00	[-0.01, 0.01]
$a_{incongruent}$ * female * Age 60-70	-0.03	[-0.05, -0.01]
$\tau_{correct}$ * female * Age 40-50	0.00	[-0.01, 0.01]
$\tau_{correct}$ * female * Age 50-60	0.00	[-0.01, 0.01]
$\tau_{correct}$ * female * Age 60-70	0.02	[0.00, 0.04]
γ * female * Age 40-50	0.00	[-0.01, 0.01]
γ * female * Age 50-60	-0.01	[-0.02, 0.00]
γ * female * Age 60-70	-0.03	[-0.04, -0.01]
s_τ * female * Age 40-50	0.00	[-0.01, 0.01]
s_τ * female * Age 50-60	0.01	[0.00, 0.02]
s_τ * female * Age 60-70	0.00	[-0.01, 0.02]
τ_{error} * female * Age 40-50	-0.01	[-0.02, 0.00]
τ_{error} * female * Age 50-60	-0.01	[-0.02, 0.00]
τ_{error} * female * Age 60-70	-0.02	[-0.04, 0.00]

Table S13

Regression results for prestige with GSR model parameters as predictors.

References

Lerche, V., & Voss, A. (2019). Experimental validation of the diffusion model based on a slow response time paradigm. *Psychological research*, *83*(6), 1194–1209.

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

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

Ratcliff, R., & Rouder, J. N. (1998). Modeling response times for two-choice decisions. *Psychological science*, *9*(5), 347–356.

Säilynoja, T., Bürkner, P.-C., & Vehtari, A. (2022). Graphical test for discrete uniformity and its applications in goodness-of-fit evaluation and multiple sample comparison. *Statistics and Computing*, *32*(2), 32.

Schad, D. J., Betancourt, M., & Vasishth, S. (2021). Toward a principled bayesian workflow in cognitive science. *Psychological Methods*, *26*(1), 103–126. https://doi.org/10.1037/met0000275

Talts, S., Betancourt, M., Simpson, D., Vehtari, A., & Gelman, A. (2020). Validating bayesian inference algorithms with simulation-based calibration. https://arxiv.org/abs/1804.06788

von Krause, M., Radev, S. T., & Voss, A. (2022). Mental speed is high until age 60 as revealed by analysis of over a million participants [Publisher: Nature Publishing Group UK London]. *Nature human behaviour*, *6*(5), 700–708.

Voss, A., Lerche, V., Mertens, U., & Voss, J. (2019). Sequential sampling models with variable boundaries and non-normal noise: A comparison of six models. *Psychonomic Bulletin & Review*, *26*(3), 813–832. https://doi.org/10.3758/s13423-018-1560-4

Voss, A., Nagler, M., & Lerche, V. (2013). Diffusion models in experimental psychology: A practical introduction. *Experimental psychology*, *60*(6), 385–402. https://doi.org/10.1027/1618-3169/a000218

Wiecki, T. V., Sofer, I., & Frank, M. J. (2013). HDDM: Hierarchical bayesian estimation of the drift-diffusion model in python. *Frontiers in Neuroinformatics*, *7*. https://doi.org/10.3389/fninf.2013.00014