

Supplementary Materials: Creative or Not? Hierarchical Diffusion Modeling of the Creative
Evaluation Process

Michelle C. Donzallaz¹, Julia M. Haaf¹, & Claire E. Stevenson¹

¹ University of Amsterdam

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Author Note

Supplementary materials of the paper “Creative or Not? Hierarchical Diffusion
Modeling of the Creative Evaluation Process”.

Correspondence concerning this article should be addressed to Claire E. Stevenson,
Nieuwe Achtergracht 129-B, 1018 WS Amsterdam. E-mail: c.e.stevenson@uva.nl

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Posterior predictive checks

Here we describe how we assessed the fit of the drift diffusion model (DDM) applied in Study 1 and 2 using posterior predictive checks. We followed the procedure described by (Singmann, 2018). The overall goal of the check was to examine whether the model was able to adequately describe the observed data. To this end, we obtained 500 samples from the posterior predictive distribution in both Study 1 and Study 2. In a first step, we examined whether the model could reproduce the general RT and response proportion pattern observed in the data. To do so, we calculated three summary statistics for all samples of the posterior predictive distribution. The summary statistics were (1) the proportion of “creative” responses, (2) the median RT for “creative” responses, and (3) the median RT for “not creative” responses. We then summarized these statistics across the posterior predictive distribution by computing the mean for the proportion of “creative” responses and the median for the RTs. Next, we calculated the same summary statistics for the observed data. Figure 1 shows the three summary statistics of the predictions (in black and grey) and of the data (in red) for Study 1 and Figure 2 shows the same for Study 2. Overall, the models were able to adequately describe the general patterns in the data.

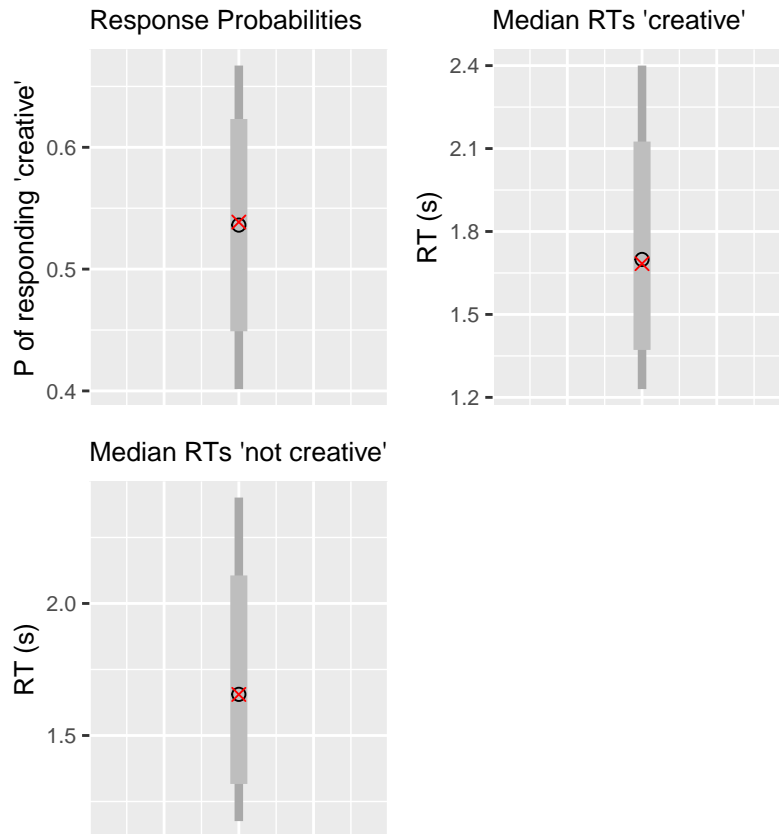


Figure 1. Posterior predictive check of Study 1. The inner vertical lines show the 80% CrIs and the outer vertical lines the 95% CrIs. The red cross denotes the observed and the black circle the predicted statistics. The model could reproduce the three summary statistics quite accurately.

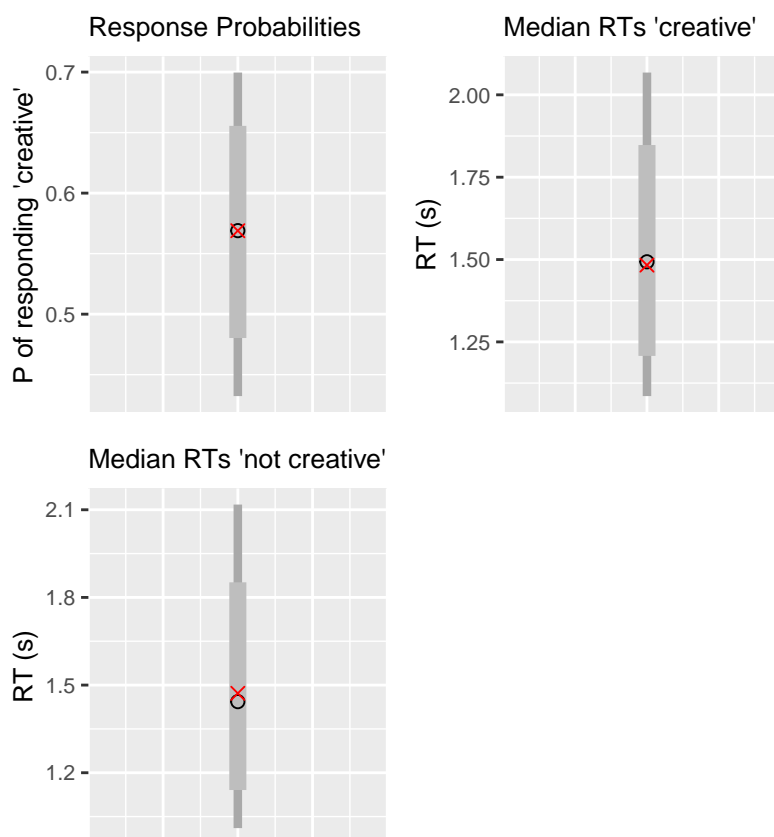


Figure 2. Posterior predictive check of Study 2. The inner vertical lines show the 80% CrIs and the outer vertical lines the 95% CrIs. The red cross denotes the observed and the black circle the predicted statistics. The model could reproduce the three summary statistics quite accurately.

In a second step, we also examined the predicted response proportions on the participant level by inspecting the proportion of “creative” responses for each participant separately. Again the models were able to reproduce the data well as they predicted the medians quite accurately. Next, we computed the coverage probabilities of the three summary statistics across participants (Singmann, 2018). For each of the statistics and for different credible intervals (CrIs), we calculated whether the three observed statistics were covered by the corresponding CrI. The coverage probabilities are shown in Table 1 for Study 1 and in Table 2 for Study 2. In both datasets, they corresponded with the width of the CrIs

and even above. For several measures, the coverage probability was even 1 for the 95% and the 99% CrIs in both datasets/studies.

Table 1

Study 1: Coverage probabilities for the three summary statistics across participants and the 50%, 80%, 95%, and 99% CrIs

Statistic	50% CrI	80% CrI	95% CrI	99% CrI
Median RT 'not creative'	0.744	0.956	0.993	0.997
Median RT 'creative'	0.700	0.959	1.000	1.000
Proportion 'creative'	0.949	0.997	1.000	1.000

Table 2

Study 2: Coverage probabilities for the three summary statistics across participants and the 50%, 80%, 95%, and 99% CrIs

Statistic	50% CrI	80% CrI	95% CrI	99% CrI
Median RT 'not creative'	0.770	0.967	1.000	1.000
Median RT 'creative'	0.789	0.967	1.000	1.000
Proportion 'creative'	0.941	0.980	0.993	0.993

Lastly, we assessed the model fit by inspecting more RT quantiles than just the median (Singmann, 2018). More specifically, we examined the observed and predicted RT quantiles (i.e., the 10th, 25th, 75th, and 90th) across participants. We first computed the quantiles for each sample of the posterior predictive distribution and then aggregated them. To assess how much the observed and predicted quantiles matched, we calculated the concordance correlation coefficient for each quantile (CCC; e.g., Barchard, 2012). The CCC indicates the extent of absolute agreement between two values and ranges from -1 to 1, whereby $CCC = 0$ stands for no agreement, $CCC = 1$ for perfect agreement, and $CCC = -1$ for perfect

disagreement. Figure 3 and Figure 4 show a QQ-plot for each quantile and for each response option. In general and across studies, the fit was slightly better for the “creative” responses compared to the “not creative” responses. The model fit was best for the medians and worst for the 10th quantiles. At the 10th and 25th quantiles, the predicted RTs were smaller than the observed ones which could be a sign of shrinkage. At the 75th quantiles, on the other hand, the model predicted slightly slower RTs than were observed, which could indicate some bias in the model. All in all, the model appeared to provide a good account of the data. Apart from some misfit in the outer quantiles, the model could reproduce the RTs and responses well.

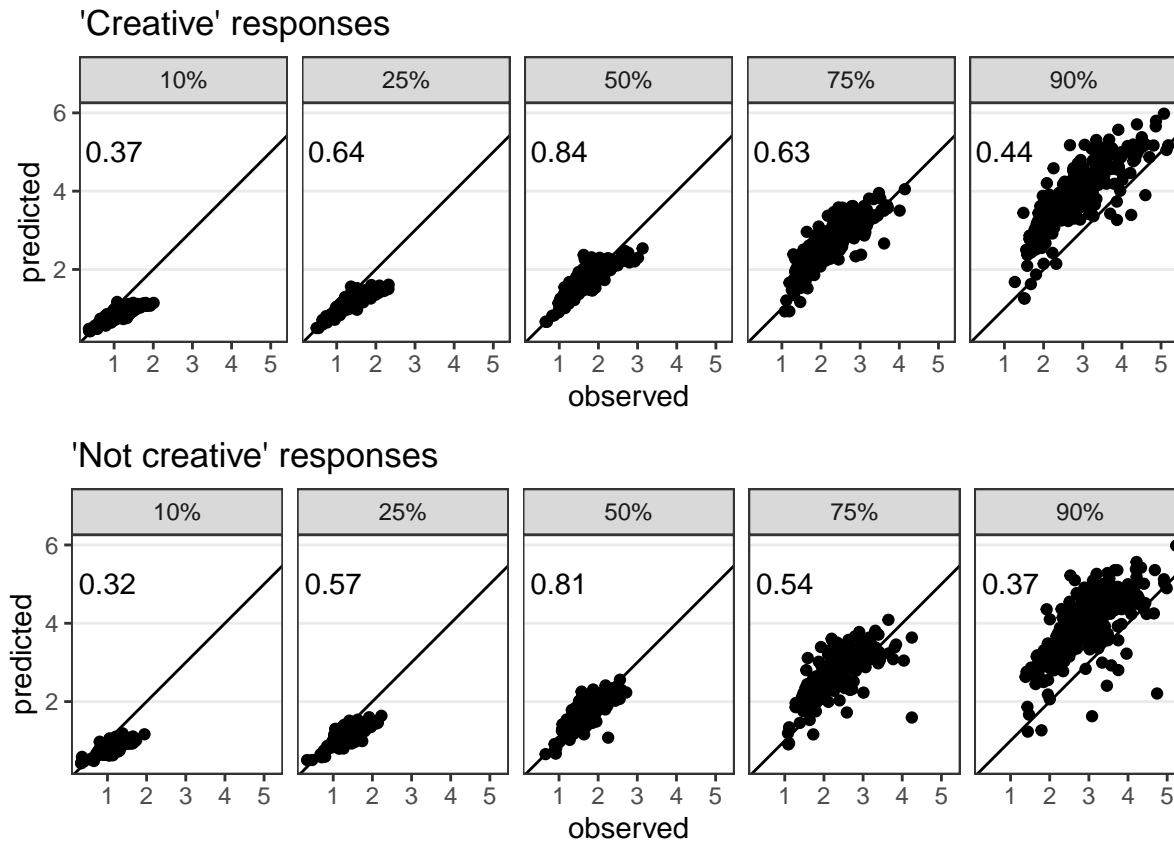


Figure 3. Posterior predictive check of Study 1. Each dot represents a participant. The model fit was slightly better for the upper responses compared to the lower responses. The fit was best for the medians and worst for the 10th quantiles. At the 10th and 25th quantiles, the predicted RTs were smaller than the observed ones. At the 75th quantiles the model predicted slightly slower RTs than were observed, which could indicate some bias in the model. Apart from that, the model fits well.

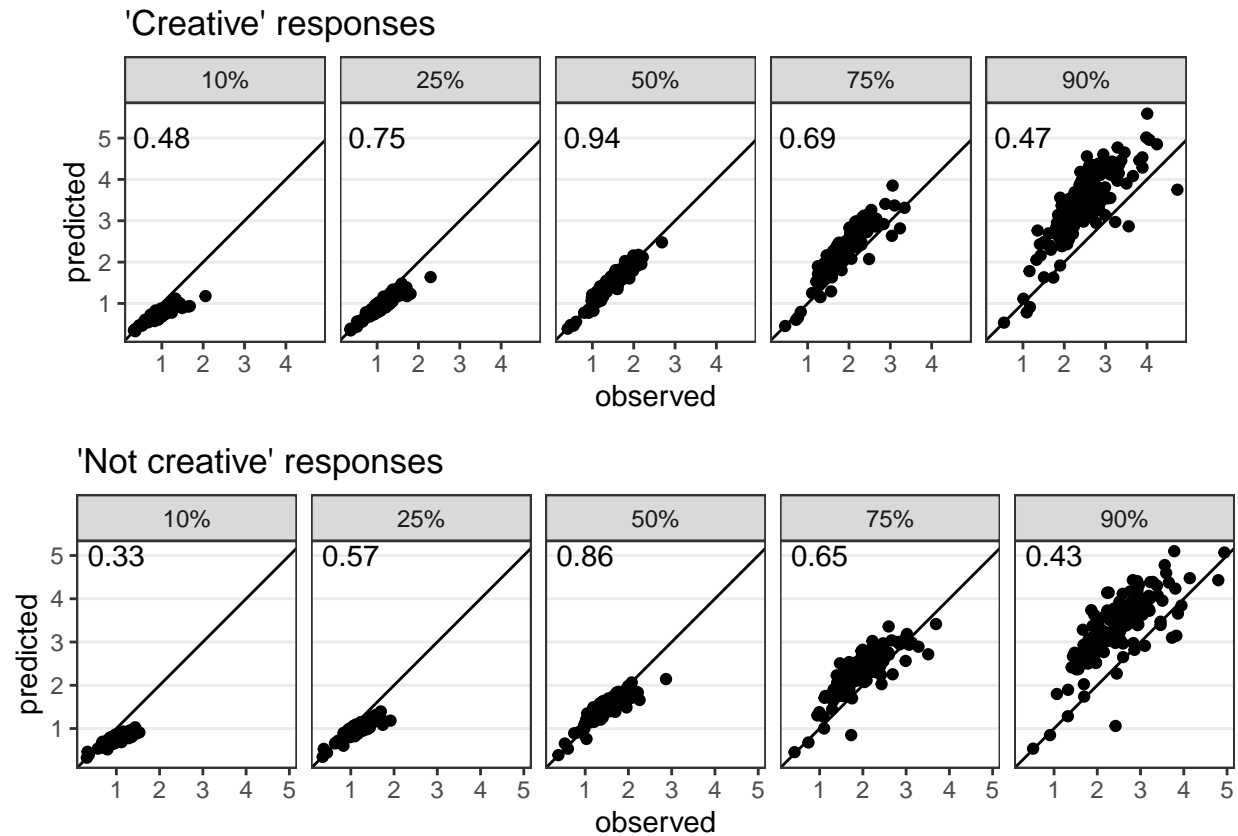


Figure 4. Posterior predictive check of Study 2. Each dot represents a participant. The model fit was slightly better for the upper responses compared to the lower responses. The fit was best for the medians and worst for the 10th quantiles. At the 10th and 25th quantiles, the predicted RTs were smaller than the observed ones. At the 75th quantiles the model predicted slightly slower RTs than were observed, which could indicate some bias in the model. Apart from that, the model fits well.

Model Estimation Including Participants Who Were Excluded Based on Too Few Trials

We re-did the key analyses including the participants that we had excluded based on too few trials (<47) to examine whether we would have arrived at the same conclusions had we included them. As shown in Table 3, 4, and 5, the model estimation results differ only slightly.

The posterior means of the originality and utility effects on the drift rate were identical for the utility effect and differed only slightly for the originality effect. Furthermore, the posterior mean of the random effects correlation between the originality and utility effects was only somewhat smaller.

Table 3

Posterior mean, standard deviation of the posterior distribution, 95% credible interval and \hat{R} statistic for the fixed effects (population-level) parameters

	Study 2 (excl.)				Study 2			
	Mean	SD	LB	UB	Mean	SD	LB	UB
μ_δ	0.14	0.05	0.04	0.24	0.15	0.05	0.05	0.25
μ_α	2.62	0.05	2.52	2.71	2.72	0.04	2.64	2.80
μ_β	0.50	0.01	0.48	0.51	0.49	0.01	0.48	0.50
$\mu_{\theta_{OR}}$	0.38	0.05	0.28	0.49	0.40	0.05	0.30	0.51
$\mu_{\theta_{UT}}$	0.10	0.05	0.01	0.20	0.10	0.05	0.01	0.20
τ	0.28	0.00	0.27	0.28	0.29	0.00	0.29	0.29

Note. $\mu_{\theta_{OR}}$, $\mu_{\theta_{UT}}$, and μ_δ are standardized estimates as the originality and utility ratings of the stimuli are z-scores.

SD = standard deviation; LB = lower bound; UB = upper bound.

Table 4

Posterior mean, standard deviation of the posterior distribution, 95% credible interval and \hat{R} statistic for the variability parameters. σ_{δ_ϕ} denotes the variability across stimuli

	Study 2 (excl.)				Study 2			
	Mean	SD	LB	UB	Mean	SD	LB	UB
σ_{δ_ϕ}	0.32	0.03	0.27	0.39	0.33	0.03	0.27	0.39
σ_{δ_v}	0.36	0.02	0.32	0.42	0.36	0.03	0.32	0.42
$\sigma_{\theta_{OR}}$	0.20	0.02	0.17	0.24	0.20	0.02	0.16	0.24
$\sigma_{\theta_{UT}}$	0.20	0.02	0.16	0.23	0.20	0.02	0.17	0.24
σ_α	0.60	0.03	0.54	0.68	0.46	0.03	0.41	0.52
σ_β	0.05	0.01	0.04	0.06	0.05	0.01	0.04	0.06

Note. SD = standard deviation; LB = lower bound; UB = upper bound.

Table 5

Posterior mean, standard deviation, and 95% credible interval for the correlations among random effects parameters

	Study 2 (excl.)				Study 2			
	Mean	SD	LB	UB	Mean	SD	LB	UB
$\rho_{\sigma_{\delta}\sigma_{\beta}}$	-0.51	0.09	-0.67	-0.32	-0.45	0.10	-0.63	-0.24
$\rho_{\sigma_{\alpha}\sigma_{\beta}}$	-0.47	0.10	-0.65	-0.27	-0.42	0.10	-0.60	-0.21
$\rho_{\sigma_{\theta_{OR}}\sigma_{\theta_{UT}}}$	-0.31	0.13	-0.57	-0.05	-0.34	0.13	-0.58	-0.09
$\rho_{\sigma_{\theta_{OR}}\sigma_{\beta}}$	-0.27	0.14	-0.53	0.01	-0.17	0.14	-0.44	0.12
$\rho_{\sigma_{\theta_{UT}}\sigma_{\alpha}}$	-0.12	0.13	-0.35	0.14	-0.21	0.12	-0.43	0.02
$\rho_{\sigma_{\delta}\sigma_{\theta_{UT}}}$	-0.07	0.11	-0.28	0.14	-0.09	0.11	-0.30	0.12
$\rho_{\sigma_{\delta}\sigma_{\theta_{OR}}}$	-0.01	0.11	-0.23	0.19	-0.04	0.11	-0.24	0.18
$\rho_{\sigma_{\delta}\sigma_{\alpha}}$	0.04	0.10	-0.15	0.24	0.02	0.10	-0.16	0.21
$\rho_{\sigma_{\theta_{UT}}\sigma_{\beta}}$	0.11	0.14	-0.16	0.39	0.14	0.14	-0.14	0.41
$\rho_{\sigma_{\theta_{OR}}\sigma_{\alpha}}$	0.34	0.12	0.11	0.55	0.24	0.11	0.02	0.44

Note. SD = standard deviation; LB = lower bound; UB = upper bound.

Estimation With Uncorrelated Stimuli Set

Study 2

In the original analysis, we found a substantial correlation between the originality and utility effects, suggesting that the more individuals take originality into account when they evaluate creativity, the less they take utility into account and vice versa. However, the originality and utility ratings were negatively correlated ($r = -0.60$). The correlation between the originality and utility effects may therefore be a function of the stimuli.

To assess whether this is indeed the case, we re-estimated the model based on an uncorrelated set of stimuli and comparing results. We excluded all stimuli with an originality rating below 1.5 and a utility rating above -1 or a utility rating below 1.5. These criteria led us to exclude 20 stimuli, reducing the stimulus set from 64 to 44 stimuli and the stimulus correlation to $r = -0.15$, $BF_{01} = 1.71$.

Across studies, the results were inconsistent. In Study 1, the posterior mean of the correlation between the stimulus originality and stimulus utility effects on the drift rate was -0.49, 95% CrI [-0.67, -0.29] whereas in Study 2 it was -0.17, 95% CrI [-0.48, 0.14]. This suggests that the correlation between the originality and utility effects on the drift rate was more robust in Study 1 than in Study 2.

Probit Model Analysis

To examine whether we could reproduce the main findings using a different, less complex method than the DDM, we conducted a Bayesian hierarchical probit model analysis. We regressed the propensity to respond with “creative” onto stimulus originality and stimulus utility and used a non-informative prior for the intercept and the two effects as well as for the variability parameters, $\text{Normal}(0, 0.3)$. For the correlation across random effects, we used an LKJ prior with shape parameter 3. As can be seen in Figure 5, the extent and nature of individual differences in the originality and utility effects on the propensity to respond with “Yes, creative” is very similar to the DDM results. The posterior mean of the correlation across random effects was similar too: it was -0.43, 95% CrI [-0.61, -0.23] in Study 1 and -0.36, 95% CrI [-0.65, -0.05] in Study 2. These results suggest that the results in the DDM are mainly driven by the task decisions and less driven by response times.

Table 6

Posterior mean, standard deviation of the posterior distribution, 95% credible interval and \hat{R} statistic for the fixed effects (population-level) parameters of the hierarchical probit model analysis (Study 1 and Study 2)

	Study 1				Study 2			
	Mean	SD	LB	UB	Mean	SD	LB	UB
μ	0.12	0.06	0.01	0.23	0.22	0.07	0.08	0.36
μ_{OR}	0.62	0.07	0.49	0.76	0.61	0.08	0.45	0.76
μ_{UT}	0.15	0.07	0.02	0.28	0.16	0.08	0.00	0.32

Note. μ_{OR} , μ_{UT} , and μ are standardized estimates as the originality and utility ratings of the stimuli are z-scores.

SD = standard deviation; LB = lower bound; UB = upper bound.

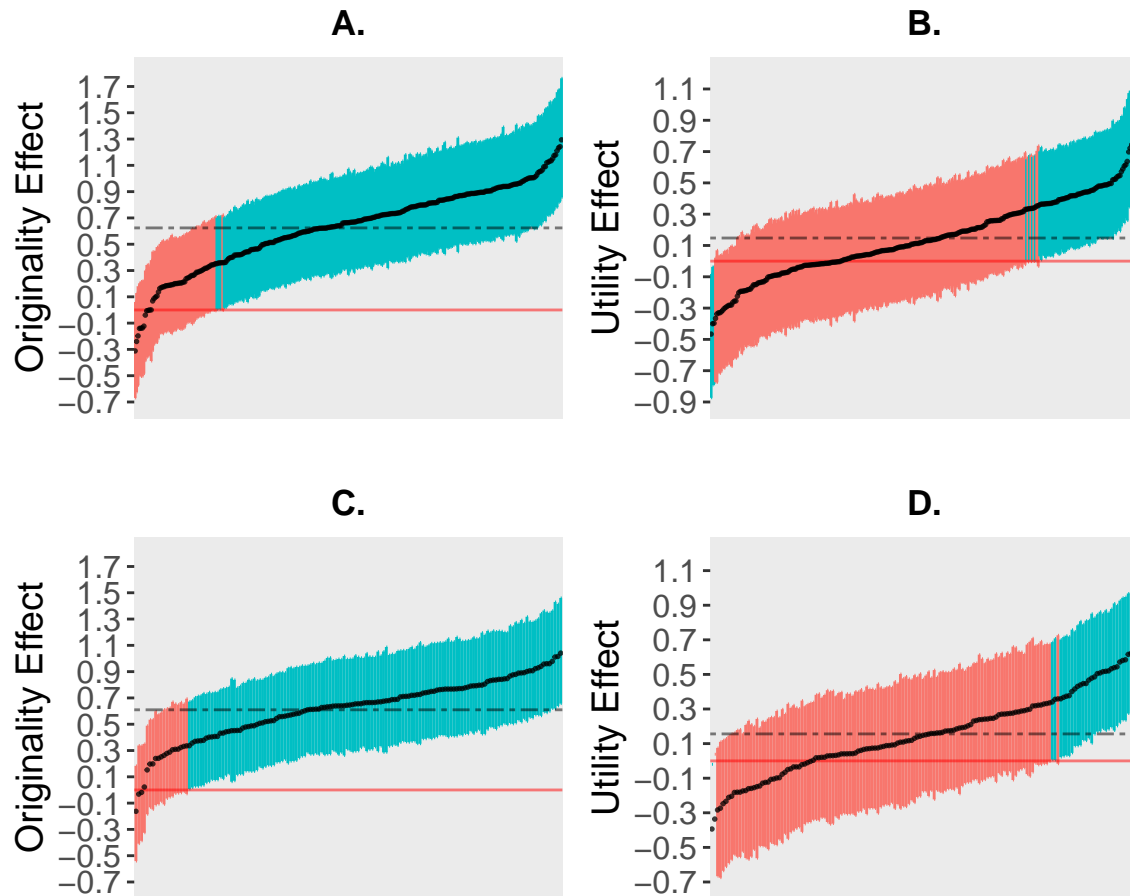


Figure 5. Hierarchical probit model analysis with data from Study 1 (A. and B.) and Study 2 (C. and D.). The plots show the posterior means and the 95 % credible interval (CrI) for each participant in increasing order. The dashed horizontal line denotes the population-level posterior means. CrIs colored in red included zero.

References

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