

# Supplement

For the article #Knowledge: Improving food-related knowledge via seeding implemented as a social media intervention

2024-11-18

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The following table shows the list of abbreviations commonly used in the supplement:

Abbreviation	Meaning
kcal	Kilocalories
CO <sub>2</sub>	Carbon dioxide
OME	Order of Magnitude Error
BF	Bayes Factor

Trained	Estimated	Age	Perc. Female/Male	Perc. GUEQ/BA/MA/Other
CO2	CO2	30.5 (9.4)	87.5 / 9.4 %	43.8 / 18.8 / 28.1 / 9.4 %
CO2	Kcal	31.1 (10.6)	80.0 / 17.1 %	48.6 / 11.4 / 25.7 / 14.3 %
Kcal	CO2	31.7 (10.4)	89.7 / 10.3 %	48.7 / 5.1 / 28.2 / 17.9 %
Kcal	Kcal	28.4 (9.5)	81.6 / 15.8 %	52.6 / 13.2 / 23.7 / 10.5 %

Estimated Criterion	Knowledge: Kcal	Knowledge: CO2
CO2	4.55 (1.76)	1.86 (1.21)
Kcal	3.71 (1.52)	2.30 (1.40)

## Demographics per Condition

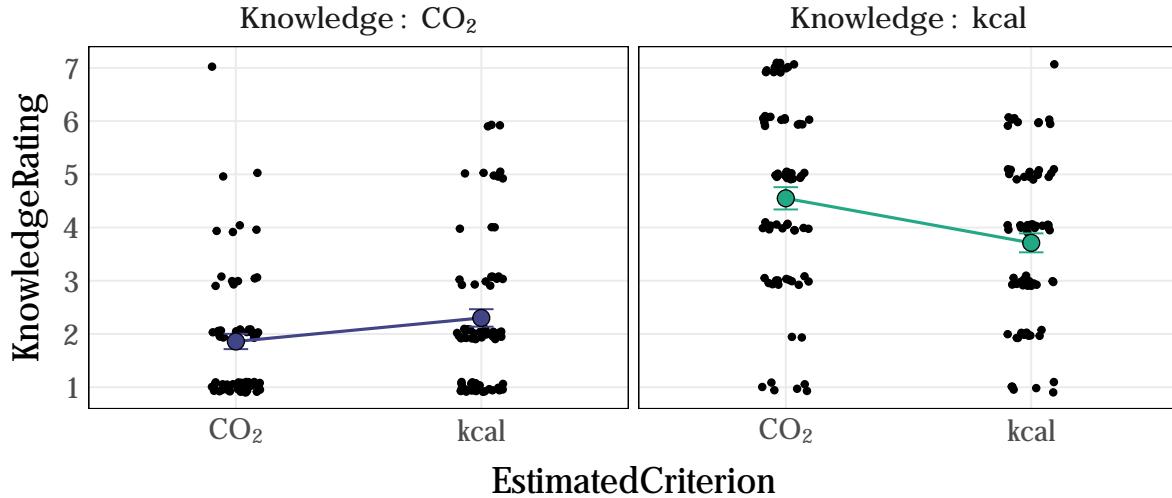
Note. GUEQ = General University Entrance Qualification , BA = Bachelor's degree, MA = Master's degree

## Reactivity Effects in General Criterion Knowledge Question

As stated in the main manuscript, participants reported knowing in general more about the calorie content of food items ( $M = 4.12$ ,  $SD = 1.69$ ) than their CO<sub>2</sub> footprint ( $M = 2.08$ ,  $SD = 1.32$ ,  $F = 2.02$  [1.67, 2.36],  $BF_{10} > 1000$ ). However, we also found a small reactivity effect, where participants rated their knowledge of a criterion lower when they had to estimate this criterion beforehand. This effect was found when participants had to estimate calories in the main task ( $BF_{10} = 11.71$ ) and also (but to smaller degree) when they had to estimate the carbon footprint ( $BF_{10} = 1.15$ ). See below for descriptive values and the corresponding figure of individual values.

Account	M	SD	Min	Max
CO2	29.25	1.58	21	30
Kcal	28.55	4.48	1	30

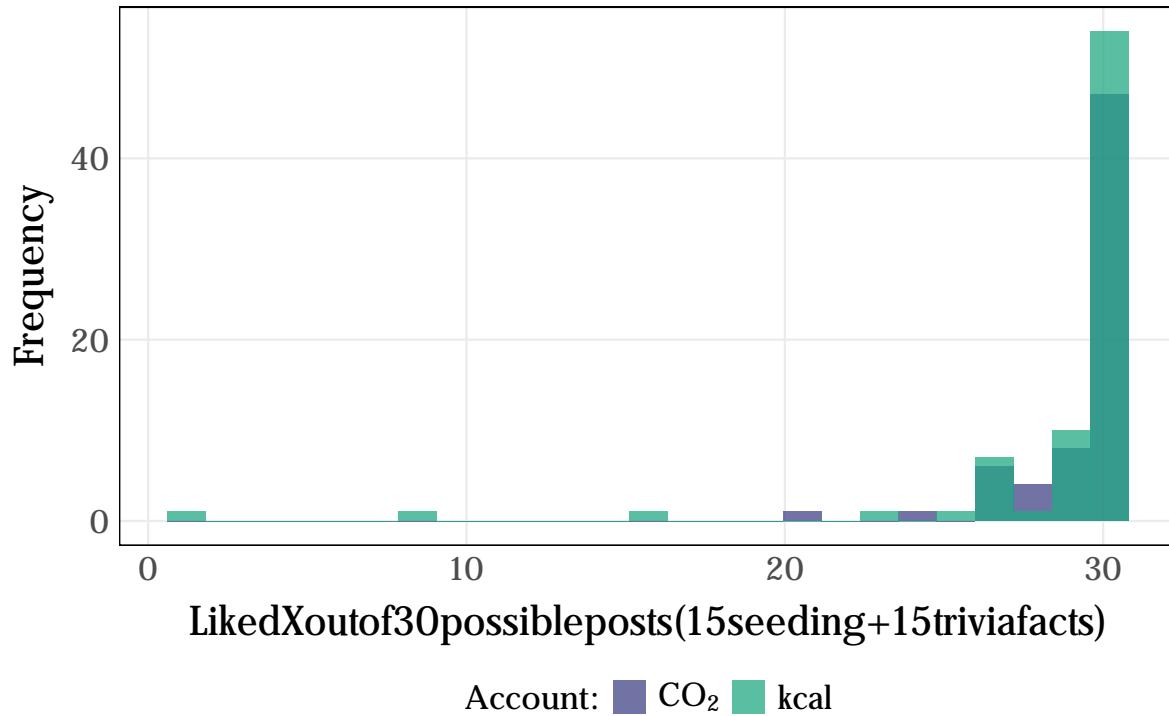
Figure 1: Figure S1. General knowledge ratings for CO<sub>2</sub> footprint and calorie content of food items, depending on the estimated criterion in the main task.



## Number of Likes Posts

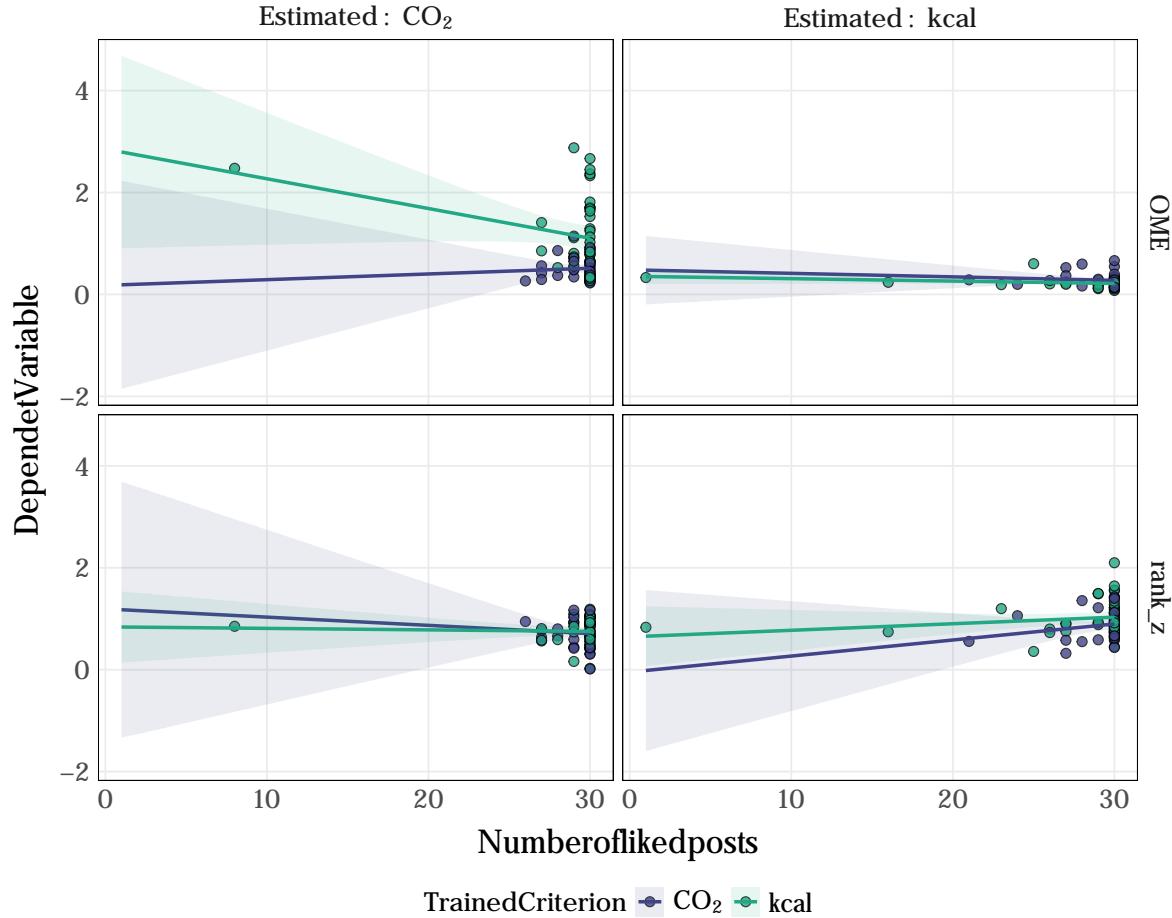
In the preregistration, we also predicted that a greater seeding effect when participants saw more posts as indicated by the number of liked posts. However, as already stated in the main text, almost all participants liked every post, see the table below for the descriptive statistics and the Figure S2 for the distribution of liked posts per participant.

Figure 2: Figure S2. Distribution of number of liked posts per participant.



In addition, Figure S3 shows the scatter plots with the estimated regression line when using the number of liked posts as an predictor of OME or  $\rho$  (all  $p > 0.05$ )

Figure 3: Figure S3. Relationship of number of liked posts and OME/rank correlation (z-transformed) per trained and estimated criterion



## Seeding Effects on Direct Learning

In the analysis of the effects of seeding on calories and CO<sub>2</sub> reported in the main text, we used only the respective 45 transfer items. Here we report the results when using only the seeding items (see file [analysis\\_Hypothesis1\\_seedingItems.R](#) for the underlying analysis code).

**Metric Knowledge:** We found strong evidence for a large seeding effect on metric knowledge (reduction in OME) on the seeding items for CO<sub>2</sub> ( $BF_{10} = 534.68$ ,  $b = -0.49 [-0.19, -0.82]$ ) and evidence for a smaller seeding effect for calories ( $BF_{10} = 7.95$ ,  $b = -0.10 [-0.21, -0.01]$ ).

**Mapping Knowledge** In contrast, there was weak evidence for an effect of seeding on the mapping knowledge (increase in  $\rho$ ) for participants who estimated calories ( $BF_{10} = 1.88$ ,  $b =$

.08 [.01, .16]) but not CO<sub>2</sub> (BF<sub>10</sub> = 0.91).

## Detailed Modeling Results

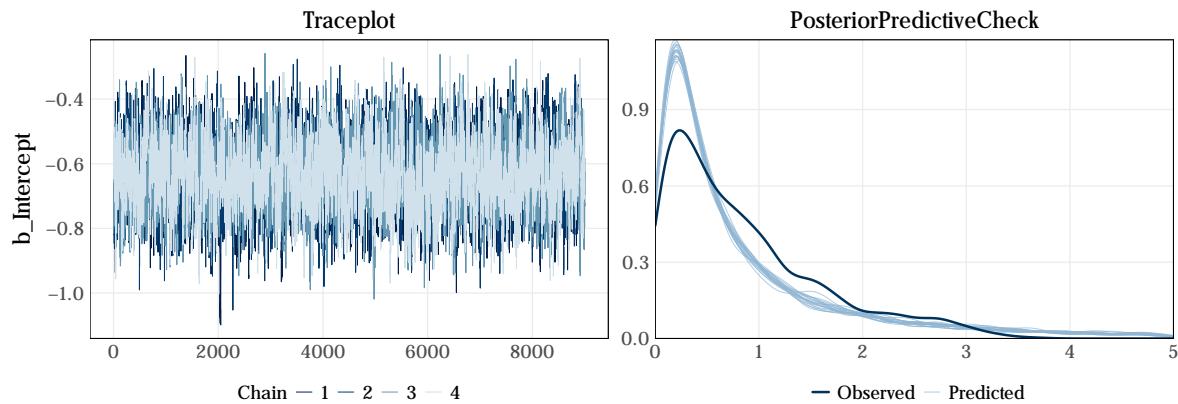
Here we provide for all models reported in the main manuscript more detailed modeling results, including a table with the mean, standard deviation, 95%-HDI, effective sample size (ESS) and  $\hat{R}$  for each estimated parameter (random and fixed), as well as figures showing the MCMC-traces for the main fixed effects parameters (intercept and effect parameter) and posterior predictive distributions of the complete model.

### Hypothesis 1a (OME)

#### CO<sub>2</sub> M0

OME\_corr ~ 1 + (1 | ID) + (match\_domain | ID\_item)

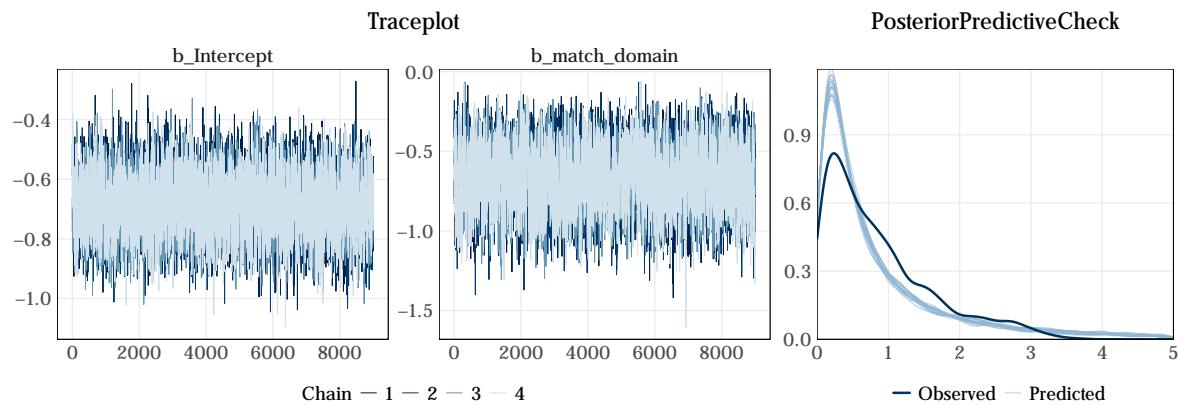
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high
b_Intercept	fixed	conditional	-0.63	0.10	0.95	-0.83	-0.4
sd_ID_Intercept	random	conditional	0.80	0.07	0.95	0.67	0.9
sd_ID_item_Intercept	random	conditional	0.33	0.03	0.95	0.26	0.4
sd_ID_item_match_domain	random	conditional	0.20	0.04	0.95	0.13	0.2
cor_ID_item_Intercept_match_domain	random	conditional	0.81	0.12	0.95	0.57	0.9
sigma	fixed	sigma	0.88	0.01	0.95	0.86	0.9



## CO<sub>2</sub> M1

`OME_corr ~ match_domain + (1 | ID) + (match_domain | ID_item)`

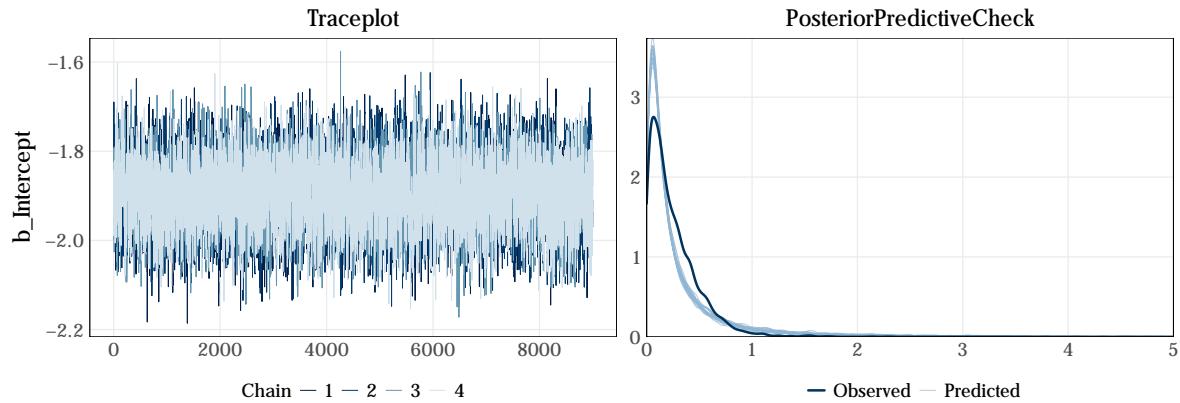
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high
b_Intercept	fixed	conditional	-0.68	0.09	0.95	-0.87	-0.5
b_match_domain	fixed	conditional	-0.67	0.18	0.95	-1.03	-0.3
sd_ID_Intercept	random	conditional	0.70	0.06	0.95	0.58	0.8
sd_ID_item_Intercept	random	conditional	0.33	0.03	0.95	0.26	0.4
sd_ID_item_match_domain	random	conditional	0.20	0.04	0.95	0.13	0.2
cor_ID_item_Intercept_match_domain	random	conditional	0.81	0.12	0.95	0.57	0.9
sigma	fixed	sigma	0.88	0.01	0.95	0.86	0.9



## kcal M0

`OME_corr ~ 1 + (1 | ID) + (match_domain | ID_item)`

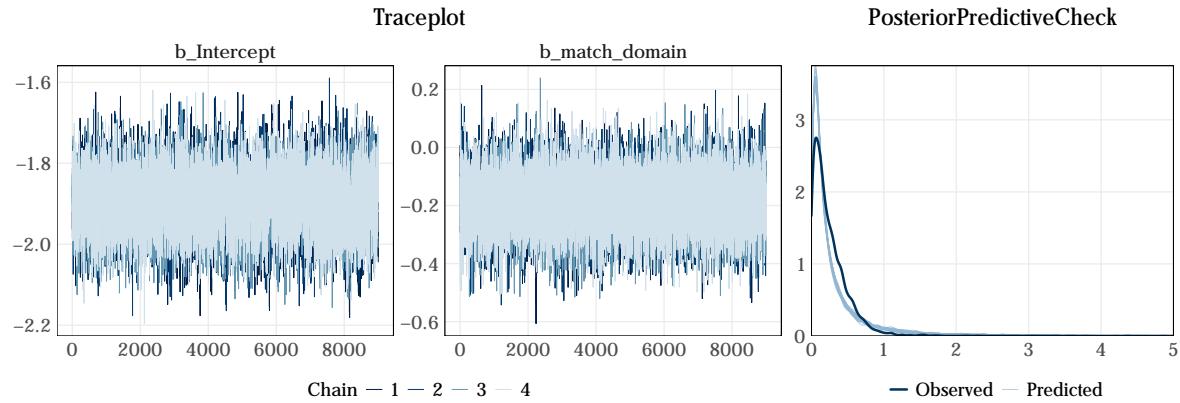
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high
b_Intercept	fixed	conditional	-1.90	0.07	0.95	-2.04	-1.7
sd_ID_Intercept	random	conditional	0.44	0.04	0.95	0.36	0.5
sd_ID_item_Intercept	random	conditional	0.35	0.04	0.95	0.28	0.4
sd_ID_item_match_domain	random	conditional	0.13	0.03	0.95	0.07	0.2
cor_ID_item_Intercept_match_domain	random	conditional	0.08	0.35	0.95	-0.61	0.7
sigma	fixed	sigma	1.19	0.01	0.95	1.17	1.2



## kcal M1

```
OME_corr ~ match_domain + (1 | ID) + (match_domain | ID_item)
```

Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high
<code>b_Intercept</code>	fixed	conditional	-1.90	0.07	0.95	-2.04	-1.76
<code>b_match_domain</code>	fixed	conditional	-0.19	0.09	0.95	-0.37	-0.00
<code>sd_ID_Intercept</code>	random	conditional	0.43	0.04	0.95	0.36	0.50
<code>sd_ID_item_Intercept</code>	random	conditional	0.35	0.04	0.95	0.27	0.43
<code>sd_ID_item_match_domain</code>	random	conditional	0.13	0.03	0.95	0.07	0.20
<code>cor_ID_item_Intercept_match_domain</code>	random	conditional	0.05	0.36	0.95	-0.64	0.74
<code>sigma</code>	fixed	sigma	1.19	0.02	0.95	1.17	1.21

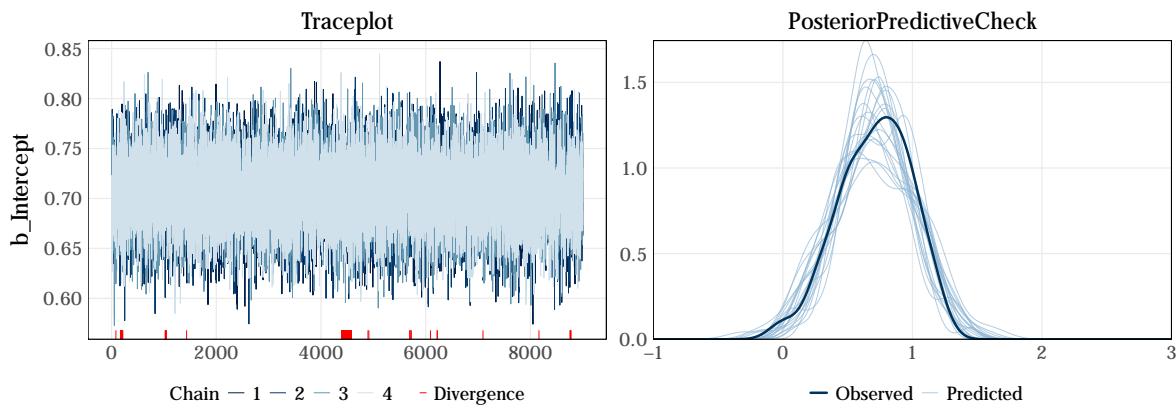


## Hypothesis 1b ( $\rho$ )

### CO<sub>2</sub> M0

`rank_z ~ 1 + (1 | ID)`

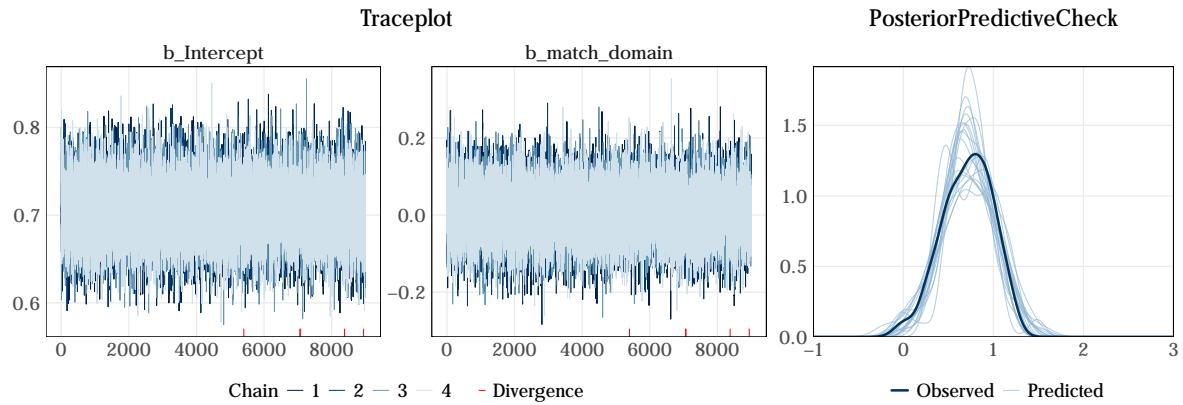
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	Rhat	ESS
b_Intercept	fixed	conditional	0.71	0.03	0.95	0.64	0.77	1	1	15250.74
sd_ID_Intercept	random	conditional	0.19	0.05	0.95	0.10	0.29	1	1	1795.40
sigma	fixed	sigma	0.19	0.05	0.95	0.10	0.28	1	1	1270.07



### CO<sub>2</sub> M1

`rank_z ~ match_domain + (1 | ID)`

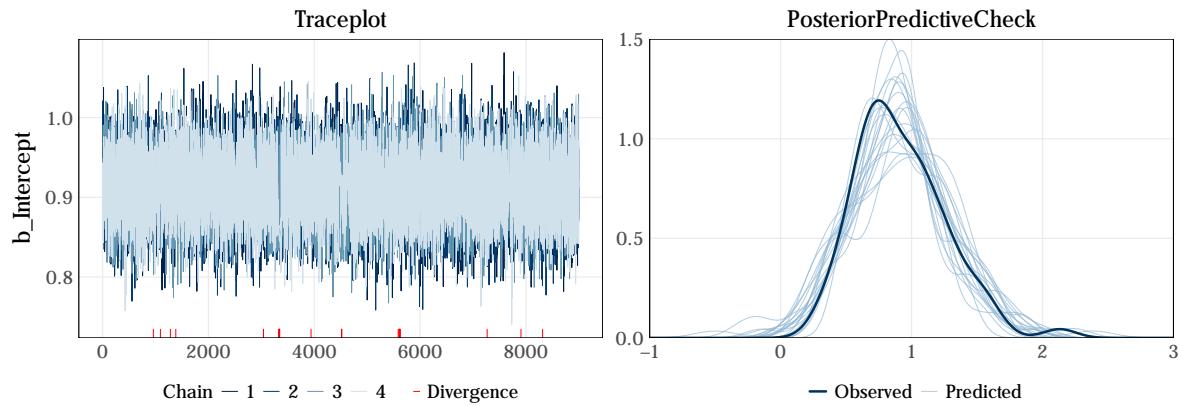
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	Rhat	ESS
b_Intercept	fixed	conditional	0.71	0.03	0.95	0.64	0.77	1.00	1	20663.2
b_match_domain	fixed	conditional	0.01	0.07	0.95	-0.12	0.14	0.55	1	20138.3
sd_ID_Intercept	random	conditional	0.19	0.05	0.95	0.10	0.28	1.00	1	2315.6
sigma	fixed	sigma	0.20	0.05	0.95	0.10	0.28	1.00	1	1868.1



## kcal M0

```
rank_z ~ 1 + (1 | ID)
```

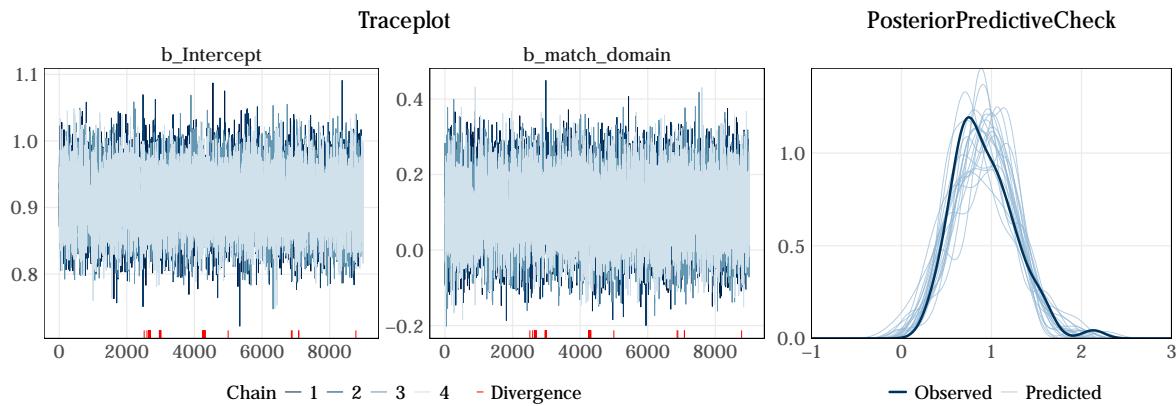
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	Rhat	ESS
<code>b_Intercept</code>	fixed	conditional	0.91	0.04	0.95	0.83	0.99	1	1	17139.45
<code>sd_ID_Intercept</code>	random	conditional	0.23	0.07	0.95	0.11	0.35	1	1	1609.94
<code>sigma</code>	fixed	sigma	0.24	0.07	0.95	0.11	0.35	1	1	1339.11



## kcal M1

```
rank_z ~ match_domain + (1 | ID)
```

Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	Rhat	ESS
b_Intercept	fixed	conditional	0.91	0.04	0.95	0.83	0.99	1.00	1	17275.0
b_match_domain	fixed	conditional	0.11	0.08	0.95	-0.05	0.26	0.92	1	15868.2
sd_ID_Intercept	random	conditional	0.23	0.07	0.95	0.11	0.35	1.00	1	1336.8
sigma	fixed	sigma	0.23	0.07	0.95	0.10	0.34	1.00	1	1003.8

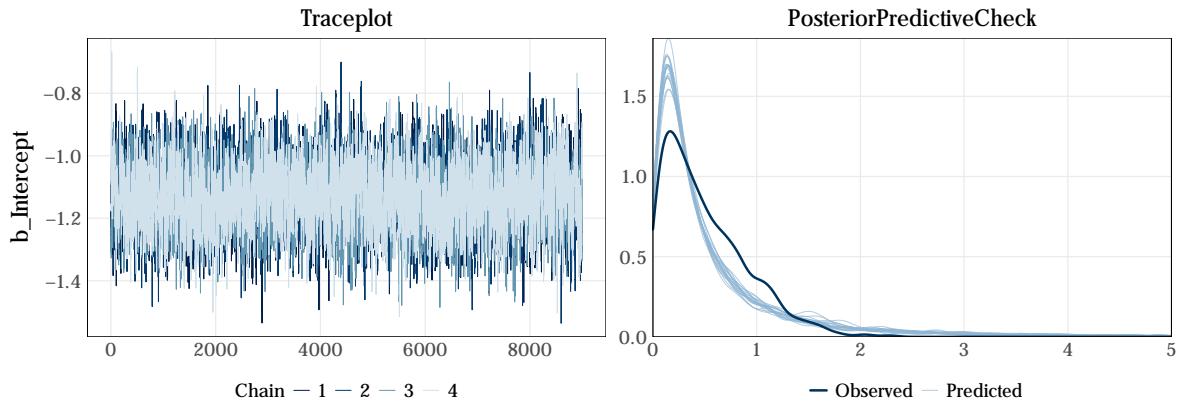


## Hypothesis 2a (OME)

### CO<sub>2</sub> M0

OME\_corr ~ 1 + (item\_type | ID) + (1 | ID\_item)

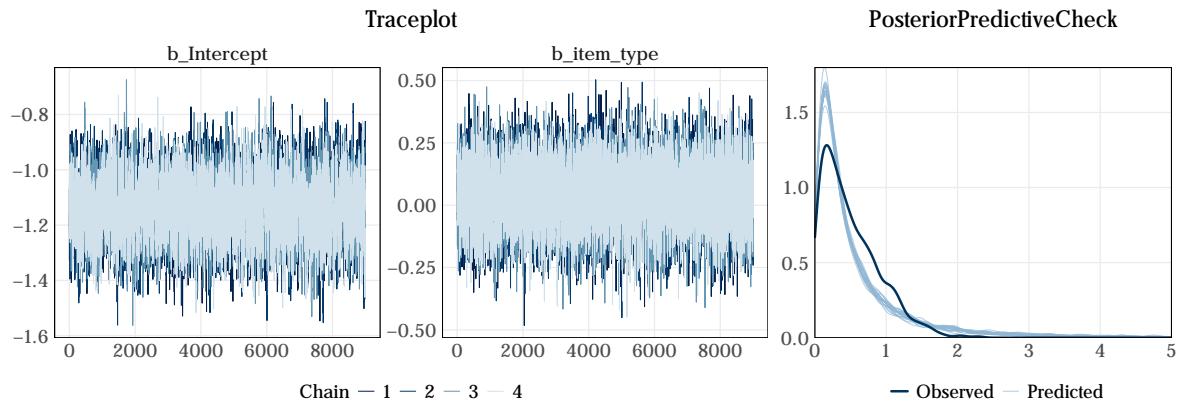
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	Rhat	ESS
b_Intercept	fixed	conditional	-1.13	0.10	0.95	-1.33	-0.93	1.00	1	17275.0
sd_ID_Intercept	random	conditional	0.47	0.06	0.95	0.36	0.60	1.00	1	15868.2
sd_ID_item_type	random	conditional	0.15	0.04	0.95	0.07	0.24	1.00	1	1336.8
sd_ID_item_Intercept	random	conditional	0.43	0.05	0.95	0.34	0.52	1.00	1	1003.8
cor_ID_Intercept_item_type	random	conditional	-0.14	0.33	0.95	-0.78	0.49	0.67	1	1003.8
sigma	fixed	sigma	0.99	0.02	0.95	0.96	1.02	1.00	1	1003.8



## CO<sub>2</sub> M1

`OME_corr ~ item_type + (item_type | ID) + (1 | ID_item)`

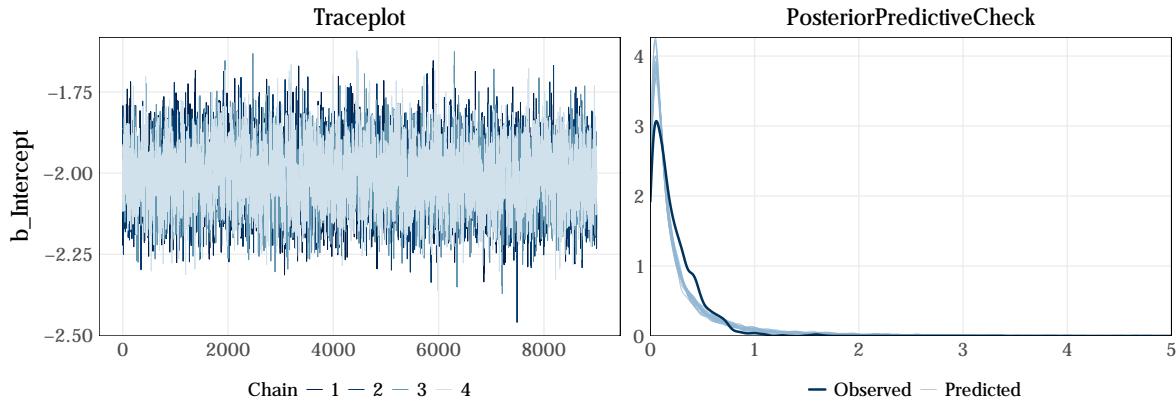
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd
$b_{\text{Intercept}}$	fixed	conditional	-1.14	0.10	0.95	-1.34	-0.93	1.00
$b_{\text{item\_type}}$	fixed	conditional	0.04	0.12	0.95	-0.19	0.27	0.65
$sd_{\text{ID}}_{\text{Intercept}}$	random	conditional	0.47	0.06	0.95	0.36	0.60	1.00
$sd_{\text{ID}}_{\text{item\_type}}$	random	conditional	0.15	0.04	0.95	0.08	0.24	1.00
$sd_{\text{ID}}_{\text{item}}_{\text{Intercept}}$	random	conditional	0.43	0.05	0.95	0.35	0.53	1.00
$\text{cor}_{\text{ID}}_{\text{Intercept}}_{\text{item\_type}}$	random	conditional	-0.14	0.33	0.95	-0.78	0.49	0.67
$\sigma$	fixed	sigma	0.99	0.02	0.95	0.96	1.02	1.00



## kcal M0

`OME_corr ~ 1 + (item_type | ID) + (1 | ID_item)`

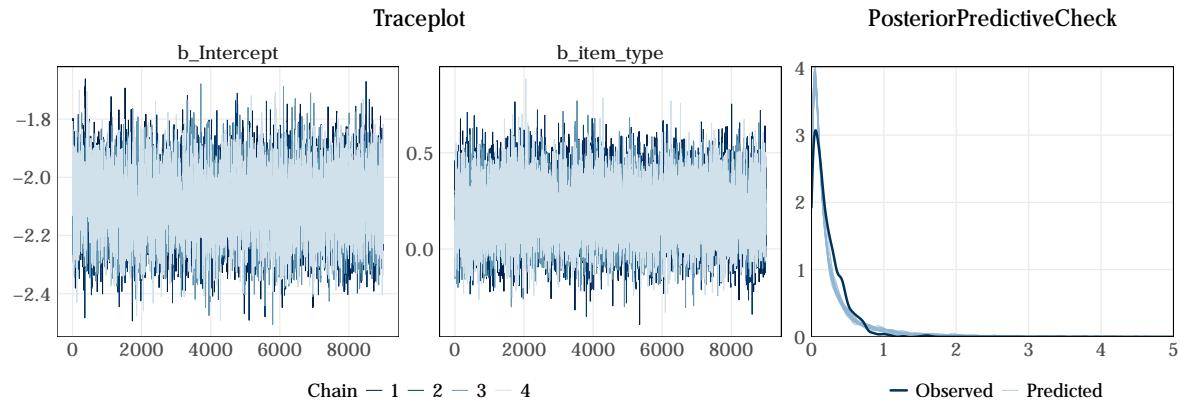
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	R
b_Intercept	fixed	conditional	-2.01	0.09	0.95	-2.19	-1.83	1	
sd_ID_Intercept	random	conditional	0.60	0.07	0.95	0.46	0.73	1	
sd_ID_item_type	random	conditional	0.78	0.10	0.95	0.58	0.97	1	
sd_ID_item_Intercept	random	conditional	0.35	0.04	0.95	0.27	0.44	1	
cor_ID_Intercept_item_type	random	conditional	-0.69	0.10	0.95	-0.86	-0.50	1	
sigma	fixed	sigma	1.21	0.02	0.95	1.18	1.25	1	



## kcal M1

`OME_corr ~ item_type + (item_type | ID) + (1 | ID_item)`

Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	R
b_Intercept	fixed	conditional	-2.09	0.10	0.95	-2.29	-1.88	1.00	
b_item_type	fixed	conditional	0.20	0.14	0.95	-0.07	0.46	0.93	
sd_ID_Intercept	random	conditional	0.59	0.07	0.95	0.46	0.73	1.00	
sd_ID_item_type	random	conditional	0.77	0.10	0.95	0.58	0.97	1.00	
sd_ID_item_Intercept	random	conditional	0.35	0.04	0.95	0.27	0.43	1.00	
cor_ID_Intercept_item_type	random	conditional	-0.68	0.10	0.95	-0.86	-0.49	1.00	
sigma	fixed	sigma	1.21	0.02	0.95	1.18	1.25	1.00	

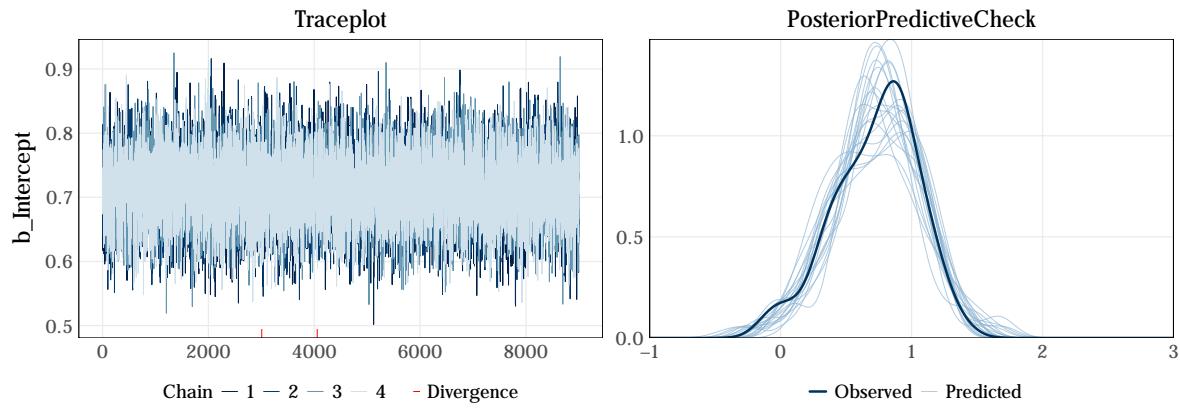


### Hypothesis 2b ( $\rho$ )

$\text{CO}_2 \text{ M0}$

`rank_z ~ 1 + (item_type | ID)`

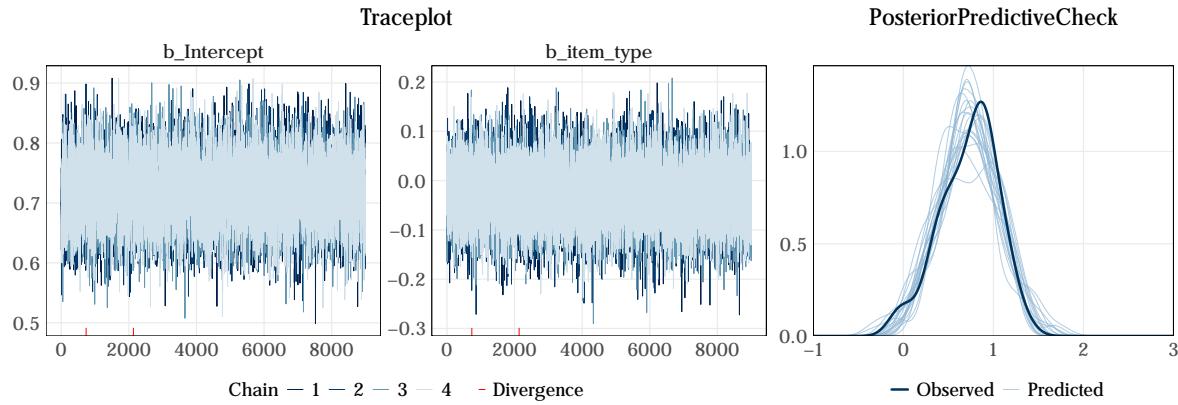
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd
<code>b_Intercept</code>	fixed	conditional	0.71	0.05	0.95	0.62	0.81	1.00
<code>sd_ID_Intercept</code>	random	conditional	0.26	0.04	0.95	0.18	0.34	1.00
<code>sd_ID_item_type</code>	random	conditional	0.18	0.05	0.95	0.09	0.27	1.00
<code>cor_ID_Intercept_item_type</code>	random	conditional	-0.48	0.30	0.95	-1.00	0.03	0.94
<code>sigma</code>	fixed	sigma	0.17	0.03	0.95	0.10	0.24	1.00



## CO<sub>2</sub> M1

`rank_z ~ item_type + (item_type | ID)`

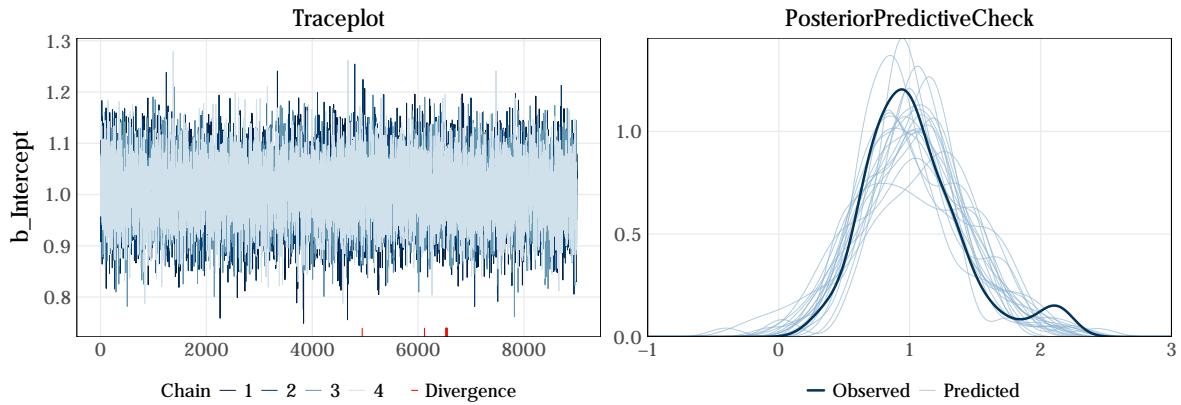
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd
b_Intercept	fixed	conditional	0.72	0.05	0.95	0.62	0.82	1.00
b_item_type	fixed	conditional	-0.03	0.06	0.95	-0.13	0.08	0.69
sd_ID_Intercept	random	conditional	0.26	0.04	0.95	0.18	0.34	1.00
sd_ID_item_type	random	conditional	0.18	0.05	0.95	0.09	0.28	1.00
cor_ID_Intercept_item_type	random	conditional	-0.48	0.30	0.95	-1.00	0.04	0.94
sigma	fixed	sigma	0.17	0.03	0.95	0.10	0.24	1.00



## kcal M0

`rank_z ~ 1 + (item_type | ID)`

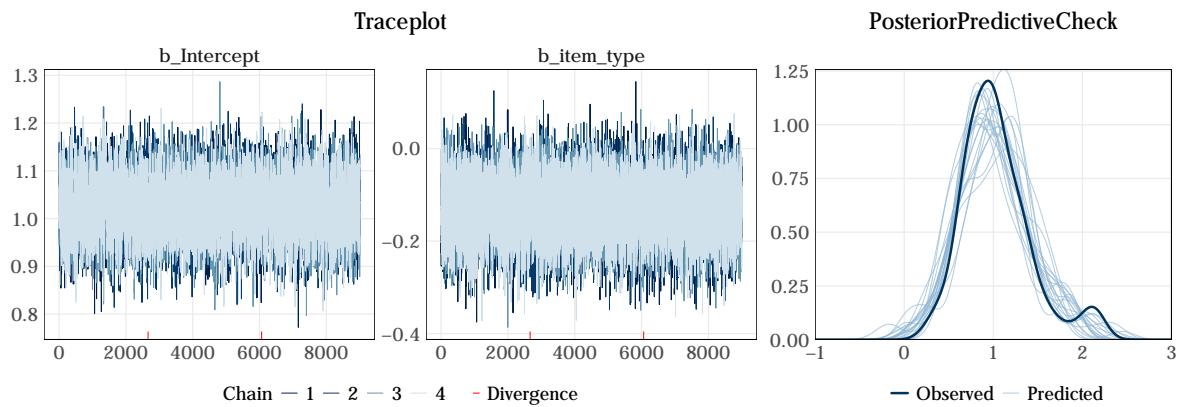
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd
b_Intercept	fixed	conditional	1.01	0.06	0.95	0.89	1.12	1.00
sd_ID_Intercept	random	conditional	0.30	0.05	0.95	0.21	0.40	1.00
sd_ID_item_type	random	conditional	0.20	0.07	0.95	0.08	0.32	1.00
cor_ID_Intercept_item_type	random	conditional	-0.34	0.34	0.95	-1.00	0.25	0.85
sigma	fixed	sigma	0.22	0.04	0.95	0.13	0.31	1.00



## kcal M1

```
rank_z ~ item_type + (item_type | ID)
```

Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd
b_Intercept	fixed	conditional	1.02	0.06	0.95	0.91	1.13	1.00
b_item_type	fixed	conditional	-0.13	0.06	0.95	-0.25	-0.01	0.99
sd_ID_Intercept	random	conditional	0.30	0.05	0.95	0.21	0.40	1.00
sd_ID_item_type	random	conditional	0.19	0.06	0.95	0.08	0.31	1.00
cor_ID_Intercept_item_type	random	conditional	-0.32	0.34	0.95	-1.00	0.26	0.83
sigma	fixed	sigma	0.21	0.04	0.95	0.12	0.29	1.00

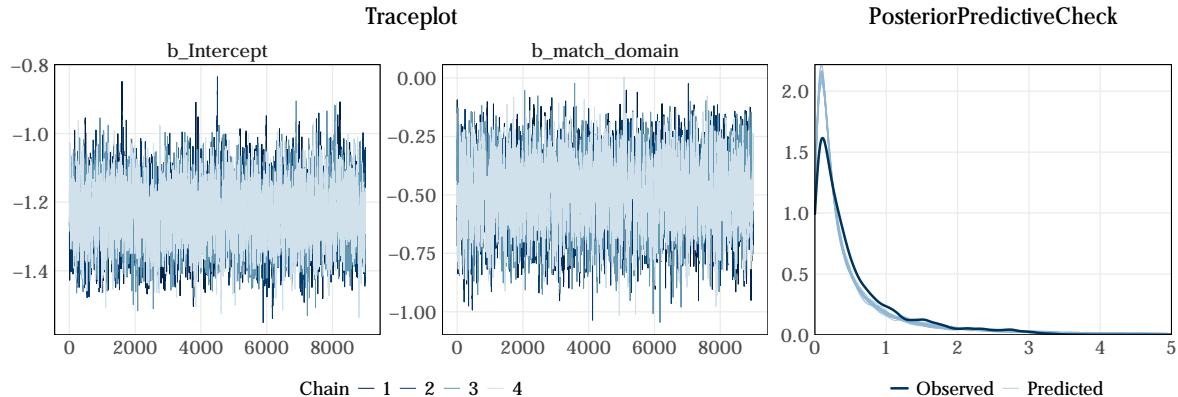


### Hypothesis 3a (OME)

M0

```
OME_corr ~ match_domain + (1 | ID) + (est_criterion * match_domain | ID_item)
```

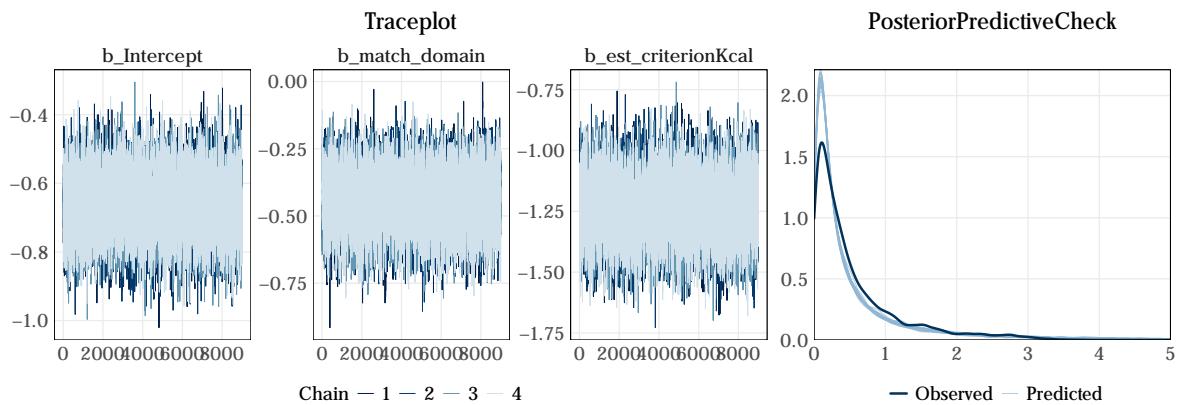
Parameter	Effects	Component	Mean	SD
b_Intercept	fixed	conditional	-1.23	0.08
b_match_domain	fixed	conditional	-0.49	0.13
sd_ID_Intercept	random	conditional	0.75	0.06
sd_ID_item_Intercept	random	conditional	0.33	0.04
sd_ID_item_est_criterionKcal	random	conditional	0.57	0.09
sd_ID_item_match_domain	random	conditional	0.16	0.03
sd_ID_item_est_criterionKcal:match_domain	random	conditional	0.17	0.05
cor_ID_item_Intercept_est_criterionKcal	random	conditional	-0.60	0.11
cor_ID_item_Intercept_match_domain	random	conditional	0.69	0.17
cor_ID_item_est_criterionKcal_match_domain	random	conditional	-0.42	0.24
cor_ID_item_Intercept_est_criterionKcal:match_domain	random	conditional	-0.45	0.20
cor_ID_item_est_criterionKcal_est_criterionKcal:match_domain	random	conditional	0.19	0.31
cor_ID_item_match_domain_est_criterionKcal:match_domain	random	conditional	-0.57	0.25
sigma	fixed	sigma	1.05	0.01



M1

```
OME_corr ~ match_domain + est_criterion + (1 | ID) + (est_criterion * match_domain | ID_item)
```

Parameter	Effects	Component	Mean	SD
b_Intercept	fixed	conditional	-0.66	0.08
b_match_domain	fixed	conditional	-0.44	0.10
b_est_criterionKcal	fixed	conditional	-1.23	0.12
sd_ID_Intercept	random	conditional	0.60	0.04
sd_ID_item_Intercept	random	conditional	0.30	0.03
sd_ID_item_est_criterionKcal	random	conditional	0.44	0.05
sd_ID_item_match_domain	random	conditional	0.16	0.03
sd_ID_item_est_criterionKcal:match_domain	random	conditional	0.17	0.05
cor_ID_item_Intercept_est_criterionKcal	random	conditional	-0.53	0.11
cor_ID_item_Intercept_match_domain	random	conditional	0.70	0.16
cor_ID_item_est_criterionKcal_match_domain	random	conditional	-0.44	0.21
cor_ID_item_Intercept_est_criterionKcal:match_domain	random	conditional	-0.50	0.24
cor_ID_item_est_criterionKcal_est_criterionKcal:match_domain	random	conditional	0.32	0.27
cor_ID_item_match_domain_est_criterionKcal:match_domain	random	conditional	-0.60	0.23
sigma	fixed	sigma	1.05	0.01

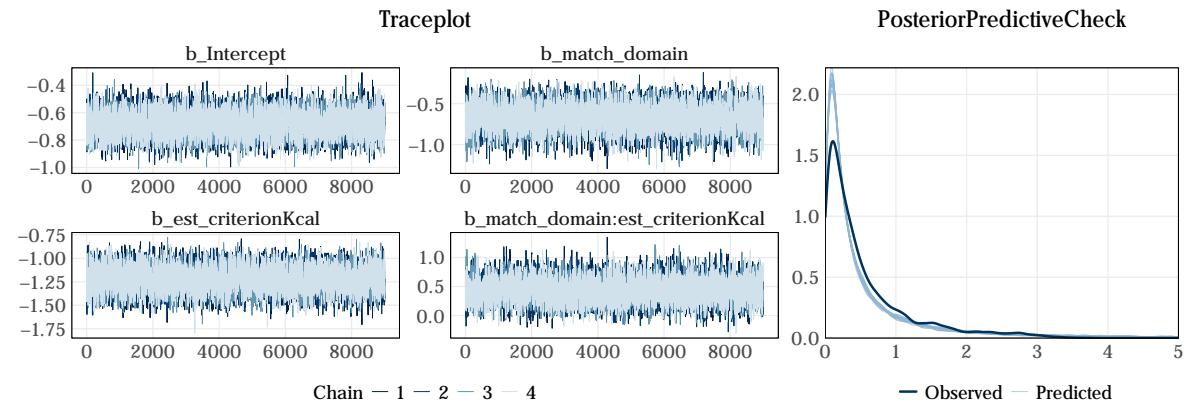


## M2

```
OME_corr ~ match_domain * est_criterion + (1 | ID) + (est_criterion * match_domain | ID_item)
```

Parameter	Effects	Component	Mean	SD
b_Intercept	fixed	conditional	-0.68	0.08
b_match_domain	fixed	conditional	-0.67	0.15
b_est_criterionKcal	fixed	conditional	-1.22	0.12

b_match_domain:est_criterionKcal	fixed	conditional	0.44	0.19
sd_ID_Intercept	random	conditional	0.58	0.04
sd_ID_item_Intercept	random	conditional	0.30	0.03
sd_ID_item_est_criterionKcal	random	conditional	0.44	0.05
sd_ID_item_match_domain	random	conditional	0.16	0.03
sd_ID_item_est_criterionKcal:match_domain	random	conditional	0.17	0.05
cor_ID_item_Intercept_est_criterionKcal	random	conditional	-0.53	0.11
cor_ID_item_Intercept_match_domain	random	conditional	0.70	0.16
cor_ID_item_est_criterionKcal_match_domain	random	conditional	-0.44	0.21
cor_ID_item_Intercept_est_criterionKcal:match_domain	random	conditional	-0.50	0.24
cor_ID_item_est_criterionKcal_est_criterionKcal:match_domain	random	conditional	0.33	0.27
cor_ID_item_match_domain_est_criterionKcal:match_domain	random	conditional	-0.59	0.24
sigma	fixed	sigma	1.05	0.01

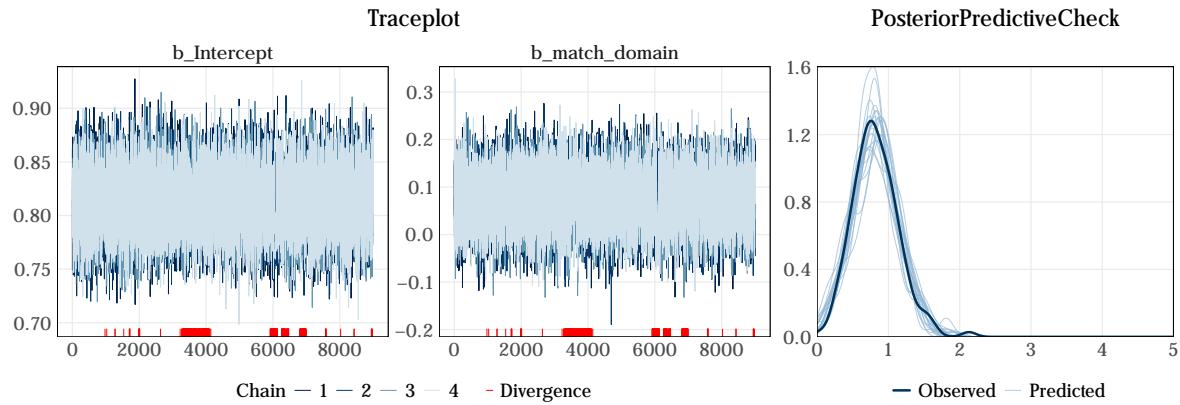


### Hypothesis 3b ( $\rho$ )

M0

rank\_z ~ match\_domain + (1 | ID)

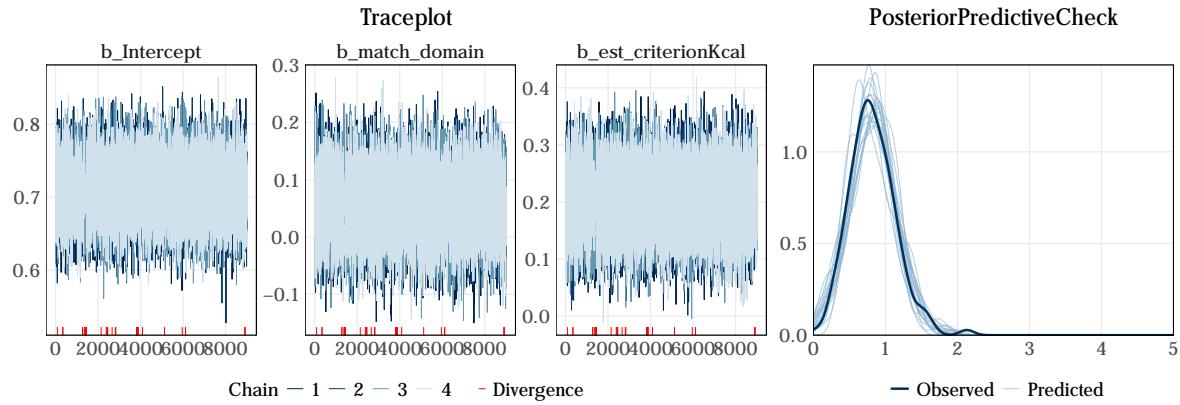
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	Rhat	ES
b_Intercept	fixed	conditional	0.81	0.03	0.95	0.76	0.87	1.00	1.00	10661.5
b_match_domain	fixed	conditional	0.07	0.05	0.95	-0.03	0.18	0.92	1.00	12139.0
sd_ID_Intercept	random	conditional	0.22	0.06	0.95	0.11	0.32	1.00	1.00	565.5
sigma	fixed	sigma	0.23	0.06	0.95	0.10	0.32	1.00	1.01	342.1



## M1

```
rank_z ~ match_domain + est_criterion + (1 | ID)
```

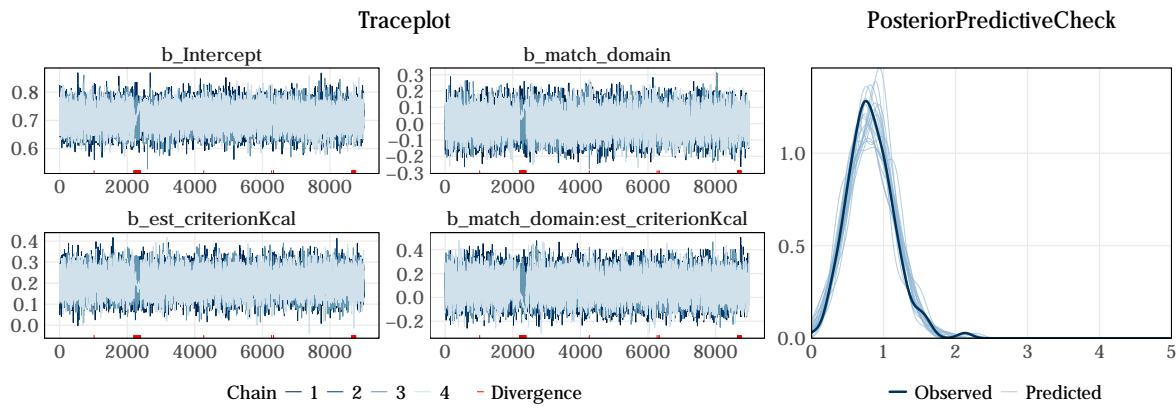
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	Rhat	E
b_Intercept	fixed	conditional	0.71	0.04	0.95	0.64	0.78	1.00	1.00	17064.
b_match_domain	fixed	conditional	0.06	0.05	0.95	-0.04	0.16	0.87	1.00	14577.
b_est_criterionKcal	fixed	conditional	0.20	0.05	0.95	0.10	0.31	1.00	1.00	15169.
sd_ID_Intercept	random	conditional	0.21	0.05	0.95	0.11	0.30	1.00	1.00	1029.
sigma	fixed	sigma	0.22	0.05	0.95	0.12	0.31	1.00	1.01	862.



## M2

```
rank_z ~ match_domain * est_criterion + (1 | ID)
```

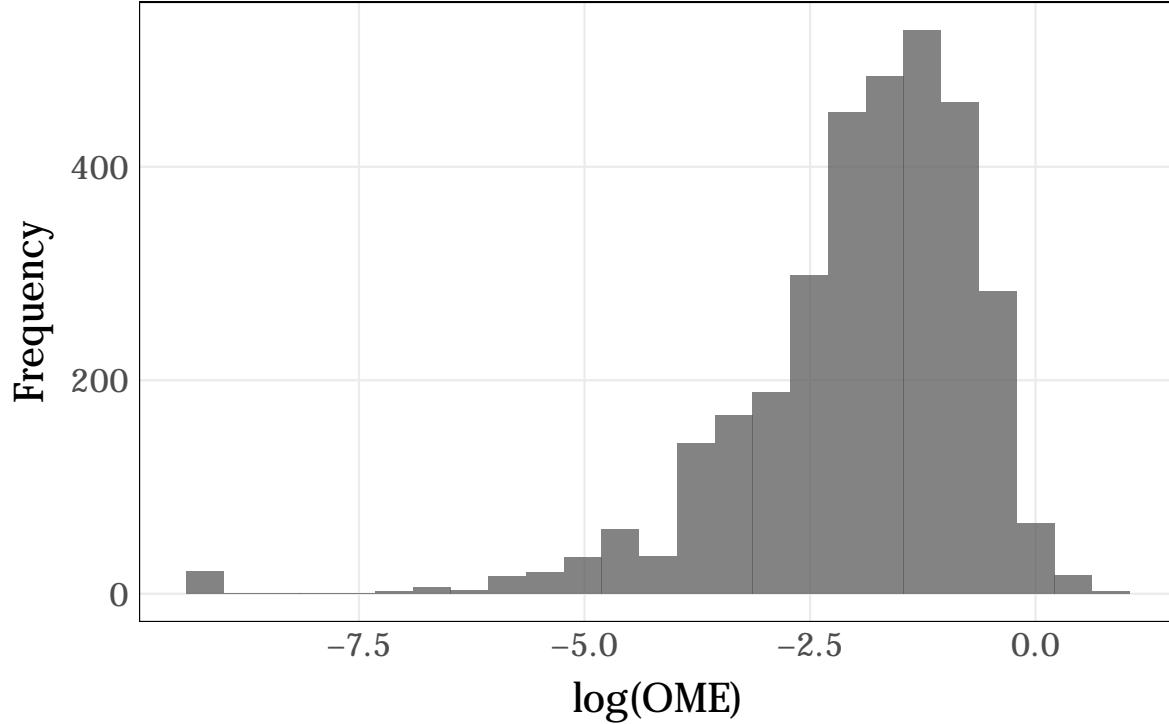
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd
b_Intercept	fixed	conditional	0.71	0.04	0.95	0.63	0.78	1.00
b_match_domain	fixed	conditional	0.01	0.07	0.95	-0.13	0.15	0.55
b_est_criterionKcal	fixed	conditional	0.21	0.05	0.95	0.10	0.31	1.00
b_match_domain:est_criterionKcal	fixed	conditional	0.10	0.10	0.95	-0.10	0.30	0.83
sd_ID_Intercept	random	conditional	0.21	0.06	0.95	0.11	0.31	1.00
sigma	fixed	sigma	0.22	0.06	0.95	0.10	0.31	1.00



## Calculation of Standardized Effect Sizes

As suggest by Westfall et al. (2014) and others (e.g., Brysbaert & Stevens, 2018) we calculated standardized effect sizes in terms of Cohens  $d$  by dividing the model based effect estimate by the total standard deviation (see file `analysis_compute_standardized_effect_sizes.R` for the underlying analysis code). However, based on simulations and some checks, we decided against using the model based variance estimate to calculate the total standard deviation and instead directly computed it from the data. The reason for this was that there are some very small OME values as can be seen here when we plot the OME values on a normalized scale which reflects the data used by the log-normal model:

Figure 4: Figure S4. Distribution of normalized OMEs (i.e.,  $\log(\text{OMEs})$ ).



These small values (e.g.,  $\text{OME} < 0.02$ ,  $\log(\text{OME}) < -3.9$ ) have a large biasing effect on the estimated standard deviation coefficients, especially for the random intercepts of items and the residual standard deviation. This increased estimates would then lead to a biased estimate of the effect size. The standard deviations on the normal scale are not influenced that much from these small values, thus we used the estimated total standard deviation from the corresponding OMEs (`sd(OME)`) and the estimated effects on the untransformed scale as reported in the paper to compute the estimated standardized effects. These effects are also more conservative (i.e., smaller) than computing the effects from aggregated data (i.e. from a *t*-test).