Supplement

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

2025-06-03

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

Abbreviation	Meaning
kcal	Kilocalories
CO₂	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

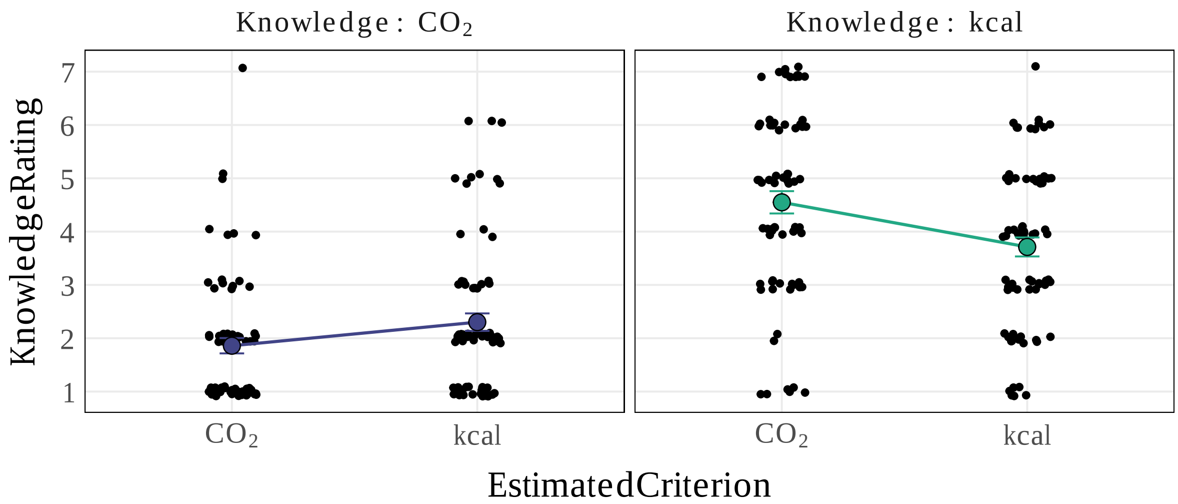
Note. GUEQ = General University Entrance Qualification , BA = Bachelor's degree, MA = Master's degree

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_2 footprint (M = 2.08, SD = 1.32, = 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

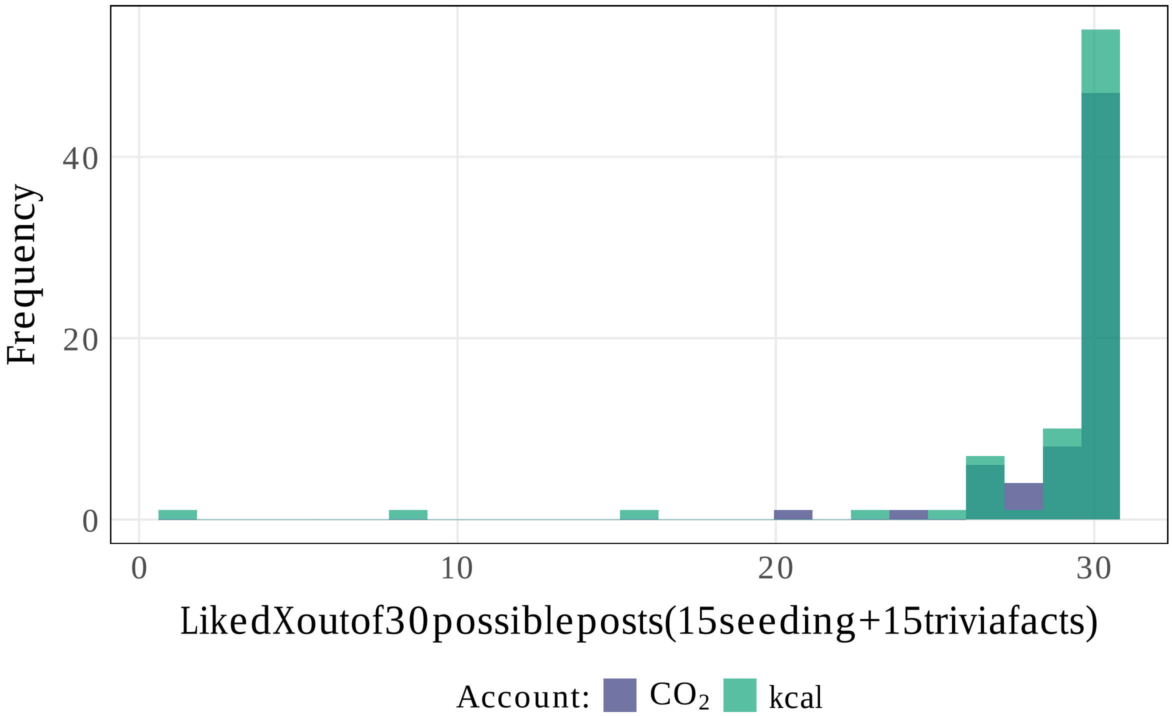
Figure 1: Figure S1. General knowledge ratings for $C0_2$ footprint and calorie content of food items, depending on the estimated criterion in the main task.



Number of Likes Posts

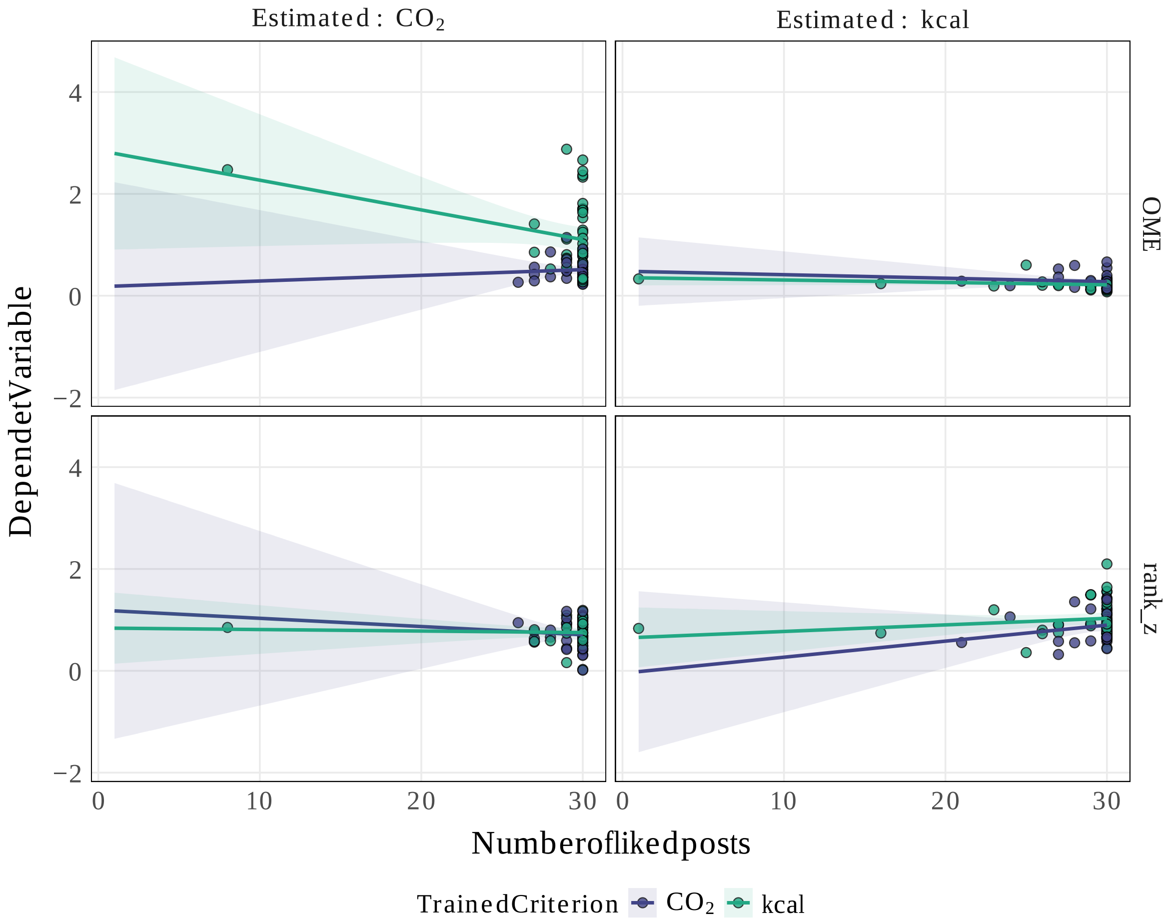
In the preregistration, we also predicted that a greater seeding effect when participants saw more posts as indicated by the number of liked posts. However, as already stated in the main text, almost all participants liked every post, see the table below for the descriptive statistics and the Figure 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 ρ (all ps > 0.05)

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



Detailed general analytical approach

Since the estimation trials are nested in a cross-classified manner within participants and items, we used multi-level modeling to analyze our data. Specifically, we used Bayesian (generalized) mixed-effects models (McElreath, 2020) implemented in the R-package `brms` (Bürkner, 2017, 2018). This approach allows us to account for the random effects from both, participants and items, and to model the different distributions of the dependent variables in a principled and relatively straightforward manner (Gelman et al., 2014; McElreath, 2020).

Given the skewed exponential distribution inherent to the OME, we used hierarchical log-normal models to analyze all hypotheses with the OME as the dependent variable and hierarchical Gaussian models when the rank-order correlation was the dependent variable. As the log-normal model cannot handle zero values, we replaced the n = 45 (0.5%) trials with an OME of 0 (i.e., when the estimated value matched the actual value) with 0.0001, which is around one order of magnitude below the smallest observed OME of 0.0008[^1 In the preregistration, we originally planned to use hurdle log-normal models to account for these 0 values. Upon further consideration, we decided against this approach, since the hurdle model would model the zeros and other non-zero values separately, although both come from the same process, thus biasing the non-zero estimates.]. Additionally, we excluded n = 2 (0.02%) trials where participants gave an estimate of 0 as this would result in an OME of -∞. We used weakly informative priors (Lee & Vanpaemel, 2018) based on previous studies (e.g., Bröder et al., 2023) for the main predictor variables, and weakly informative priors for the other parameters (e.g., the standard deviation of random effects and the correlation between random effects) to support model convergence and to prevent estimation issues by ensuring priors covered realistic values for the various model parameters. Detailed descriptions of the priors can be found in Appendix B in the main text.

The models were implemented in the `brms`-package (Bürkner, 2017, 2018) using four Hamiltonian Monte Carlo chains with 1,000 warm-up and 10,000 post-warm-up samples. The convergence of the chains was checked by visual inspection and the standard ˆR statistic ($\hat{R} < 1.01$, Gelman and Rubin, 1992). Hypotheses were tested via model comparison, wherethe full model ($\mathcal{M}_1$) that includes the fixed-effect predictor of interest and all possible random effects was compared to a reference model that only includes the random effects, but not the fixed-effect predictor ($\mathcal{M}_0$, Van Doorn et al., 2023). Thus, although both models assume varying random effects across participants and items, only $\mathcal{M}_1$ assumes an overall $\mathcal{M}_1$ effect of the respective fixed-effects predictor, whereas $\mathcal{M}_0$ assumes that the overall effect is 0 on average (Van Doorn et al., 2023).

We compared the models using Bayes factors (Jeffreys, 1961; Kass & Raftery, 1995; Myung & Pitt, 1997; see Heck et al., 2023 for a review) calculated through bridge sampling (Gronau et al., 2017, 2018). The resulting Bayes factor BF_{10} quantifies the relative evidence for $\mathcal{M}_1$ compared to $\mathcal{M}_0$, indicating how much more probable the data are under $\mathcal{M}_1$ compared to $\mathcal{M}_0$, or framed differently, how much better $\mathcal{M}_1$ is able to predict the observed data than $\mathcal{M}_0$ (Kass & Raftery, 1995; Morey et al., 2016;Vandekerckhove et al., 2015). For example, a Bayes factor of $BF_{10} = 5$ suggests that the data are five times more likely to occur under M1 than under M0. One convention is that a Bayes factor greater than 3 can be considered as "substantial" evidence and a Bayes factor greater than 10 as "strong" evidence against the competing model (Wetzels et al., 2011).

We also report the posterior mean and 95% highest density intervals (HDI) of the fixed-effect parameters of interest when the Bayes Factor indicates evidence in favor of M1 (i.e., $BF_{10} >$ 1, Ly et al., 2020). For the log-normal model, we report the transformed values on the normal response scale for easier interpretation.

Seeding Effects on Direct Learning

In the analysis of the effects of seeding on calories and CO_2 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_2 (BF_{10} = 550.81, b = -0.49 [-0.19, -0.82]) and evidence for a smaller seeding effect for calories (BF_{10} = 8.00, 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 ρ) for participants who estimated calories (BF_{10} = 1.86, b = .08 [.01, .16]) but not CO_2 (BF_{10} = 0.89).

Detailed Modeling Results

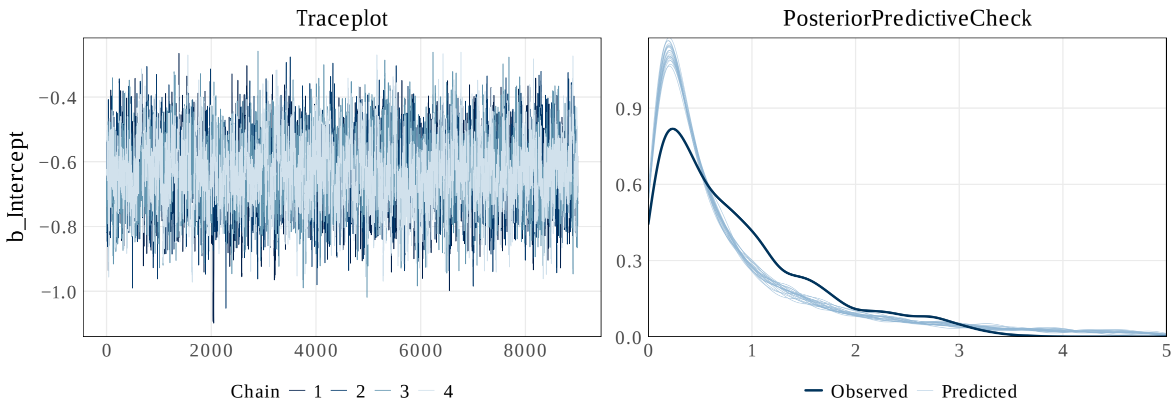
Here we provide for all models reported in the main manuscript more detailed modeling results, including a table with the mean, standard deviation, 95%-HDI, effective sample size (ESS) and $\hat{R}$ for each estimated parameter (random and fixed), as well as figures showing the MCMC-traces for the main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

Hypothesis 1a (OME)

CO_2 M0

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

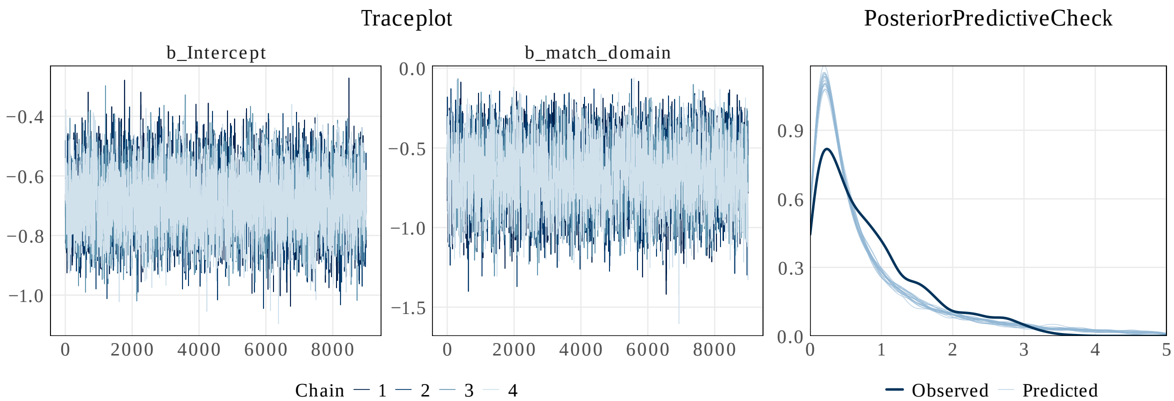
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_hig
b_Intercept	fixed	conditional	-0.63	0.10	0.95	-0.83	-0.4
sd_ID__Intercept	random	conditional	0.80	0.07	0.95	0.67	0.9
sd_ID_item__Intercept	random	conditional	0.33	0.03	0.95	0.26	0.4
sd_ID_item__match_domain	random	conditional	0.20	0.04	0.95	0.13	0.2
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_2 M1

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

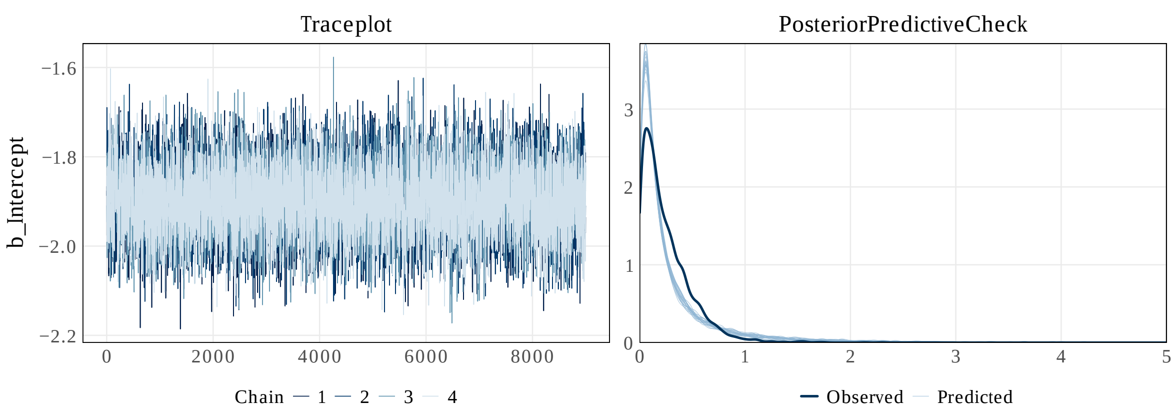
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_hig
b_Intercept	fixed	conditional	-0.68	0.09	0.95	-0.87	-0.5
b_match_domain	fixed	conditional	-0.67	0.18	0.95	-1.03	-0.3
sd_ID__Intercept	random	conditional	0.70	0.06	0.95	0.58	0.8
sd_ID_item__Intercept	random	conditional	0.33	0.03	0.95	0.26	0.4
sd_ID_item__match_domain	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)
```

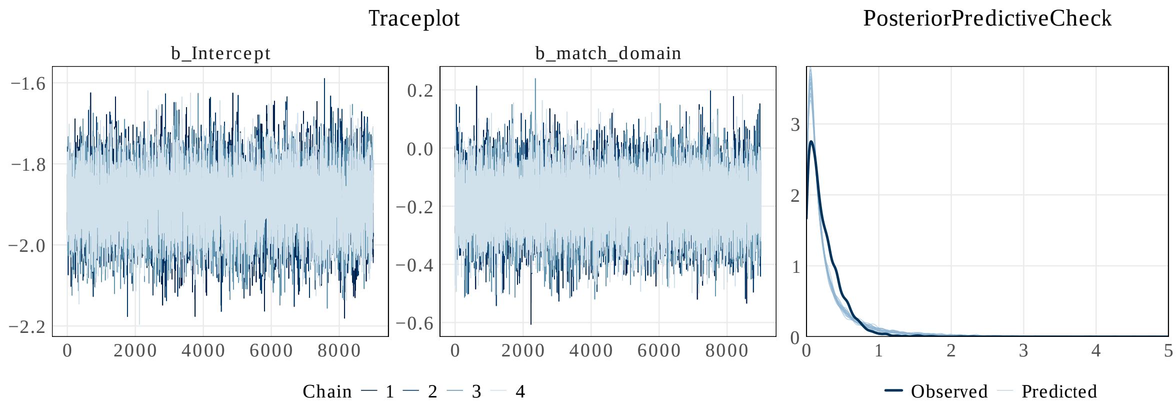
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_hig
b_Intercept	fixed	conditional	-1.90	0.07	0.95	-2.04	-1.7
sd_ID___Intercept	random	conditional	0.44	0.04	0.95	0.36	0.5
sd_ID_item___Intercept	random	conditional	0.35	0.04	0.95	0.28	0.4
sd_ID_item___match_domain	random	conditional	0.13	0.03	0.95	0.07	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_hig
b_Intercept	fixed	conditional	-1.90	0.07	0.95	-2.04	-1.7
b_match_domain	fixed	conditional	-0.19	0.09	0.95	-0.37	-0.0
sd_ID___Intercept	random	conditional	0.43	0.04	0.95	0.36	0.5
sd_ID_item___Intercept	random	conditional	0.35	0.04	0.95	0.27	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	0.05	0.36	0.95	-0.64	0.7
sigma	fixed	sigma	1.19	0.02	0.95	1.17	1.2

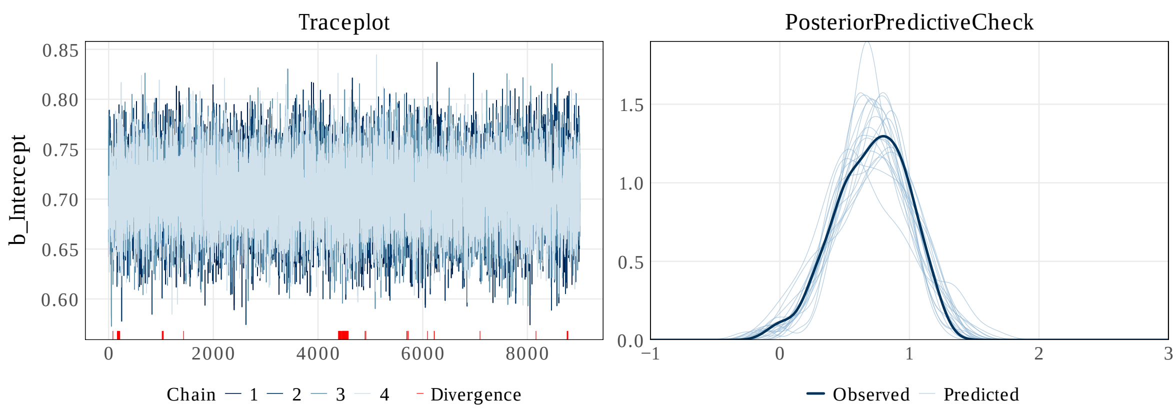


Hypothesis 1b (ρ)

CO_2 M0

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

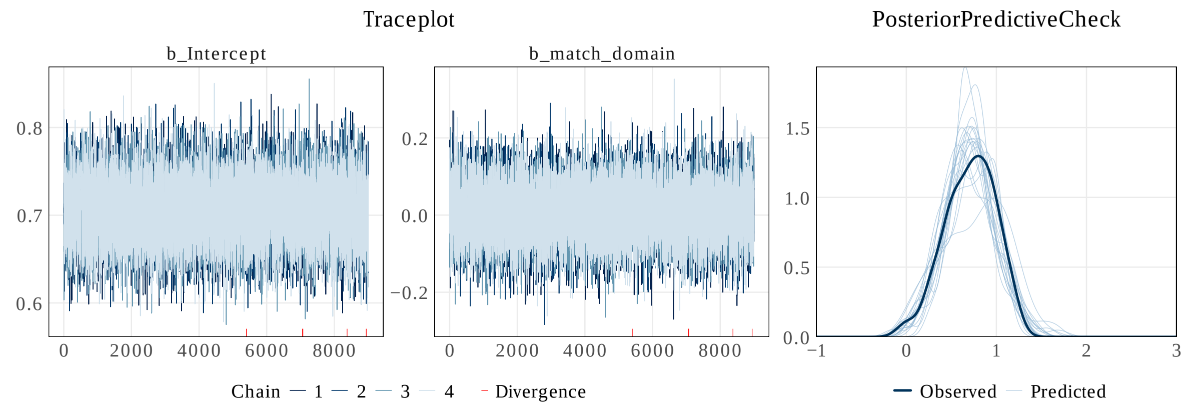
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	Rhat	ESS
b_Intercept	fixed	conditional	0.71	0.03	0.95	0.64	0.77	1	1	15250.74
sd_ID___Intercept	random	conditional	0.19	0.05	0.95	0.10	0.29	1	1	1795.40
sigma	fixed	sigma	0.19	0.05	0.95	0.10	0.28	1	1	1270.07



CO_2 M1

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

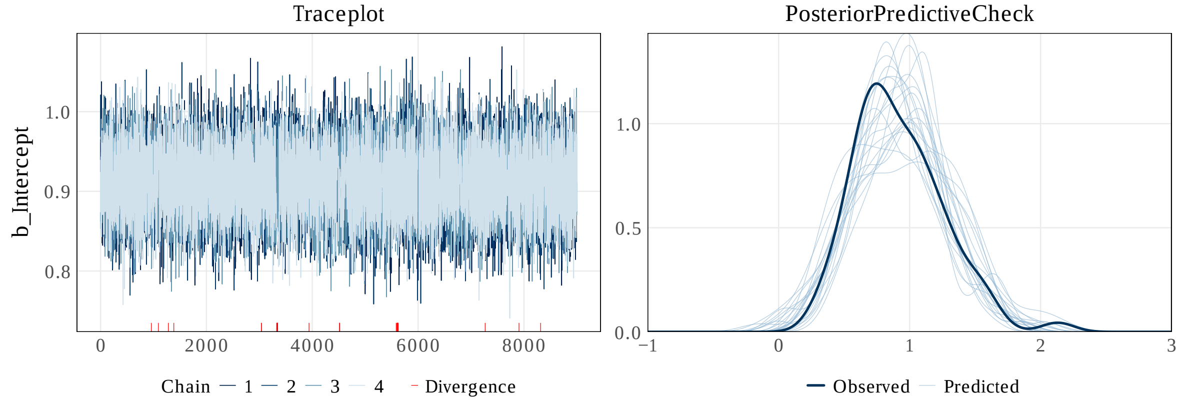
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	Rhat	ES
b_Intercept	fixed	conditional	0.71	0.03	0.95	0.64	0.77	1.00	1	20663.2
b_match_domain	fixed	conditional	0.01	0.07	0.95	-0.12	0.14	0.55	1	20138.3
sd_ID___Intercept	random	conditional	0.19	0.05	0.95	0.10	0.28	1.00	1	2315.6
sigma	fixed	sigma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



kcal M0

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

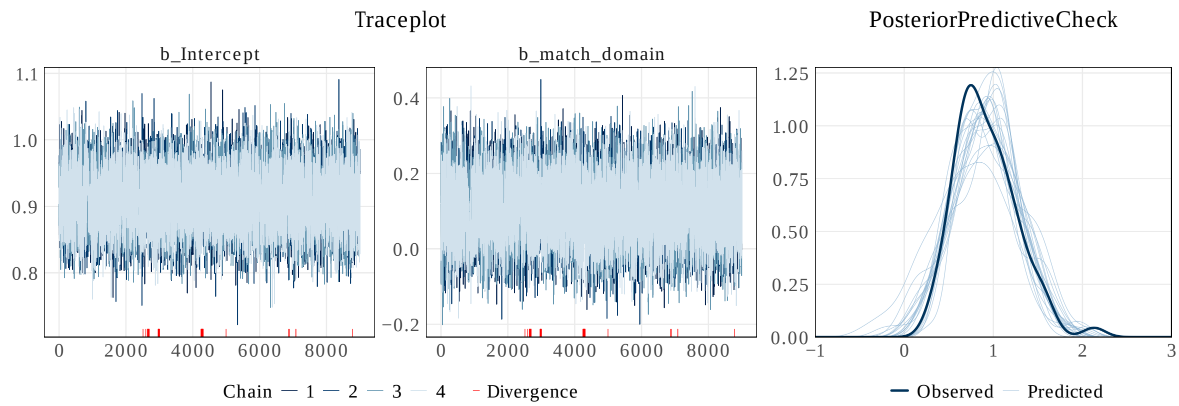
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	Rhat	ESS
b_Intercept	fixed	conditional	0.91	0.04	0.95	0.83	0.99	1	1	17139.45
sd_ID___Intercept	random	conditional	0.23	0.07	0.95	0.11	0.35	1	1	1609.94
sigma	fixed	sigma	0.24	0.07	0.95	0.11	0.35	1	1	1339.11



kcal M1

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

Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	Rhat	ES
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

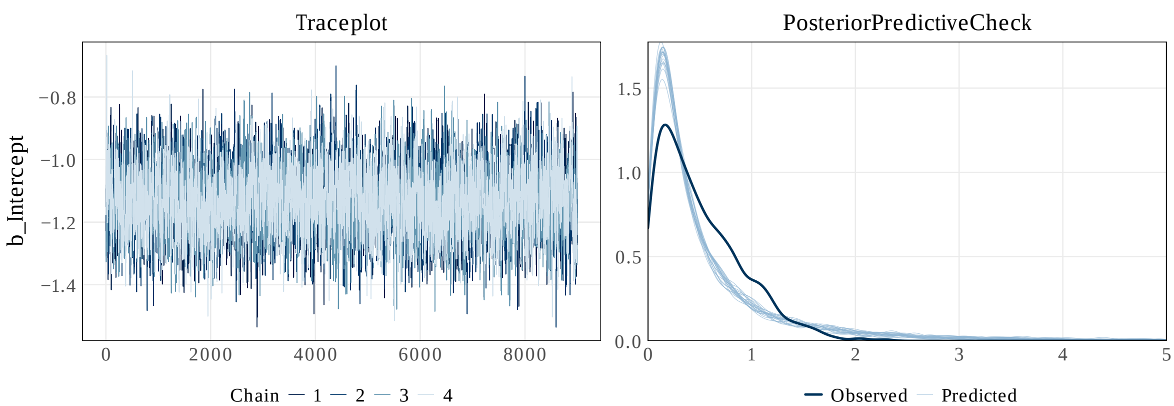


Hypothesis 2a (OME)

CO_2 M0

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

Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd
b_Intercept	fixed	conditional	-1.13	0.10	0.95	-1.33	-0.93	1.00
sd_ID___Intercept	random	conditional	0.47	0.06	0.95	0.36	0.60	1.00
sd_ID___item_type	random	conditional	0.15	0.04	0.95	0.07	0.24	1.00
sd_ID_item___Intercept	random	conditional	0.43	0.05	0.95	0.34	0.52	1.00
cor_ID___Intercept___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

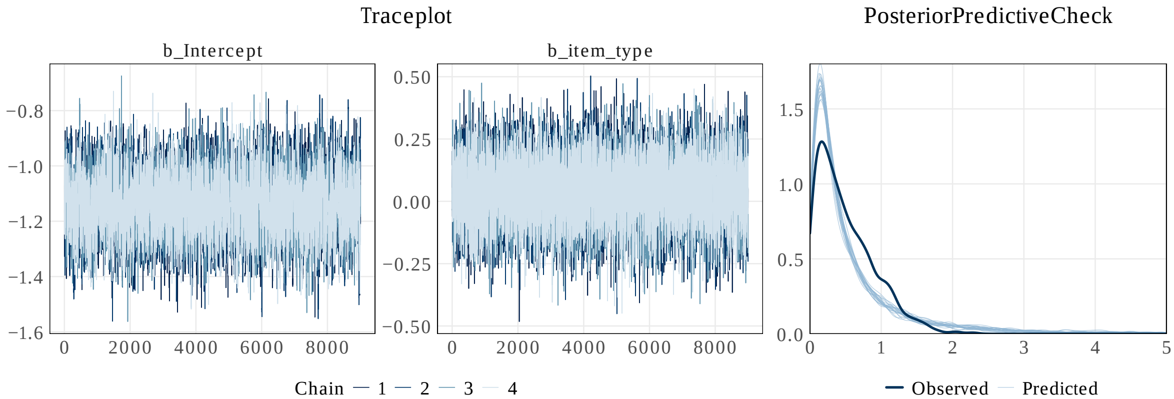


CO_2 M1

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

Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd
b_Intercept	fixed	conditional	-1.14	0.10	0.95	-1.34	-0.93	1.00
b_item_type	fixed	conditional	0.04	0.12	0.95	-0.19	0.27	0.65
sd_ID___Intercept	random	conditional	0.47	0.06	0.95	0.36	0.60	1.00
sd_ID___item_type	random	conditional	0.15	0.04	0.95	0.08	0.24	1.00
sd_ID_item___Intercept	random	conditional	0.43	0.05	0.95	0.35	0.53	1.00
cor_ID___Intercept___item_type	random	conditional	-0.14	0.33	0.95	-0.78	0.49	0.67

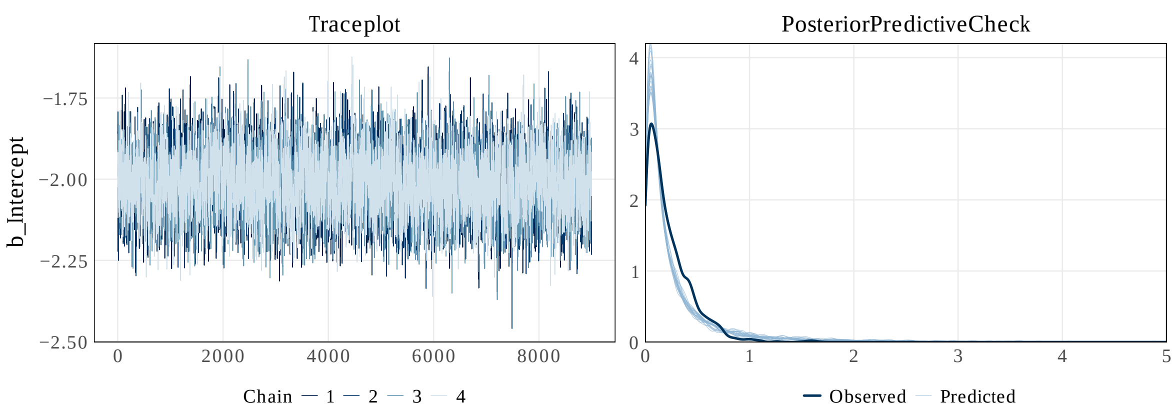
sigma	fixed	sigma	0.99	0.02	0.95	0.96	1.02	1.00



kcal M0

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

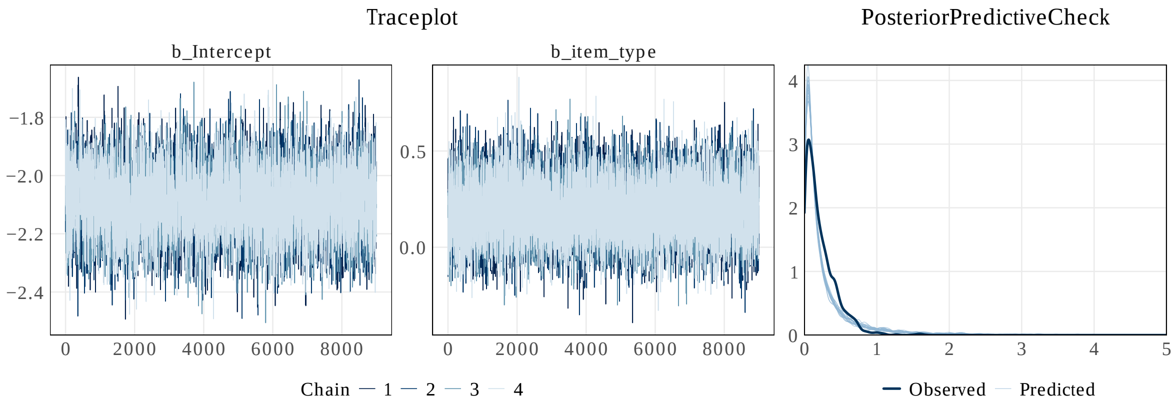
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	R
b_Intercept	fixed	conditional	-2.01	0.09	0.95	-2.19	-1.83	1	
sd_ID___Intercept	random	conditional	0.60	0.07	0.95	0.46	0.73	1	
sd_ID___item_type	random	conditional	0.78	0.10	0.95	0.58	0.97	1	
sd_ID_item___Intercept	random	conditional	0.35	0.04	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
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



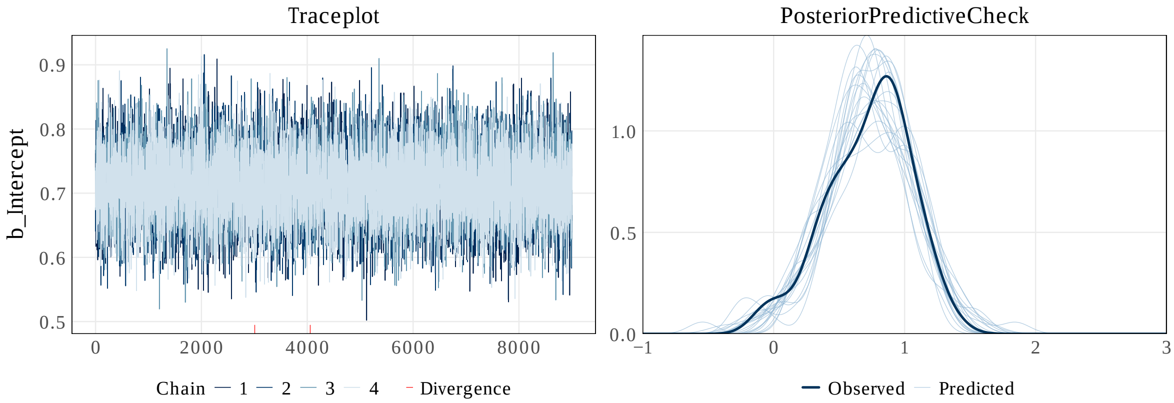
Hypothesis 2b (ρ)

CO_2 M0

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

Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd
b_Intercept	fixed	conditional	0.71	0.05	0.95	0.62	0.81	1.00
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	0.27	1.00
cor_ID___Intercept___item_type	random	conditional	-0.48	0.30	0.95	-1.00	0.03	0.94

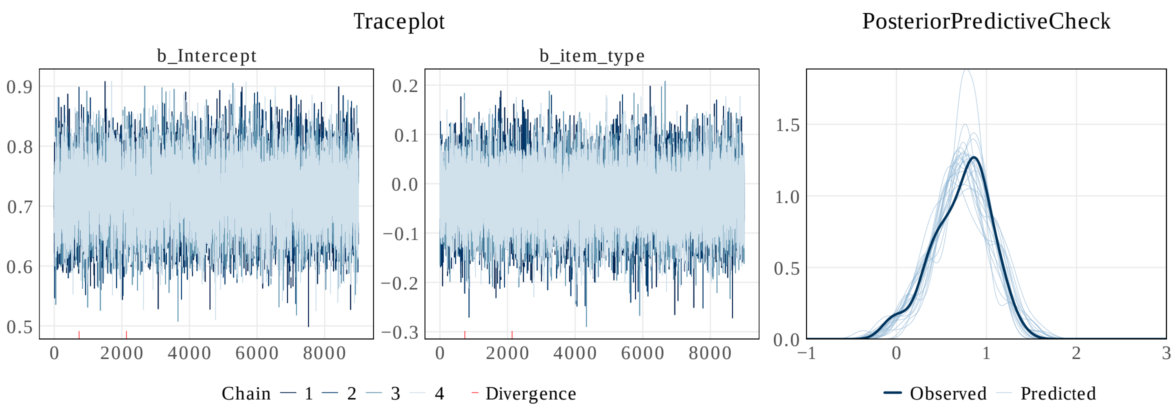
sigma	fixed	sigma	0.17	0.03	0.95	0.10	0.24	1.00



CO_2 M1

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

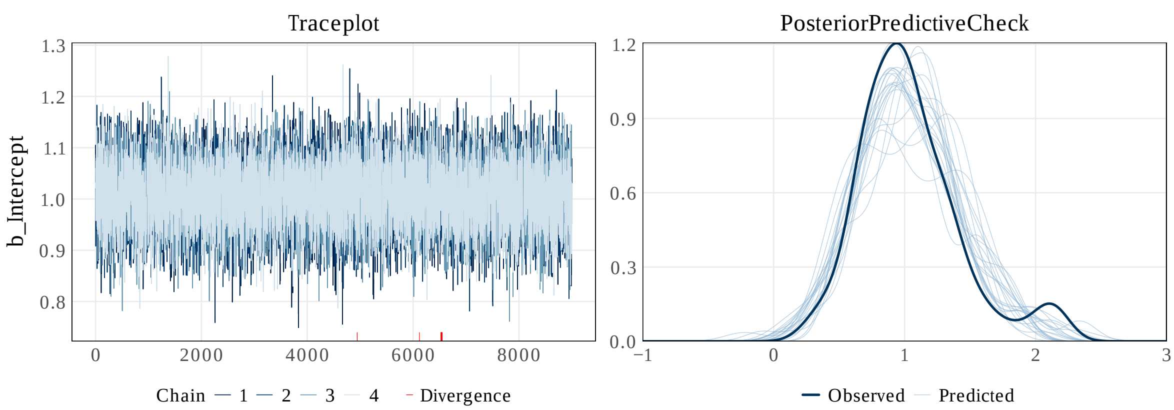
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd
b_Intercept	fixed	conditional	0.72	0.05	0.95	0.62	0.82	1.00
b_item_type	fixed	conditional	-0.03	0.06	0.95	-0.13	0.08	0.69
sd_ID__Intercept	random	conditional	0.26	0.04	0.95	0.18	0.34	1.00
sd_ID__item_type	random	conditional	0.18	0.05	0.95	0.09	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)
```

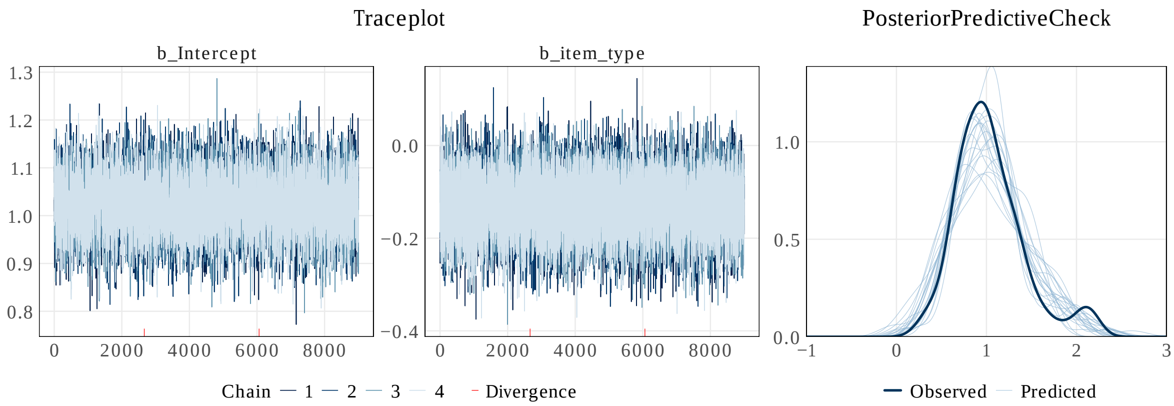
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd
b_Intercept	fixed	conditional	1.01	0.06	0.95	0.89	1.12	1.00
sd_ID___Intercept	random	conditional	0.30	0.05	0.95	0.21	0.40	1.00
sd_ID___item_type	random	conditional	0.20	0.07	0.95	0.08	0.32	1.00
cor_ID___Intercept___item_type	random	conditional	-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

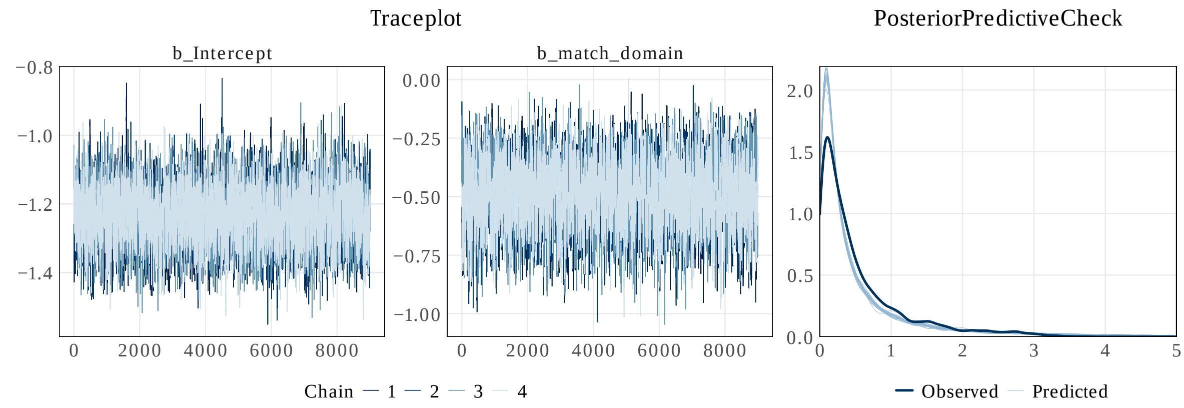


Hypothesis 3a (OME)

M0

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

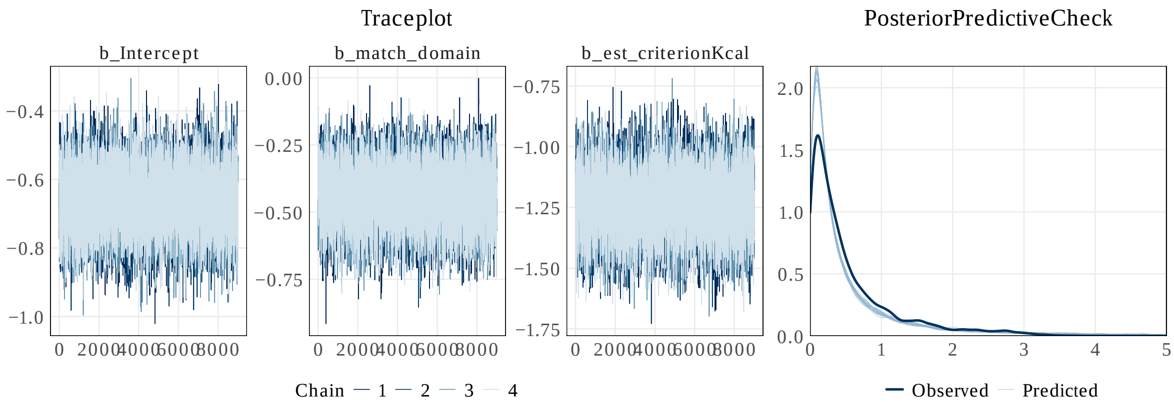
Parameter	Effects	Component	Mean	SD
b_Intercept	fixed	conditional	-1.23	0.08
b_match_domain	fixed	conditional	-0.49	0.13
sd_ID___Intercept	random	conditional	0.75	0.06
sd_ID_item___Intercept	random	conditional	0.33	0.04
sd_ID_item___est_criterionKcal	random	conditional	0.57	0.09
sd_ID_item___match_domain	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	0.26
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)
```

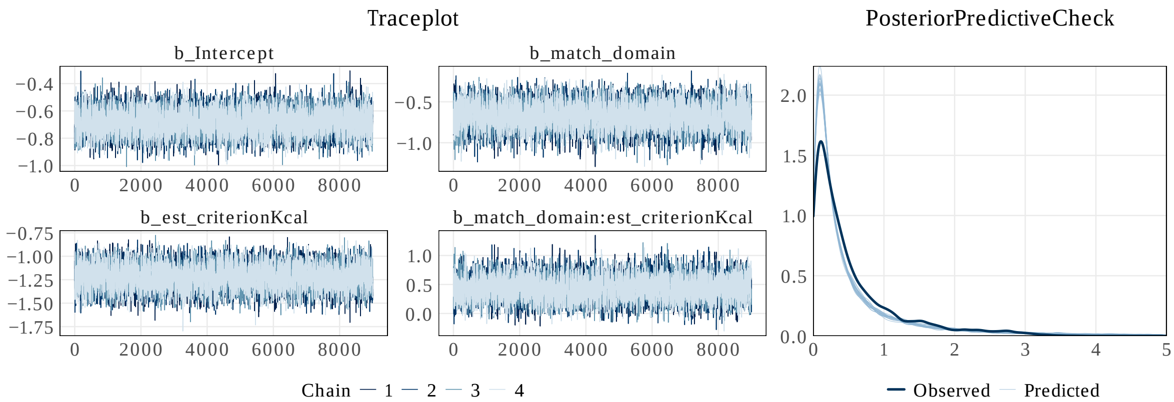
Parameter	Effects	Component	Mean	SD
b__Intercept	fixed	conditional	-0.66	0.08
b__match__domain	fixed	conditional	-0.44	0.10
b__est__criterionKcal	fixed	conditional	-1.23	0.12
sd__ID___Intercept	random	conditional	0.60	0.04
sd__ID__item___Intercept	random	conditional	0.30	0.03
sd__ID__item___est__criterionKcal	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

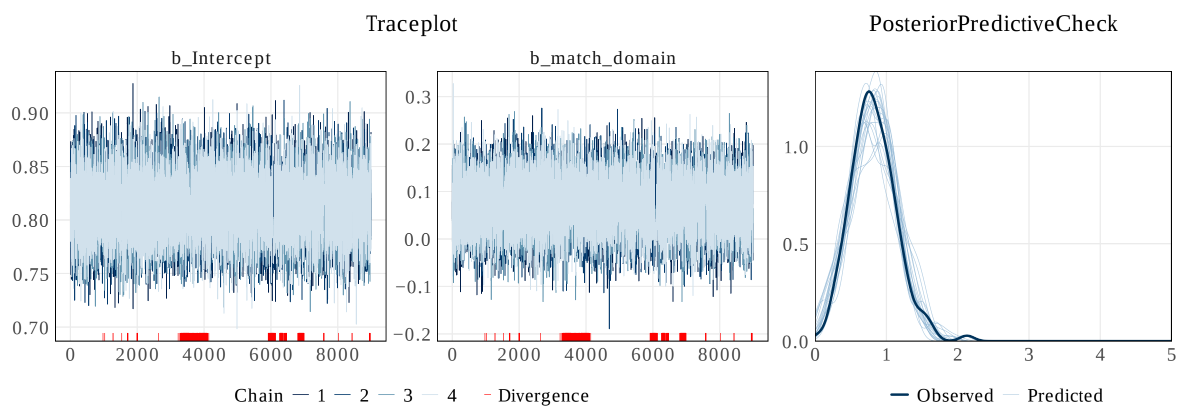


Hypothesis 3b (ρ)

M0

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

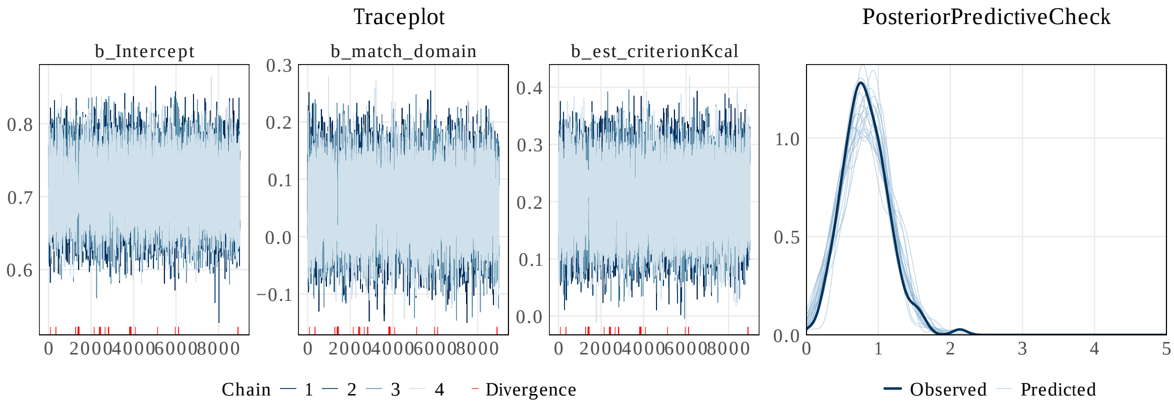
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	Rhat	ES
b_Intercept	fixed	conditional	0.81	0.03	0.95	0.76	0.87	1.00	1.00	10661.5
b_match_domain	fixed	conditional	0.07	0.05	0.95	-0.03	0.18	0.92	1.00	12139.0
sd_ID___Intercept	random	conditional	0.22	0.06	0.95	0.11	0.32	1.00	1.00	565.5
sigma	fixed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

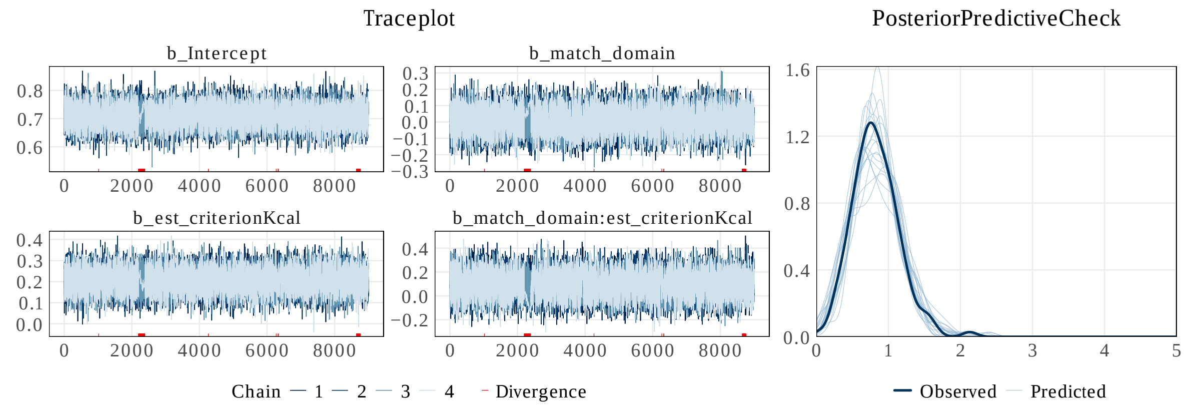
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd	Rhat	E
b_Intercept	fixed	conditional	0.71	0.04	0.95	0.64	0.78	1.00	1.00	17064.
b_match_domain	fixed	conditional	0.06	0.05	0.95	-0.04	0.16	0.87	1.00	14577.
b_est_criterionKcal	fixed	conditional	0.20	0.05	0.95	0.10	0.31	1.00	1.00	15169.
sd_ID__Intercept	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)
```

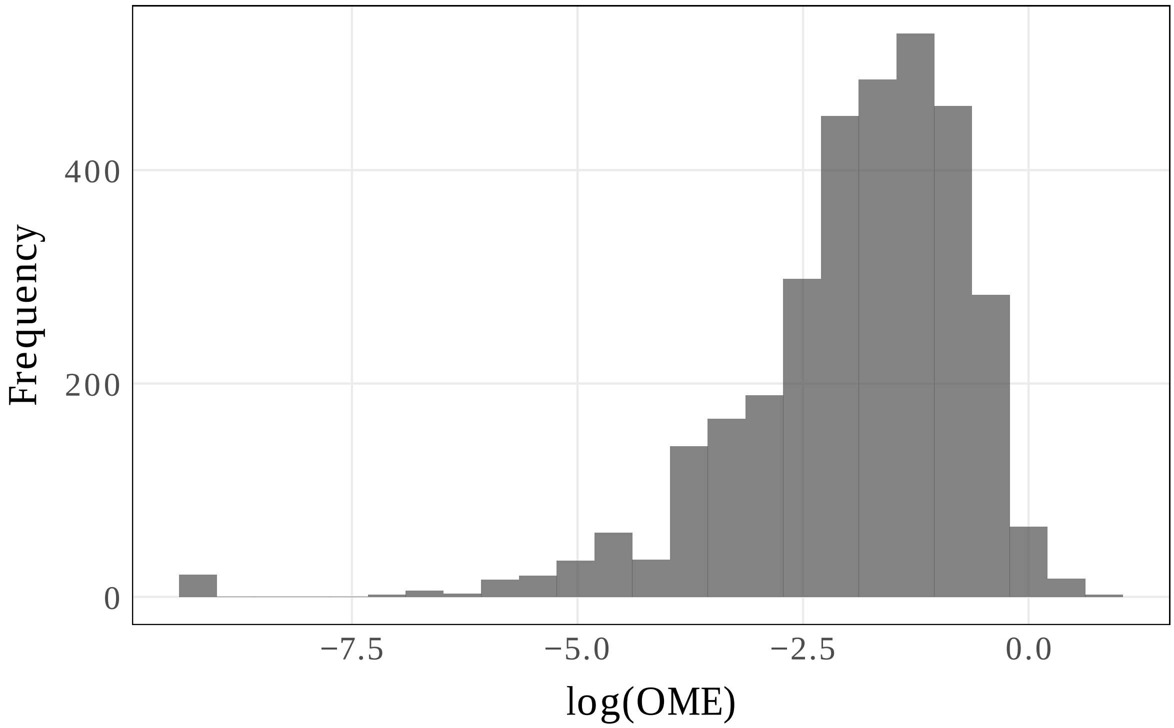
Parameter	Effects	Component	Mean	SD	CI	CI_low	CI_high	pd
b_Intercept	fixed	conditional	0.71	0.04	0.95	0.63	0.78	1.00
b_match_domain	fixed	conditional	0.01	0.07	0.95	-0.13	0.15	0.55
b_est_criterionKcal	fixed	conditional	0.21	0.05	0.95	0.10	0.31	1.00
b_match_domain:est_criterionKcal	fixed	conditional	0.10	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(OMEs)).



These small values (e.g., OME $<$ 0.02, log(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).