**Supplement A**

Supplement A presents the instructions provided to participants before the memory task and the dichotomous evaluation task.

**Memory Task**

Instructions presented to participants before the memory task in Experiments 1, 2, and 3 (translated from German):

*The next task is a memory task. You will be presented with each picture again. You have to indicate for each picture whether it started a positive sound, ended a positive sound, started a negative sound, or ended a negative sound.*

*Pictures that started a positive sound and pictures that ended a negative sound had a positive meaning. They started something positive, or ended something negative. Press ‘M’ when the picture had a positive meaning.*

*Pictures that started a negative sound and pictures that ended a positive sound had a negative meaning. They started something negative, or ended something positive. Press ‘Y’ when the picture had a negative meaning.*

*Therefore: - Started a positive sound: Press ‘M’ (positive meaning) - Ended a positive sound: Press ‘Y’ (negative meaning) - Started a negative sound: Press ‘Y’ (negative meaning) - Ended a negative sound: Press ‘M’ (positive meaning).*

*When you do not remember the meaning of the picture, please respond in line with your feelings towards the picture.*

In Experiment 4, memory task instructions were different depending on condition (role vs. meaning). Instructions in the role condition were identical to the instructions from Experiments 1-3 except for the last sentence. Specifically, participants were not instructed ‘… *please respond in line with your feelings towards the picture.’*, but ‘*… please guess the meaning of the picture.’*

Instructions for the meaning condition are provided below. Note that instructions about the CS meaning were already provided before the conditioning procedure.

*The next task is a memory task. You will be presented with each picture again. You have to indicate for each picture whether it had a positive or negative meaning. Press ‘M’ when the picture had a positive meaning. Press ‘Y’ when the picture had a negative meaning.*

*When you do not remember the meaning of the picture, please guess the meaning of the picture.*

**Dichotomous evaluation task**

Instructions presented to participants before the dichotomous evaluation task were identical for Experiments 3 and 4:

*In the next task, you will be asked to indicate your opinion about pictures. Please indicate for each picture, whether you regard the picture to be positive or negative. When you regard the picture to be positive, press ‘M’. When you regard the picture to be negative, press ‘Y’. It is possible that you think the picture is (n)either positive (n)or negative. In this case, please indicate the answer that represents your opinion best.*

**Supplement B**

 In Supplement B, we present additional MPT analyses performed on memory task data in order to test the robustness of our parameter estimates. The hierarchical MPT approach employed in the main text assumes that parameter estimates are normally distributed. Descriptive statistics however suggested that parameter estimates were characterized by a bimodal distribution, potentially violating the before-mentioned assumption. For this reason, we reanalyzed the data (a) by modeling individual response data without making any assumptions about how individual parameter estimates are distributed (i.e., without assuming hyper-distributions; henceforth called the ‘traditional approach’) and (b) by modeling the data using the latent-class approach (Klauer, 2006). Below, we outline the findings from these approaches.

**Traditional approach**

In the first approach, memory data were analyzed using the package ‘MPTinR’ (Singmann & Kellen, 2013) in R (R core team, 2018). An MPT model was estimated for each participant individually. As indicated in Table B.1, each model fitted data satisfactorily. Mean parameter estimates aggregated across participants can be found in Table B.1. A comparison with Table 1(main text) shows that parameter estimates between the traditional approach and the latent-trait approach roughly correspond. In addition, Table B.1 provides Pearson-rank correlations between the MPT parameters estimated with the latent-trait approach and the traditional approach. The correlations between the *p*- and *m*-parameters range between *r* = .78-.99, indicating that both models largely agree about the rank of participants.

**Latent-class approach**

In the second approach, memory data were analyzed with the latent-class approach using the program ‘HMMtree’ (Stahl & Klauer, 2007). The number of latent classes was set to 2, assuming that data originate from two latent classes with different parameter values.

Although the models described the mean structure of the data reasonably well (see Table B.2), none of the models described heterogeneity adequately. Adjusting the number of classes did not solve this issue.

Parameter estimates for each class across experiments is provided in Table B.3. They indicate that participants either had high *p-* and *m-* parameters or low *p-* and *m-*parameters. These findings correspond to the correlations found between parameters in the latent-trait approach (i.e., positive correlations between the *p*- and *m*-parameters; see Table 2 in the main text).

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| --- | --- | --- | --- | --- | --- |
|  |  | **Experiment 1** | **Experiment 2** | **Experiment 3** | **Experiment 4** |
|  |  |  |  | **memory task** | **evaluation task** | **role condition** | **meaning condition** |
|  | *fit* | 1.03 | 28.66 | 0.01 | 0.25 | 2.04 | 0.01 |
| **parameter estimates** | *m* | .29 [.03, .45] | .40 [.16, .59] | .37 [.00, .74] | .22 [.00, .39] | .44 [.08, .57] | .59 [.16, .67] |
| *p* | .20 [.00, .49] | .33 [.08, .50] | .29 [.02, .50] | .38 [.15, .59] | .31 [.00, .47] | .28 [.00, .69] |
| *g* | .52 [.42, .65] | .50 [.40, .57] | .48 [.33, .61] | .49 [.29, .73] | .50 [.30, .94] | .59 [.10, .69] |
| **correlations** | *m-m* | .99 | .99 | .97 | .95 | .99 | .99 |
| *p-p* | .93 | .90 | .86 | .92 | .86 | .78 |
| *g-g* | .79 | .20 | .86 | .85 | .78 | .67 |

*Table B.1.* Model fit, mean parameter estimates, and correlations between parameters elicited with the traditional approach vs. the hierarchical approach. The model fit statistic is a G-squared value with one degree-of-freedom. The critical G-squared value (i.e., when *p* < .05) is *G*2 = 2.16. Values in brackets for the mean parameter estimates represent the 25% and 75% quantiles. All correlations between the methods are significant on the level of *p* < .05.

*Note.* The MPT model did not fit data in Experiment 2. Fitting a model with two *m*-parameters did predict data for a satisfactory degree. However, since the parameters between the one *m*-parameter model and two *m*-parameter model ranged between *r* = [.77, .98], only the model with one m-parameter is reported here (the latent trait model had a similar issue. See main text for a detailed explanation).

|  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- |
|  |  |  |  |  |  |  |  |
|  | **df** | **Exp. 1** | **Exp. 2** | **Exp. 3** | **Exp. 4** |
|  |  |  |  | **memory** | **evaluation** | **role** | **meaning** |
| *M1* | 1 | 1.11 | 34.13\* | 0.25 | 0.13 | 2.45 | 0.06 |
| *M2* | 2 | 3.92 | 35.30\* | 414.37\* | 1036.13\* | 3.67 | 2.12 |
| *S1* | 4 | 22.74\* | 47.60\* | 168.19\* | 127.83\* | 20.17\* | 10.24\* |
| *S2* | 10 | 187.95\* | 296.36\* | 527.86\* | 649.81\* | 32.35\* | 64.67\* |

*Table B.2.* Model fit statistics for the latent-class MPT model of Experiments 1, 2, 3, and 4.

*Note.* \**p* < .05.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | *Class*  | *m* | *p* | *g* |
| **Experiment 1** |  |  |  |  |
|  class 1  | .56 [.50, .61] | .47 [.44, .52] | .47 [.43, .51] | .54 [.48, .61] |
|  class 2  | .44 [.41, .47] | .01 [-.04, .06] | .03 [-.02, .08] | .51 [.50, .61] |
| **Experiment 2** |  |  |  |  |
|  class 1 | .57 [.50, .65] | .67 [.65, .70] | .50 [.43, 58] | .53 [.46, .61] |
|  class 2 | .43 [.35, .50] | .19 [.16, .22] | .17 [.13, .21] | .56 [.50, .61] |
| **Experiment 3** |  |  |  |  |
|  evaluation task |  |  |  |  |
|  class 1 | .25 [.13, .36] | .71 [.66, .76] | .27 [.11, .44] | .60 [.49, .71] |
|  class 2 | .75 [.59, .92] | .05 [.01, .09] | .37 [.33, .41] | .47 [.44, .50] |
|  memory task |  |  |  |  |
|  class 1 | .40 [.29, .51] | .78 [.75, .82] | .31 [.16, .46] | .50 [.39, .61] |
|  class 2 | .59 [.44, .75] | .08 [.04, .13] | .28 [.23, .33] | .48 [.44, .51] |
| **Experiment 4** |  |  |  |  |
|  role condition |  |  |  |  |
|  class 1 | .41 [.17, .64] | .85 [.80, .90] | .31 [.00, .63] | .51 [.28, .75] |
|  class 2 | .59 [.27, .91] | .13 [.05, .21] | .23 [.15, .32] | .47 [.41, .53] |
|  meaning condition |  |  |  |  |
|  class 1 | .64 [.54, .75] | .82 [.78, .86] | .19 [-.02, .41] | .35 [.21, .48] |
|  class 2 | .36 [.29, .42] | .12 [.02, .21] | .24 [.14, .35] | .53 [.47, .61] |

*Table B.3.* Posterior classification probabilities (‘Class’) and parameter estimates for the latent-class MPT model of Experiments 1, 2, 3, and 4.

**Supplement C**

In Supplement C, we present additional analyses on the data from Experiment 4. First, we tested whether there was a difference between the meaning and role condition with respect to the *m*-parameter using the Hierarchical Bayesian MPT approach. Second, we tested whether the *m*-parameter was also different between the role and meaning condition in the dichotomous evaluation task. Finally, we test the relation between MPT parameters and evaluative change from pre- and postratings.

**Hierarchical Bayesian Approach**

Hierarchical Bayesian MPT models were fitted for each condition separately. There was considerable variance in the response frequencies across participants (role condition: χ2(108) = 307.21, *p* < .001, meaning condition: χ2(116) = 402.65, *p* < .001). The MPT models, including an *m*-, *p*-, and *g*-parameter predicted the data to a satisfactory degree for the role condition, t1 obs = 0.157, t1 pred = 0.117, p = .312, and the meaning condition, t1 obs = 0.073, t1 pred = 0.100, p = .635. Subsequently, 95% credible intervals for the difference between each parameter was estimated by subtracting the posteriors of the role condition model from the posteriors of the meaning condition model. An average positive difference score (indicating that the respective parameter is larger in the meaning condition compared to the role condition) with credible intervals that do not include zero can be taken as evidence that the respective parameter is larger in the meaning condition than in the role condition.

Credible intervals for the difference between parameters indicated no differences between conditions with respect to the *p*-parameter (*M*Δ*p* = .009, two-tailed 95% CI = [-.585, .130]), the *g*-parameter (*M*Δ*g* = .066, two-tailed 95% CI = [-.099, .237]), and the *m*-parameter (*M*Δ*m* = -.245, two-tailed 95% CI = [.-568, .130]).

**Dichotomous evaluation task**

In order to investigate whether the *m*-parameter differed between the role and meaning conditions in the dichotomous evaluation task, data were analyzed in similar fashion as the memory task data. Hence, we tested the difference between conditions using two methods.

First, hierarchical Bayesian MPT models were fitted for each condition separately. Subsequently, posterior distributions of the *m*-parameters were compared with each other (see Table C.1 for corresponding statistics). There was considerable variance in the response frequencies across participants, role condition: χ2(108) = 258.94, *p* < .001, meaning condition: χ2(116) = 395.47, *p* < .001. The MPT models, including an *m*-, *p*-, and *g*-parameter predicted the data to a satisfactory degree for the role condition, t1 obs = 0.114, t1 pred = 0.119, p = .508, and the meaning condition, t1 obs = 0.071, t1 pred = 0.098, p = .632. Credible intervals for the difference between parameters indicated no differences between conditions with respect to the *p*-parameter (*M*Δ*p* = .167, two-tailed 95% CI = [-.069, .316]) and the *g*-parameter (*M*Δ*g* = .123, two-tailed 95% CI = [-.069, .316]). There was marginal support that the *m*-parameter was different between conditions (*M*Δ*m* = -.406, two-tailed 95% CI = [-.703, -.082]).

 Second, in order to compare the model fit of a model that assumed equal *m*-parameters across conditions to a model that assumed different *m*-parameters across conditions, data were analyzed in a non-hierarchical fashion using the "MPTinR" package (Singmann & Kellen, 2013) in R (R core team, 2018). In the first model, the *p*-, *m*- and *g*-parameters were estimated for each condition separately. In the second model, the *m*-parameter was constrained to be equal across conditions. Neither model predicted data to a satisfactory degree, *G2*(5) = 76.54, *p* < .001; *G2*(4) = 11.13, *p* = .03. However, the difference in the models’ ability to predict the data was significant, Δ*G2*(1) = -65.41, *p* < .001, indicating that participants remembered the meaning of the CS better in the meaning condition compared to participants in the role condition (see Table C.1 for corresponding statistics).

Next, it was tested whether the model fitted data adequately when estimating separate *p*-parameters in addition to separate *m*-parameters per condition. These results indicated that the model with two *p*- and *m*-parameters did describe the data to a satisfactory degree, Δ*G2*(3) = 3.35, *p* = .341. This model significantly improved the model fit compared to the model with one *p*-parameter and two *m*-parameters, Δ*G2*(1) = 7.78, *p* = .006, indicating that participants responded in line with the CS-US pairing more often in the role condition compared to participants in the meaning condition. Furthermore, a model with two separate *p*-parameters per condition, but equal *m*-parameters, did not predict data to a satisfactory degree, Δ*G2*(1) = 61.95, *p* < .0001. Finally, comparing a constrained to an unconstrained model for the *g*-parameters did not indicate a significant improvement for the unconstrained compared to the constrained model, Δ*G2*(1) = -0.04, *p* = .498.

In sum, results indicated that the *p*- and *m*-parameters differed across conditions.

**MPT parameters and evaluative change**

We tested whether MPT parameters predicted evaluative change from pre- and postratings using a linear mixed model approach using the “lmer” function of the lme4 package (Bates, Maechler, Bolker, & Walker, 2013) in R (R core team, 2018). The model included a fixed intercept, fixed effects for the *m*- and *p-*predictors, and fixed effects for the factors US valence, relation, and instruction. Additionally, fixed effects for all interaction terms between instruction, US valence, relation, and the *m*-parameter, and instruction, US valence, relation, and the *p*-parameter were included. All MPT parameters were centered. Contrasts were set to sum-to-zero (US valence: positive = -1, negative = 1; relation: start = 1, stop = -1), instruction: meaning = -1, role = 1). The random effect structure was identical to the models estimated in Experiments 2 and 3.

The relationship to evaluative change was estimated separately for MPT parameters obtained from the memory task and the dichotomous evaluation task (see Table C.2 for corresponding statistics). The *p*-parameter from the memory task did not predict the standard EC effect (Figure C.1a). However, replicating earlier findings, the *p*-parameter from the dichotomous evaluation task predicted standard EC effects (Figure C.1c). Specifically, while the *p*-parameter predicted a positive evaluative change in positively paired CSs, it predicted a negative change in negatively paired CSs. This difference was significant.

The *m*-parameter of both the dichotomous and memory task predicted standard EC effects for CSs that started a US, but reversed EC effects for CSs that stopped a US (Figure C.1.5b and Figure C.1.5d), as indicated by the significant interaction between the *m*-parameter, US valence, and relation on evaluative change. Specifically, while the *m*-parameter predicted a negative evaluative change in SN and EP stimuli, it predicted a positive change in SP and EN stimuli.

[FIGURE C.1 AROUND HERE]

*Figure C.1.* Evaluative change in Experiment 4 as a function of MPT parameters estimated on data from the memory task (Figures C.1a-C.1b) and estimated on data from the dichotomous evaluation task (Figures C.1c-C.1d). Figures C.1a and C.1c display the relationship between the *p*-parameter (*x*) and evaluative change (*y*) for positively and negatively paired CSs separately. The solid line (grey dots) represents data when the pairing was negative. The dashed line (black dots) represents data when the pairing was positive. Figures C.1b and C.1d present the interaction between the *m*-parameter, the valence of the pairing, and the relational qualifier on evaluative change. To visualize this three-way interaction, the interaction between the *m*-parameter and relational qualifier on evaluative change is plotted separately for positively paired CSs and negatively paired CSs. The left panel (“negative”) displays the relation between the *m*-parameter (*x*) and evaluative change (*y*) for starting and stopping CSs when the pairing was negative. The solid line (grey dots) represents data when the CS started a sound. The dashed line (black dots) represents data when the CS stopped a sound. The right panel (“positive”) displays the relation between the *m*-parameter (*x*) and evaluative change (*y*) for starting and stopping CSs when the pairing was positive.

|  |  |  |  |
| --- | --- | --- | --- |
|  |  | **role condition** | **meaning condition** |
| **response frequencies** | SP | 203 (75%) | 234 (78%) |
| EP | 119 (44%) | 217 (72%) |
| SN | 203 (75%) | 245 (82%) |
| EN | 132 (48%) | 206 (69%) |
| **parameter estimates** | *m* | .206 [.071, .278] | .512 [.215, .779] |
| *p* | .324 [.146, .507] | .157 [.018, .356] |
| *g* | .513 [.395, .628] | .390 [.236, .538] |
| **correlations** | *m-p* | -.030 [-.613, .539] | .132 [-.593, .762] |
| *m-g* | .283 [-.403, .825] | -.319 [-.817, .330] |
| *p-g* | -.263 [-.762, .343] | -.085 [-.748, .592] |

*Table C.1.* Response frequencies (SP: Start Positive, EP: End Positive, SN: Start Negative, EN: End Negative), parameters estimates, and estimated correlations between the parameters for the MPT models. Percentages of answering the correct implication for each CS type are given in braces. Credibility intervals for parameter estimates are given in brackets.

|  |  |  |
| --- | --- | --- |
| **Effect** | **memory task** | **evaluation task** |
|  | Estimate | *χ2* | *p* | Estimate | *χ2* | *p* |
| US valence × *p* | -13.92 | 1.90 | .168 | -45.17 | 35.08 | < .001 |
|  negative valence | -11.31 | 0.44 | .507 | -47.93 | 14.28 | .002 |
|  positive valence | 16.32 | 1.27 | .259 | 42.49 | 11.51 | .007 |
|  |  |  |  |  |  |  |
| US valence × qualifier × *m* | -34.45 | 21.04 | < .001 | -49.69 | 30.76 | < .001 |
|  negative valence |  |  |  |  |  |  |
|  relation × *m* | -38.09 | 20.71 | < .001 | -56.28 | 36.67 | < .001 |
|  start | -34.12 | 11.00 | .009 | -43.64 | 15.57 | < .001 |
|  stop | 40.93 | 14.87 | .001 | 67.81 | 37.69 | < .001 |
|  positive valence |  |  |  |  |  |  |
|  relation × *m* | 30.97 | 17.41 | < .001 | 43.48 | 28.52 | < .001 |
|  start | 31.14 | 11.69 | .006 | 41.37 | 18.62 | < .001 |
|  stop | -30.90 | 11.52 | .007 | -45.69 | 19.03 | < .001 |

*Table C.2.* Modeling results on the relationship between MPT parameters and evaluative change for the continuous and dichotomous evaluation tasks in Experiment 4. Follow-up models for interactions were only computed if the respective interaction was significant. All chi-square tests had one degree of freedom. Note that due to the large number of effects in the model, we only report significant effects. In addition, significant main effect or lower order effects are omitted when a higher order effect containing those effects was significant.

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