**Supplementary information** with *The unpleasantness of thinking: A meta-analytic review of the association between mental effort and negative affect*

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**Associations between moderators**

**Table S1.** Association strength (Cramer’s V) between all categorical moderators.

|  |  |  |  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  |  | **1** | **3** | **4a** | **4b** | **5** | **6** | **7** | **8** | **9** | **10** | **14** | **15** |
| 1 | Education (2) | 1 |  |  |  |  |  |  |  |  |  |  |  |
| 3 | Skill–task fit (2) | .29 | 1 |  |  |  |  |  |  |  |  |  |  |
| 4a | Continent (3) | .10 | .16 | 1 |  |  |  |  |  |  |  |  |  |
| 4b | Country (3) | .05 | .15 | 1 | 1 |  |  |  |  |  |  |  |  |
| 5 | Skill variety (2) | .26 | .56 | .16 | .25 | 1 |  |  |  |  |  |  |  |
| 6 | Monitoring feedback (2) | .09 | .14 | .09 | .17 | .13 | 1 |  |  |  |  |  |  |
| 7 | Performance feedback (2) | .01 | .04 | .21 | .50 | .05 | .21 | 1 |  |  |  |  |  |
| 8 | Control (2) | .25 | .48 | .13 | .14 | .66 | .10 | .06 | 1 |  |  |  |  |
| 9 | Task significance (2) | .19 | .66 | .16 | .21 | .66 | .22 | .00 | .48 | 1 |  |  |  |
| 10 | Task identity (2) | .09 | .58 | .13 | .28 | .68 | .07 | .09 | .61 | .57 | 1 |  |  |
| 14 | Physical activity (2) | .01 | .09 | .08 | .21 | .10 | .11 | .09 | .04 | .09 | .03 | 1 |  |
| 15 | Group setting (3) | .27 | .33 | .14 | .25 | .28 | .05 | .13 | .24 | .29 | .21 | .40 | 1 |

*Note:* The numbering in the leftmost column corresponds to the numbering in Table 1 in the main text. Numbers between brackets refer to the number of categories of that moderator. Derived from χ2, Cramer’s V is an effect size measure for pairs of nominal variables. V can range between 0 (no association) and 1 (perfect association). V is sometimes referred to as φC.

Following common rules of thumb (Cohen, 1988, *Statistical power for the behavioral sciences*, 2nd Ed.), the interpretation of V depends on the lowest number of categories in the variable pair.

* If the variable with the lowest number of categories has 2 categories, V is considered large when V ≥ .50.
* If the variable with the lowest number of categories has 3 categories, V is considered large when V ≥ .35.

Shaded cells in Table S1 contain effect sizes that can be considered large, following these rules of thumb.

To interpret the 10 large associations in Table S1, we computed odds ratios (ORs). We report these by going through Table S1 column by column, from left to right:

* Tasks that had high skill–task fit, were more likely to also have high task variety (OR = 15.6), high task significance (OR = 95.5), and high task identity (17.3)
* Naturally, there was a perfect association between continent and country.
* Tasks from Canada were more likely to have continuous performance feedback, when compared to tasks form the USA (OR = 11.9) and Germany (OR = 15.4).
* Tasks that had high skill variety, were more likely to also have high control (OR = 29.9), high task significance (OR = 28.4), and high task identity (OR = 27.8).
* Tasks that had high control, were more likely to also have high task significance (OR = 10.2).
* Tasks that had high task significance, were more likely to also have high task identity (OR = 15.2).

**Table S2.** Association strength (η2) between the four continuous moderators (columns) with the categorical moderators (rows).

|  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- |
|  |  | **Work experience** | **Age** | **Gender** | **Duration of task** |
| 1 | Education | .00 | .32 | .02 | .02 |
| 3 | Skill–task fit | .02 | .07 | .00 | .06 |
| 4a | Continent | .16 | .02 | .00 | .02 |
| 4b | Country | .01 | .12 | .02 | .06 |
| 5 | Skill variety | .00 | .05 | .01 | .03 |
| 6 | Monitoring feedback | .06 | .02 | .04 | .01 |
| 7 | Performance feedback | .00 | .00 | .01 | .00 |
| 8 | Control | .02 | .01 | .02 | .01 |
| 9 | Task significance | - | .09 | .02 | .04 |
| 10 | Task identity | .01 | .02 | .00 | .01 |
| 14 | Physical activity | .10 | .02 | .00 | .01 |
| 15 | Group setting | .14 | .00 | .03 | .17 |

*Note:* η2 is an effect size measure that can be used to quantify the strength of association between continuous and categorical variables. Shaded cells contain effect sizes that can be considered large, η2 ≥ .14, following common rules of thumb (Cohen, 1988). We were unable to compute η2 for the link between task significance and work experience, because where we could code work experience (k = 58), task significance was always high.

To interpret the 4 large associations in Table S1, we interpreted the means of the continuous moderators separately for all levels of the relevant categorical moderators. We report these by going through Table S2 column by column, from left to right:

On average, participants in studies conducted in Europe (M = 13.3y, SD = 8.8y) and Asia (M = 10.5y, SD = 11.8y) had more work experience than participants in studies conducted in North-America (M = 4.1y, SD = 3.9y).

On average, participants who took part in studies individually (M = 11.3y, SD = 9.9y) or with observers present (M = 15.0y, SD = 10.1y), had more work experience than participants who took part in studies that required them to engage with others (M = 5.9y, SD = 6.5y).

On average, participants without university education (M = 35.8y, SD = 12.2y) were older than participants with university education (M = 24.4y, SD = 4.0y).

On average, tasks that were administered with observers present were relatively short (M = 14.7m, SD = 16.6m). Tasks that required participants to engage with others were relatively long (M = 84.3m), though there was a lot of variation (SD = 123.0). Tasks that were conducted individually fell in between (M = 38.7m, SD = 16.6m).

**Table S3.** Association strength (Pearson r) between the four continuous moderators.

|  |  |  |  |  |
| --- | --- | --- | --- | --- |
|  | **Work experience** | **Age** | **Gender** | **Duration of task** |
| Work experience | 1 |  |  |  |
| Age | .89 | 1 |  |  |
| Gender | -.29 | -.20 | 1 |  |
| Duration of task | -.16 | .03 | .24 | 1 |

*Note:* Work experience and age were coded in years; gender was coded as the proportion of females in the sample; duration of task was coded in minutes.

Following common rules of thumb (Cohen, 1988), we note the strong correlation between age and work experience. Naturally, participants with more work experience also tended to be older.

**Detailed results of moderator analyses**

**Table S4.** Moderator analyses for learning history moderators.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Moderator** | **Term** | **β** |  | **95%CI** | **QM** |  | **QE** |  | **I2** |
| 1 | Education | Intercept | 32.6 | \*\*\* | [23.0, 42.3] | 341.7 | \*\*\* | 35486.8 | \*\*\* | 97.8 |
|  |  | Effort | 0.8 | \*\* | [0.3, 1.3] |  |  |  |  |  |
|  |  | Education = University | 3.0 |  | [-6.6, 12.7] |  |  |  |  |  |
|  |  | Effort × Education | 0.1 |  | [-0.3, 0.6] |  |  |  |  |  |
| 2 | Work experience | Intercept | 34.4 | \*\*\* | [24.4, 44.4] | 296.1 | \*\*\* | 8436.5 | \*\*\* | 98.8 |
|  |  | Effort | 1.0 | \*\* | [0.5, 1.5] |  |  |  |  |  |
|  |  | Work experience | -0.3 |  | [-1.5, 0.9] |  |  |  |  |  |
|  |  | Effort × Work experience | 0.0 |  | [-0.1, 0.1] |  |  |  |  |  |
| 3 | Skill-task fit | Intercept | 35.5 | \*\*\* | [32.8, 38.2] | 554.9 | \*\*\* | 33284.2 | \*\*\* | 97.2 |
|  |  | Effort | 0.8 | \*\*\* | [0.7, 1.0] |  |  |  |  |  |
|  |  | Skill–task fit = High | -0.7 |  | [-5.8, 4.3] |  |  |  |  |  |
|  |  | Effort × Skill–task fit | 0.0 |  | [-0.3, 0.3] |  |  |  |  |  |
| 4a | Continent | Intercept | 34.3 | \*\*\* | [30.2, 38.4] | 657.7 | \*\*\* | 25830.8 | \*\*\* | 97.2 |
|  |  | Effort | 1.1 | \*\*\* | [0.8, 1.3] |  |  |  |  |  |
|  |  | Continent = Asia | -1.7 |  | [-7.2, 3.9] |  |  |  |  |  |
|  |  | Continent = Europe | 3.4 |  | [-2.0, 8.9] |  |  |  |  |  |
|  |  | Effort × Continent = Asia | -0.5 | \*\* | [-0.8, -0.2] |  |  |  |  |  |
|  |  | Effort × Continent = Europe | -0.2 |  | [-0.5, 0.1] |  |  |  |  |  |
| 4b | Country | Intercept | 36.2 | \*\*\* | [32.3, 40.1] | 285.0 | \*\*\* | 1324.1 | \*\*\* | 91.1 |
|  |  | Effort | 1.1 | \*\*\* | [0.9, 1.3] |  |  |  |  |  |
|  |  | Country = Canada | -7.9 |  | [-17.4, 1.6] |  |  |  |  |  |
|  |  | Country = Germany | 7.9 | \* | [0.4, 15.3] |  |  |  |  |  |
|  |  | Effort × Country = Canada | -0.4 |  | [-1.1, 0.3] |  |  |  |  |  |
|  |  | Effort × Country = Germany | -0.4 |  | [-0.9, 0.2] |  |  |  |  |  |

*Note:* Each moderator is tested in a separate model. In all models, the dependent variable was negative affect. \* p < .05; \*\* p < .01; \*\*\* p < .001.**Table S5.** Moderator analyses for task design moderators.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Moderator** | **Term** | **β** |  | **95%CI** | **QM** |  | **QE** |  | **I2** |
| 5 | Skill variety | Intercept | 35.2 | \*\*\* | [32.9, 37.5] | 567.9 | \*\*\* | 22433.9 | \*\*\* | 97.2 |
|  |  | Effort | 0.8 | \*\*\* | [0.7, 1.0] |  |  |  |  |  |
|  |  | Skill variety = High | 0.0 |  | [-4.5, 4.4] |  |  |  |  |  |
|  |  | Effort × Skill variety | 0.1 |  | [-0.2, 0.3] |  |  |  |  |  |
| 6 | Monitoring feedback | Intercept | 34.8 | \*\*\* | [30.3, 39.3] | 553.0 | \*\*\* | 24414.0 | \*\*\* | 97.2 |
|  |  | Effort | 0.9 | \*\*\* | [0.7, 1.1] |  |  |  |  |  |
|  |  | Monitoring feedback = Yes | 0.6 |  | [-4.2, 5.4] |  |  |  |  |  |
|  |  | Effort × Monitoring feedback | -0.1 |  | [-0.3, 0.2] |  |  |  |  |  |
| 7 | Performance feedback | Intercept | 35.2 | \*\*\* | [32.9, 37.6] | 552.5 | \*\*\* | 38745.8 | \*\*\* | 97.3 |
|  |  | Effort | 0.9 | \*\*\* | [0.7, 1.0] |  |  |  |  |  |
|  |  | Performance feedback = Throughout | 0.6 |  | [-3.1, 4.4] |  |  |  |  |  |
|  |  | Effort × Performance feedback | -0.1 |  | [-0.6, 0.4] |  |  |  |  |  |
| 8 | Control | Intercept | 34 | \*\*\* | [32.0, 36.0] | 578.7 | \*\*\* | 18501.6 | \*\*\* | 97.1 |
|  |  | Effort | 0.8 | \*\*\* | [0.7, 0.9] |  |  |  |  |  |
|  |  | Control = High | 3.4 |  | [-1.3, 8.0] |  |  |  |  |  |
|  |  | Effort × Control | 0.1 |  | [-0.1, 0.3] |  |  |  |  |  |
| 9 | Task significance | Intercept | 34.8 | \*\*\* | [32.2, 37.4] | 548.3 | \*\*\* | 23351.9 | \*\*\* | 97.1 |
|  |  | Effort | 0.9 | \*\*\* | [0.7, 1.0] |  |  |  |  |  |
|  |  | Task significance = High/medium | 0.8 |  | [-3.6, 5.3] |  |  |  |  |  |
|  |  | Effort × Task significance | 0.0 |  | [-0.3, 0.2] |  |  |  |  |  |
| 10 | Task identity | Intercept | 34.4 | \*\*\* | [32.0, 36.9] | 581.7 | \*\*\* | 21226.0 | \*\*\* | 97.2 |
|  |  | Effort | 0.8 | \*\*\* | [0.6, 0.9] |  |  |  |  |  |
|  |  | Task identity = High | 1.8 |  | [-3.1, 6.7] |  |  |  |  |  |
|  |  | Effort × Task identity | 0.1 |  | [-0.1, 0.4] |  |  |  |  |  |

*Note:* Each moderator was tested in a separate model. In all models, the dependent variable was negative affect. \* p < .05; \*\* p < .01; \*\*\* p < .001.

**Table S6.** Moderator analyses for task design moderators.

|  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- |
| **Term** | **β** |  | **95%CI** | **QM** |  | **QE** |  | **I2** |
| Intercept | 33.5 | \*\*\* | [29.4, 37.7] | 601.9 | \*\*\* | 13342.3 | \*\*\* | 97.1 |
| Effort | 0.9 | \*\*\* | [0.6, 1.1] |  |  |  |  |  |
| Skill variety | -2.4 |  | [-7.0, 2.1] |  |  |  |  |  |
| Monitoring feedback | 1.4 |  | [-4.3, 7.1] |  |  |  |  |  |
| Performance feedback | 1.1 |  | [-3.1, 5.2] |  |  |  |  |  |
| Control | 4.0 |  | [-0.8, 8.8] |  |  |  |  |  |
| Task significance | -1.0 |  | [-6.2, 4.2] |  |  |  |  |  |
| Task identity | 2.1 |  | [-5.4, 9.6] |  |  |  |  |  |
| Effort × Skill variety | 0.0 |  | [-0.4, 0.4] |  |  |  |  |  |
| Effort × Monitoring feedback | -0.1 |  | [-0.3, 0.2] |  |  |  |  |  |
| Effort × Performance feedback | -0.1 |  | [-0.5, 0.4] |  |  |  |  |  |
| Effort × Control | 0.1 |  | [-0.3, 0.5] |  |  |  |  |  |
| Effort × Task significance | -0.3 |  | [-0.6, 0.1] |  |  |  |  |  |
| Effort × Task identity | 0.3 |  | [-0.3, 0.8] |  |  |  |  |  |

*Note:* All moderators were tested together in the same model. The dependent variable was negative affect. \* p < .05; \*\* p < .01; \*\*\* p < .001.

**Table S7.** Moderator analyses for exploratory moderators.

|  |  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Moderator** | **Term** | **β** |  | **95%CI** | **QM** |  | **QE** |  | **I2** |
| 11 | Age | Intercept | 35.6 | \*\*\* | [32.8, 38.4] | 356.2 | \*\*\* | 38291.5 | \*\*\* | 98.0 |
|  |  | Effort | 0.8 | \*\*\* | [0.6, 0.9] |  |  |  |  |  |
|  |  | Age | -0.2 |  | [-0.5, 0.1] |  |  |  |  |  |
|  |  | Effort × Age | 0.0 |  | [0.0, 0.0] |  |  |  |  |  |
| 12 | Gender | Intercept | 34.2 | \*\*\* | [32.2, 36.2] | 513.2 | \*\*\* | 2384.1 | \*\*\* | 95.2 |
|  |  | Effort | 0.8 | \*\*\* | [0.7, 0.9] |  |  |  |  |  |
|  |  | Gender | -5.0 |  | [-15.2, 5.3] |  |  |  |  |  |
|  |  | Effort × Gender | -0.3 |  | [-0.7, 0.1] |  |  |  |  |  |
| 13 | Duration | Intercept | 35.8 | \*\*\* | [32.6, 39.0] | 286.4 | \*\*\* | 1258.0 | \*\*\* | 92.5 |
|  |  | Effort | 0.8 | \*\*\* | [0.6, 1.0] |  |  |  |  |  |
|  |  | Duration | 0.0 |  | [-0.1, 0.1] |  |  |  |  |  |
|  |  | Effort × Duration | 0.0 |  | [0.0, 0.0] |  |  |  |  |  |
| 14 | Physical activity | Intercept | 36.3 | \*\*\* | [33.7, 38.9] | 635.0 | \*\*\* | 36818.5 | \*\*\* | 97.5 |
|  |  | Effort | 0.8 | \*\*\* | [0.7, 0.9] |  |  |  |  |  |
|  |  | Physical activity = Light activity | -2.3 |  | [-6.8, 2.2] |  |  |  |  |  |
|  |  | Effort × Physical activity | 0.2 |  | [0.0, 0.4] |  |  |  |  |  |
| 15 | Group setting | Intercept | 36.9 | \*\*\* | [33.4, 40.4] | 551.4 | \*\*\* | 37516 | \*\*\* | 97.2 |
|  |  | Effort | 0.8 | \*\*\* | [0.7, 0.9] |  |  |  |  |  |
|  |  | Group setting = Together with others | -2.8 |  | [-8.7, 3.1] |  |  |  |  |  |
|  |  | Group setting = Observers present | -2.8 |  | [-6.8, 1.2] |  |  |  |  |  |
|  |  | Effort × Group Setting: Together w. others | 0.0 |  | [-0.5, 0.5] |  |  |  |  |  |
|  |  | Effort × Group Setting: Observers present | 0.1 |  | [-0.1, 0.4] |  |  |  |  |  |

*Note:* Each moderator was tested in a separate model. In all models, the dependent variable was negative affect. \* p < .05; \*\* p < .01; \*\*\* p < .001.

**Detailed results of robustness analysis**

**Table S8.** Robustness analysis.

|  |  |  |  |  |  |  |  |  |  |
| --- | --- | --- | --- | --- | --- | --- | --- | --- | --- |
|  | **Term** | **β** |  | **95%CI** | **QM** |  | **QE** |  | **I2** |
|  | Intercept | 35.8 | \*\*\* | [28.5, 43.2] | 597.2 | \*\*\* | 10030.0 | \*\*\* | 97.3 |
|  | Effort | 0.9 | \*\*\* | [0.8, 1.0] |  |  |  |  |  |
| 3 | Skill–task fit = High | -1.4 |  | [-11.3, 8.4] |  |  |  |  |
| 4a | Continent = Asia | -2.7 |  | [-9.9, 4.6] |  |  |  |  |  |
| 4a | Continent = Europe | 3.8 |  | [-1.9, 9.6] |  |  |  |  |  |
| 5 | Skill variety = High | -2.8 |  | [-10.3, 4.7] |  |  |  |  |
| 6 | Monitoring feedback = Yes | 0.1 |  | [-5.6, 5.8] |  |  |  |  |  |
| 7 | Performance feedback = Throughout | 0.6 |  | [-3.8, 4.9] |  |  |  |  |  |
| 8 | Control = High | 5.2 | \* | [0.2, 10.3] |  |  |  |  |
| 9 | Task significance = High/medium | -0.1 |  | [-7.5, 7.2] |  |  |  |  |  |
| 10 | Task identity = High | 1.9 |  | [-5.2, 9.0] |  |  |  |  |  |
| 14 | Physical activity = Light activity | -3.1 |  | [-9.7, 3.5] |  |  |  |  |  |
| 15 | Group setting = Together with others | -1.7 |  | [-8.7, 5.4] |  |  |  |  |  |
| 15 | Group setting = Observers present | -2.8 |  | [-7.1, 1.4] |  |  |  |  |  |

*Note:* All moderators are tested together in the same model. The dependent variable was negative affect. \* p < .05; \*\* p < .01; \*\*\* p < .001.

**Simulations to examine if individual-level response biases can account for the results**

***Background***

One may suspect that our main finding—i.e., the association between effort and negative affect—does not reflect a true association between effort and negative affect, but that it can be explained from individual-level response biases. For example, people who are more likely to agree with questionnaire statements (i.e., people higher in acquiescence bias) will likely score higher both on effort *and* on negative affect. As a result of such variation in response tendencies, within individual samples, the correlation between effort and negative affect could be inflated or even fully spurious. However, our meta-analysis was done *across samples*, i.e., on summary statistics that were computed on the sample level. It is an open question whether within-samples correlations (which may be due to response biases) can explain our main finding. We conducted simulations to explore this question.

***Method***

We present four sets of simulations. In each set, we assumed a different true correlation between effort and negative affect (within individual samples). In the first set, we assumed ρ = .30; in the second, ρ = .50; in the third, ρ = .70; in the fourth, ρ = .90.

The core part of our simulation script (<https://osf.io/mktbr/>) worked as follows:

1. We first simulated individual datasets. In several ways, these simulated datasets mirrored the datasets that we included in our meta-analysis. That is, they had similar N (Nmean = 26, Nsd = 16, Nmin = 10). Also, the sample means and standard deviations for effort and negative affect were similar to those from the real datasets. However, as described above, we assumed different correlations between effort and negative affect in the populations from which the simulated samples were drawn (i.e., different ρs). We constructed these datasets using the rnorm\_multi() function from the *faux* package in R (DeBruine, 2021, https:/doi.org/10.5281/zenodo.2669586).
2. From these datasets, we constructed a meta-analysis dataset. This meta-analysis dataset included means and standard deviations for effort and negative affect, computed for each of the simulated samples. As in our meta-analysis, this meta-analysis dataset contained summary data from 357 individual samples.
3. We ran a meta-analysis on the dataset constructed at step #2, using the same procedures as described in the main text.
4. We stored the β-value for the effect of effort on negative affect.

We ran the core part of our script 4 x 1000 times, i.e., 1000 times for each correlation. We report the distributions of β-values and compare these distributions to the β of 0.85 that we found in our meta-analysis.

If within-samples correlations did not affect the outcome of the meta-analysis at all, βs should be distributed around 0 (as we did not manufacture any across-samples association in our simulations). By contrast, if our main finding can be fully explained by within-samples correlations, βs should be in same range as the β we found in our meta-analysis.

***Results***

**Figure S1.** Simulation results.

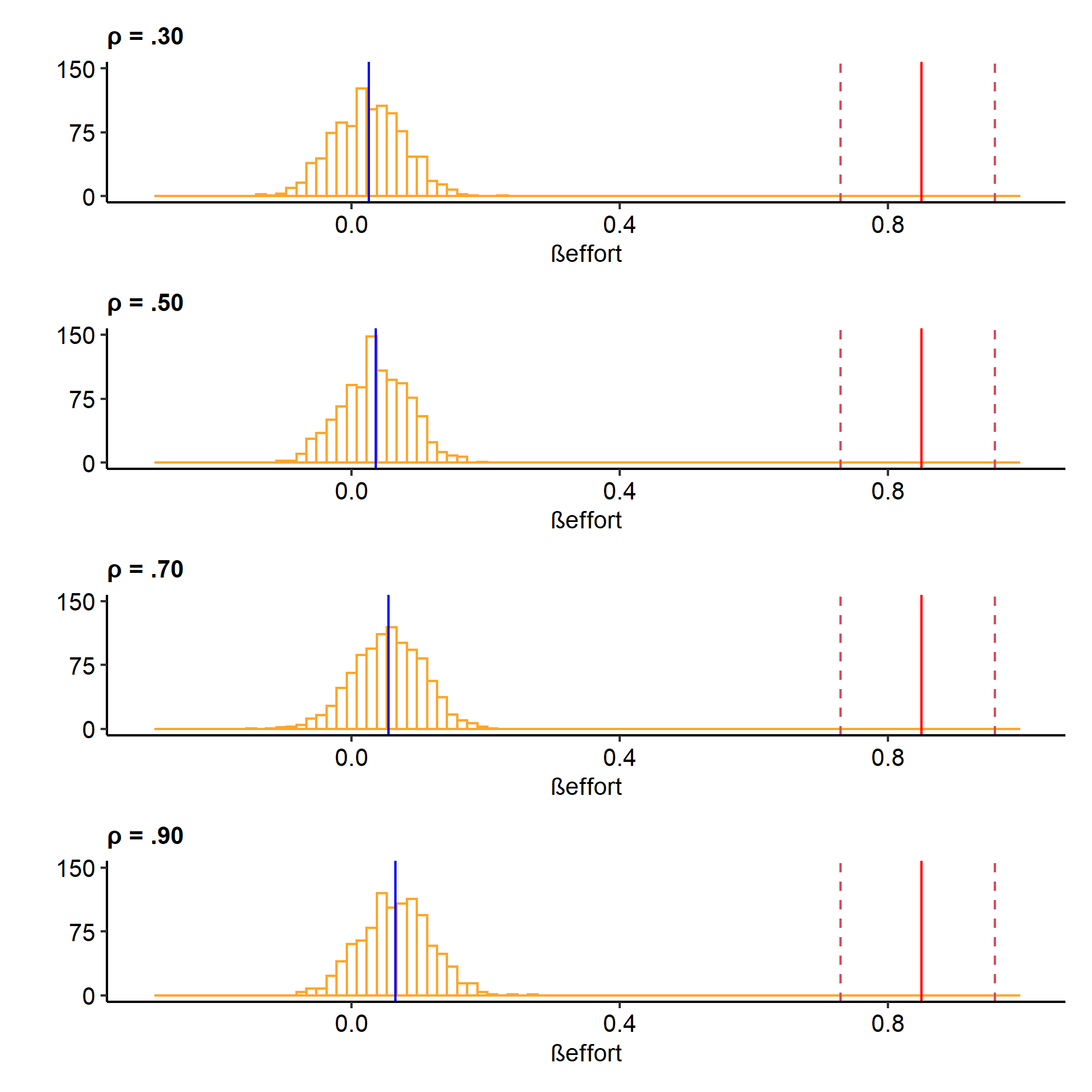


Figure S1 shows results from four sets of simulations, each with a different correlation (within individual samples). Histograms reflect the distribution of simulated β-values for the meta-analytic effect of effort on negative affect. Red vertical lines mark the β-value of 0.85 that we found in our main meta-analysis (with the 95% confidence intervals in dashed lines).

***Discussion***

Inspection of Figure S1 reveals that the simulated meta-analyses yielded β-values that were, on average, slightly above 0. So, if within-samples correlations were present in the original datasets (which, in turn, could be due to response biases), these may have slightly inflated the overall effect size that we found. We say ‘slightly’ because even when within-samples correlations were unrealistically strong (ρ = .90), the distribution of β-values centered only at around 0.07. Importantly, inspection of Figure S1 further reveals that the β-value we found in our meta-analysis was well outside the range of our simulations, suggesting that within-samples correlations (and, thus, potential response biases) cannot account for our findings.

**List of papers included in the meta-analysis**

Abd Rahman, N. I., Md Dawal, S. Z., & Yusoff, N. (2020). Driving mental workload and performance of ageing drivers. *Transportation Research Part F: Traffic Psychology and Behaviour*, *69*, 265–285. https://doi.org/10.1016/j.trf.2020.01.019

Alagi, H., Navarro, S. E., Hergenhan, J., Music, S., & Hein, B. (2020). Teleoperation with tactile feedback based on a capacitive proximity sensor array. *2020 IEEE International Instrumentation and Measurement Technology Conference (I2MTC)*, 1–6. https://doi.org/10.1109/I2MTC43012.2020.9128701

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