**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

Armougum, A., Gaston-Bellegarde, A., Marle, C. J.-L., & Piolino, P. (2020). Expertise reversal effect: Cost of generating new schemas. *Computers in Human Behavior*, *111*, 106406. https://doi.org/10.1016/j.chb.2020.106406

Aromaa, S., Väätänen, A., Aaltonen, I., Goriachev, V., Helin, K., & Karjalainen, J. (2020). Awareness of the real-world environment when using augmented reality head-mounted display. *Applied Ergonomics*, *88*, 103145. https://doi.org/10.1016/j.apergo.2020.103145

Arsintescu, L., Chachad, R., Gregory, K. B., Mulligan, J. B., & Flynn-Evans, E. E. (2020). The relationship between workload, performance and fatigue in a short-haul airline. *Chronobiology International*, *37*(9–10), 1492–1494. https://doi.org/10.1080/07420528.2020.1804924

Ataya, A., Kim, W., Elsharkawy, A., & Kim, S. (2020). Gaze-head input: Examining potential interaction with immediate experience sampling in an autonomous vehicle. *Applied Sciences*, *10*(24), 9011. https://doi.org/10.3390/app10249011

Badesa, F. J., Diez, J. A., Catalan, J. M., Trigili, E., Cordella, F., Nann, M., Crea, S., Soekadar, S. R., Zollo, L., Vitiello, N., & Garcia-Aracil, N. (2019). Physiological responses during hybrid BCNI control of an upper-limb exoskeleton. *Sensors*, *19*(22), 4931. https://doi.org/10.3390/s19224931

Beege, M., Nebel, S., Schneider, S., & Rey, G. D. (2021). The effect of signaling in dependence on the extraneous cognitive load in learning environments. *Cognitive Processing*, *22*(2), 209–225. https://doi.org/10.1007/s10339-020-01002-5

Berg, M., Bayazit, D., Mathew, R., Rotter-Aboyoun, A., Pavlick, E., & Tellex, S. (2020). Grounding language to landmarks in arbitrary outdoor environments. *2020 IEEE International Conference on Robotics and Automation (ICRA)*, 208–215. https://doi.org/10.1109/ICRA40945.2020.9197068

Bier, L., Emele, M., Gut, K., Kulenovic, J., Rzany, D., Peter, M., & Abendroth, B. (2019). Preventing the risks of monotony related fatigue while driving through gamification. *European Transport Research Review*, *11*(1), 44. https://doi.org/10.1186/s12544-019-0382-4

Blundell, J., Scott, S., Harris, D., Huddlestone, J., & Richards, D. (2020a). With flying colours: Pilot performance with colour-coded head-up flight symbology. *Displays*, *61*, 101932. https://doi.org/10.1016/j.displa.2019.101932

Blundell, J., Scott, S., Harris, D., Huddlestone, J., & Richards, D. (2020b). Workload benefits of colour coded head-up flight symbology during high workload flight. *Displays*, *65*, 101973. https://doi.org/10.1016/j.displa.2020.101973

Bogaard, T., Wielemaker, J., Hollink, L., Hardman, L., & van Ossenbruggen, J. (2020). Understanding user behavior in digital libraries using the MAGUS session visualization tool. In M. Hall, T. Merčun, T. Risse, & F. Duchateau (Eds.), *Digital Libraries for Open Knowledge* (Vol. 12246, pp. 171–184). Springer International Publishing. https://doi.org/10.1007/978-3-030-54956-5\_13

Braarud, P. Ø. (2020). An efficient screening technique for acceptable mental workload based on the NASA Task Load Index—Development and application to control room validation. *International Journal of Industrial Ergonomics*, *76*, 102904. https://doi.org/10.1016/j.ergon.2019.102904

Caggianese, G., Capece, N., Erra, U., Gallo, L., & Rinaldi, M. (2020). Freehand-steering locomotion techniques for immersive virtual environments: A comparative evaluation. *International Journal of Human–Computer Interaction*, *36*(18), 1734–1755. https://doi.org/10.1080/10447318.2020.1785151

Cai, S., Ke, P., Narumi, T., & Zhu, K. (2020). ThermAirGlove: A pneumatic glove for thermal perception and material identification in virtual reality. *2020 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, 248–257. https://doi.org/10.1109/VR46266.2020.00044

Calvi, A., D’Amico, F., Ciampoli, L. B., & Ferrante, C. (2020). Evaluation of driving performance after a transition from automated to manual control: A driving simulator study. *Transportation Research Procedia*, *45*, 755–762. https://doi.org/10.1016/j.trpro.2020.02.101

Caria, M., Todde, G., Sara, G., Piras, M., & Pazzona, A. (2020). Performance and usability of smartglasses for augmented reality in precision livestock farming operations. *Applied Sciences*, *10*(7), 2318. https://doi.org/10.3390/app10072318

Cecotti, H., Day-Scott, Z., Huisinga, L., & Gordo-Pelaez, L. (2020). Virtual reality for immersive learning in art history. *2020 6th International Conference of the Immersive Learning Research Network (ILRN)*, 16–23. https://doi.org/10.23919/iLRN47897.2020.9155108

Chacko, S. M., Granado, A., & Kapila, V. (2020). An augmented reality framework for robotic tool-path teaching. *Procedia CIRP*, *93*, 1218–1223. https://doi.org/10.1016/j.procir.2020.03.143

Chan, W. P., Sakr, M., Quintero, C. P., Croft, E., & Van der Loos, H. F. M. (2020). Towards a multimodal system combining augmented reality and electromyography for robot trajectory programming and execution. *2020 29th IEEE International Conference on Robot and Human Interactive Communication (RO-MAN)*, 419–424. https://doi.org/10.1109/RO-MAN47096.2020.9223526

Chen, Y., Katsuragawa, K., & Lank, E. (2020). Understanding viewport- and world-based pointing with everyday smart devices in immersive augmented reality. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–13. https://doi.org/10.1145/3313831.3376592

Ciumedean, C.-B., Patras, C., Cibulskis, M., Váradi, N., & Nilsson, N. C. (2020). Mission impossible spaces: Using challenge-based distractors to reduce noticeability of self-overlapping virtual architecture. *Symposium on Spatial User Interaction*, 1–4. https://doi.org/10.1145/3385959.3418453

Czarnek, G., Strojny, P., Strojny, A., & Richter, M. (2020). Assessing engagement during rescue operation simulated in virtual reality: A psychophysiological study. *International Journal of Human–Computer Interaction*, *36*(5), 464–476. https://doi.org/10.1080/10447318.2019.1655905

Datta, R. R., Schönhage, S., Dratsch, T., Toader, J., Müller, D. T., Wahba, R., Kleinert, R., Thomas, M., Dieplinger, G., Stippel, D. L., Bruns, C. J., & Fuchs, H. F. (2021). Learning curve of surgical novices using the single-port platform SymphonX: Minimizing OR trauma to only one 15-mm incision. *Surgical Endoscopy*, *35*(9), 5338–5351. https://doi.org/10.1007/s00464-020-07998-3

de Melo, C. M., Kim, K., Norouzi, N., Bruder, G., & Welch, G. (2020). Reducing cognitive load and improving warfighter problem solving with intelligent virtual assistants. *Frontiers in Psychology*, *11*, 554706. https://doi.org/10.3389/fpsyg.2020.554706

DeLucia, P. R., & Greenlee, E. T. (2020). Tactile vigilance is stressful and demanding. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, 001872082096529. https://doi.org/10.1177/0018720820965294

Desolda, G., Matera, M., & Lanzilotti, R. (2020). Metamorphic data sources: A user-centric paradigm to consume linked data in interactive workspaces. *Future Generation Computer Systems*, *102*, 992–1015. https://doi.org/10.1016/j.future.2019.09.032

Dickinson, P., Gerling, K., Wilson, L., & Parke, A. (2020). Virtual reality as a platform for research in gambling behaviour. *Computers in Human Behavior*, *107*, 106293. https://doi.org/10.1016/j.chb.2020.106293

Ding, Y., Cao, Y., Duffy, V. G., Wang, Y., & Zhang, X. (2020). Measurement and identification of mental workload during simulated computer tasks with multimodal methods and machine learning. *Ergonomics*, *63*(7), 896–908. https://doi.org/10.1080/00140139.2020.1759699

Do, S., & Lee, B. (2020). Improving reliability of virtual collision responses: A cue integration technique. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–12. https://doi.org/10.1145/3313831.3376819

Dodwell, A., & Trick, L. M. (2020). The effects of secondary tasks that involve listening and speaking on young adult drivers with traits associated with autism spectrum disorders: A pilot study with driving simulation. *Transportation Research Part F: Traffic Psychology and Behaviour*, *69*, 120–134. https://doi.org/10.1016/j.trf.2019.12.011

Ezcurdia, I., Arregui, A., Ardaiz, O., Ortiz, A., & Marzo, A. (2020). Content adaptation and depth perception in an affordable multi-view display. *Applied Sciences*, *10*(20), 7357. https://doi.org/10.3390/app10207357

Filho, J. A. W., Stuerzlinger, W., & Nedel, L. (2020). Evaluating an immersive space-time cube geovisualization for intuitive trajectory data exploration. *IEEE Transactions on Visualization and Computer Graphics*, *26*(1), 514–524. https://doi.org/10.1109/TVCG.2019.2934415

Ganni, S., Li, M., Botden, S. M. B. I., Nayak, S. R., Ganni, B. R., Rutkowski, A.-F., Goossens, R. H. M., & Jakimowicz, J. (2020). Virtual operating room simulation setup (vorss) for procedural training in minimally invasive surgery – a pilot study. *Indian Journal of Surgery*, *82*(5), 810–816. https://doi.org/10.1007/s12262-020-02131-z

Gerull, W., Zihni, A., & Awad, M. (2020). Operative performance outcomes of a simulator-based robotic surgical skills curriculum. *Surgical Endoscopy*, *34*(10), 4543–4548. https://doi.org/10.1007/s00464-019-07243-6

Ghaleb, A. M., Khalaf, T. M., Ramadan, M. Z., Ragab, A. E., & Badwelan, A. (2020). Effect of cycling on a stationary bike while performing assembly tasks on human physiology and performance parameters. *International Journal of Environmental Research and Public Health*, *17*(5), 1761. https://doi.org/10.3390/ijerph17051761

Gilardi, F., De Falco, F., Casasanta, D., Andellini, M., Gazzellini, S., Petrarca, M., Morocutti, A., Lettori, D., Ritrovato, M., Castelli, E., Raponi, M., Magnavita, N., & Zaffina, S. (2020). Robotic technology in pediatric neurorehabilitation: A pilot study of human factors in an italian pediatric hospital. *International Journal of Environmental Research and Public Health*, *17*(10), 3503. https://doi.org/10.3390/ijerph17103503

Glimne, S., Brautaset, R., & Österman, C. (2020). Visual fatigue during control room work in process industries. *Work*, *65*(4), 903–914. https://doi.org/10.3233/WOR-203141

Gold, B., & Windscheid, J. (2020). Observing 360-degree classroom videos – Effects of video type on presence, emotions, workload, classroom observations, and ratings of teaching quality. *Computers & Education*, *156*, 103960. https://doi.org/10.1016/j.compedu.2020.103960

Golmohammadi, R., Darvishi, E., Faradmal, J., Poorolajal, J., & Aliabadi, M. (2020). Attention and short-term memory during occupational noise exposure considering task difficulty. *Applied Acoustics*, *158*, 107065. https://doi.org/10.1016/j.apacoust.2019.107065

Greenhalgh, M., Blaauw, E., Deepak, N., St. Laurent, C. O. L. M., Cooper, R., Bendixen, R., Koontz, A. M., & Cooper, R. A. (2020). Usability and task load comparison between a robotic assisted transfer device and a mechanical floor lift during caregiver assisted transfers on a care recipient. *Disability and Rehabilitation: Assistive Technology*, 1–7. https://doi.org/10.1080/17483107.2020.1818137

Greenlee, E. T., Lui, T. G., & Maw, E. L. (2021). Is physiobehavioral monitoring nonintrusive? An examination of transcranial doppler sonography in a vigilance task. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *63*(7), 1256–1270. https://doi.org/10.1177/0018720820920118

Gross, I. T., Whitfill, T., Redmond, B., Couturier, K., Bhatnagar, A., Joseph, M., Joseph, D., Ray, J., Wagner, M., & Auerbach, M. (2020). Comparison of two telemedicine delivery modes for neonatal resuscitation support: A simulation-based randomized trial. *Neonatology*, *117*(2), 159–166. https://doi.org/10.1159/000504853

Guo, W., & Kim, J. H. (2020). How augmented reality influences student workload in engineering education. In C. Stephanidis, D. Harris, W.-C. Li, D. D. Schmorrow, C. M. Fidopiastis, P. Zaphiris, A. Ioannou, X. Fang, R. A. Sottilare, & J. Schwarz (Eds.), *HCI International 2020 – Late Breaking Papers: Cognition, Learning and Games* (Vol. 12425, pp. 388–396). Springer International Publishing. https://doi.org/10.1007/978-3-030-60128-7\_29

Hafiz, P., & Bardram, J. E. (2020). The ubiquitous cognitive assessment tool for smartwatches: Design, implementation, and evaluation study. *JMIR MHealth and UHealth*, *8*(6), e17506. https://doi.org/10.2196/17506

Hangli, G., Hamada, T., Sumitomo, T., & Koshizuka, N. (2020). Intellevator: An intelligent elevator system proactive in traffic control for time-efficiency improvement. *IEEE Access*, *8*, 35535–35545. https://doi.org/10.1109/ACCESS.2020.2975020

Hoppe, A. H., Marek, F., Camp, F. van de, & Stiefelhagen, R. (2020). Extending movable surfaces with touch interaction using the VirtualTablet: An extended view. *Advances in Science, Technology and Engineering Systems Journal*, *5*(2), 328–337. https://doi.org/10.25046/aj050243

Hsia, L., & Hwang, G. (2020). From reflective thinking to learning engagement awareness: A reflective thinking promoting approach to improve students’ dance performance, self‐efficacy and task load in flipped learning. *British Journal of Educational Technology*, *51*(6), 2461–2477. https://doi.org/10.1111/bjet.12911

Ishibashi, T., Nakao, Y., & Sugano, Y. (2020). Investigating audio data visualization for interactive sound recognition. *Proceedings of the 25th International Conference on Intelligent User Interfaces*, 67–77. https://doi.org/10.1145/3377325.3377483

Jafari, M., Zaeri, F., Jafari, A. H., Payandeh Najafabadi, A. T., Al‐Qaisi, S., & Hassanzadeh‐Rangi, N. (2020). Assessment and monitoring of mental workload in subway train operations using physiological, subjective, and performance measures. *Human Factors and Ergonomics in Manufacturing & Service Industries*, *30*(3), 165–175. https://doi.org/10.1002/hfm.20831

Jain, M., Tripathi, R., Bhansali, I., & Kumar, P. (2019). Automatic generation and evaluation of usable and secure audio reCAPTCHA. *The 21st International ACM SIGACCESS Conference on Computers and Accessibility*, 355–366. https://doi.org/10.1145/3308561.3353777

Keunecke, J. G., Gall, C., Birkholz, T., Moritz, A., Eiche, C., & Prottengeier, J. (2019). Workload and influencing factors in non-emergency medical transfers: A multiple linear regression analysis of a cross-sectional questionnaire study. *BMC Health Services Research*, *19*(1), 812. https://doi.org/10.1186/s12913-019-4638-4

Khairat, S., Coleman, C., Ottmar, P., Bice, T., Koppel, R., & Carson, S. S. (2019). Physicians’ gender and their use of electronic health records: Findings from a mixed-methods usability study. *Journal of the American Medical Informatics Association*, *26*(12), 1505–1514. https://doi.org/10.1093/jamia/ocz126

Khalaf, A. S., Alharthi, S. A., Alshehri, A., Dolgov, I., & Toups, Z. O. (2020). A comparative study of hand-gesture recognition devices for games. In M. Kurosu (Ed.), *Human-Computer Interaction. Multimodal and Natural Interaction* (Vol. 12182, pp. 57–76). Springer International Publishing. https://doi.org/10.1007/978-3-030-49062-1\_4

Krekhov, A., Cmentowski, S., Waschk, A., & Kruger, J. (2019). Deadeye visualization revisited: Investigation of preattentiveness and applicability in virtual environments. *IEEE Transactions on Visualization and Computer Graphics*, 1–1. https://doi.org/10.1109/TVCG.2019.2934370

Kruger, J. M., & Bodemer, D. (2020). Different types of interaction with augmented reality learning material. *2020 6th International Conference of the Immersive Learning Research Network (ILRN)*, 78–85. https://doi.org/10.23919/iLRN47897.2020.9155148

Kurzhals, K., Göbel, F., Angerbauer, K., Sedlmair, M., & Raubal, M. (2020). A view on the viewer: Gaze-adaptive captions for videos. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–12. https://doi.org/10.1145/3313831.3376266

Large, D. R., Harrington, K., Burnett, G., & Georgiou, O. (2019). Feel the noise: Mid-air ultrasound haptics as a novel human-vehicle interaction paradigm. *Applied Ergonomics*, *81*, 102909. https://doi.org/10.1016/j.apergo.2019.102909

Lee, J.-I., Asente, P., Kim, B., Kim, Y., & Stuerzlinger, W. (2020). Evaluating automatic parameter control methods for locomotion in multiscale virtual environments. *26th ACM Symposium on Virtual Reality Software and Technology*, 1–10. https://doi.org/10.1145/3385956.3418961

Lee, L.-H., Zhu, Y., Yau, Y.-P., Braud, T., Su, X., & Hui, P. (2020). One-thumb text acquisition on force-assisted miniature interfaces for mobile headsets. *2020 IEEE International Conference on Pervasive Computing and Communications (PerCom)*, 1–10. https://doi.org/10.1109/PerCom45495.2020.9127378

Léger, É., Reyes, J., Drouin, S., Popa, T., Hall, J. A., Collins, D. L., & Kersten-Oertel, M. (2020). MARIN: An open-source mobile augmented reality interactive neuronavigation system. *International Journal of Computer Assisted Radiology and Surgery*, *15*(6), 1013–1021. https://doi.org/10.1007/s11548-020-02155-6

Lewis, B., & Vogel, D. (2020). Longer delays in rehearsal-based interfaces increase expert use. *ACM Transactions on Computer-Human Interaction*, *27*(6), 45:1-45:41. https://doi.org/10.1145/3418196

Li, M., Ganni, S., Ponten, J., Albayrak, A., Rutkowski, A.-F., & Jakimowicz, J. (2020). Analysing usability and presence of a virtual reality operating room (VOR) simulator during laparoscopic surgery training. *2020 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, 566–572. https://doi.org/10.1109/VR46266.2020.1581301697128

Li, S., Zhang, T., Zhang, W., Liu, N., & Lyu, G. (2020). Effects of speech-based intervention with positive comments on reduction of driver’s anger state and perceived workload, and improvement of driving performance. *Applied Ergonomics*, *86*, 103098. https://doi.org/10.1016/j.apergo.2020.103098

Li, W.-C., Horn, A., Sun, Z., Zhang, J., & Braithwaite, G. (2020). Augmented visualization cues on primary flight display facilitating pilot’s monitoring performance. *International Journal of Human-Computer Studies*, *135*, 102377. https://doi.org/10.1016/j.ijhcs.2019.102377

Li, W.-C., Yan, Z., Zhang, J., Braithwaite, G., Court, S., Lone, M., & Thapa, B. (2020). Evaluating pilot’s perceived workload on interacting with augmented reality device in flight operations. In D. Harris & W.-C. Li (Eds.), *Engineering Psychology and Cognitive Ergonomics. Cognition and Design* (Vol. 12187, pp. 332–340). Springer International Publishing. https://doi.org/10.1007/978-3-030-49183-3\_26

Lowndes, B. R., Forsyth, K. L., Blocker, R. C., Dean, P. G., Truty, M. J., Heller, S. F., Blackmon, S., Hallbeck, M. S., & Nelson, H. (2020). NASA-TLX assessment of surgeon workload variation across specialties. *Annals of Surgery*, *271*(4), 686–692. https://doi.org/10.1097/SLA.0000000000003058

Lu, F., Davari, S., Lisle, L., Li, Y., & Bowman, D. A. (2020). Glanceable AR: Evaluating information access methods for head-worn augmented reality. *2020 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)*, 930–939. https://doi.org/10.1109/VR46266.2020.00113

MacCormick, D., & Zaman, L. (2020). Echo: Analyzing gameplay sessions by reconstructing them from recorded data. *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, 281–293. https://doi.org/10.1145/3410404.3414254

Mandlekar, A., Booher, J., Spero, M., Tung, A., Gupta, A., Zhu, Y., Garg, A., Savarese, S., & Fei-Fei, L. (2019). Scaling robot supervision to hundreds of hours with roboturk: Robotic manipulation dataset through human reasoning and dexterity. *2019 IEEE/RSJ International Conference on Intelligent Robots and Systems (IROS)*, 1048–1055. https://doi.org/10.1109/IROS40897.2019.8968114

Markov-Vetter, D., Luboschik, M., Islam, A. T., Gauger, P., & Staadt, O. (2020). The effect of spatial reference on visual attention and workload during viewpoint guidance in augmented reality. *Symposium on Spatial User Interaction*, 1–10. https://doi.org/10.1145/3385959.3418449

Matsuda, Y., & Komuro, T. (2020). Dynamic layout optimization for multi-user interaction with a large display. *Proceedings of the 25th International Conference on Intelligent User Interfaces*, 401–409. https://doi.org/10.1145/3377325.3377481

Mazur, L. M., Adams, R., Mosaly, P. R., Stiegler, M. P., Nuamah, J., Adapa, K., Chera, B., & Marks, L. B. (2020). Impact of simulation-based training on radiation therapists’ workload, situation awareness, and performance. *Advances in Radiation Oncology*, *5*(6), 1106–1114. https://doi.org/10.1016/j.adro.2020.09.008

Medathati, N. V. K., Desai, R., & Hillis, J. (2020). Towards inferring cognitive state changes from pupil size variations in real world conditions. *ACM Symposium on Eye Tracking Research and Applications*, 1–10. https://doi.org/10.1145/3379155.3391319

Meena, Y. K., Cecotti, H., Wong-Lin, K., & Prasad, G. (2019). Design and evaluation of a time adaptive multimodal virtual keyboard. *Journal on Multimodal User Interfaces*, *13*(4), 343–361. https://doi.org/10.1007/s12193-019-00293-z

Mendes, H. C. M., Costa, C. I. A. B., da Silva, N. A., Leite, F. P., Esteves, A., & Lopes, D. S. (2020). PIÑATA: Pinpoint insertion of intravenous needles via augmented reality training assistance. *Computerized Medical Imaging and Graphics*, *82*, 101731. https://doi.org/10.1016/j.compmedimag.2020.101731

Mendes, V., Bruyere, F., Escoffre, J. M., Binet, A., Lardy, H., Marret, H., Marchal, F., & Hebert, T. (2020). Experience implication in subjective surgical ergonomics comparison between laparoscopic and robot-assisted surgeries. *Journal of Robotic Surgery*, *14*(1), 115–121. https://doi.org/10.1007/s11701-019-00933-2

Milleville-Pennel, I., & Marquez, S. (2020). Comparison between elderly and young drivers’ performances on a driving simulator and self-assessment of their driving attitudes and mastery. *Accident Analysis & Prevention*, *135*, 105317. https://doi.org/10.1016/j.aap.2019.105317

Mills, B., Dykstra, P., Hansen, S., Miles, A., Rankin, T., Hopper, L., Brook, L., & Bartlett, D. (2020). Virtual reality triage training can provide comparable simulation efficacy for paramedicine students compared to live simulation-based scenarios. *Prehospital Emergency Care*, *24*(4), 525–536. https://doi.org/10.1080/10903127.2019.1676345

Mingardi, M., Pluchino, P., Bacchin, D., Rossato, C., & Gamberini, L. (2020). Assessment of implicit and explicit measures of mental workload in working situations: Implications for industry 4.0. *Applied Sciences*, *10*(18), 6416. https://doi.org/10.3390/app10186416

Mohanavelu, K., Poonguzhali, S., Ravi, D., Singh, P. K., Mahajabin, M., K., R., Singh, U. K., & Jayaraman, S. (2020). Cognitive workload analysis of fighter aircraft pilots in flight simulator environment. *Defence Science Journal*, *70*(2), 131–139. https://doi.org/10.14429/dsj.70.14539

Muñoz, A., Martí, A., Mahiques, X., Gracia, L., Solanes, J. E., & Tornero, J. (2020). Camera 3D positioning mixed reality-based interface to improve worker safety, ergonomics and productivity. *CIRP Journal of Manufacturing Science and Technology*, *28*, 24–37. https://doi.org/10.1016/j.cirpj.2020.01.004

Nadj, M., Maedche, A., & Schieder, C. (2020). The effect of interactive analytical dashboard features on situation awareness and task performance. *Decision Support Systems*, *135*, 113322. https://doi.org/10.1016/j.dss.2020.113322

Navratil, G., Konturek, P., & Giannopoulos, I. (2020). Interacting with 3d models – 3D-CAD vs. Holographic models. *ISPRS Annals of the Photogrammetry, Remote Sensing and Spatial Information Sciences*, *VI-4/W1-2020*, 129–134. https://doi.org/10.5194/isprs-annals-VI-4-W1-2020-129-2020

Nino, L., Marchak, F., & Claudio, D. (2020). Physical and mental workload interactions in a sterile processing department. *International Journal of Industrial Ergonomics*, *76*, 102902. https://doi.org/10.1016/j.ergon.2019.102902

Nuamah, J. K., Seong, Y., Jiang, S., Park, E., & Mountjoy, D. (2020). Evaluating effectiveness of information visualizations using cognitive fit theory: A neuroergonomics approach. *Applied Ergonomics*, *88*, 103173. https://doi.org/10.1016/j.apergo.2020.103173

Panganiban, A. R., Matthews, G., & Long, M. D. (2020). Transparency in autonomous teammates: Intention to support as teaming information. *Journal of Cognitive Engineering and Decision Making*, *14*(2), 174–190. https://doi.org/10.1177/1555343419881563

Parent, M., Albuquerque, I., Tiwari, A., Cassani, R., Gagnon, J.-F., Lafond, D., Tremblay, S., & Falk, T. H. (2020). PASS: A multimodal database of physical activity and stress for mobile passive body/ brain-computer interface research. *Frontiers in Neuroscience*, *14*, 542934. https://doi.org/10.3389/fnins.2020.542934

Ponathil, A., Ozkan, F., Welch, B., Bertrand, J., & Chalil Madathil, K. (2020). Family health history collected by virtual conversational agents: An empirical study to investigate the efficacy of this approach. *Journal of Genetic Counseling*, *29*(6), 1081–1092. https://doi.org/10.1002/jgc4.1239

Ramirez Gomez, A., & Gellersen, H. (2020). More than looking: Using eye movements behind the eyelids as a new game mechanic. *Proceedings of the Annual Symposium on Computer-Human Interaction in Play*, 362–373. https://doi.org/10.1145/3410404.3414240

Reiser, J. E., Wascher, E., & Arnau, S. (2019). Recording mobile EEG in an outdoor environment reveals cognitive-motor interference dependent on movement complexity. *Scientific Reports*, *9*(1), 13086. https://doi.org/10.1038/s41598-019-49503-4

Reiser, J. E., Wascher, E., Rinkenauer, G., & Arnau, S. (2021). Cognitive‐motor interference in the wild: Assessing the effects of movement complexity on task switching using mobile EEG. *European Journal of Neuroscience*, *54*(12), 8175–8195. https://doi.org/10.1111/ejn.14959

Romanowski, A., Chaniecki, Z., Koralczyk, A., Woźniak, M., Nowak, A., Kucharski, P., Jaworski, T., Malaya, M., Rózga, P., & Grudzień, K. (2020). Interactive timeline approach for contextual spatio-temporal ECT data investigation. *Sensors*, *20*(17), 4793. https://doi.org/10.3390/s20174793

Saito, Y., & Raksincharoensak, P. (2019). Effect of risk-predictive haptic guidance in one-pedal driving mode. *Cognition, Technology & Work*, *21*(4), 671–684. https://doi.org/10.1007/s10111-019-00558-3

Schwarz, S., Regal, G., Kempf, M., & Schatz, R. (2020). Learning success in immersive virtual reality training environments: Practical evidence from automotive assembly. *Proceedings of the 11th Nordic Conference on Human-Computer Interaction: Shaping Experiences, Shaping Society*, 1–11. https://doi.org/10.1145/3419249.3420182

Shuggi, I. M., Oh, H., Wu, H., Ayoub, M. J., Moreno, A., Shaw, E. P., Shewokis, P. A., & Gentili, R. J. (2019). Motor performance, mental workload and self-efficacy dynamics during learning of reaching movements throughout multiple practice sessions. *Neuroscience*, *423*, 232–248. https://doi.org/10.1016/j.neuroscience.2019.07.001

Solanes, J. E., Muñoz, A., Gracia, L., Martí, A., Girbés-Juan, V., & Tornero, J. (2020). Teleoperation of industrial robot manipulators based on augmented reality. *The International Journal of Advanced Manufacturing Technology*, *111*(3–4), 1077–1097. https://doi.org/10.1007/s00170-020-05997-1

Souders, D. J., Charness, N., Roque, N. A., & Pham, H. (2020). Aging: Older adults’ driving behavior using longitudinal and lateral warning systems. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *62*(2), 229–248. https://doi.org/10.1177/0018720819864510

Spinelli, R., Magagnotti, N., & Labelle, E. R. (2020). The effect of new silvicultural trends on mental workload of harvester operators. *Croatian Journal of Forest Engineering*, *41*(2), 177–190. https://doi.org/10.5552/crojfe.2020.747

Szychowska, M., & Wiens, S. (2020). Visual load does not decrease the auditory steady‐state response to 40‐Hz amplitude‐modulated tones. *Psychophysiology*, *57*(12). https://doi.org/10.1111/psyp.13689

Takizawa, R., Verhulst, A., Seaborn, K., Fukuoka, M., Hiyama, A., Kitazaki, M., Inami, M., & Sugimoto, M. (2019). Exploring perspective dependency in a shared body with virtual supernumerary robotic arms. *2019 IEEE International Conference on Artificial Intelligence and Virtual Reality (AIVR)*, 25–257. https://doi.org/10.1109/AIVR46125.2019.00014

Tokadli, G., Dorneich, M. C., Matessa, M., & Eda, S. (2019). The evaluation of a playbook interface for human-autonomy teaming in single pilot operations. *2019 IEEE/AIAA 38th Digital Avionics Systems Conference (DASC)*, 1–7. https://doi.org/10.1109/DASC43569.2019.9081620

Turner, C. J., Chaparro, B. S., & He, J. (2021). Typing on a smartwatch while mobile: A comparison of input methods. *Human Factors: The Journal of the Human Factors and Ergonomics Society*, *63*(6), 974–986. https://doi.org/10.1177/0018720819891291

Van Cutsem, J., De Pauw, K., Vandervaeren, C., Marcora, S., Meeusen, R., & Roelands, B. (2019). Mental fatigue impairs visuomotor response time in badminton players and controls. *Psychology of Sport and Exercise*, *45*, 101579. https://doi.org/10.1016/j.psychsport.2019.101579

Varas-Diaz, G., Kannan, L., & Bhatt, T. (2020). Effect of mental fatigue on postural sway in healthy older adults and stroke populations. *Brain Sciences*, *10*(6), 388. https://doi.org/10.3390/brainsci10060388

Verschueren, J., Tassignon, B., Proost, M., Teugels, A., Van Cutsem, J., Roelands, B., Verhagen, E., & Meeusen, R. (2020). Does mental fatigue negatively affect outcomes of functional performance tests? *Medicine & Science in Sports & Exercise*, *52*(9), 2002–2010. https://doi.org/10.1249/MSS.0000000000002323

Vurgun, N., Vongsurbchart, T., Myszka, A., Richter, P., & Rogula, T. (2021). Medical student experience with robot-assisted surgery after limited laparoscopy exposure. *Journal of Robotic Surgery*, *15*(3), 443–450. https://doi.org/10.1007/s11701-020-01129-9

Wang, I., Buchweitz, L., Smith, J., Bornholdt, L.-S., Grund, J., Ruiz, J., & Korn, O. (2020). Wow, you are terrible at this! An intercultural study on virtual agents giving mixed feedback. In *Proceedings of the 20th ACM International Conference on Intelligent Virtual Agents* (pp. 1–8). Association for Computing Machinery. https://doi.org/10.1145/3383652.3423887

Wang, Y., Hu, Y., & Chen, Y. (2021). An experimental investigation of menu selection for immersive virtual environments: Fixed versus handheld menus. *Virtual Reality*, *25*(2), 409–419. https://doi.org/10.1007/s10055-020-00464-4

Wang, Y., Wang, K., Huang, Y., Wu, D., Wu, J., & He, J. (2020). An assessment method and toolkit to evaluate keyboard design on smartphones. *Journal of Visualized Experiments*, *164*, 61796. https://doi.org/10.3791/61796

Warner, D. O., Nolan, M., Garcia-Marcinkiewicz, A., Schultz, C., Warner, M. A., Schroeder, D. R., & Cook, D. A. (2020). Adaptive instruction and learner interactivity in online learning: A randomized trial. *Advances in Health Sciences Education*, *25*(1), 95–109. https://doi.org/10.1007/s10459-019-09907-3

Widyanti, A., & Firdaus, M. (2020). Assessment of mental workload of flight attendants based on flight duration: An effort to provide safe working condition. *Aviation*, *23*(3), 97–103. https://doi.org/10.3846/aviation.2019.11847

Wikström, V., Martikainen, S., Falcon, M., Ruistola, J., & Saarikivi, K. (2020). Collaborative block design task for assessing pair performance in virtual reality and reality. *Heliyon*, *6*(9), e04823. https://doi.org/10.1016/j.heliyon.2020.e04823

Woźniak, M. P., Dominiak, J., Pieprzowski, M., Ładoński, P., Grudzień, K., Lischke, L., Romanowski, A., & Woźniak, P. W. (2020). Subtletee: Augmenting posture awareness for beginner golfers. *Proceedings of the ACM on Human-Computer Interaction*, *4*(ISS), 204:1-204:24. https://doi.org/10.1145/3427332

Xu, W., Liang, H.-N., Zhang, Z., & Baghaei, N. (2020). Studying the effect of display type and viewing perspective on user experience in virtual reality exergames. *Games for Health Journal*, *9*(6), 405–414. https://doi.org/10.1089/g4h.2019.0102

Xu, X., Shi, H., Yi, X., Liu, W., Yan, Y., Shi, Y., Mariakakis, A., Mankoff, J., & Dey, A. K. (2020). EarBuddy: Enabling on-face interaction via wireless earbuds. *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–14. https://doi.org/10.1145/3313831.3376836

Xu, X., Yu, C., Wang, Y., & Shi, Y. (2020). Recognizing unintentional touch on interactive tabletop. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *4*(1), 1–24. https://doi.org/10.1145/3381011

Yang, Y., Karreman, J., & de Jong, M. (2020). Comparing the effects of paper and mobile augmented reality instructions to guide assembly tasks. *2020 IEEE International Professional Communication Conference (ProComm)*, 96–104. https://doi.org/10.1109/ProComm48883.2020.00021

Yi, H., Hong, J., Kim, H., & Lee, W. (2019). DexController: Designing a VR controller with grasp-recognition for enriching natural game experience. *25th ACM Symposium on Virtual Reality Software and Technology*, 1–11. https://doi.org/10.1145/3359996.3364263

Yu, D., Zhou, Q., Newn, J., Dingler, T., Velloso, E., & Goncalves, J. (2020). Fully-occluded target selection in virtual reality. *IEEE Transactions on Visualization and Computer Graphics*, *26*(12), 3402–3413. https://doi.org/10.1109/TVCG.2020.3023606

Yuksel, B. F., Fazli, P., Mathur, U., Bisht, V., Kim, S. J., Lee, J. J., Jin, S. J., Siu, Y.-T., Miele, J. A., & Yoon, I. (2020). Human-in-the-loop machine learning to increase video accessibility for visually impaired and blind users. *Proceedings of the 2020 ACM Designing Interactive Systems Conference*, 47–60. https://doi.org/10.1145/3357236.3395433

Yuksel, B. F., Kim, S. J., Jin, S. J., Lee, J. J., Fazli, P., Mathur, U., Bisht, V., Yoon, I., Siu, Y.-T., & Miele, J. A. (2020). Increasing video accessibility for visually impaired users with human-in-the-loop machine learning. *Extended Abstracts of the 2020 CHI Conference on Human Factors in Computing Systems*, 1–9. https://doi.org/10.1145/3334480.3382821

Zargari Marandi, R., Fjelsted, C. A., Hrustanovic, I., Dan Olesen, R., & Gazerani, P. (2020). Eye movements in response to pain-related feelings in the presence of low and high cognitive loads. *Behavioral Sciences*, *10*(5), 92. https://doi.org/10.3390/bs10050092

Zeller, R., Williamson, A., & Friswell, R. (2020). The effect of sleep-need and time-on-task on driver fatigue. *Transportation Research Part F: Traffic Psychology and Behaviour*, *74*, 15–29. https://doi.org/10.1016/j.trf.2020.08.001