Unconscious Visual Working Memory. A critical review and Bayesian meta-analysis

Supplementary Materials

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Contents

1 General Information

This is a general supplementary file for the meta-analysis paper. Within the OSF repository is also available the entire script in order to reproduce the analysis.

1.1 R Project

The R project allow to reproduce all the analytic approach of the paper. The project is organized as:

- `\data`: contains raw and cleaned data in `.xlsx`, `.rds` and `.csv` format
- `\objects`: contains all models and files as `.rds`
- `\function`: contains all custom functions
- `\figures`: contains all figures
- `\mod`: contains all fitted models. Given the size of the folder, the content is not present in the repository but can be easily recreated from the `1_models.R` script. The `\objects` folder contains all tables and post-processing objects of relevant models.
- `\tables`: contains all tables as `.pdf` and `docx`
- `\supplementary_materials`: contains the `.Rmd` file to reproduce this document

In the root folder there are the following scripts:

- `0_preprocessing.R`: takes the raw data and create the cleaned version for the analysis
- `1_models.R`: for fitting all the relevant models
- `2_sensitivity_analysis.R`: for computing the prior and LOO sensitivity analysis
- `3_post_processing_models.R`: for creating models tables and summary statistics
- `4_post_processing_sensitivity.R`: for creating sensitivity analysis tables and summary statistics
- `5_creating_figures.R`: to reproduce figures of the paper
- `6_creating_tables.R`: to reproduce tables of the paper

Custom functions are:

- `\functions\plotting_functions.R`: all functions to create plots
- `\functions\utils.R`: wrappers and simple functions to work in the project
- `\functions\post_processing_functions.R`: functions to compute all sensitivity analyses and post-processing of fitted models

1.2 The dataset

The main dataset for the meta-regression has the following columns:

```
##  [1] "study"               "substudy"            "first_author"
##  [4] "first_author_mod"    "study_id"            "study_meta"
##  [7] "published"           "year"                "paradigm"
## [10] "blinding_paradigm"   "target_duration"     "target_type"
## [13] "task_type"           "treshold_stimulus"   "aware_question"
## [16] "retention_interval"  "implicit"            "sample_size"
## [19] "ntrials"             "n_trials_valid"      "mean_acc"
## [22] "chance_level"        "acc_measure"         "eff_size_g"
## [25] "eff_size_variance_g" "tot_trials"          "ntrials0"
## [28] "sample_size0"        "eff_size_se_g"
```

- `study`: index of the paper
- `substudy`: index of the substudy
- `first_author/first_author_mod`: the first author name (for plotting)
- `study_id`: index of the study with the author name
- `study_meta`: index of the paper with the author name
- `published`: if the study is published or not
- `year`: publication year
- `paradigm`: the Working Memory paradigm
- `blinding_paradigm`: the consciousness manipulation paradigm
- `target_duration`: the target presentation time (ms)
- `target_type`: the category of the target
- `task_type`: the working memory task category
- `treshold_stimulus`: if the to-be-remembered stimulus is at detection threshold
- `aware_question`: the method to assess consciousness
- `retention_interval`: the lenght of the retention interval (ms)
- `implicit`: is the Working Memory task explicit or not
- `sample_size`: The number of included participants
- `ntrials`: the actual average number of trials per participant after selecting unseen trials
- `ntrials_valid`: the total number of trials per participant potentially valid (e.g., no catch trials)
- `tot_trials`: the estimate number of valid-unseen trials of the full experiment (i.e., `sample_size x ntrials`)
- `mean_acc`: the mean accuracy score in WM task (percentage or d')
- `chance_level`: the chance level of the experiment (e.g., 0.5 for binary accuracy or 0 for d')
- `acc_measure`: percentage of correct response or d'
- `eff_size_g`: the effect size measure
- `eff_size_variance_g`: the variance of the effect size
- `eff_size_se_g`: the standard error of the effect size
- `ntrials0`: mean-centered version of `ntrials`
- `sample_size0`: mean-centered version of `sample_size`

1.3 The meta-analysis model

The three-level meta-analysis extend the standard 2 level random-effect meta-analysis adding a clustering level at the paper (level 3) level (Cheung, 2019a, 2014a, 2015; Van den Noortgate et al., 2013) Effect sizes within the paper are assumed to be independent. The model takes into account the within-cluster dependency (i.e., an effect from the paper 1 is more similar to another effect from same paper compared to another effect nested in another paper) estimating both the within-paper and between-paper heterogeneity.

Relevant information for the meta-analysis is:

- Mean accuracy scores or equivalent performance score
- Standard deviation of accuracy/performance scores
- Mean number of analyzed trials per participant[1]

1.4 Effect size computation

We computed the Cohen's d_z as effect size measure because all papers adopted a one-sample t-test analysis against the chance level. The effect size is computed as:

$$d_z = \frac{\hat{\mu} - \mu_0}{\hat{\sigma}}$$

[1]This information has been extracted from raw data if available or estimated from aggregated data

Where $\hat{\mu}$ and $\hat{\sigma}$ are the sample mean and standard deviation and μ_0 is the chance level.

The effect size variance is computed as:

$$V_d = \frac{1}{n} + \frac{d^2}{2n}$$

Where n is the sample size and d is the effect size.

Then we trasform it to an Hedges's g measure applying a correction for small samples J with df is $n-1$ as:

$$J = 1 - \frac{3}{4df - 1}$$

The correction factor is applied to the effect size as $g = J \times d$ and the variance $V_g = J^2 \times V_d$.

1.5 Other relevant computations

Relevant measures in three-level meta-analysis models are the percentage of explained heterogeneity (R^2) and the percentage of heterogeneity associated with a specific clustering level (*intra-class correlation*). We use the formulas provided by Cheung (2019b; 2014b). We used the **median** of each relevant posterior distribution parameter in order to compute the formula. The computation of the R^2 values can be sometimes negative due to the τ estimation, in that case the value was truncated to 0.

1.6 Models

Following the Williams and collegues (2018) and Molto and colleagues (2020) notation, the equation for the Bayesian multilevel model is:

$$\begin{gathered} \hat{\mu}_{ij} = \alpha + \alpha_{paper_j} + \alpha_{study_{ij}} + \epsilon_{ij} \\ \epsilon_{ij} \sim Normal(0, \sigma_{ij}) \end{gathered} \tag{1}$$

Each observed effect is a linear combination of the overall average effect α. Then each effect has a τ_{paper_i} and a $\tau_{study_{ij}}$ for being part of a given paper (cluster).

Bayesian modelling requires prior distributions on each estimated parameter:

$$\begin{gathered} \alpha_{paper_j} \sim Normal(0, \tau_{paper}) \\ \alpha_{study_{ij}} \sim Normal(0, \tau_{study}) \\ \alpha \sim Normal(0, 2) \\ \tau_{paper,study} \sim HalfCauchy(0, 1) \end{gathered} \tag{2}$$

Models are fitted using the `brms` package (Bürkner, 2017, 2018). The general setup of a `brms` model is the following:

```
brm(yi|se(sei) ~ 0 + Intercept + (1|paper_id/effect_id),
    iter = 15000, # number of iterations for each MCMC chain
    chains = 6)  # number of MCMC chains
```

We choose an high number of iterations and chains in order to have more stable results and a high effective sample size (ESS) for each estimated parameter.

The `(1|paper_id/effect_id)` part is the way `brms` handle the **three-level** meta-analysis model estimating a nested random-effect where a particular effect size i is nested within the paper j.

The general form of the meta-regression:

```
brm(yi|se(sei) ~ 0 + <predictors> + (1|paper_id/effect_id),
    iter = 15000, # number of iterations for each MCMC chain
    chains = 6)  # number of MCMC chains
```

In particula for categorical predictors, we used the **cell-mean parametrization** `0 +` (i.e., removing the intercept) in order to compute directly the estimated mean for each predictor level and eventually compute the desired contrast from the posterior distribution (**?**)

Given that we are essentially estimating the average effect size for each experimental condition, we used the same prior distribution for each parameter.

1.7 Studies description

1.7.1 Soto et al. (2011)

We included all four experiments and we requested authors further information about data.

1.7.2 Pan et al. (2014)

We included the Experiment 2 where the to-be-memorized target is directly manipulated in terms of visibility. Moreover, in line with other papers, we considered only change-detection accuracy and not the reaction times effect.

1.7.3 Dutta et al. (2014)

We included all studies.

1.7.4 Bergström et al. (2014)

We considered separately the Experiment 1 (behavioral only), the Experiment 2 (pre-fMRI session) and the Experiment 3 (post-fMRI session). We requested authors additional information about aggregated data.

1.7.5 Bergström et al. (2015)

We included all studies. We requested authors additional information about aggregated data.

1.7.6 Bergström et al. (2018)

We included all studies. We requested authors additional information about aggregated data.

1.7.7 Nakano et al. (2020)

We included all studies. Authors had different conditions and made a separate analysis on visibility conditions:

We selected:

- NcNc (1st and 2nd stimulus low visibility **AND** PAS 1 ratings)

- NcC (1st stimulus low visibility 2nd stimulus high-visibility **AND** PAS 1 ratings)
- CNc (1st stimulus high visibility 2nd stimulus low visibility **AND** PAS 1 ratings)

We requested authors additional information about aggregated data.

1.7.8 King et al. (2016)

We included all studies. We requested authors additional information about aggregated data.

1.7.9 Trübutschek et al. (2017)

We included all studies. The reported behavioral results refers to the working memory accuracy task and not the working memory precision. We requested authors additional information about aggregated data.

1.7.10 Trübutschek et al. (2019a)

We included all studies. The reported behavioral results refers to the working memory accuracy task and not the working memory precision. We requested authors additional information about aggregated data.

1.7.11 Trübutschek et al. (2019b)

We included all studies. The reported behavioral results refers to the working memory accuracy task and not the working memory precision. We requested authors additional information about aggregated data.

1.7.12 Taglialatela-Scafati (2019)

We included all studies. The thesis has several different studies divided in:

- Experiments 1-6: continuous flash suppression manipulation + WM paradigm
- Experiments 7-9: backward masking manipulation + WM paradigm
- Experiments 10-11: conceptual replication of Soto et al.(2011) using a similar paradigm as previous experiments
- Experiment 12-15: direct Soto et al.(2011) replications with variants

The thesis is a single manuscript but given the methodological heterogeneity and the different scopes of experiments we divided as follows:

- Paper 1: Experiments 1-6
- Paper 2: Experiments 7-9
- Paper 3: Experiments 10-11
- Paper 4: Experiment 12-15

The idea was to divide experiments is a way similar to a published paper in order to better model the dependency structure. Having 15 effect sizes on a single paper is an artifact of the thesis organization. Considering 15 experiments should have given too much weight to a single paper with the assumption of estimating the same effect size. We requested authors additional information about aggregated data.

1.7.13 Barton (2018)

We included all studies. We requested authors additional information about aggregated data.

2 Model Diagnostics

2.1 Fitting diagnostic

Models are evaluated using the $\hat{R}$ value Gelman and Rubin (1992) and the **Effective Sample Size**. The Table 1. provide the diagnostic features for each fitted model.

Table 1: Details of all fitted models

mod	term	estimate	std.error	conf.low	conf.high	Rhat	Bulk_ESS	Tail_ESS
~ Author	Tau Paper	0.1632342	0.1087700	0.0000034	0.2954288	1.0008000	8061	15224
	Tau Study	0.0752982	0.0548471	0.0000090	0.1478304	1.0005219	18560	21640
	Barton	0.0162816	0.2476574	-0.3717328	0.3907951	1.0004825	39220	26558
	Bergstrom	0.5951091	0.1476695	0.3630974	0.8207524	1.0000770	37128	27674
	Dutta	0.6113502	0.2604084	0.2089583	1.0087121	1.0002771	40615	27895
	King	0.3693544	0.3227981	-0.1395305	0.8737060	1.0000770	52103	32020
	Nakano	0.4026102	0.3150839	-0.0803115	0.9095044	1.0000222	49433	32455
	Pan	0.2491987	0.3021308	-0.2381170	0.7065930	1.0000719	48755	30529
	Soto	1.0619636	0.2863389	0.6277326	1.5193391	1.0002825	48112	30145
	TaglialatelaScafati	0.0687087	0.1190628	-0.1128832	0.2493507	1.0001125	31424	25558
	Trubutschek	1.3061630	0.1633313	1.0473565	1.5555734	1.0001382	42407	27030
~ Blinding Paradigm	Tau Paper	0.3118392	0.0993018	0.1582891	0.4541990	1.0001878	15347	22314
	Tau Study	0.0681155	0.0512002	0.0000004	0.1355565	1.0000873	20948	23987
	AB	0.7862206	0.3490089	0.2372458	1.3341324	1.0003008	38485	29406
	BM	0.3440149	0.1346838	0.1312464	0.5545413	1.0002270	23187	27027
	CFS	0.2481478	0.1810013	-0.0401560	0.5289794	1.0000881	23293	26595
	MM	1.3302354	0.2215780	0.9777253	1.6739545	1.0002244	29956	29468
~ WM Paradigm	Tau Paper	0.3498762	0.1010571	0.1993453	0.4980295	1.0002116	16146	24546
	Tau Study	0.0691752	0.0515342	0.0000010	0.1365562	1.0002335	18987	21084
	CDT	0.3843864	0.1671351	0.1213325	0.6470504	1.0002662	17265	24606
	DD	0.2476034	0.1950886	-0.0533735	0.5632934	1.0001902	17259	23253
	DET	1.3333099	0.2414840	0.9431122	1.7027030	1.0001944	21674	26134
	DMS	0.4517104	0.2370899	0.0826241	0.8311307	1.0001807	20488	25767
	Tau Paper	0.5381554	0.1293543	0.3417546	0.7235739	0.9999992	15855	25396
	Tau Study	0.0711336	0.0537289	0.0000013	0.1414983	1.0003411	20490	24926

~ Target Duration	150-500ms	0.2953486	0.3225366	-0.2090203	0.8109502	1.0000552	21583	25509
	16-50ms	0.6240776	0.1767134	0.3493552	0.9074739	1.0001406	16449	21235
	3000ms	0.4609050	0.3996622	-0.1521211	1.1053858	1.0002398	27357	28650
~ Trials + Sample Size	Tau Paper	0.5493943	0.1334239	0.3444083	0.7389157	1.0004648	12085	21122
	Tau Study	0.0732682	0.0555809	0.0000073	0.1459219	1.0001336	15998	19383
	Average	0.5695365	0.1546020	0.3307920	0.8170545	1.0006013	10033	17523
	Trials	0.0004674	0.0008660	-0.0009179	0.0018445	1.0001248	31511	32400
	Sample Size	-0.0008269	0.0077118	-0.0128866	0.0117104	1.0001355	34893	34102
Overall Model (only published)	Tau Paper	0.4164279	0.1593117	0.1634622	0.6636152	1.0002896	9426	7681
	Tau Study	0.1367061	0.1059805	0.0000003	0.2772240	1.0004560	9468	12956
	Average	0.7846042	0.1509476	0.5528006	1.0260373	1.0000113	19160	25509
Overall Model	Tau Paper	0.5112205	0.1163356	0.3311104	0.6791467	1.0001198	13347	22242
	Tau Study	0.0724255	0.0545252	0.0000030	0.1437591	1.0001055	16648	21055
	Average	0.5394952	0.1394915	0.3138278	0.7577041	1.0006414	9171	16678

2.2 Prior sensitivity analysis

The impact of prior distribution on Bayesian models is often discussed (Gelman et al., 2008). The prior sensitivity analysis consist of evaluating the model parameters estimation as a function of different prior uncertainty (i.e., the scale parameter of the prior distribution). Figure 2 represents the average effect size and τ estimation as a function of prior uncertainty. For the average effect priors uncertainty is determined by the standard deviation $Effect \sim Normal(0, sd_i)$ and for τ the uncertainty is the scale parameter of the half-cauchy distribution $\tau_{paper,study} \sim HalfChaucy(0, scale_i)$. The Figure 1 represents the chosen prior distributions:

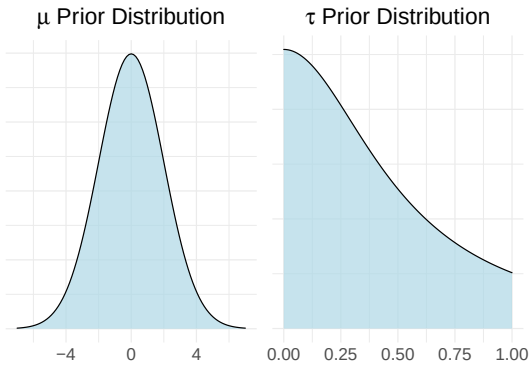

Figure 1: Prior distributions for the average effect and the heterogeneity

Is clear that using reasonable prior distribution (i.e., when the range of plausible values is compatible with the phenomenon of interest) do not impact the parameters estimation.

2.3 Leave-one-out sensitivity analysis

Another important diagnostic also in the meta-analysis field is the outliers analysis. Especially when the amount of studies is small, a single effect size or cluster of effect size can have a great impact on the estimation. We refitted the same model removing one effect/papers and reporting the impact on the the estimation average effect and τ estimation.

2.3.1 Removing papers

The figure 3 present the effect of removing one paper on the mean effect and taus estimation.

The table 2 represents some statistics about the loo analysis:

Table 2: Loo paper

.param	.sd	.min	.max
Average	0.03	0.47	0.58
Tau Paper	0.03	0.41	0.52
Tau Study	0.00	0.05	0.07

2.3.2 Removing studies

The figure 4 present the effect of removing one paper on the mean effect and taus estimation.

The table 3 represents some statistics about the loo analysis:

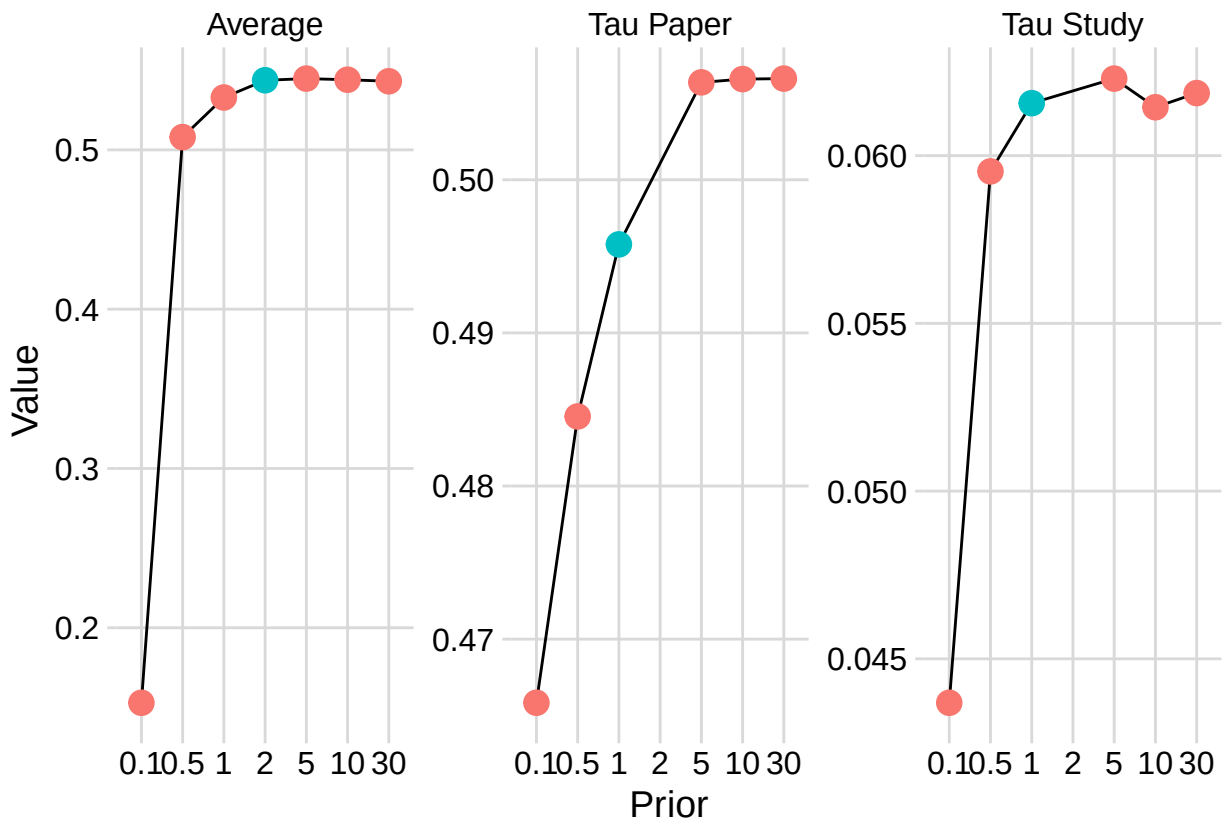

Figure 2: Prior sensitivity analysis. In blue are represented the priors used in the main analysis

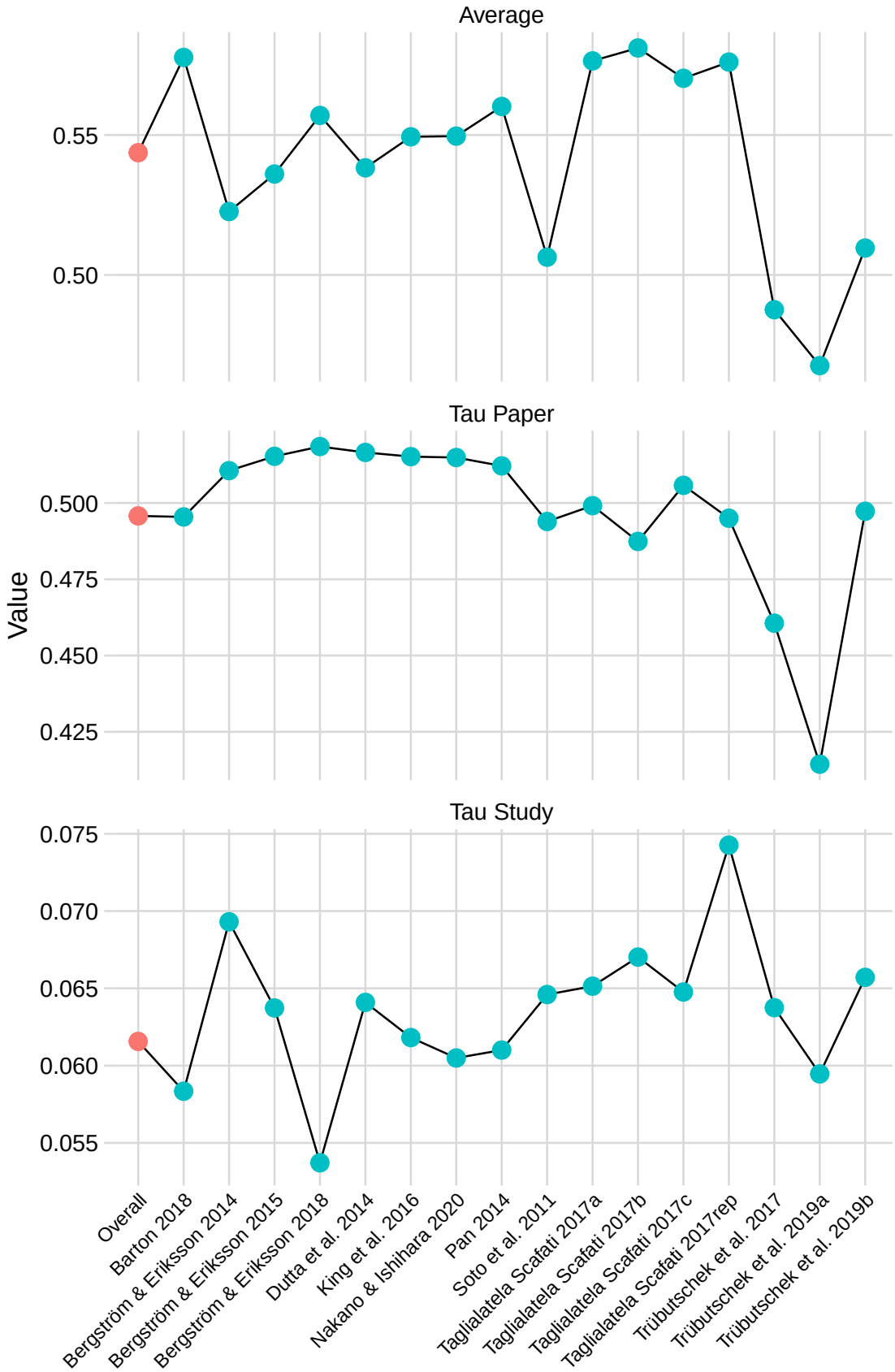

Figure 3: Removing one paper

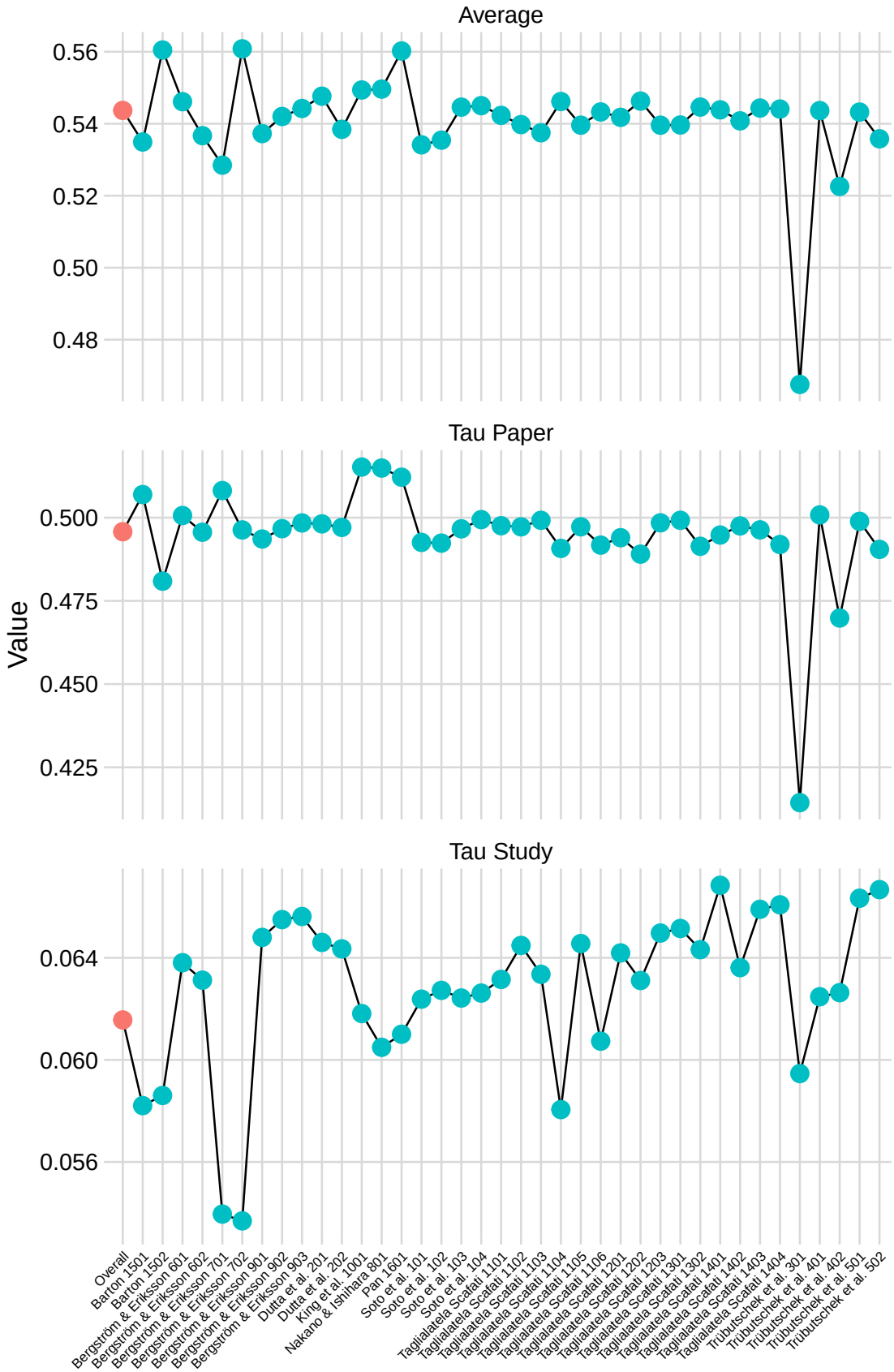

Figure 4: Removing one study

Table 3: Loo study

.param	.sd	.min	.max
Average	0.01	0.47	0.56
Tau Paper	0.02	0.41	0.52
Tau Study	0.00	0.05	0.07

In general, there are no highly influential results. Some paper/study are more relevant for the final estimation but the range of variability is very low.

2.4 Publication Bias

The publication bias is assessed using the Egger regression approach (see https://wviechtb.github.io/metafor/reference/regtest.html). For this reason we fitted a non-bayesian random-effects model and used it for the **funnel plot** and the **egger-regression**:

```
##
## Random-Effects Model (k = 38; tau^2 estimator: REML)
##
## tau^2 (estimated amount of total heterogeneity): 0.1786 (SE = 0.0566)
## tau (square root of estimated tau^2 value):      0.4226
## I^2 (total heterogeneity / total variability):   75.21%
## H^2 (total variability / sampling variability):  4.03
##
## Test for Heterogeneity:
## Q(df = 37) = 147.4098, p-val < .0001
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.4680  0.0804  5.8227  <.0001  0.3105  0.6256  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

##
## Regression Test for Funnel Plot Asymmetry
##
## Model:     mixed-effects meta-regression model
## Predictor: standard error
##
## Test for Funnel Plot Asymmetry: z = 2.3545, p = 0.0185
## Limit Estimate (as sei -> 0):   b = -0.2916 (CI: -0.9404, 0.3572)
```

An important point is that the funnel plot analysis or the regression approach are only possible indicators of publication bias, without providing clear evidence. The publication bias assessment is also undermined by the presence of high heterogeneity (Terrin et al., 2003; Peters et al., 2010).

3 Models Analysis

Table 4: ICC table for relevant models

mod	icc2	icc3
~ Author	0.16	0.84
~ Blinding Paradigm	0.03	0.97
~ WM Paradigm	0.03	0.97
~ Target Duration	0.01	0.99
~ Trials + Sample Size	0.01	0.99
Overall Model	0.01	0.99
Overall Model (only published)	0.07	0.93

The Table 5 contains parameters and ROPE analysis for each relevant model.

Table 5: Rope table of relevant models

mod	.param	.value	.lower	.upper	.se	within_rope	outside_rope
~ Author	Barton	0.01	-0.36	0.41	0.25	0.66	0.34
	Bergstrom	0.60	0.37	0.82	0.15	0.00	1.00
	Dutta	0.61	0.20	1.01	0.26	0.00	1.00
	King	0.37	-0.13	0.90	0.32	0.18	0.82
	Nakano	0.40	-0.09	0.89	0.31	0.14	0.86
	Pan	0.25	-0.23	0.73	0.30	0.29	0.71
	Soto	1.07	0.61	1.51	0.29	0.00	1.00
	TaglialatelaScafati	0.07	-0.11	0.25	0.12	0.63	0.37
	Trubutschek	1.30	1.06	1.57	0.16	0.00	1.00
	Tau Paper	0.15	0.00	0.29	0.11		
	Tau Study	0.07	0.00	0.15	0.05		
~ Blinding Paradigm	AB	0.78	0.23	1.33	0.35	0.00	1.00
	BM	0.34	0.13	0.55	0.13	0.01	0.99
	CFS	0.25	-0.03	0.54	0.18	0.17	0.83
	MM	1.33	0.98	1.68	0.22	0.00	1.00
	Tau Paper	0.30	0.16	0.46	0.10		
	Tau Study	0.06	0.00	0.14	0.05		
~ WM Paradigm	CDT	0.38	0.11	0.64	0.17	0.02	0.98
	DD	0.25	-0.05	0.56	0.20	0.19	0.81
	DET	1.34	0.95	1.71	0.24	0.00	1.00
	DMS	0.45	0.07	0.82	0.24	0.04	0.96
	Tau Paper	0.34	0.20	0.49	0.10		
	Tau Study	0.06	0.00	0.14	0.05		
~ Target Duration	150-500ms	0.30	-0.22	0.81	0.32	0.25	0.75
	16-50ms	0.63	0.35	0.91	0.18	0.00	1.00
	3000ms	0.46	-0.16	1.11	0.40	0.16	0.84
	Tau Paper	0.52	0.34	0.72	0.13		
	Tau Study	0.06	0.00	0.14	0.05		
Overall Model	Average	0.54	0.32	0.77	0.14	0.00	1.00
	Tau Paper	0.50	0.33	0.68	0.12		
	Tau Study	0.06	0.00	0.14	0.05		

The table 6 The study by Pan and colleagues (2014) do not report the number of analyzed trials so is not included in the table.

Table 6: Trials table for each blinding paradigm

new_blind	.mean	.mean_drop
Attentional Blink	49.33	70.92
Backward Masking	76.47	56.91
Continuous Flash Suppression	205.42	19.11
Metacontrast Masking	98.40	64.33

The mean percentage of discarded trials is 46.7927526 with a minimum of 0.9259259 and a maximum of 95.2777778.

The prediction interval is one of the most important information from a random-effect meta-analysis because represents the range of plausible values, taking into account both the variability in estimating the mean effect and the heterogeneity. In this case the prediction interval is computed using the formula provided by Riley (2011)

$$CI = \hat{\mu} \pm z\sqrt{\tau^2_{paper} + \tau^2_{study} + +SE_{\hat{\mu}^2}}$$

Table 7: prediction interval

mu	mu_se	lower	upper	width	mod
0.54	0.14	0.09	0.99	89%	Overall model
0.78	0.15	0.43	1.14	89%	Overall model (only published literature)

4 Extra analysis

4.1 Individual power level

As reported in the section 1.4, the majority of papers reported a one-sample t-test against the chance-level for supporting the unconscious WM effect.This can be considered a reasonable approach, however the more appropriate way is to consider this situation as a **multilevel model**.

The probability of success for each participant $\hat{p}_i$ is estimated from the available trials and all participants contribute to estimate the true probability of success for the WM effect $\hat{p}$. We have two source of variation here, the subject-level precision determined by the amount of analyzed trials and the population-level precision determined by the variability between-subjects.

In the majority of included papers is performed a post-hoc trial selection according to the participant reported experience. This bring an important source of variability because each participant has a different amount of trials (i.e., precision). The figure 5 depict the power curves for a single-subject proportion for different number of trials.

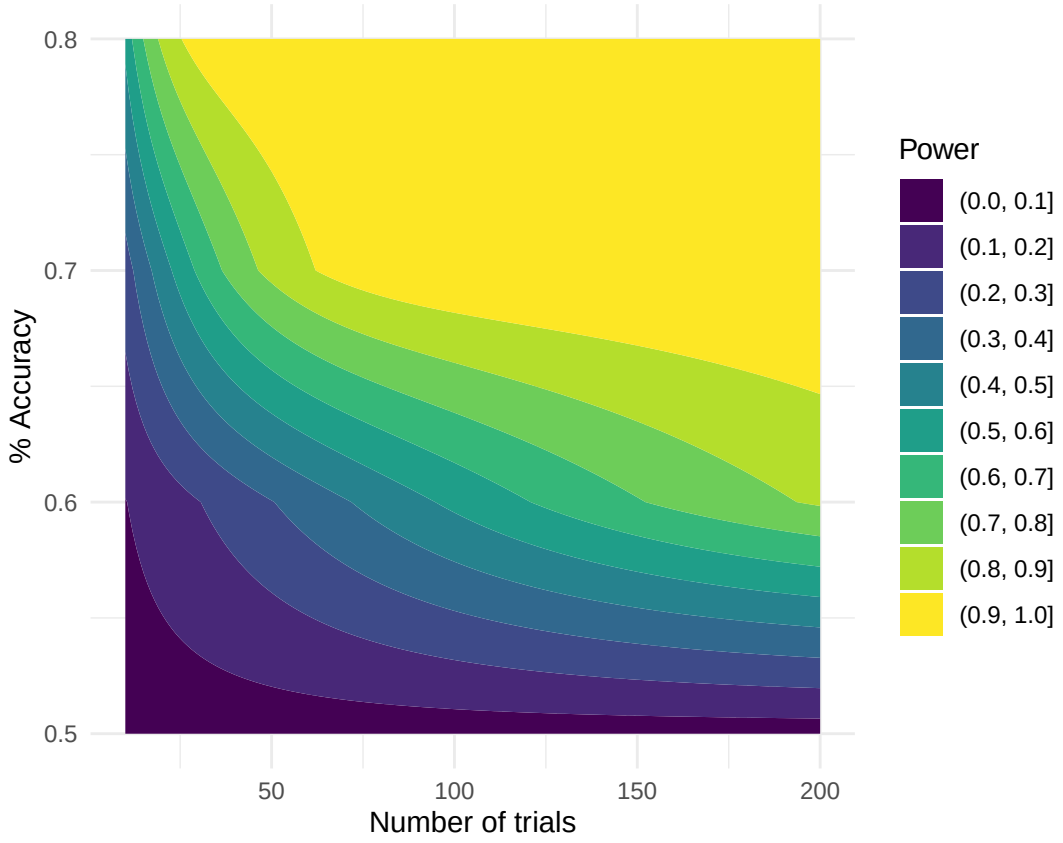

Figure 5: Power curves for a single participant using a range of probability of success and number of trials.

In a real scenario each subject will have a different *true* proportion of correct responses and a different number of *available trials* for each participant after the post-hoc selection.

5 Packages

This is the list of all used packages:

- tidyverse
- stringr
- brms
- metafor
- tidybayes
- bayestestR
- broomExtra
- pwr
- gridExtra
- latex2exp
- PRISMAstatement
- cowplot
- ggthemes
- metaviz
- pdftools
- flextable
- officer
- kableExtra
- here

6 Credits

For the general idea of the (Bayesian) multilevel meta-analysis

- The book "Doing meta-analysis in R" by Harrer et al. (2021)

For the implementation of the meta-analysis in `brms` and for the model specification

- https://mvuorre.github.io/blog/posts/2016-09-29-bayesian-meta-analysis/
- https://solomonkurz.netlify.app/post/bayesian-meta-analysis/
- The supplementary materials by Molto et al. (2020)

For the **forest plot**

- https://github.com/mvuorre/brmstools#forest-plots

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