

SPMeta Website Tutorial

This is a tutorial for the website located at

<http://www.singlepapermetaanalysis.com>

and

<https://blakemcshane.shinyapps.io/spmeta/>

which conducts meta-analysis as detailed in

McShane, B.B. and Böckenholt, U. (2017), “Single Paper Meta-analysis: Benefits for Study Summary, Theory-testing, and Replicability.” *Journal of Consumer Research*, 43(6), 1048-1063.

and the accompanying supplementary materials, which are available at the *JCR* website and at

http://www.blakemcshane.com/Papers/jcr_spm_supplement.pdf

The tutorial walks the user through each of the three case studies that appear in the paper and concludes with a list of frequently asked questions.

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Frequently Asked Questions

Case Study I: Maimaran and Fishbach (2014)

Preliminaries

The first step required for SPM is to determine:

- (i) The total number of experiments.
- (ii) The total number of experimental factors varied across all experiments.
- (iii) The levels of each factor across all experiments.
- (iv) The extent to which each experiment follows a between-subjects versus a within-subjects design.

In Maimaran and Fishbach (2014), there were five experiments that varied a total of one experimental factor across three unique levels (Control, Instrumental, Yummy). All experiments followed between-subjects designs.

The second step required is to obtain the summary information for each condition of each study. If the dependent measure is continuous or integer-scaled, the summary information required are means, standard deviations, and sample sizes. If the dependent measure is binary, the summary information required are proportions and sample sizes.

This summary information for the studies of Maimaran and Fishbach (2014) is presented in Table 1 of McShane and Bockenholt (2017) and is also given below:

Study	Factor1	Mean	SD	n
Study 1	Control	9.07	5.60	19
	Instrumental	3.10	3.25	19
	Yummy	7.20	6.13	19
Study 2	Control	10.00	5.93	22
	Instrumental	4.67	5.54	22
	Yummy	.	.	.
Study 3	Control	7.11	4.77	19
	Instrumental	3.58	2.38	19
	Yummy	6.53	4.68	19
Study 4	Control	8.14	7.40	21
	Instrumental	3.61	4.62	21
	Yummy	.	.	.
Study 5	Control	10.78	4.80	24
	Instrumental	5.32	5.01	24
	Yummy	.	.	.

Table A: Maimaran and Fishbach (2014) Summary Information.

We note a “.” denotes a study in which the given condition was not observed. We also note that the means and standard deviations reported in Table A reproduce those reported in Table 2 of Maimaran and Fishbach (2014) except the measurements for Study 4 have been converted from

grams to morsels using the conversion rate of forty-two grams per twenty morsels reported there. As the sample sizes per condition per study were not reported but total sample sizes per study were reported, we assume subjects were split evenly across the conditions of each study.

We provide an overview of all input information required for Maimaran and Fishbach (2014) below and then discuss each piece in depth.

Number of experiments:

5

Number of experimental factors:

1

☒ All experiments are between subjects.

Experimental factor 1:

Control, Instrumental, Yu

Note: Separate labels by a comma.

Means or Proportions (y):

9.07 3.10 7.20 10.00 4.6

Standard Deviations (sd):

5.60 3.25 6.13 5.93 5.54

Sample Sizes (n):

19 19 19 22 22 . 19 19 1

Note: Separate numbers by a space. Use a period for a missing value. For proportions, use a period for the sd.

Note: You may cut and paste a column from Excel.

Number of experimental contrasts:

2

Contrast 1:

1 -1 0

Contrast 2:

1 0 -1

Note: Contrasts should be numeric entries of length equal to the number of unique conditions and must sum to zero. Separate numbers by a space.

Input
Results
Case Studies & Tutorial

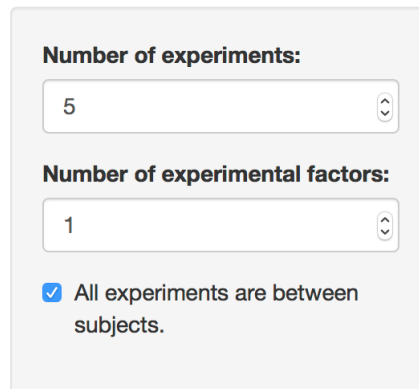
Summary Data from Experiments

Study	Factor1	y	sd	n
1	Control	9.07	5.60	19.00
1	Instrumental	3.10	3.25	19.00
1	Yummy	7.20	6.13	19.00
2	Control	10.00	5.93	22.00
2	Instrumental	4.67	5.54	22.00
2	Yummy	NA	NA	NA
3	Control	7.11	4.77	19.00
3	Instrumental	3.58	2.38	19.00
3	Yummy	6.53	4.68	19.00
4	Control	8.14	7.40	21.00
4	Instrumental	3.61	4.62	21.00
4	Yummy	NA	NA	NA
5	Control	10.78	4.80	24.00
5	Instrumental	5.32	5.01	24.00
5	Yummy	NA	NA	NA

Input I: Basic Information

The first three pieces of information required by the SPM website are the total number of experiments, the total number of experimental factors varied across all experiments, and whether

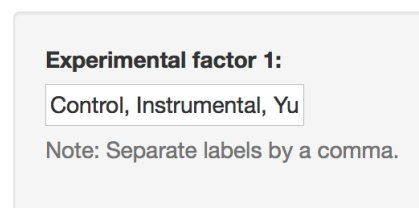
or not all experiments follow a between-subjects design. We input this information into the sidebar panel pictured below:



A sidebar panel with a light gray background. It contains three sections: 1. 'Number of experiments:' with a dropdown menu showing the value '5'. 2. 'Number of experimental factors:' with a dropdown menu showing the value '1'. 3. A checkbox labeled 'All experiments are between subjects.' which is checked with a blue checkmark.

Input II: Factor Levels

The next piece of information required by the SPM website are the names of the factor levels. We input this information into the sidebar panel pictured below:



A sidebar panel with a light gray background. It contains one section: 'Experimental factor 1:' with a text input field containing the text 'Control, Instrumental, Yu'. Below the input field is a note: 'Note: Separate labels by a comma.'

We note that names of the factor levels are not used by the SPM website; the SPM website makes use of only the number of factor levels and thus arbitrary names (e.g., a, b, c) would work identically in this case. We allow for the input of the names of the factor levels as it makes the Summary Data from Experiments table more interpretable.

Once this information has been entered, a blank summary input table pictured below appears in the main panel of the Input tab:

Summary Data from Experiments

Study	Factor1	y	sd	n
1	Control	NA	NA	NA
1	Instrumental	NA	NA	NA
1	Yummy	NA	NA	NA
2	Control	NA	NA	NA
2	Instrumental	NA	NA	NA
2	Yummy	NA	NA	NA
3	Control	NA	NA	NA
3	Instrumental	NA	NA	NA
3	Yummy	NA	NA	NA
4	Control	NA	NA	NA
4	Instrumental	NA	NA	NA
4	Yummy	NA	NA	NA
5	Control	NA	NA	NA
5	Instrumental	NA	NA	NA
5	Yummy	NA	NA	NA

Input III: Basic Summary Information

The next piece of information required by meta-ANOVA is the basic summary information that appears in Table A above. We input this information into the sidebar panel pictured below:

Means or Proportions (y):

Standard Deviations (sd):

Sample Sizes (n):

Note: Separate numbers by a space. Use a period for a missing value. For proportions, use a period for the sd.

Note: You may cut and paste a column from Excel.

If Table A were in an Excel sheet, the third through fifth columns could be directly pasted into the textboxes in the picture above. Alternatively, one can directly paste the following:

Means or Proportions (y):

9.07 3.10 7.20 10.00 4.67 . 7.11 3.58 6.53 8.14 3.61 . 10.78 5.32 .

Standard Deviations (sd):

5.60 3.25 6.13 5.93 5.54 . 4.77 2.38 4.68 7.40 4.62 . 4.80 5.01 .

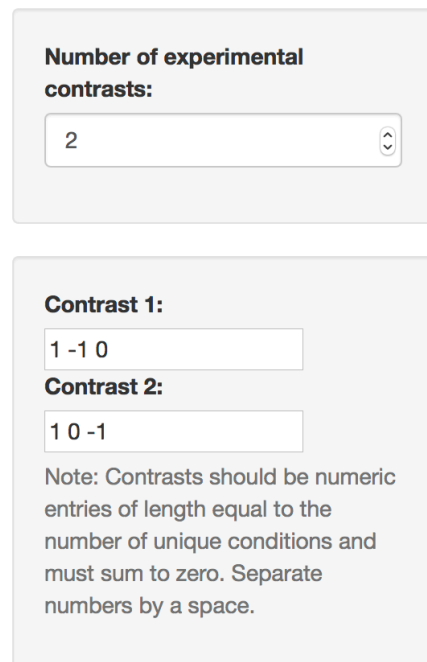
Sample Sizes (n):

19 19 19 22 22 . 19 19 19 21 21 . 24 24 .

As noted above and in the picture, a “.” denotes a study in which the given condition was not observed.

Input IV: Contrasts

The final piece of information required by the SPM website are the experimental contrasts (or effects) of interest which are typically determined based on theory. We input this information into the sidebar panels pictured below:



The image shows two input panels from the SPM website. The top panel is titled "Number of experimental contrasts:" and has a dropdown menu set to "2". The bottom panel is titled "Contrast 1:" and "Contrast 2:". Under "Contrast 1:", there is a text input field containing "1 -1 0". Under "Contrast 2:", there is a text input field containing "1 0 -1". Below these fields, a note states: "Note: Contrasts should be numeric entries of length equal to the number of unique conditions and must sum to zero. Separate numbers by a space."

Maimaran and Fishbach (2014) were interested in two contrasts, the difference between the Instrumental and Control conditions (Contrast 1) as well as the difference between the Yummy and Control conditions (Contrast 2) which are respectively given by:

Contrast 1:

1 -1 0

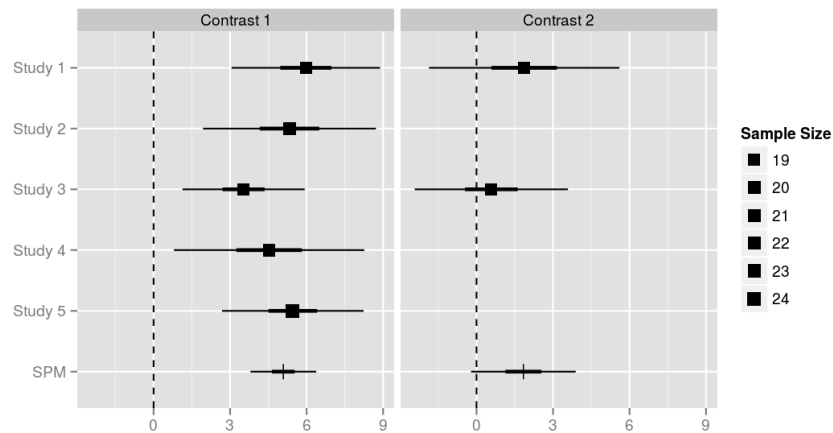
Contrast 2:

1 0 -1

Output I: Contrasts and Condition Estimates

The output for the SPM website can be obtained by clicking on the Results tab. The first few pieces of output consist of the estimates of the contrasts and conditions including the graphical summary. This output is pictured below:

Contrast Estimates



Contrast	Estimate	SE
Contrast 1	5.0887	0.6583
Contrast 2	1.8382	1.0457

Condition Estimates

Factor1	Estimate	SE
Control	9.0932	0.6390
Yummy	4.0044	0.5113
Instrumental	7.2550	0.9616

This output consists of three items: a graphical summary of the contrast estimates, a table of SPM estimates for each contrast, and table of SPM estimates for each condition. The graphical summary provides several estimates for each contrast of interest, namely a point estimate and 50% and 95% confidence interval estimate for each study from which the contrast can be estimated as well as for the overall SPM estimate; the average sample size per study is indicated by the square. The first table provides meta-analysis estimates for each contrast and its standard error; these estimates are used to construct the SPM point and interval estimates depicted in the graphical summary. The second table provides meta-analysis estimates of each condition and its standard error; contrast estimates can be obtained from this table (e.g., $5.0887 = 9.0932 - 4.0044$ but for rounding).

As can be seen in the graphical summary, the second contrast can only be estimated in the first and third studies because it requires the presence of both the Control and Instrumental conditions and these conditions were present in only these studies.

We believe the graphical summary and the table of SPM estimates for the contrasts will prove most useful for users. We note the user interested in null hypothesis significance testing can

obtain z -statistics by dividing estimates by standard errors and can obtain p -values from such z -statistics.

Output II: Heterogeneity Estimates

The next pieces of output consist of the heterogeneity estimates. This output is pictured below:

Heterogeneity Estimates

Heterogeneity (Var)	0.5806
Heterogeneity (SD)	0.7619
I^2 (Estimate)	18.6289
I^2 (CI Lower)	0.0000
I^2 (CI Upper)	59.4473

The output consists of the estimate of the variance of each element of β (i.e., the random effects for each study condition as detailed in the supplementary materials to McShane and Bockenholt (2017)); its square root; and a point estimate and 95% interval estimate of I^2 . We believe the point and interval estimate of I^2 will prove most useful for users.

Output III: Sample Size Requirements

The SPM website provides sample size requirements so that future studies and future sets of studies of each effect of interest are adequately powered. This output is pictured below:

Single Experiment Sample Size Requirements

Contrast	n
Contrast 1	14
Contrast 2	199

Note: This gives the sample size per condition required to achieve 80% power for each contrast. Inf means that 80% power cannot be achieved.

Meta-analysis Sample Size Requirements

Contrast	2 Exps.	3 Exps.	4 Exps.	5 Exps.
Contrast 1	7	5	4	3
Contrast 2	100	67	50	40

Note: This gives the sample size per condition per experiment required to achieve 80% power for each contrast in a meta-analysis of 2, 3, 4, and 5 experiments. Inf means that 80% power cannot be achieved.

The first table provides the sample size per condition that is required for a single study to have 80% power for a given contrast.

The second table provides the sample size per condition per study that is required for a meta-analysis of two, three, four, and five studies respectively to have 80% power for a given contrast.

Output IV: Variance-Covariance Matrix Estimates

The SPM website provides the estimates of the variance-covariance matrices of the contrasts and the conditions. This output is pictured below:

Contrast Estimated Variance-Covariance Matrix

0.4333	0.3228
0.3228	1.0935

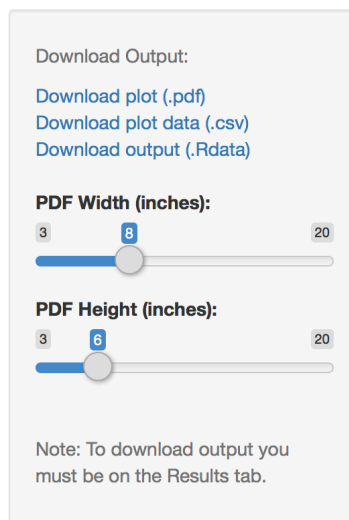
Condition Estimated Variance-Covariance Matrix

0.4083	0.1182	0.1198
0.1182	0.2615	0.1525
0.1198	0.1525	0.9247

This information will generally only be used by more sophisticated users, for example to simultaneously test hypotheses about multiple linear combinations of the condition means using for example approximate Wald tests (i.e., z-tests and Chi-square tests).

Concluding Remark

The graphical summary and other output may be downloaded as indicated in the sidebar panel pictured below:



Case Study II: Shah, Bettman, Ubel, Keller, and Edell (2014)

Note: Be sure to have read Case Study I: Maimaran and Fishbach (2014) before attempting this case study.

Preliminaries

Shah *et al.* (2014) conducted four experiments. Across all experiments, there were four experimental factors which were varied, two primary ones that were utilized in all experiments and two secondary ones that were each utilized in only one experiment. The two primary factors and their factor levels were an unhealthy label (absent, present) and a price surcharge (absent, present). In addition to these two primary experimental factors, a health / calorie information factor (absent, present) was also utilized in Experiment 1b and a dining partner factor (alone, with a same-sex friend) was utilized in Experiment 2. All experiments followed between-subjects designs.

Because the experimental factors in Experiment 1b and Experiment 2 were not identical to those in the other experiments, one must make a judgment about how to treat the data from these experiments.

As Experiment 1b utilized a health / calorie information factor and no other experiment did, one option would be to drop all data from Experiment 1b. Alternatively, because health / calorie information was absent from all other experiments, another option would be to keep the data from the conditions of Experiment 1b where the health / calorie information was absent and drop the data from the conditions where it was present. Additionally, one could collapse over the health / calorie information factor (i.e., pool the individual observations from conditions where the health / calorie information was absent versus present). A final option is to simply keep all the data from Experiment 1b treating the conditions where the health / calorie information was absent versus present as separate studies; while this generally may not be the most attractive option, since there was no main effect of health / calorie information, it is the one we pursue here.

As Experiment 2 utilized a dining partner factor and no other experiment did, one option would be to drop all data from Experiment 2. Alternatively, because the experimental context involved ordering from restaurant menus, one might reason that subjects in the other experiments naturally assumed that they would not be dining alone; consequently, another option would be to keep the data from the conditions of Experiment 2 where the dining partner was with a same-sex friend was absent and drop the data from the conditions where it was alone. Additionally, one could collapse over the health / calorie information factor (i.e., pool the individual observations from conditions where the dining partner was alone versus with a same sex friend). A final option is to simply keep all the data from Experiment 2 treating the conditions where the dining partner was alone versus with a same-sex friend alone as separate studies; while this generally may not be the most attractive option, since there was no main effect of dining partner, it is the one we pursue here.

This summary information for the studies of Shah *et al.* (2014) is presented in Table 2 of McShane and Bockenholt (2017) and is also given below:

Study	Factor 1	Factor 2	Proportion	n
Study 1A	No Label	No Surcharge	0.422	300
	No Label	Surcharge	0.358	300
	Label	No Surcharge	0.333	300
	Label	Surcharge	0.252	300
Study 1B (No Information)	No Label	No Surcharge	0.426	149
	No Label	Surcharge	0.349	149
	Label	No Surcharge	.	.
	Label	Surcharge	0.262	149
Study 1B (Information)	No Label	No Surcharge	0.389	149
	No Label	Surcharge	0.366	149
	Label	No Surcharge	.	.
	Label	Surcharge	0.257	149
Study 2 (Alone)	No Label	No Surcharge	0.454	248
	No Label	Surcharge	0.430	248
	Label	No Surcharge	0.390	248
	Label	Surcharge	0.322	248
Study 2 (Friend)	No Label	No Surcharge	0.487	248
	No Label	Surcharge	0.463	248
	Label	No Surcharge	0.414	248
	Label	Surcharge	0.272	248
Study 3	No Label	No Surcharge	0.499	116
	No Label	Surcharge	0.457	116
	Label	No Surcharge	0.297	116
	Label	Surcharge	0.291	116

Table B: Shah *et al.* (2014) Summary Information.

We note a “.” denotes a study in which the given condition was not observed. We also note this the proportions reproduce those reported in Tables 1-4 of Shah *et al.* (2014). As the sample sizes per condition per study were not reported but total sample sizes per study were reported, we assume subjects were split evenly across the conditions of each study.

Input I: Basic Information

As per Table B, we input:

Number of experiments: 6
Number of experimental factor: 2

As all experiments followed between-subjects designs, we leave the “All experiments are between subjects” radio button checked.

Input II: Factor Levels

As per Table B, we input:

Experimental factor 1: No Label, Label
Experimental factor 2: No Surcharge, Surcharge

Input III: Basic Summary Information

As per Table B, we input:

Means or Proportions (y): 0.422 0.358 0.333 0.252 0.426 0.349 . 0.262 0.389 0.366 .
0.257 0.454 0.430 0.390 0.322 0.487 0.463 0.414 0.272 0.499 0.457 0.297 0.291

Standard Deviations (sd): Because the dependent measure is a proportion we leave this blank.

Sample Sizes (n): 300 300 300 300 149 149 . 149 149 149 . 149 248 248 248 248 248
248 248 248 116 116 116 116

As noted above and in the picture, a “.” denotes a study in which the given condition was not observed.

Input IV: Contrasts

The authors’ analysis focused on three contrasts, the difference in the proportion of unhealthy entrees ordered between a control menu (i.e., no surcharge and no label) and each of three intervention menus (i.e., surcharge only, label only, both surcharge and label). We also consider main and interaction effects. Thus, there are six contrasts in total which are given by:

Contrast 1: 1 -1 0 0
Contrast 2: 1 0 -1 0
Contrast 3: 1 0 0 -1
Contrast 4: -1 1 -1 1
Contrast 5: -1 -1 1 1
Contrast 6: 1 -1 -1 1

The first gives the simple effect of the surcharge only menu versus the control menu, the second gives the simple effect of the label only menu versus the control menu, and the second gives the simple effect of the surcharge and label menu versus the control menu.

The fourth gives the surcharge main effect, the fifth gives the label main effect, and the sixth gives the interaction effect.

Output

Output is as discussed in Case Study I: Maimaran and Fishbach (2014).

Case Study IIIa: Anonymous Consumer Behavior Researcher

Note: Be sure to have read Case Study I: Maimaran and Fishbach (2014) before attempting this case study.

Preliminaries

The anonymous consumer behavior researcher (ACBR) conducted five experiments. Across all experiments, there were two experimental factors which were varied, the choice task difficulty (low, high) and the choice set size (small, large). Experiments 1, 2, and 5 followed between-subjects designs; experiment 3 followed a partially within-subjects design; and experiment 4 followed a fully within-subjects design.

When one or more experiments follows a within-subjects design, one may *optionally* provide information on the designs—in particular a subject group ID for each subject group as discussed below. We advocate that authors provide this information as it results in a more appropriate statistical treatment of the data.

This summary information for the studies of the ACBR is presented in Table 3 of McShane and Bockenholt (2017) and is also given below:

Study	Factor 1	Factor 2	Mean	SD	n	wi
Study 1	Low	Small	-0.227	0.868	50	1
	Low	Large	0.330	0.939	50	2
	High	Small
	High	Large
Study 2	Low	Small	0.167	0.881	100	3
	Low	Large	0.747	0.858	100	4
	High	Small	-0.145	1.039	100	5
	High	Large	-0.009	1.003	100	6
Study 3	Low	Small	-0.258	1.072	75	7
	Low	Large	0.175	0.918	75	8
	High	Small	-0.145	0.908	75	7
	High	Large	-0.540	1.005	75	8
Study 4	Low	Small	0.234	0.894	125	9
	Low	Large	0.706	0.961	125	9
	High	Small	-0.026	0.917	125	9
	High	Large	0.082	0.840	125	9
Study 5	Low	Small	-0.277	0.922	150	10
	Low	Large	0.196	1.037	150	11
	High	Small	-0.324	0.911	150	12
	High	Large	-0.581	0.861	150	13

Table C: Anonymous Consumer Behavior Researcher Summary Information.

We note a “.” denotes a study in which the given condition was not observed. The wi column that provides the subject group ID can be interpreted as follows:

- The 1 and 2 entered for Study 1 indicate that Study 1 followed a between-subjects design (i.e., because the ID entered for each row was distinct).
- The 3, 4, 5, and 6 entered for Study 2 indicate that Study 2 followed a between-subjects design (i.e., because the ID entered for each row was distinct) and that the subjects in Study 2 were distinct individuals from those in Study 1 (i.e., because the IDs given in Study 2 were not 1 or 2).
- The 7, 8, 7, and 8 entered for Study 3 indicate that Study 3 followed a partially within-subjects design with one group of subjects exposed to both low and high choice task difficulty given a small choice set size and another group of subjects exposed to both low and high choice task difficulty given a large choice set size.
- The 9, 9, 9, and 9 entered for Study 4 indicate that Study 4 followed a fully within-subjects design with one group of subjects exposed to all four conditions.
- The 10, 11, 12, and 13 entered for Study 5 indicate that Study 5 followed a between-subjects design.

Input I: Basic Information

As per Table C, we input:

Number of experiments: 5
Number of experimental factor: 2

As not all experiments followed between-subjects designs, we uncheck the “All experiments are between subjects” radio button.

Input II: Factor Levels

As per Table C, we input:

Experimental factor 1: Low, High
Experimental factor 2: Small, Large

Input III: Basic Summary Information

As per Table C, we input:

Means or Proportions (y): -0.227 0.330 . . 0.167 0.747 -0.145 -0.009 -0.258 0.175 -
0.145 -0.540 0.234 0.706 -0.026 0.082 -0.277 0.196 -0.324 -0.581

Standard Deviations (sd): 0.868 0.939 . . 0.881 0.858 1.039 1.003 1.072 0.918 0.908
1.005 0.894 0.961 0.917 0.840 0.922 1.037 0.911 0.861

Sample Sizes (n): 50 50 . . 100 100 100 100 75 75 75 75 125 125 125 125 150 150 150 150

As noted above and in the picture, a “.” denotes a study in which the given condition was not observed.

Input IV: Within-Subjects Information

When the “All experiments are between subjects” radio button is unchecked, a new panel appears in the sidebar. This panel is depicted below:

Within subjects group IDs (wi):

Within subjects covariances (cov):

Note: After entering within subjects groups, see bottom of main panel for required covariances.

Note: Separate numbers by a space. Use a period for a missing value. Missing covariances will be treated as zero

As discussed above, one may *optionally* provide information on the study designs; if one does so, one may then also *optionally* provide information on covariances. We advocate that authors provide this information as it results in a more appropriate statistical treatment of the data.

As per Table C, we input:

Within subjects group IDs (wi): 1 2 . . 3 4 5 6 7 8 7 8 9 9 9 10 11 12 13

When this is input, the wi column of the Summary Data from Experiments table is populated. Based on the values input, an additional table appears below. This table is depicted below:

Study	Factor1	Factor2	Study	Factor1	Factor2	cov
3	Low	Small	3	High	Small	NA
3	Low	Large	3	High	Large	NA
4	Low	Small	4	Low	Large	NA
4	Low	Small	4	High	Small	NA
4	Low	Small	4	High	Large	NA
4	Low	Large	4	High	Small	NA
4	Low	Large	4	High	Large	NA
4	High	Small	4	High	Large	NA

For every pair of rows in the main Summary Data from Experiments table that shares the same value of w_i , there is a corresponding row in this table. This allows one to input the covariance between the individual-level observations in these pairs of conditions.

We input this information as:

Within subjects covariances (cov): 0.515 0.153 0.320 0.238 0.247 0.301 0.181 0.228

This cov column is then populated. The table is depicted below:

Study	Factor1	Factor2	Study	Factor1	Factor2	cov
3	Low	Small	3	High	Small	0.52
3	Low	Large	3	High	Large	0.15
4	Low	Small	4	Low	Large	0.32
4	Low	Small	4	High	Small	0.24
4	Low	Small	4	High	Large	0.25
4	Low	Large	4	High	Small	0.30
4	Low	Large	4	High	Large	0.18
4	High	Small	4	High	Large	0.23

Input V: Contrasts

The ACBR's analysis focused on three contrasts: the simple effect of the choice set size when choice task difficulty was low, the simple effect of choice task difficulty when the choice set size was small, and the interaction effect. These are given respectively by:

Contrast 1: -1 1 0 0

Contrast 2: -1 0 1 0

Contrast 3: 1 -1 -1 1

Output

Output is as discussed in Case Study I: Maimaran and Fishbach (2014).

Case Study IIIb: Anonymous Consumer Behavior Researcher (Hedonic / Utilitarian)

Note: Be sure to have read Case Study I: Maimaran and Fishbach (2014) and Case Study IIIa: Anonymous Researcher before attempting this case study.

Case Study IIIb is identical to Case Study IIIa except the fact that Experiments 1, 3, and 5 featured utilitarian products whereas Experiments 2 and 4 featured hedonic products is accounted for in the analysis. This is done by treating the studies as if they had followed a two-by-two-by-two (rather than two-by-two) design where the additional factor reflects the utilitarian versus hedonic distinction. See McShane and Bockenholt (2017) for a discussion of the motivation for this analysis.

Because this Case Study is thus highly similar to Case Study IIIa, we leave it as an exercise to the reader providing below for the reader's convenience the revised table of summary information as well as the contrasts.

Study	Factor 1	Factor 2	Factor 3	Mean	SD	n	wi
Study 1	Utilitarian	Low	Small	-0.227	0.868	50	1
	Utilitarian	Low	Large	0.330	0.939	50	2
	Utilitarian	High	Small
	Utilitarian	High	Large
	Hedonic	Low	Small
	Hedonic	Low	Large
	Hedonic	High	Small
	Hedonic	High	Large
Study 2	Utilitarian	Low	Small
	Utilitarian	Low	Large
	Utilitarian	High	Small
	Utilitarian	High	Large
	Hedonic	Low	Small	0.167	0.881	100	3
	Hedonic	Low	Large	0.747	0.858	100	4
	Hedonic	High	Small	-0.145	1.039	100	5
	Hedonic	High	Large	-0.009	1.003	100	6
Study 3	Utilitarian	Low	Small	-0.258	1.072	75	7
	Utilitarian	Low	Large	0.175	0.918	75	8
	Utilitarian	High	Small	-0.145	0.908	75	7
	Utilitarian	High	Large	-0.540	1.005	75	8
	Hedonic	Low	Small
	Hedonic	Low	Large
	Hedonic	High	Small
	Hedonic	High	Large

Study 4	Utilitarian	Low	Small
	Utilitarian	Low	Large
	Utilitarian	High	Small
	Utilitarian	High	Large
	Hedonic	Low	Small	0.234	0.894	125	9
	Hedonic	Low	Large	0.706	0.961	125	9
	Hedonic	High	Small	-0.026	0.917	125	9
	Hedonic	High	Large	0.082	0.840	125	9
Study 5	Utilitarian	Low	Small	-0.277	0.922	150	10
	Utilitarian	Low	Large	0.196	1.037	150	11
	Utilitarian	High	Small	-0.324	0.911	150	12
	Utilitarian	High	Large	-0.581	0.861	150	13
	Hedonic	Low	Small
	Hedonic	Low	Large
	Hedonic	High	Small
	Hedonic	High	Large

Table D: Anonymous Consumer Behavior Researcher Summary Information.

The contrasts are given by:

Contrast 1: -1 1 0 0 0 0 0 0
Contrast 2: -1 0 1 0 0 0 0 0
Contrast 3: 1 -1 -1 1 0 0 0 0
Contrast 4: 0 0 0 0 -1 1 0 0
Contrast 5: 0 0 0 0 -1 0 1 0
Contrast 6: 0 0 0 0 1 -1 -1 1

where the first three contrasts provide the ACBR's three contrasts of interest for utilitarian products and the last three contrasts provide the ACBR's three contrasts of interest for hedonic products.

The covariances (cov) are exactly the same as in Case Study IIIa.

Frequently Asked Questions

- [1] As an author who is presenting an SPM in my paper, what information should I report and how should I report it?
 - [2] How do I interpret P ?
 - [3] I do not see any p -values on the SPM website. Where can I find these?
 - [4] One or more of my studies involves a continuous covariate. Can I use the SPM website?
 - [5] Does the SPM website require my dependent measure to assess the same construct and be measured on the same measurement scale across studies?
 - [6] When using the SPM website, how do I determine which conditions of a given study map onto of other studies, if for example a factor (e.g., moderator, measured variable) appears in only one or a subset of the studies?
 - [7] Is it possible to conduct a meta-mediation-analysis using the SPM website?
 - [8] Can the SPM website only be used only for the meta-analysis of the set of studies contained in a single paper?
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[1] As an author who is presenting an SPM in my paper, what information should I report and how should I report it?

In terms of input information, authors should report the table of summary information; when all studies follow a between-subjects design, this table is the analogue of Tables A and B, and, when one or more studies follow a within-subjects design, this table is the analogue of Tables C and D. When one or more studies follow a within-subjects design, authors should also report the relevant covariances (see the *Input IV: Within-Subjects Information* of Case Study IIIa: Anonymous Consumer Behavior Researcher for more details).

In terms of output information, at minimum authors should report (i) estimates of contrasts and their standard errors (or confidence intervals) and (ii) the point and interval estimate of P . Authors may also report additional information such as the graphical summary, point estimates of heterogeneity, or sample size analyses.

Because the graphical summary allows for the easy and rapid communication and comparison of results both at the single study level and in aggregate, we strongly encourage authors to report this; as discussed in the *Concluding Remarks* to Case Study I: Maimaran and Fishbach (2014), the graphical summary may be downloaded as a high quality pdf file of dimensions set by the user.

For examples of verbal summaries of an SPM that could be used in, for example, a paper's General Discussion, see McShane and Bockenholt (2017).

[2] How do I interpret I^2 ?

The variation in the observations reported in the rows of the table of summary information can be decomposed into three sources:

1. Variation caused by differences in the experimental factors.
2. Variation caused by sampling error (i.e., measuring only a subset, or sample, of the population).
3. Variation caused by differences in method factors (e.g., seemingly major factors such as the operationalization of the dependent measure, the operationalization of the experimental manipulation(s), or unaccounted for moderators but also seemingly minor factors such as the social context, the subject pool, or the time of day (for a comprehensive list, see Brown et al. [2014])).

I^2 assesses gives the percentage of the variation caused by the second and third sources that is due to the third source.

[3] I do not see any p -values on the SPM website. Where can I find these?

This omission was deliberate.

We note the user interested in null hypothesis significance testing can use the graphical summary as a device for null hypothesis significance tests of the contrasts; in addition, such a user can obtain z -statistics by dividing estimates by standard errors and can obtain p -values from such z -statistics. More sophisticated users interested in, for example, simultaneous null hypothesis significance tests regarding multiple linear combinations of the condition means using for example approximate Wald tests (i.e., z -tests and Chi-square tests) can obtain test statistics using the estimates of the condition means and variance-covariance matrix.

[4] One or more of my studies involves a continuous covariate. Can I use the SPM website?

Section 7 of McShane and Bockenholt (2017) deals with this issue and we quote from there:

[O]ur SPM methodology accommodates only discrete covariates such as the discretely manipulated experimental factors used in the vast majority of behavioral research studies, but it does not accommodate continuous covariates such as continuous measured variables. This is a conscious design choice with genuine benefits: it allows for a model that requires only basic summary information rather than individual-level observations yet is equivalent to that underlying the gold standard meta-analytic approach thus providing greater ease of use and allowing readers as well as authors to conduct an SPM. Models that accommodate continuous covariates require access to the individual-

level observations, and we encourage authors who possess individual-level observations with continuous covariates to model this data directly via a hierarchical model.

...

[O]ur SPM methodology may in some cases be applicable to only a subset of the studies that appear in a typical behavioral research paper. In this case, we believe an SPM of the subset is still valuable and advocate this practice. However, we also note that an SPM of the full set may still be possible. For example, consider a set of studies in which one of the studies has a continuous covariate. If this covariate is, say, an experimental factor that was manipulated discretely in the other studies but continuously in the one study, then we would advocate an SPM of the subset. On the other hand, if this covariate is, say, a measured variable used as a control variable, then an SPM of the full set but omitting the variable is also possible.

[5] Does the SPM website require my dependent measure to assess the same construct and be measured on the same measurement scale across studies?

This question is briefly discussed in first paragraph of Section 7 of McShane and Bockenholt (2017) and is expounded on here. We first repeat the relevant paragraph of McShane and Bockenholt (2017) and then elaborate.

[S]trictly speaking, our SPM methodology accommodates a single dependent measure that is measured on the same measurement scale across studies. Nonetheless, insofar as the dependent measures employed across studies assess different but related constructs or are measured on different but similar measurement scales, the studies may be analyzed via our SPM methodology; however, these differences will tend to increase heterogeneity. Further, when secondary dependent measures that assess unrelated constructs are measured and are of interest, they may be analyzed via an additional separate SPM.

Let's start with the easiest case: suppose studies have dependent measures that assess unrelated constructs. In this case, the differing dependent measures should not be combined using the website. Instead, one might:

1. Use the website to conduct a separate SPM for each dependent measure.
2. Use alternative meta-analytic tools to conduct a multivariate meta-analysis that accounts for the fact that the dependent measures assess unrelated constructs.

We note that for the purposes of SPM the first option is almost always sufficient (we further note that the two options are identical if each study assesses only one dependent measure).

Given the above, we can now suppose studies are deemed to have dependent measures that assess the same (or at least a sufficiently similar*) construct. Now, one must determine whether this dependent measure is measured on the same or a sufficiently similar measurement scale across studies.

Given that it is obvious if the dependent measure is measured on the *same* measurement scale across studies, we need only discuss what qualifies as *sufficiently similar*. As noted in McShane

and Bockenholt (2017), to some degree this is something to be determined by the researcher and differences in the measurement scale will tend to increase heterogeneity. However, we here provide some more detailed guidance.

At one extreme, consider a set of studies that employ quite similar measurement scales for the dependent measure; for example, suppose some employ a seven-point integer scale and others employ a nine-point integer scale. Subjects likely utilize these two similar scales in a similar manner and thus use of the SPM website is appropriate (see also *Note 1* and *Note 2* below).

At the other extreme, consider a set of studies that employ quite different measurement scales for the dependent measure but the researcher believes these all assess the same construct; for example, suppose some employ a continuous time measure, others employ a word count measure, and still others employ a calorie measure. These measurement scales are sufficiently different that subjects are likely to utilize them in quite a different manner and thus use of the SPM website would not be appropriate (see also *Note 3* below).

Note 1: If the measurement scales are flipped in some studies, dependent measures should be reverse coded before being input into the SPM website.

Note 2: If a set of studies employ a similar but different measurement scale, one possibility that is likely to mitigate some of the increase in heterogeneity associated with using different measurement scales is to convert all studies to a common scale via a linear transformation. For instance, in the example given above where some studies employ a seven-point integer scale for the dependent measure and others employ a nine-point integer scale, one could convert means and standard deviations of the studies that employ a seven-point integer scale to a nine-point scale by using the following formulae:

$$\text{New Mean} = 1 + \frac{9-1}{7-1} (\text{Old Mean} - 1)$$

$$\text{New SD} = \frac{9-1}{7-1} (\text{Old SD})$$

Alternatively, one could convert means and standard deviations of the studies that employ a nine-point integer scale to a seven-point scale by using the following formulae:

$$\text{New Mean} = 1 + \frac{7-1}{9-1} (\text{Old Mean} - 1)$$

$$\text{New SD} = \frac{7-1}{9-1} (\text{Old SD})$$

In general, a linear transformation from a scale with minimum m_1 and maximum M_1 to a scale with minimum m_2 and maximum M_2 is given by the following formulae:

$$\text{New Mean} = m_2 + \frac{M_2 - m_2}{M_1 - m_1} (\text{Old Mean} - m_1)$$

$$\text{New SD} = \frac{M_2 - m_2}{M_1 - m_1} (\text{Old SD})$$

This linear transformation need not be employed however and should only be employed when it is deemed reasonable.

Note 3: We recommend researchers with a set of studies that employ quite different measurement scales for the dependent measure that are all deemed to assess the same construct use the MCSM meta-analytic approach located at

that adjusts for differences in the measurement scales used for the dependent measure across studies (McShane & Bockenholt (2021), *Journal of Consumer Psychology*). First, however, see the subsection Adjustment for Differences in Measurement Scales of the Discussion of that paper.

[6] When using the SPM website, how do I determine which conditions of a given study map onto other studies, if for example a factor (e.g., moderator, measured variable) appears in only one or a subset of the studies?

When a given factor appears in only one or a subset of the studies, one faces a choice of how to set up the SPM Summary Data from Experiments table. These options can involve:

1. Dropping conditions or studies and potentially conducting an additional SPM of the dropped conditions or studies.
2. Splitting studies and conducting a single SPM.
3. Collapsing over the factor and conducting a single SPM.

Determining which option is best requires subject matter expertise.

We provide a detailed example of this in the *Preliminaries* of Case Study II: Shah, Bettman, Ubel, Keller, and Edell (2014) and suggest the reader begin there and then return here. Here, we discuss this in the abstract and then provide another example.

Consider a case where a researcher conducts six studies, three of which follow a simple two condition study design with one factor with levels (a, A) and three of which follow a two-by-two study with the same factor with levels (a, A) as well as additional factor with levels (b, B). The researcher faces the following options when conducting SPM:

1. If the researcher believes, say, the b level of the second factor corresponds to the unmoderated studies, the researcher could conduct an SPM of all six studies using only the two b conditions of the studies that follow a two-by-two study design. The researcher could potentially also conduct a secondary SPM of the B conditions of the studies that follow a two-by-two study design.
2. If the researcher believes neither level of the second factor corresponds to the unmoderated studies, the researcher could conduct one SPM of the studies that follow a simple two condition study design as well as a second SPM of the studies that follow a two-by-two study design.
3. If the researcher believes the additional factor with levels (b, B) is relatively secondary or potentially even orthogonal to the other factor, the researcher could split each study that follows a two-by-two design treating it as two separate studies each of which follows a simple two condition study design with one factor with levels (a, A) and conduct a single SPM of nine studies.
4. If the researcher believes the additional factor with levels (b, B) is relatively secondary or potentially even orthogonal to the other factor, the researcher could collapse over the factor (i.e., pool the individual level observations from these two conditions) in effect turning each study that follows a two-by-two design into a study that follows a simple

two condition study design with one factor with levels (a, A) and conduct a single SPM of the six studies.

In cases where 3 and 4 are applicable, we note we prefer 3 because it provides greater opportunity for assessing heterogeneity.

Alternatively, consider a case where a researcher conducts five studies, three of which follow a simple two condition study design with one factor with levels (a, A); one of which follows a two-by-two study with the same factor with levels (a, A) as well as additional factor with levels (b, B); and a one of which follows a two-by-two study with the same factor with levels (a, A) as well as additional factor with levels (c, C). The researcher faces the following options when conducting SPM:

1. If the researcher believes, say, the b level of the second factor in the fourth study and the C level of the second factor in the fifth study correspond to the unmoderated studies, the researcher could conduct an SPM of all five studies using only the b conditions the fourth study and the C conditions of the fifth study (as there is only one observation of the non-corresponding B conditions of the fourth study and the non-corresponding c conditions of the fifth study, no secondary SPM is possible).
2. If the researcher believes neither level of the second factor corresponds to the unmoderated studies, the researchers could conduct one SPM of the studies that follow a simple two condition study design (as there is only one observation of the factor with levels (b, B) and only one observation of the factor with levels (c, C), no secondary SPM is possible).
3. If the researcher believes the additional factors with levels (b, B) and (c, C) are relatively secondary or potentially even orthogonal to the other factor, the researcher could split each study that follows a two-by-two design treating it as two separate studies each of which follows a simple two condition study design with one factor with levels (a, A) and conduct of single SPM of seven studies.
4. If the researcher believes the additional factors with levels (b, B) and (c, C) are relatively secondary or potentially even orthogonal to the other factor, the researcher could collapse over the factor (i.e., pool the individual level observations from these two conditions) in effect turning each study that follows a two-by-two design into a study that follows a simple two condition study design with one factor with levels (a, A) and conduct a single SPM of the five studies.

In cases where 3 and 4 are applicable, we note we prefer 3 because it provides greater opportunity for assessing heterogeneity.

A related case involves collapsing over continuous variables because continuous variables are not accommodated by the website. As noted in Section 7 of McShane and Bockenholt (2017)

[O]ur SPM methodology may in some cases be applicable to only a subset of the studies that appear in a typical behavioral research paper. In this case, we believe an SPM of the subset is still valuable and advocate this practice. However, we also note that an SPM of the full set may still be possible. For example, consider a set of studies in which one of the studies has a continuous covariate. If this covariate is, say, an experimental factor that was manipulated discretely in the other studies but continuously in the one study, then we would advocate an SPM of the subset. On the other hand, if this covariate is, say,

a measured variable used as a control variable, then an SPM of the full set but omitting the variable is also possible.

We conclude with an example that mirrors our second hypothetical scenario above and, like that discussed in the *Preliminaries* of Case Study II: Shah, Bettman, Ubel, Keller, and Edell (2014), comes from published research (Toure-Tillery and Fishbach (2017), *JSPS*). Toure-Tillery and Fishbach (2017) were interested in conducting an SPM of four studies that followed the following designs

- Two-by-two: (Near, Far) x (Consistent, Inconsistent)
- Two condition: (Near, Far)
- Two condition: (Near, Far)
- Two-by-two: (Near, Far) x (Outcome, Signal)

In the paradigm of Toure-Tillery and Fishbach (2017), the Consistent conditions and Outcome conditions correspond to unmoderated studies. Consequently, Toure-Tillery and Fishbach (2017) used these conditions to conduct an SPM of the four studies (as there is only one observation of the non-corresponding Inconsistent conditions and of the non-corresponding Signal conditions, no secondary SPM is possible).

[7] Is it possible to conduct a meta-mediation-analysis using the SPM website?

The SPM website does not support meta-mediation-analyses. The reason for this is that our literature review revealed that (i) most papers that feature mediation analyses feature it in only one study thus making a single paper meta-mediation-analysis not possible and (ii) the small number that feature it in two or more studies tend to use different mediator variables in those studies thus again making a single paper meta-mediation-analysis not possible.

Of course, studies that conduct mediation analyses can be included in an SPM by simply ignoring the mediator variable(s) and focusing on the manipulated experimental factors and dependent variable.

[8] Can the SPM website only be used only for the meta-analysis of the set of studies contained in a single paper?

No, it can be used more widely.

Specifically, the SPM website, like many meta-analytic approaches, assumes (conditional) independence of the studies included in the meta-analysis. This amounts to assuming each study has the same relationship to each other study. This assumption seems tenable for meta-analyses of the small number of studies from a single paper or meta-analyses of a large number of studies from multiple papers in which each paper contributes a single study.

However, it seems less tenable for, for example, meta-analyses of a large number of studies from multiple papers in which each paper contributes multiple studies because studies from the same paper will typically have a closer relationship to one another than studies from different papers.

Multilevel multivariate meta-analytic approaches are typically required for such meta-analyses (Berkey, Hoaglin, Antczak-Bouckoms, Mosteller, & Colditz, 1998; Cheung, 2015; Kalaian & Raudenbush, 1996; McShane & Böckenholt, 2018).

Nonetheless, in practice, researchers often employ meta-analytic approaches that assume (conditional) independence of the studies like the SPM website—even when this assumption is less tenable, for example, for meta-analyses of a large number of studies from multiple papers in which each paper contributes multiple studies because studies from the same paper.