UNIVERSITÄT RERN

Why do we need systematic reviews and meta-analyses?

PD Marija Glisic, MD, M.H.S., PhD

Institute of Social and Preventive Medicine (ISPM), University of Bern, Switzerland & Swiss Paraplegic Research, Nottwil

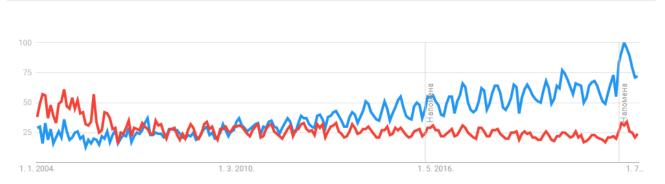


Google trends 2014-2022



Red: meta-analysis

Blue: systematic review



Value of 100 represents the highest popularity for given term

Purposes of Systematic Review

UNIVERSITÄT

- To provide a clear and comprehensive overview of available evidence on a given topic.
- To identify research gaps in our current understanding of a field
- To highlight methodological concerns in research studies that can be used to improve future work in the topic area
- To identify questions for which the available evidence provide clear answers and thus for which further research is not necessary

Purposes of Meta-analysis

- Increase power and improve precision of estimates of effect from numerous smaller studies by pooling the total sample sizes across a number of investigations
- Explain contradictory results (heterogeneity) that arise between studies conducted in different settings
- Conduct subgroup analyses that could not be conducted or were not thought of in the initial studies and help generate new hypotheses

UNIVERSITÄT BERN

Real life example

Endocrinological and inflammatory markers in individuals with spinal cord injury: A systematic review and meta-analysis

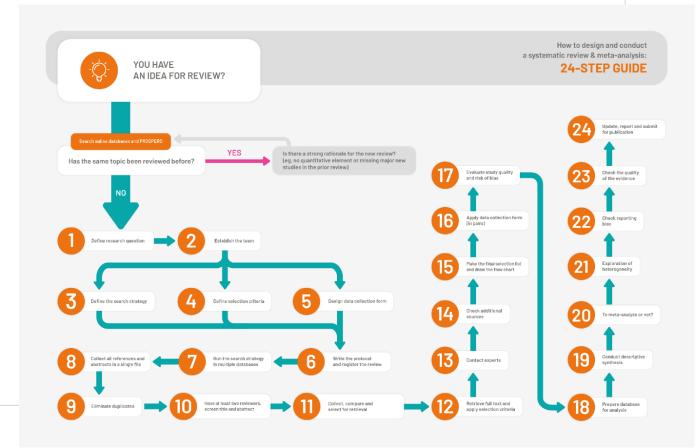
Table 2 Weighted mean difference of biomarkers among spinal cord injury and able-bodied population

Outcome (units)	Studies which reported higher levels in SCI	Studies which reported lower levels in SCI	No association	Number of studies		ABI, N	Weighted Mean Difference	95% confidence interval	I ² test for heterogeneity	x^2 test for heterogeneity (p^{χ^2})
Inflammatory marker	s									
CRP (mg/L)	[11, 23, 37, 84-86]	-	[87, 88]	8	330	249	2.79	1.75, 3.83*	87.3%	< 0.001*
hsCRP (mg/L)	[89]	-	[90]	2	114	113	0.07	-0.07, 0.20	66.3%	0.085
IL-6 (pg/mL)	[11, 91, 92]	-	[24]	4	150	104	2.52	1.82, 3.21*	81.1%	0.001*
TNF alpha (pg/mL)	[91]	-	[24]	2	68	45	18.51	-26.14, 63.15	85.0%	0.010*
Insulin										
Insulin (pmol/L)	[93, 94]	[95]	[11, 87, 89, 90, 96–101]	13	493	485	3.99	-2.84, 10.83	50.5%	0.019*
Glucose (mmol/L)	[102]	[93, 96, 103]	[11, 86–90, 94, 95, 97–101, 104–108]	22	1073	1003	-0.08	-0.19, 0.03	83.8%	<0.001*
Creatinine										
Creatinine(µmol/L)	-	[11, 109–111]	[57, 84, 108]	7	260	136	-14.23	-21.57, -6.89*	90.3%	< 0.001*
Vitamin D										
25(OH)D (nmol/L)	-	[60, 84]	[56, 57, 111]	5	289	123	-10.32	-20.47, -0.18*	57.2%	0.053
1,25(OH)D (pmol/L)	[56]	-	[57]	2	140	64	6.82	-50.10, 63.73	96.8%	< 0.001*
Hormone and Growth	Factors									
Total Testosterone (nmol/L)	-	[22, 47, 111–117]	[26, 65, 66, 110, 119–122]	18	601	512	-2.61	-4.42, -0.79*	89.6%	<0.001*
Free Testosterone (nmol/L)	-	[25, 115, 117]	[26, 66, 123]	6	141	123	-0.01	-0.024, 0.004	81.8%	<0.001*
TSH (mU/L)	-	-	[62, 65, 124]	3	135	99	-0.03	-0.26, 0.20	0.0%	0.490
T3 (nmol/L)	-	[125]	[65, 124, 126]	4	108	100	-0.05	-0.29, 0.19	82.4%	0.001*
LH (IU/L)	[26]	[22, 47]	[65, 66, 110, 111, 114, 116, 117, 119–123, 126]	15	452	365	0.27	-0.61, 1.14	85.6%	<0.001*
FSH (IU/L)	[65, 110, 111, 121]	[22, 47]	[66, 114–117, 119, 123]	13	388	305	0.59	-1.24, 2.43	95.7%	< 0.001*
GH (μg/L)	-	-	[65, 66, 98]	3	48	42	-0.32	-0.67, 0.04	0.0%	0.550
Cortisol (nmol/L)	[43, 127]	-	[65, 126]	4	90	76	103.43	10.75, 196.11*	67.5%	0.026*
ACTH (pmol/L)	-	-	[126, 127]	2	36	28	1.59	-0.40, 3.58	0.0%	0.786
Adiponectin (µg/mL)	-	-	[87, 89]	2	29	29	0.92	-3.12, 4.96	24.6%	0.249
Aldosterone (pmol/l)	-	-	[128, 129]	2	32	22	100.62	-69.57, 270.81	40.2%	0.196
IGF-1 (nmol/L)	-	[65]	[66, 84, 97]	4	76	59	-6.82	-9.24, -4.40*	0.0%	0.529
Leptin (nmol/L)	[67, 89, 94, 97, 130, 131]	-	[98]	7	176	141	0.19	0.10, 0.27*	53.1%	0.047*
Prolactin (µg/L)	-	-	[22, 47, 65, 121, 126, 127]	6	209	134	0.80	-1.01, 2.61	76.5%	0.001*

Detailed steps to systematic reviews:

ub

"The 24"

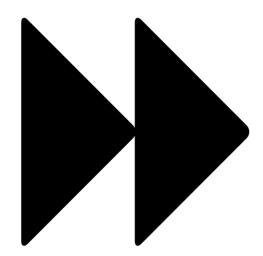


Fast forward mode towards understanding meta-analysis

 $u^{\scriptscriptstyle b}$

UNIVERSITÄ BERN

5 day-course --- 3-hour-course



First:

Decide whether narrative/descriptive data synthesis or meta-analysis is suitable

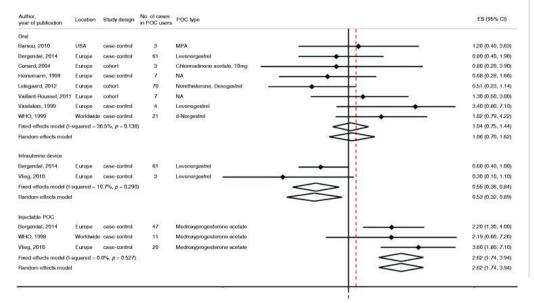
- How many studies are sufficient for meta-analysis?
- What information is essential for meta-analysis?
- When is heterogeneity too large?
- Do "study quality" and methodological rigor determine whether to meta-analyze the evidence?
- Does study design determine whether to meta-analyze the evidence?

$u^{\scriptscriptstyle b}$

UNIVERSITÄT RERN

How many studies are sufficient for meta-analysis

 Meta-analysis is possible if association estimates from two studies are available The association between progestin-only contraceptive (POC) use and risk of venous thromboembolism by route of administration



What information is essential for meta-analysis?

 To combine study results, measurements of association estimates, such as relative risk or odds ratio), from individual studies and standard errors or 95% confidence intervals (CIs) of the estimate are needed

Original Article

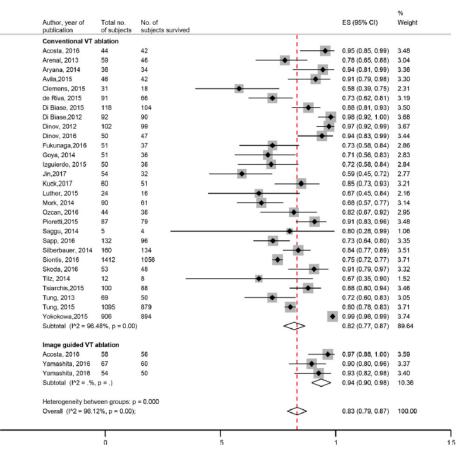


Fig. 3 Forest plot survival—image-guided versus non-image-guided. (CI confidence interval, ES effect size, VT ventricular tachycardia)



When is heterogeneity too large?

- Subjective
- No widely accepted, automated quantitative measures to grade it
- Deciding to perform meta-analyses should not be based solely on statistical heterogeneity

To decide on non-statistical heterogeneity (e.g., clinical heterogeneity), authors should review the included studies and check whether:

- Studies used different methods to define exposure and/or outcome
- 2 Different study designs were used
- Different analyses and methods were applied to generate the estimates
- Different estimates with different levels of confounding adjustments were reported across studies
- There were variations in populations included across different studies and
- 6 Studies differ by their quality/risk of bias
- Few studies are available to make a meaningful analysis that could account for the differences across studies



UNIVERSITA

Do "study quality" and methodological rigor determine whether to meta-analyze the evidence?

Table 2. The subgroup analyses by study characteristics

- "Study quality" is a complex term
- Involves assessing methodological rigor (what was done) and completeness or accuracy of reporting (what is reported to have been done) within individual studies.

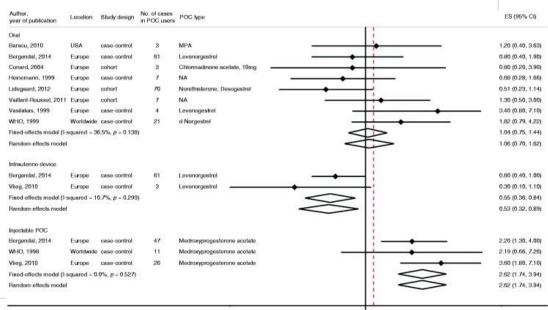
Subgroups by Stu	dy Characteristics	Number of studies	¹ Difference, Mean (95 % CI)	² l ² for heterogeneity	³ P value for heterogeneity	
	Phytoes	strogen use and mea	n body weight change			
Primary study goal of	Body composition	7	-0.04 (-0.68; 0.60)	68.7%		
the RCT	Other	11	-0.21 (-0.64; 0.23)	62.3%	0.59	
Madian	≤4.1 years	4	-0.23 (-0.6; 0.14)	16.5%		
Median years since	>4.1 years	8	0.07 (-0.51; 0.64)	68.2%	0.87	
menopause onset	Unknown	6	-0.29 (-0.63; 0.04)	0%		
Route of	Tablet/capsule	10	-0.17 (-0.82; 0.47)	76.4%		
administration	Diet	8	-0.17 (-0.42; 0.07)	0%	0.52	
	Soy products	6	-0.49 (-1.21;0.23)	65.4%		
dintervention type	Isoflavone mix	10	-0.24(-0.46; -0.01)	0%	0.83	
	Daidzein	2	0.92 (0.24; 1.59)	55%)	
eMedian number of	≤66women	9	-0.49 (-0.87; -0.11)	0%	0.00	
study participants	>66 women	9	0.11 (-0.31; 0.52)	75.2%	0.22	
Intervention duration	s24 weeks	15	-0.10 (-0.51; 0.30)	69.5%	0.9	
Intervention duration	> 24weeks	3	-0.32 (-1.02; 0.37)	53.2%	0.9	
	Asia	7	0.22 (-0.25; 0.69)	76.8%		
Location	Europe	4	-0.35 (-0.78; 0.07)	11%	0.48	
Location	North America	4	-0.6 (-1.44; 0.24)	0%		
	South America	3	-0.48 (-1.13; 0.17)	0%		
hRisk of bias	High	2	-0.85 (-1.93; 0.22)	0%	0.39	
NISK OF DIGS	Low to medium	16	-0.09 (-0.45; 0.27)	69.6%	0.33	

Does study design determine whether to meta-analyze the evidence?

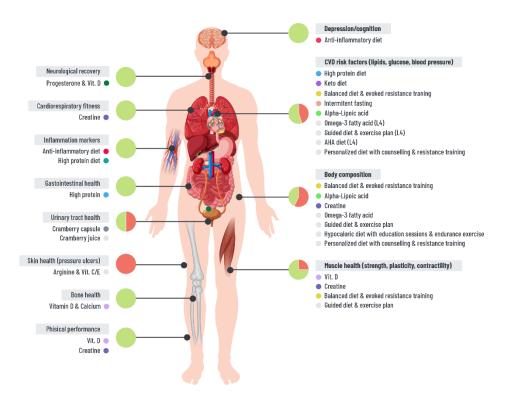
- $u^{\scriptscriptstyle b}$
- UNIVERSITÄT

The association between progestin-only contraceptive (POC) use and risk of venous thromboembolism by route of administration

- Including all study designs in systematic reviews reduces subjective interpretations of potential biases and inappropriate study exclusions
- The decision to meta-analyze results across all study designs depends on research questions



Descriptive data synthesis





UNIVERSITÄT BERN

Table 1. S	Steps for synthesiz	ring data effectively
		Choose an appropriate grouping rationale.
Step 1	Group studies	A PECO [population (male only participants vs mixed population; healthy vs individuals with comorbidities; animal vs human evidence)], exposure/comparison and outcome (reported on continuous vs dichotomized scale) B. Study design (cross-sectional vs longitudinal studies) C. Risk of bias (low quality vs moderate or high-quality evidence) D. Association estimates: consider type (beta coefficients, risk ratios, odds ratios, hazard ratios, etc.) and direction of association (higher risk in exposed population vs no association). To accurately interpret <i>p-values</i> and 95% confidence intervals, identify and understand the direction of associations.
Step 2	Follow the same synthesis consistently	A. Create additional tables using study groupings to find patterns among studies. Provide separate tables for cross-sectional and observational studies, for example. B. Convert association estimates if possible. For comparison among studies, convert odds ratios to standardized mean differences (72). C. Present most interesting findings using graphical methods, such as arrows indicating increased or decreased risk between groups. D. If meta-analysis is not possible, use the data extraction sheet to conduct minimal statistical analyses. For example, calculate total numbers of study participants, mean age, mean number of male participants, or other relevant study population, exposure, or outcome characteristic.
Step 3	Report findings clearly	A. Use appropriate language. B. Keep reporting style uniform across results section. For instance, if studies are grouped, start with a paragraph explaining grouping variables. C3. Provide summary tables and/or figures to support findings reported in results section.
Step 4	Discuss findings objectively	Summarizing what best reflects reviewed evidence can be challenging. D1. Report based on grouping parameters from Step 1. Graphical summaries support interpreting findings (especially when analyzing many methodologically different studies). D2. Discuss methodological strengths and limitations of reviewed evidence. For example, levels of adjustment across studies, heterogeneity that precluded quantitative synthesis, or risks of bias. D3. Identify literature gaps and provide directions for future research

$u^{\scriptscriptstyle b}$

UNIVERSITÄ BERN

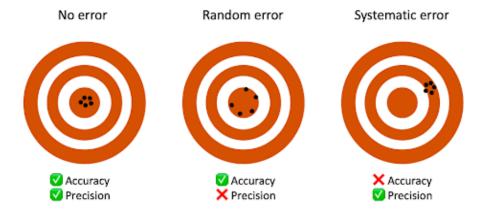
Second:

Understand the concept of meta-analysis and different models

 Meta-analysis mathematically combines different study results, it computes summary statistics for each study, then further summarizes and interprets studylevel summary statistics

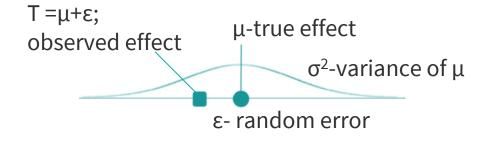


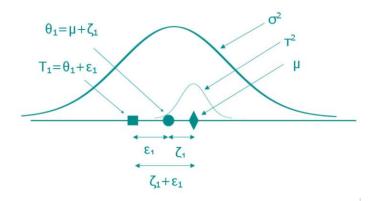
UNIVERSITÄT BERN





UNIVERSITÄT BERN





All studies share a common true overall effect. The differences in observed effect between studies is due to random noise. True effect One true effect. True effect One frue effect. Fooled estimate is common effect. Goal of study Variability accounted for the identified population. Variability accounted for All study characteristics are identical to a large degree. Interpretation of target population Interpretation of target population Interpretation of target population Interpretation of target population When to pool the effects? All study characteristics are identical to a large degree. Interpretation of target population Interpretation of target population included in the study. Implication Interpretation of target population included in the study. Implication Interpretation of target population included in the study. Implication Interpretation of target population included in the study. Implication Interpretation of target population included in the study. Implication Interpretation of target population included in the study. Implication Interpretation of target population included in the study. Implication Interpretation of target population included in the study. Implication Interpretation of target population included in the study. Iarge studies are less influential (receive more weight) in analysis as compared to fixed effect model. a more equal distribution of weights. Under heterogeneity Interpretation of target population included in the study. Interpretation of target population included in the study. Iarget population population included in the study. Iarget pop		Fixed effect model	Random effects model
True effect between studies is due to random noise. True effect One true effect. True effect avaires. True effect varies. Pooled effect is mean effect of all true study effects. Goal is to estimate the true effect for the identified population. Variability accounted for Accounts for within study variability. Between-study variability is ignored. All study characteristics are identical to a large degree. Variability accounts for within study variability is ignored. All study characteristics are identical to a large degree. Variability accounts for within study variability is ignored. All study characteristics are identical to a large degree. Variability accounts for within study variability. Between-study variability. Between-study variability. Studies have enough in common to statistically pool the information, but it is not required that these studies have an identical true effect size. Inference is relevant for the (homogenous) population included in the study. Large studies are less influential (receive more weight) in analysis as compared to fixed effect model: a more equal distribution of weights. Under heterogeneity More likely to lead to incorrect statistically significant findings than in the random effects model. Correct statistical inference. Versume and wider confidence intervals than in the fixed effect model. Inverse-variance fixed effect Models for continuous Orect statistical inference. Poolds ratio Inverse-variance fixed effect; Inverse-variance random effects (DecSimonian-Laird) Inverse-variance random effects Orect mander effects Correct mean estimate, with too wide confidence intervals and too large a p-value. Inverse-variance random effects Orect model. Inverse-variance random effects Orect model. Inverse-var	Assumption	All studies share a common true	Each study has an effect of its
between studies is due to random noise. True effect One true effect. Interpretation of pooled estimate is common effect. estimate Goal of study Variability accounted for Accounts for within study variability. Between-study variability is ignored. All study characteristics are identical to a large degree. Interpretation of target population Implication Under heterogeneity Without heterogeneity Detween-study variance fixed effect; Worls between study variability to lead to incorrect statistical inference. Oracret statistical inference. Descriptional continuous on Risk Inverse-variance fixed effect; Mantel-Haenszel Inverse-variance random effects Dooled effect sizes. Pooled effect varies. Proveded froct is mean effect of all true effects. Pooled effect sizes. Pooled effect size is dealthical true effect. Studies have an identical true effect size. Inference is relevant for the (homogenous) population included in the study. Large studies are more influential (receive more weight) in analysis as compared to random effects model. Accounts for within study variability. Between-study variability. Studies have enough in common to statistically pool the information, but it is not required that these studies have an identical true effect size. Inference is relevant for the (heterogenous) population types included in the study. Large studies are less influential (receive less weight) in analysis as compared to fixed effect model: a more equal distribution of weights. Larger p-values and wider confidence intervals than in the fixed effect model. Correct statistical inference. Correct mean estimate, with too wide confidence intervals and too large a p-value. Inverse-variance fixed effect; Mantel-Haenszel Peto Risk Inverse-variance random effects (DerSimonian-Laird) Inverse-variance random effects (DerSimonian-Laird)		overall effect.	own, where each study effect
True effect Interpretation of pooled estimate Goal of study When to pool the effects? Interpretation of target population Interpretation of target Interpretation		The differences in observed effect	
True effect		between studies is due to random	overall effect, plus a difference
True effect varies Pooled estimate is common effect. Pooled effect is mean effect of all true study effects. Goal is to estimate the true effect for the identified population. Goal is to estimate the true effect for the identified population. Accounts for within study variability between study variability is ignored. Accounts for within study variability between study variability is ignored. All study characteristics are identical to a large degree. All study characteristics are identical to a large degree. Inference is relevant for the (homogenous) population included in the study. Inference is relevant for the (homogenous) population included in the study. Large studies have an identical true effect size. Inference is relevant for the (homogenous) population included in the study. Large studies are more influential (receive more weight) in analysis as compared to random effects model. Larger studies are less influential (receive more weight) in analysis as compared to fixed effect model: a more equal distribution of weights. Larger p-values and wider confidence intervals than in the random effects model. Larger p-values and wider confidence intervals and too large a p-value. Inverse-variance fixed effect Qersimonian-Laird Inverse-variance random effects (Qersimonian-Laird) Invers		noise.	
Interpretation of pooled estimate Pooled estimate is common effect. Goal is to estimate the true effect for the identified population. Goal is to estimate the mean of all true effect sizes.			variation and random noise.
estimate Goal of study Goal is to estimate the true effect for the identified population. Variability accounted for Between-study variability. Between-study variability is ignored. Accounts for within study variability. Between-study variability is ignored. All study characteristics are identical to a large degree. All study characteristics are identical to a large degree. Inference is relevant for the (homogenous) population included in the study. Implication Implication Large studies are more influential (receive more weight) in analysis as compared to random effects model. Under heterogeneity More likely to lead to incorrect statistically significant findings than in the random effects model. Without heterogeneity Correct statistical inference. Models for continuous outcomes Namel-Haenszel Risk ratio Risk Inverse-variance fixed effect; Mantel-Haenszel; Peto Inverse-variance random effects Inverse-variance random effects (DerSimonian-Laird)	True effect		Trab bilost railos.
Goal of study Goal is to estimate the true effect for the identified population. Variability accounted for Between-study variability. Between-study variability is ignored. All study characteristics are identical to a large degree. All study characteristics are identical to a large degree. Interpretation of target population Inference is relevant for the (homogenous) population included in the study. Implication Large studies are more influential (receive more weight) in analysis as compared to random effects model. Under heterogeneity More likely to lead to incorrect statistically significant findings than in the random effects model. Without heterogeneity More statistically significant findings than in the random effect model. Without heterogeneity Correct statistical inference. Odds ratio Inverse-variance fixed effect; Mantel-Haenszel Odds ratio Risk Inverse-variance; Inverse-variance random effects (DerSimonian-Laird)	Interpretation of pooled	Pooled estimate is common effect.	Pooled effect is mean effect of all
the identified population. Variability accounted for Accounts for within study variability. Between-study variability is ignored. All study characteristics are identical to a large degree. Interpretation of target population (homogenous) population included in the study. Implication Carget population (receive more weight) in analysis as compared to random effects model. Under heterogeneity More likely to lead to incorrect statistically significant findings than in the random effects model. Without heterogeneity Correct statistical inference. Models for continuous outcomes Odds ratio Inverse-variance fixed effect; Mantel-Haenszel; Peto O Risk Inverse-variance; Inverse-variance random effects Accounts for within study and between study variability. Studies have enough in common to statistically pool the information, but it is not required that these studies have enough in common to statistically pool the information, but it is not required that these studies have enough in common to statistically pool the information, but it is not required that these studies are identical true effect situdies have enough in common to statistically pool the information, but it is not required that these studies are identical true effect situdies have enough in common to statistically pool the information, but it is not required that these studies are identical true effect situdies have enough in common to statistically pool the information, but it is not required that these studies are identical true effect situdies have enough in common to statistically pool the information, but it is not required that these studies are identical true effect situdies are leaving in common to statistically pool the information, but it is not required that these studies are identical true effect situdies are leavi	estimate		true study effects.
Variability accounted for Between-study variability Between-study variability between study variability between study variability. Between-study variability is ignored.	Goal of study		Goal is to estimate the mean of all
Between-study variability is ignored. Between study variability.		the identified population.	true effect sizes.
When to pool the effects? All study characteristics are identical to a large degree. All study characteristics are identical to a large degree. Interpretation of target population Interpretation of target population Implication Impli	Variability accounted for	Accounts for within study variability.	Accounts for within study and
to a large degree. to a large degree. to statistically pool the information, but it is not required that these studies have an identical true effect size. Interpretation of target population Inference is relevant for the (homogenous) population included in the study. Implication Large studies are more influential (receive more weight) in analysis as compared to random effects model. Under heterogeneity More likely to lead to incorrect statistically significant findings than in the random effects model. Without heterogeneity Correct statistical inference. Without heterogeneity Correct statistical inference. Inverse-variance fixed effect outcomes Nodels for continuous outcomes Risk ratio Risk ratio Risk Inverse-variance fixed effect; Mantel-Haenszel; Peto Risk Inverse-variance; Inverse-variance random effects (DerSimonian-Laird)		Between-study variability is ignored.	between study variability.
Interpretation of target population	When to pool the effects?	All study characteristics are identical	
Interpretation of target population		to a large degree.	to statistically pool the information,
Interpretation of target population (homogenous) population included in the study. Implication Large studies are more influential (receive more weight) in analysis as compared to random effects model. Under heterogeneity More likely to lead to incorrect statistically significant findings than in the random effects model. Without heterogeneity Correct statistical inference. Models for continuous outcomes Risk ratio Inverse-variance fixed effect; Mantel-Haenszel; Peto Odds ratio Inverse-variance; Inverse-variance random effects (DerSimonian-Laird)			
Inference is relevant for the (homogenous) population included in the study. Implication Large studies are more influential (receive more weight) in analysis as compared to random effects model. Under heterogeneity More likely to lead to incorrect statistically significant findings than in the random effects model. Without heterogeneity Correct statistical inference. Models for continuous outcomes Risk ratio Nerse-variance fixed effect; Mantel-Haenszel; Peto Odds ratio Inference is relevant for the (heterogenous) population types included in the study. Large studies are less influential (receive less weight) in analysis as compared to fixed effect model: a more equal distribution of weights. Larger p-values and wider confidence intervals than in the fixed effect model. Correct mean estimate, with too wide confidence intervals and too large a p-value. Inverse-variance random effects (DerSimonian-Laird) Nodels for binary outcomes Odds ratio Nantel-Haenszel; Peto Nantel-Haenszel; Inverse-variance random effects (DerSimonian-Laird) Norese-variance random effects (DerSimonian-Laird) Inverse-variance random effects (DerSimonian-Laird) Norese-variance random effects (DerSimonian-Laird) Norese-variance random effects (DerSimonian-Laird) Norese-variance random effects (DerSimonian-Laird) Norese-variance random effects (DerSimonian-Laird)			studies have an identical true
Correct statistical inference. Correct mean estimate, with too wide confidence intervals and too large a p-value.			effect size.
the study. Implication Large studies are more influential (receive more weight) in analysis as compared to random effects model. Under heterogeneity More likely to lead to incorrect statistically significant findings than in the random effects model. Without heterogeneity Correct statistical inference. Models for continuous outcomes Risk ratio Nerse-variance fixed effect; Mantel-Haenszel; Peto Odds ratio Risk Inverse-variance random effects (DerSimonian-Laird) Nerse-variance random effects (DerSimonian-Laird)	Interpretation of target		Inference is relevant for the
Large studies are more influential (receive more weight) in analysis as compared to random effects model. Large studies are less influential (receive less weight) in analysis as compared to random effects model. a more equal distribution of weights.	population	(homogenous) population included in	(heterogenous) population types
(receive less weight) in analysis as compared to random effects model. Under heterogeneity More likely to lead to incorrect statistically significant findings than in the random effects model. Without heterogeneity Correct statistical inference. Correct mean estimate, with too wide confidence intervals and too large a p-value. Models for continuous outcomes Risk ratio Risk ratio Odds ratio Risk Nantel-Haenszel Nantel-Haenszel; Peto Risk Inverse-variance; Inverse-variance random effects (DerSimonian-Laird) Inverse-variance random effects			
Compared to random effects model. as compared to fixed effect model: a more equal distribution of weights. Under heterogeneity More likely to lead to incorrect statistically significant findings than in the random effects model. Without heterogeneity Correct statistical inference. Correct mean estimate, with too wide confidence intervals and too large a p-value. Inverse-variance random effects (DerSimonian-Laird) Models for binary outcomes Risk ratio Nantel-Haenszel Odds ratio Risk Inverse-variance fixed effect; (DerSimonian-Laird) Nantel-Haenszel; (DerSimonian-Laird) Risk Nantel-Haenszel; (DerSimonian-Laird) Nerse-variance random effects (DerSimonian-Laird) Nerse-variance random effects (DerSimonian-Laird) Nantel-Haenszel; (DerSimonian-Laird) Nerse-variance random effects (DerSimonian-Laird) Nantel-Haenszel; (DerSimonian-Laird) Nerse-variance random effects (DerSimonian-Laird)	Implication		, ,
Under heterogeneity More likely to lead to incorrect statistically significant findings than in the random effects model. Without heterogeneity Correct statistical inference. Correct mean estimate, with too wide confidence intervals and too large a p-value. Models for continuous outcomes Nedles for binary outcomes Risk ratio Risk ratio Risk ratio Nantel-Haenszel; Peto Noverse-variance random effects (DerSimonian-Laird) Inverse-variance random effects (DerSimonian-Laird) Inverse-variance random effects (DerSimonian-Laird) Noverse-variance random effects (DerSimonian-Laird)			
Weights. Under heterogeneity More likely to lead to incorrect statistically significant findings than in the random effects model. Without heterogeneity Correct statistical inference. Correct me an estimate, with too wide confidence intervals and too large a p-value. Models for continuous outcomes Nodels for binary outcomes Risk ratio Nantel-Haenszel Nantel-Haenszel; Peto Risk Inverse-variance random effects (DerSimonian-Laird) Peto Inverse-variance random effects		compared to random effects model.	
Under heterogeneity More likely to lead to incorrect statistically significant findings than in the random effects model. Without heterogeneity Correct statistical inference. Correct mean estimate, with too wide confidence intervals and too large a p-value. Models for continuous outcomes Risk ratio Nedels for binary outcomes Risk ratio Nantel-Haenszel Odds ratio Risk Nantel-Haenszel; Nantel-Haenszel; Peto Risk Nore likely to lead to incorrect Larger p-values and wider confidence intervals than in the fixed effect model. Correct mean estimate, with too wide confidence intervals and too large a p-value. Inverse-variance random effects (DerSimonian-Laird) Nore likely to lead to incorrect Larger p-values and wider confidence intervals than in the fixed effect model. Correct mean estimate, with too wide confidence intervals than in the fixed effect model. Correct mean estimate, with too wide confidence intervals than in the fixed effect model. Correct mean estimate, with too wide confidence intervals than in the fixed effect model. Correct mean estimate, with too wide confidence intervals than in the fixed effect model. Correct mean estimate, with too wide confidence intervals than in the fixed effect model. Correct mean estimate, with too wide confidence intervals than in the fixed effect model. Correct mean estimate, with too wide confidence intervals than in the fixed effect model. Inverse-variance random effects (DerSimonian-Laird) Inverse-variance random effects (DerSimonian-Laird) Inverse-variance random effects (DerSimonian-Laird)			
statistically significant findings than in the random effects model. Without heterogeneity Correct statistical inference. Correct mean estimate, with too wide confidence intervals and too large a p-value. Models for continuous outcomes Risk ratio New ratio Inverse-variance fixed effect; (DerSimonian-Laird) Nantel-Haenszel Nantel-Haenszel; (DerSimonian-Laird) New ratio Inverse-variance fixed effect; (DerSimonian-Laird) New ratio Inverse-variance random effects (DerSimonian-Laird) New ratio Inverse-variance fixed effect; (DerSimonian-Laird) New ratio Inverse-variance random effects (DerSimonian-Laird)			3
the random effects model. Without heterogeneity Correct statistical inference. Correct mean estimate, with too wide confidence intervals and too large a p-value. Models for continuous outcomes Nodels for binary outcomes Risk ratio Nantel-Haenszel Nantel-Haenszel; Nantel-Haenszel; Peto Risk Inverse-variance random effects (DerSimonian-Laird)	Under heterogeneity		
Without heterogeneity Correct statistical inference. Correct mean estimate, with too wide confidence intervals and too large a p-value. Models for continuous outcomes Risk ratio Risk ratio Odds ratio Nantel-Haenszel Mantel-Haenszel; Peto Risk Inverse-variance fixed effect; Mantel-Haenszel; Peto Risk Inverse-variance random effects (DerSimonian-Laird) Risk Inverse-variance random effects			1
wide confidence intervals and too large a p-value.			
large a p-value.	Without heterogeneity	Correct statistical inference.	
Models for continuous outcomes ORISK Inverse-variance fixed effect (DerSimonian-Laird) Inverse-variance random effects (DerSimonian-Laird) Inverse-variance random effects (DerSimonian-Laird) Inverse-variance fixed effect; Inverse-variance random effects (DerSimonian-Laird) Inverse-variance random effects (DerSimonian-Laird) Inverse-variance random effects (DerSimonian-Laird) Peto Inverse-variance random effects (DerSimonian-Laird) Peto Inverse-variance random effects			
outcomes (DerSimonian-Laird) Models for binary outcomes Risk ratio Inverse-variance fixed effect; (DerSimonian-Laird) Odds ratio Inverse-variance fixed effect; (DerSimonian-Laird) Inverse-variance random effects (DerSimonian-Laird) Inverse-variance random effects (DerSimonian-Laird) Risk Inverse-variance; Inverse-variance random effects			
Models for binary outcomes Risk ratio Inverse-variance fixed effect; Inverse-variance random effects (DerSimonian-Laird) Odds ratio Inverse-variance fixed effect; Inverse-variance random effects (DerSimonian-Laird) Inverse-variance random effects (DerSimonian-Laird) Risk Inverse-variance; Inverse-variance random effects		Inverse-variance fixed effect	
 Risk ratio Inverse-variance fixed effect; (DerSimonian-Laird) Odds ratio Inverse-variance random effects (DerSimonian-Laird) Inverse-variance random effects (DerSimonian-Laird) Risk Inverse-variance random effects (DerSimonian-Laird) Risk Inverse-variance random effects 			(DerSimonian-Laird)
Mantel-Haenszel (DerSimonian-Laird) Odds ratio Inverse-variance fixed effect; Inverse-variance random effects Mantel-Haenszel; (DerSimonian-Laird) Peto Risk Inverse-variance; Inverse-variance random effects			
Odds ratio Inverse-variance fixed effect; Inverse-variance random effects (DerSimonian-Laird) Peto Risk Inverse-variance; Inverse-variance random effects	 Risk ratio 		
Mantel-Haenszel; (DerSimonian-Laird) Peto Risk Inverse-variance; Inverse-variance random effects			(30000000000000000000000000000000000000
Peto Risk Inverse-variance; Inverse-variance random effects	 Odds ratio 		
Risk Inverse-variance; Inverse-variance random effects		,	(DerSimonian-Laird)
invoise variance,		***************************************	
omerence Mantel-Haenszel (<u>DerSimonian</u> -Laird)	2 111011		
	difference	Mantel-Haenszel	(DerSimonian-Laird)

Example: the effect of phytoestrogens on menopausal symptoms



Figure 2. Meta-analysis of Randomized Clinical Trials on the Associations Between Use of Phytoestrogen Supplementation and Menopausal Symptoms

	No. of Participants		Change, Mean (95% CI)		Difference, Mean	Favors	Favors	Weight,
Source	Intervention	Control	Intervention	Control	(95% CI) ^b	Intervention	Control	%
No. of Hot Flashes in 24 Hours								
Dietary soy isoflavones								
Lewis et al, ⁴⁷ 2006	33	33	-0.71 (-3.79 to 2.37)	-0.93 (-4.67 to 2.81)	0.22 (-0.62 to 1.06)	-	-	6.0
Cheng et al, ³³ 2007	30	30	-0.80 (-2.47 to 0.87)	0.0 (-1.37 to 1.37)	-0.80 (-1.19 to -0.41)	-		6.50
Albertazzi et al, ²⁶ 1998	51	53	-5.01 NR	-3.42 NR	-1.59 (-1.95 to -1.20)	-		6.5
Van Patten et al, ⁵⁹ 2002	78	79	-1.8 (-7.01 to 3.41)	-2.5 (-10.4 to 5.40)	0.70 (-0.37 to 1.77)	-	-	5.74
Supplements and extracts of s								
Aso et al, ²⁸ 2012	77	83	-1.9 (-5.43 to 1.63)	-1 (-4.92 to 2.92)	-0.90 (-1.49 to -0.31)	-		6.3
Nahas et al, 51 2007	40	40	-6.5 (-11.4 to -1.64)	-4.2 (-10.0 to 1.60)	-2.30 (-3.50 to -1.10)	-		5.5
Faure et al, ³⁹ 2002	39	36	-6.4 (-18.6 to 5.83)	-2.2 (-16.3 to 11.9)	-4.20 (-7.26 to -1.14)			2.93
Penotti et al, 52 2003	28	34	-5.3 (-10.6 to 0.01)	-4.6 (-9.30 to 0.10)	-0.70 (-1.98 to 0.58)	-	┝	5.43
Ferrari et al, 40 2009	85	95	-3.7 (-8.8 to 1.40)	-2.4 (-7.01 to 2.21)	-1.30 (-2.03 to -0.57)	-		6.19
Hachul et al,41 2011	19	19	-4.33 (-6.92 to -1.74)	-4.9 (-7.41 to -2.39)	0.57 (-0.26 to 1.40)		-	6.0
Red clover								
Knight et al,44 1999	13	12	-3.1 (-9.27 to 3.07)	-2.8 (-8.44 to 2.84)	-0.30 (-2.66 to 2.06)			3.79
Baber et al, 30 1999	25	26	-1.18 (-4.98 to 2.62)	-1.77 (-5.26 to 1.72)	0.59 (-0.43 to 1.61)	-	-	5.8
Jeri et al, ⁴³ 2002	30	30	-3.4 (-6.97 to 0.17)	-0.60 (-3.58 to 2.38)	-2.80 (-3.65 to -1.95)			6.0
Atkinson et al, 29 2004	102	103	-0.8 (-4.92 to 3.32)	-1.0 (-4.53 to 2.53)	0.20 (-0.34 to 0.74)	-	-	6.3
Lipovac et al, ²⁴ 2012	50	59	-8.6 (-14.3 to -2.92)	-0.9 (-7.51 to 5.71)	-7.70 (-8.88 to -6.52)			5.5
van de Weijer et al, ⁵⁸ 2002	16	14	-2.08 (-8.14 to 3.98)	0.29 (-11.0 to 11.6)	-2.37 (-5.75 to 1.01)		_	2.6
Tice et al, 56 2003	84	85	-3.4 (-9.20 to 2.40)	-2.8 (-7.05 to 1.45)	-0.60 (-1.38 to 0.18)	-	+	6.1
Other phytoestrogens								
Dánna et al,36 2007	198	191	-2.5 (-8.09 to 3.09)	0.0 (-5.68 to 5.68)	2.50 (-3.07 to -1.93)			6.3
Random effects					-1.31 (-2.02 to -0.61)			100
Fixed effects					-1.12 (-1.29 to -0.95)	♦		
No. of Night Sweats in 24 Hours								
Dietary soy isoflavones								
Cheng et al,33 2007	30	30	-0.60 (-2.21 to 1.01)	-0.20 (-1.63 to 1.23)	-0.40 (-0.79 to -0.01)			50.2
Red clover								
Lipovac et al,24 2012	50	59	-3.9 (-6.84 to -0.96)	0.0 (-3.37 to 3.37)	-3.90 (-4.50 to -3.30)	-		49.7
Random effects					-2.14 (-5.57 to 1.29)		_	100
Fixed effects					-1.44 (-1.77 to -1.11)	♦		
Vaginal Dryness Score						*		
Supplements and extracts of s	ov isoflavones							
Kotsopoulos et al. 46 2000	44	50	-0.35 (-0.59 to -0.11)	-0.15 (-0.35 to 0.05)	-0.20 (-0.24 to -0.16)			60.6
Colacurci et al.34 2004	15	15		-0.08 (-1.16 to 1.00)	-0.46 (-0.83 to -0.09)	-	Ī	20.7
Other phytoestrogens			,,	,,	,,			
Brzezinski et al. 31 1997	78	36	-0.93 (-3.03 to 1.17)	-0.44 (-2.34 to 1.46)	-0.49 (-0.89 to -0.09)			18.6
Random effects			. (2-2/)	. (=== : == =: 10)	-0.31 (-0.51 to -0.10)	_ 0		100
Fixed effects					-0.21 (-0.25 to -0.17)	Y.		

Third:

Follow the statistical analysis plan

When preparing statistical analysis plans, consider how the plan answers the following questions:

- 1. What is the direction and size of the summary association estimate?
- 2. What is the statistical heterogeneity?
- 3. Does a single study drive the overall association estimate?
- 4. What study and study population characteristics influence the size of pooled association estimate?
- 5. Are the results reliable?
- 6. Is there a serious risk from reporting bias, such as publication or selective?

$u^{\scriptscriptstyle b}$



Fourth:

Prepare datasets for meta-analysis

- Convert units for consistency before combining and meta-analyzing.
- Resolve differences in reporting summary statistics, such as measures of central tendency and spread
- Pool multiple intervention groups
- Map adjusted variables

24-STEP GUIDE

Meta-analysis of continuous and binary data

PD Marija Glisic, MD, M.H.S., PhD

Institute of Social and Preventive Medicine (ISPM), University of Bern, Switzerland & Swiss Paraplegic Research, Nottwil

Data needed for meta-analysis



UNIVERSITÄT Bern

Box 1. Information needed to meta-analyze specific association estimates

Association estimates	Extracted information from original studies
Prevalence	Study name (ID)
	Study size
	Number of cases
	Prevalence
	95% confidence interval
Odds ratio	Study name (ID)
Hazards ratio	Number of cases
Relative risk	Number of events in cases
	Number of non-events in cases
	Number of controls
	Number of events in controls
	Number of non-events in controls
Correlation coefficient	Study name (ID)
	Study size
	Correlation coefficient
	95% confidence interval
Beta from regression	Study name (ID)
coefficient	Study size
	Beta coefficient
	95% confidence interval
Mean difference	Study name (ID)
	Number of individuals in group 1
	Mean value in group 1
	Standard deviation of the mean in group 1
	Number of individuals in group 2
	Mean value in group 2
	Standard deviation of the mean in group 2

Continuous Data

- u^{b}
- UNIVERSITÄT BERN

- Weighted mean difference (WMD)
- Standardized mean difference (SMD)

Table S4. Meta-analysis for continuous outcomes using Stata (metan) and R (meta/metacont)

	Stata	R
Data input (for each	Size of group 1 and 2:	n1, n2
study)	Mean effect size in group 1 an	id 2: m1, m2
	Standard deviation of effect in	group 1 and 2: sd1, sd2
Method	Inverse variance weighting	
Assumptions	Normality in effect sizes within	trial arms.
	Between trial variations in star	ndard deviations are attributed to differences in
	precision, and are assumed equal in both	study arms.
Fixed effect estimate	metan n1 mean1 sd1 n2 mean2 sd2, nostandard fixed	metacont (n1, m1, sd1, n2, m2, sd2, comb.fixed=TRUE, comb.random=FALSE, sm="MD", data=dat)
Random effects estimate	metan n1 mean1 sd1 n2 mean2 sd2, nostandard random	Metacont (n1, m1, sd1, n2, m2, sd2, comb.fixed=FALSE, comb.random=TRUE, sm="MD", data=dat)
Random effects estimate, standardized mean differences (Hedges g)	metan n1 mean1 sd1 n2 mean2 sd2, hedges random	<pre>metacont(n1, m1, sd1, n2, m2, sd2, comb.fixed=FALSE, comb.random=TRUE, sm="SMD", method.smd="Hedges", data=dat)</pre>

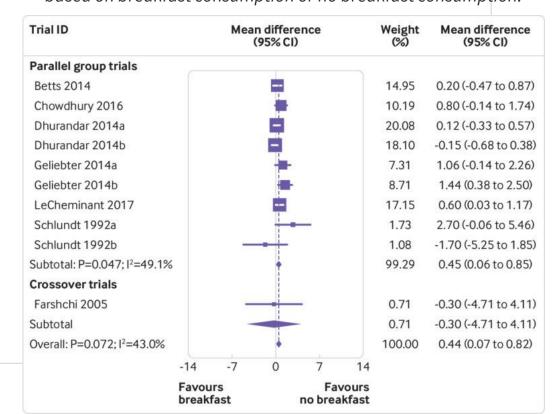
Continuous Data

- Weighted mean difference (WMD)
- Standardized mean difference (SMD)

Random effects meta-analysis of the mean difference in weight (kg), based on breakfast consumption or no breakfast consumption.

 $u^{\scriptscriptstyle b}$

UNIVERSITÄT



$u^{\scriptscriptstyle \mathsf{b}}$

UNIVERSITÄT BERN

Continuous Data

Review: Yoga for Depression: A Meta-Analysis

- Weighted mean difference (WMD)
- Standardized mean difference (SMD)

Depression

	,	Yoga		С	ontrol			Std. Mean Difference	Std. Mean Difference
Comparison / Study	Mean	SD	Total	Mean	SD	Total	Weight	IV, Fixed, 95% CI	IV, Fixed, 95% CI
Yoga vs. Usual Care									
Butler et al. (2008)	14.25	8.99	12	12.9	8.14	11	13.5%	0.15 [-0.67, 0.97]	
Field et al. (2012b)	20.12	10.51	28	19.27	10.12	28	33.0%	0.08 [-0.44, 0.61]	-
Khumar et al. (1993)	57.52	13.49	25	77.92	6.04	25	19.6%	-1.92 [-2.60, -1.24]	
Sahidi et al. (2011)	10	6.9	20	15.2	6.1	20	21.7%	-0.78 [-1.43, -0.14]	
Woolery et al. (2004)	3.9	4.66	13	11	4.32	15	12.2%	-1.54 [-2.40, -0.68]	
Subtotal (95% CI)			98			99	100.0%	-0.69 [-0.99, -0.39]	•
Heterogeneity: Chi ² = 2	28.81, 0	df = 4 (P < 0.0	0001);	l ² = 86	6%			
Test for overall effect:	Z = 4.4	8 (P <	0.0000	1)					
Yoga vs. Relaxation									
Lavretsky et al. (2012)	-7.4	3.7	23	-5.3	4.5	16	39.4%	-0.51 [-1.16, 0.14]	-
Rohini et al. (2000)	11.1	5.2	15	15.6	7.7	15	30.5%	-0.67 [-1.40, 0.07]	-
Sharma et al. (2005)	8.27	4.37	15	11.53	4.26	15	30.1%	-0.74 [-1.48, 0.01]	_
Subtotal (95% CI)			53			46	100.0%	-0.62 [-1.03, -0.22]	•
Heterogeneity: Chi ² = (0.22, df	= 2 (P	= 0.90); ² = (0%				
Test for overall effect:	Z = 3.0	1 (P =	0.003)						
Yoga vs. Aerobic Exe	ercise								
Sahidi et al. (2011)	10	6.9	20	11.1	6.2	20	42.3%	-0.16 [-0.79, 0.46]	
Veale et al. (1992)	13.31	1.86	22	14.96	1.8	46	57.7%	-0.90 [-1.43, -0.37]	
Subtotal (95% CI)			42			66	100.0%	-0.59 [-0.99, -0.18]	•
Heterogeneity: Chi ² = 3	3.08, df	= 1 (P	= 0.08); l² = 6	88%				-
Test for overall effect:	Z = 2.8	5 (P =	0.004)						
		,	,						
Test for subgroup diffe	rences	: Chi² =	0.17,	df = 2 (P = 0.	92), I²	= 0%		
									-2 -1 0 1 2 Favours yoga Favours cont

11

Binary Data

- $u^{^{\scriptscriptstyle b}}$
- UNIVERSITÄT BERN

- Proportion and prevalence
- Risk ratio
- Odds ratio
- Relative risk
- Hazard ratio
- Risk differences

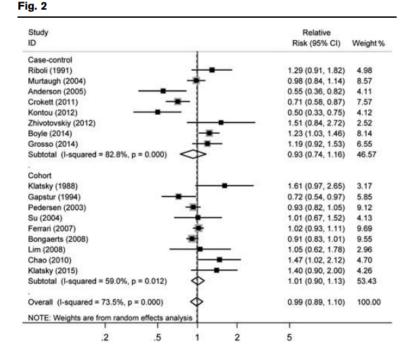
Table S3. Overview on effect sized measures for dichotomous data, with normalizing transformation and example codes in Stata (metan) and R (meta/metacont)

	Risk ratio	Odds ratio	Risk difference
Effect size	Ratio of the probability of	Ratio of the odds of the	Difference in risks of an
Where:	an event of both arms:	event in one arm to the	event of both arms:
Ptreat, Pcontr; Probability		odds of the event in the	
of event in treatment		other arm:	
and control arm			
n1, n2: number of	ES=Ptreat/Pcontr	ES= OddStreat/OddScontr	ES=Ptreat - Pcontr
events in treatment	=(n1/N1) / (n2/N2)	= A*D / B*C	=(n1/N1) - (n2/N2)
and control arm			
N1, N2: sample size in			
treatment and control			
arm			
For the odds ratio			
notation we use:			
n1=A; N1-n1=B;			
n2=C; N2-n2=D			
Interpretation	Risk ratio of 1 means that	Odds ratio of 1 means that	Risk difference of 0 means
	the risk is the same in	the odds is the same in	that the risk is the same in
	both arms, indicating no	both arms, indicating no	both arms, indicating no
	effect, while a risk ratio	effect, while a odds ratio	effect, while a negative of
	less or greater than 1	less or greater than 1	positive risk difference
	would mean that the risk	would mean that the odds	would mean that the risk
	was relatively lower or	was relatively lower or	was relatively lower or
	higher in one or the other	higher in one or the other	higher in one or the other
	arm, respectively	arm, respectively	arm, respectively
Usage	Used in prospective	Commonly used as output	Less common than risk
	studies (cohort studies).	of logistic regression	ratio or odds ratio, but
	Cannot be used in	analyses	better understandable
	retrospective (case		
	control) studies		
Transformation	TES= <u>log(</u> ES)	TES=log(ES)	TES=ES
			(no transformation
I	1		needed)

Binary Data

- - UNIVERSITÄT BERN

- Proportion and prevalence
- Risk ratio
- Odds ratio
- Relative risk
- Hazard ratio
- Risk differences



Meta-analysis of wine consumption and the risk of colorectal cancer for any drinkers versus nondrinkers. Cl, confidence interval.

Binary Data



UNIVERSITÄT BERN

- Fixed-effect methods (Mantel-Haenszel, Peto and inverse variance)
- Random-effects method (DerSimonian and Laird inverse variance).

- Double- and single-zero studies
- Continuity correction
- Generalized linear mixed models
- Beta-binomial regression

metan package in Stata and the metabin command from the meta library in R correct by these by default

Can we combine continuous and binary data?

Chinn et al. 2000

$$SMD = \frac{\sqrt{3}}{\pi} lnOR.$$

- SE of the log odds ratio can be converted to the standard error of a SMD by multiplying by the constant of 0.5513
- SMDs can be re-expressed as log odds ratios by multiplying by $\pi/\sqrt{3}=1.814$.
- Once SMDs (or log odds ratios) and their standard errors have been computed for all studies in the meta-analysis, they can be combined using the generic inverse-variance method.

A Hands-On Guide by Peter

