

The logic of generalization: From systematic reviews and meta-analyses to diverse policy and practice contexts

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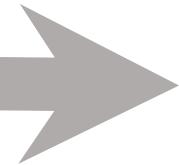
Introduction

- **Central questions:** Can we use results of systematic reviews and meta-analyses (SRMAs) to make inferences about wider policy/practice contexts?
- Focus on SRMAs of research on *intervention effects*
- **Generalizability**, external validity: extrapolation beyond the data at hand (Shadish, Cook, & Campbell, 2002)
 - To what Populations/Problems, Interventions, Comparisons, Outcomes, Times, and Settings (PICOTS) are results of our SRMA likely to apply?
- **Applicability:** relevance for specific target context(s)
 - From a policymaker's or practitioner's viewpoint: What are the likely effects of this intervention in my context (with my PICOTS)?

Generalization: From one set of multi-attribute contexts to others



Study designs, participants, interventions, comparisons, outcome measures, endpoints



Generalizing from... versus applying to...



Generalizing from SRMA results ...



Which PICOTS?

Which (if any)
SRMA results?

... apply to specific context(s)



Known PICOTS

Generalizability assessment

- How do/can we assess the generalizability/applicability of results of a SRMA?
 - Is generalizability assessment a thing?
- Parallel to **evaluability assessment**, a process used to determine whether/when interventions are ready for rigorous outcome/impact evaluation (Rossi et al., 2019).
 - Pre-requisites:
 - Logic model or theory of change
 - Descriptive data on participants, intervention processes, outcomes
 - Running smoothly for at least one year
 - “Proud”

Generalizability assessment - 2

- Developing generalizability assessments -- by muddling through
 - **Two case studies:** SRMAs of effects of two “evidence-based” programs
 - **Three frameworks for generalization**
 1. Probability theory and sampling methods
 2. Principles of generalized causal inference (Shadish, Cook, & Campbell, 2002)
 3. Common rubrics and rhetoric of generalization

Two case studies: SRMAs of effects of...

- Multisystemic Therapy (MST) (Littell, Pigott, et al., 2021)
- Functional Family Therapy (FFT) (Littell, Pigott, et al., 2023)
- Prominent, “evidence-based” psychosocial treatments
 - For families of youth with social, emotional, and/or behavioral (SEB) problems
 - Short-term (3-6 months), home- and community-based treatment
 - Use techniques from various cognitive-behavioral and family therapies
 - Involve social networks and social service systems
 - “Branded interventions” require training and licensing by companies (LLCs) founded by program developers
 - Strong assumptions about “proven effectiveness” and generalizability

Generalizability claims

Multisystemic Therapy (MST)

- Effectiveness of MST has been demonstrated “across **problems, therapists, and settings**... [showing] that the treatment and methods of decision making can be extended and that treatment effects are reliable” (Kazdin & Weisz, 1998, p. 28).
- “MST is superior in reducing [**outcomes**] delinquency, drug use, and emotional and behavioral problems and increasing school attendance and family functioning, in **comparison to [a variety of] other procedures**, including ‘usual services,’...individual counseling, and community-based eclectic treatment” (Kazdin, 2015, p. 150).

Functional Family Therapy (FFT)

- FFT outcome studies demonstrate effectiveness “with a wide variety of adolescent related **problems** including youth violence, drug abuse, and other delinquency related behaviors. The positive outcomes of FFT remain relatively stable [over **time**] even after a five-year follow-up” (Sexton & Turner, 2010, p. 339).
- FFT is said to be effective across presenting problems, **populations** (gender, race/ethnicity), and **outcome measures** (Robbins, Alexander, Turner, & Hollimon, 2016).
- Kazdin (1998) claimed that FFT is more effective than “**various control conditions**” including family groups, youth groups, family therapy, and no treatment controls.

Generalizability assessment

- Do *sampling* methods (or sample representativeness) support broader generalizations?
- What is our *confidence* in pooled estimates? (pre-requisite for generalization)
- What can we learn about generalizability of effects from *heterogeneity, subgroup, and/or moderator* analysis? (to inform the following)
- Application of *principles of generalized causal inference* (Shadish, Cook, & Campbell, 2002)

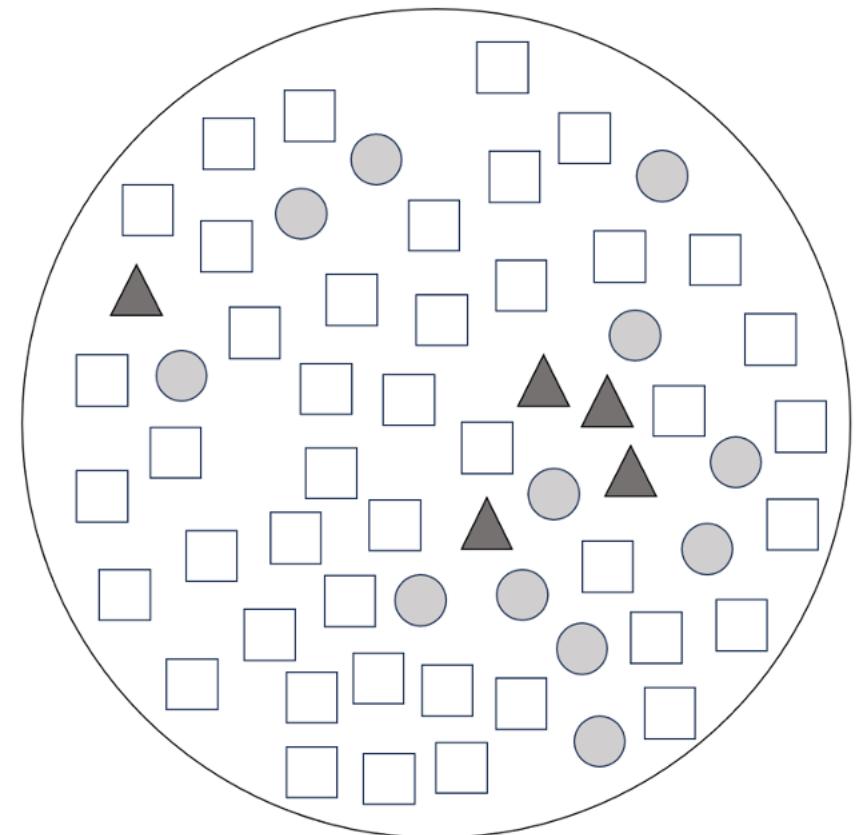
Probability theory and sampling methods

- Probability samples are the “gold standard” for generalizing from sample data to a larger population
 - Support use of inferential statistics to estimate population parameters.
- Types of **studies** often included in SRMAs of intervention effects—i.e., randomized controlled trials (RCTs) and quasi-experimental designs (QEDs) **rarely use probability samples**.
- **SRMAs themselves do not use probability samples of studies** from some larger population of studies.

Sampling problem

Consider a hypothetical universe of all relevant interventions

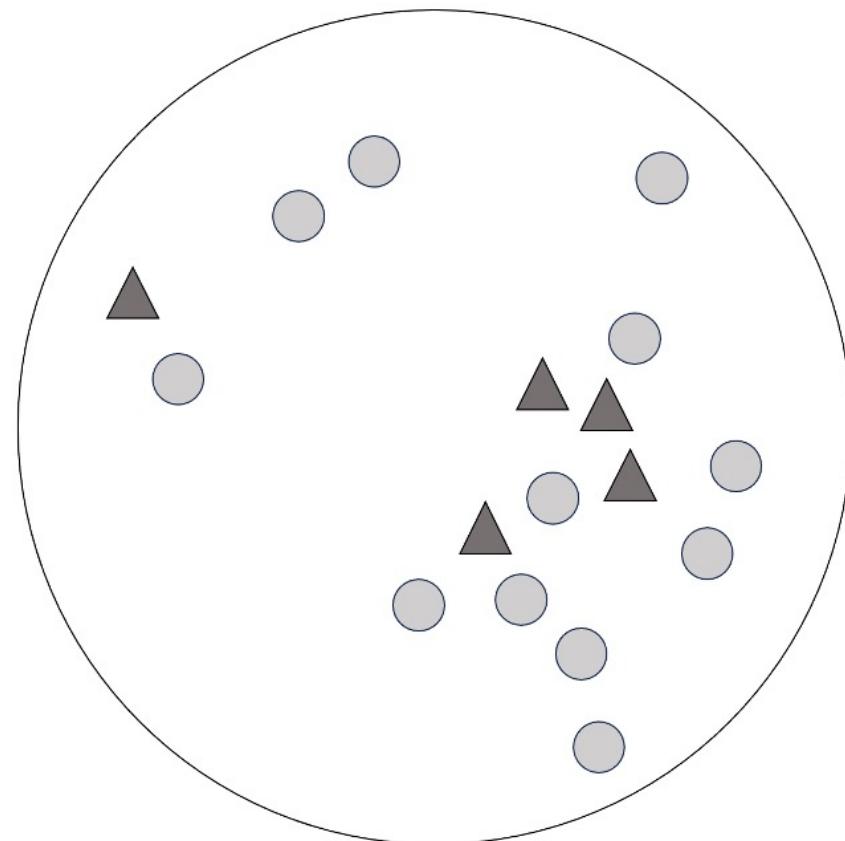
- Many have no impact evaluations
- Some are evaluated with QEDs
- Few are evaluated with RCTs



Sample of studies for SRMA

A sample of available impact evaluations (RCTs and QEDs)

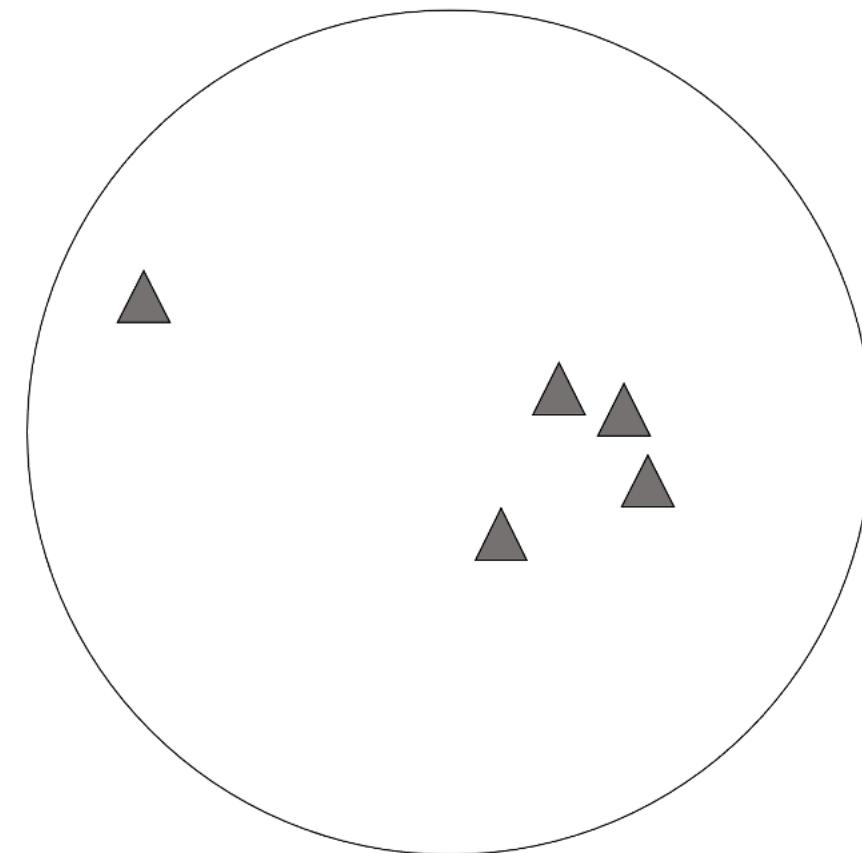
Programs that have been evaluated are not a representative sample of all relevant programs.



Sample of studies for SRMA

A sample of available RCTs.

Programs evaluated with RCTs are not representative of all programs that have been evaluated.



Licensed MST programs and completed trials

- 558 MST programs in 15 countries
- 23 MST trials in 6 countries
- Most in the USA
- Some countries not represented at all

Country/State	Licensed MST programs ^a		MST <u>trials</u> ^b	
	N	Column %	k	Column %
Australia	17	3.0		
Belgium	1	0.2		
Canada	2	0.4	1	4.3
Chile	1	0.2		
England	6	1.1	3	13.0
France	1	0.2		
Germany	2	0.4		
Iceland	3	0.5		
Ireland	3	0.5		
Netherlands	41	7.3	1	4.3
New Zealand	8	1.4		
Norway	24	4.3	1	4.3
Sweden	6	1.1	1	4.3
Switzerland	3	0.5		
USA	440	78.9	16	69.6
Total	558		23	

(Continued)

Licensed MST programs and completed trials: USA

- 440 MST programs in 34 U.S. states
- 16 MST trials in 7 states

USA states	N	Column %	k	Column %
Delaware	2	0.5	1	6.3
Hawaii	6	1.4	1	6.3
Illinois	6	1.4	1	6.3
Missouri	1	0.2	4	25.0
Ohio	11	2.5	1	6.3
South Carolina	3	0.7	6	37.6
Tennessee	8	1.8	2	12.5
27 other states	403	91.6	0	
Remaining 16 states	0		NA	
Subtotal	440		16	

^a Licensed MST organizations not including adaptations of MST which target different populations and/or include services other than MST (49 programs). Accessed August 27, 2023 at: <https://www.mstservices.com/licensed-organizations>

^b Randomized controlled trials of licensed MST programs for social, emotional, and behavioral problems among youth ages 10-17, as of April 2020 (Littell et al., 2021).

Licensed MST programs and completed trials: USA

- 2 states contain
- < 1% of MST programs in USA
 - 63% of MST trials in USA
 - 43% of all MST trials in the world

USA states	N	Column %	k	Column %
Delaware	2	0.5	1	6.3
Hawaii	6	1.4	1	6.3
Illinois	6	1.4	1	6.3
Missouri	1	0.2	4	25.0
Ohio	11	2.5	1	6.3
South Carolina	3	0.7	6	37.6
Tennessee	8	1.8	2	12.5
27 other states	403	91.6	0	
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Licensed FFT programs and completed trials

- 334 FFT programs in 12 countries
- 20 FFT evaluations in 6 countries
- Most in the USA:
- 275 programs in 38 states + DC
- 15 evaluations in 8 states

Country/State	Licensed FFT programs ^a		FFT RCTs/QEDs ^b	
	N	Column %	k	Column %
Australia	21	6.3		
Canada	2	0.6		
Denmark	8	2.4		
England	9	2.7	1	5.0
Ireland ^c	1	0.3	1	5.0
Netherlands	3	0.9	1	5.0
New Zealand	6	1.8		
Norway		0.0	1	5.0
Sweden		0.0	1	5.0
Scotland	7	2.1		
Singapore	2	0.6		
USA ^d	275	82.3	15	75.0
Total	334		20	
USA states				
Florida	16	5.8	1	6.7
Indiana	2	0.7	3	20.0
New Jersey	2	0.7	1	6.7
New Mexico ^d	1	0.4	6	40.0
Pennsylvania	15	5.5	1	6.7
Utah	2	0.7	1	6.7
Washington	12	4.4	1	6.7
31 states plus DC	225	81.8	1	6.7
Remaining 12 states	0		NA	
Subtotal	275		15	

^a Licensed FFT programs; accessed on August 27, 2023 at: <https://www.fftllc.com/sites> and <https://functionalfamilytherapy.com/sites>

^b Randomized controlled trials (RCTs) and quasi-experimental designs (QEDs) of FFT for behavior problems among youth ages 11-18 as of August 2020, not including 5 studies that provided no usable data.

^c Includes 1 study that provided no usable data.

^d Includes 4 studies conducted in New Mexico that provided no usable data.

Licensed FFT programs and completed trials

2 states contain

- ~ 1% of FFT programs in USA
- 60% of FFT evaluations in USA
- 45% of FFT evaluations in the world

Country/State	Licensed FFT programs ^a		FFT RCTs/QEDs ^b	
	N	Column %	k	Column %
Australia	21	6.3		
Canada	2	0.6		
Denmark	8	2.4		
England	9	2.7	1	5.0
Ireland ^c	1	0.3	1	5.0
Netherlands	3	0.9	1	5.0
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USA states				
Florida	16	5.8	1	6.7
Indiana	2	0.7	3	20.0
New Jersey	2		1	
New Mexico ^d	1	0.4	6	40.0
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Generalizability assessment

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Do sampling methods (or sample representativeness) support broader generalizations?

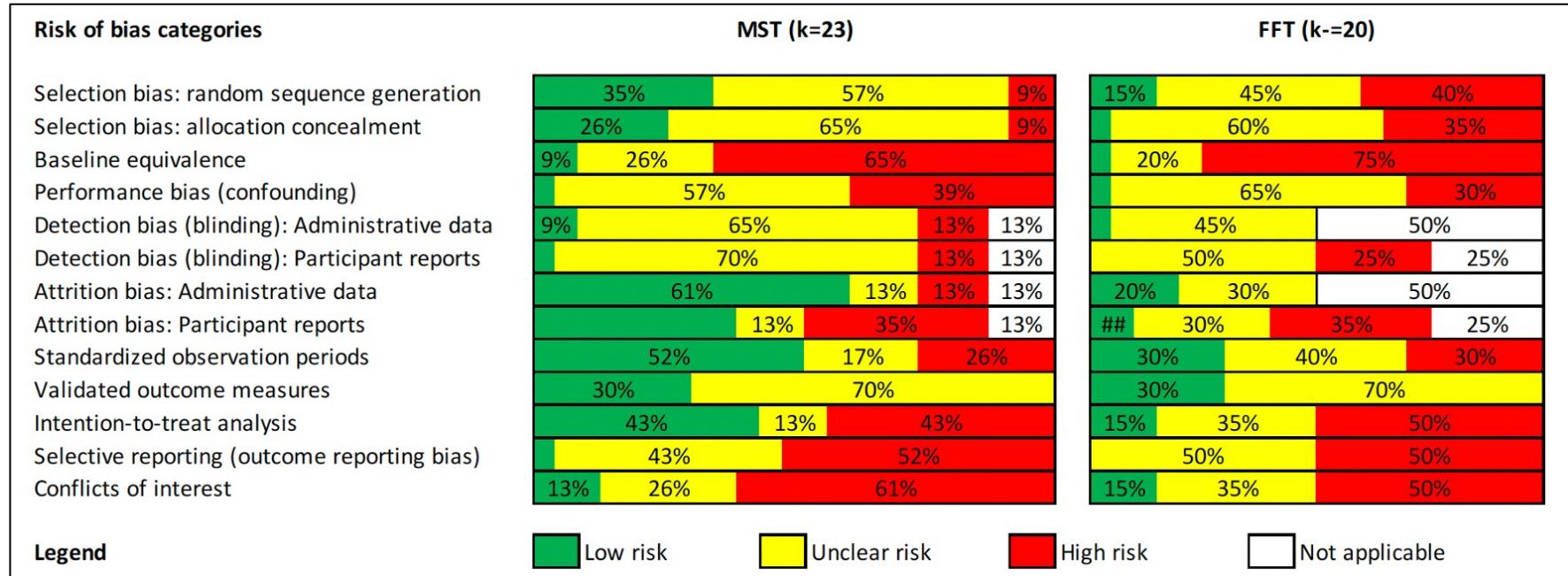
No.

- Probability theory provides no basis for generalization from results of SRMAs based on
 - Nonprobability samples of studies
 - Studies that relied on nonprobability samples of participants
- Analysis suggests that available studies are not representative of MST/FFT programs in the countries or states in which they have been implemented.

Generalizability assessment

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Confidence in results: Risk of bias ratings



- High risks of bias in > 50% of studies on: baseline equivalence, selective reporting of outcomes, conflicts of interest.
- 96% of MST trials and 100% of FFT impact evaluations have high risks of bias on at least one indicator.

Sources: Littell et al., (2021, 2023)

Consistency (PIs) and coverage (sparse data)

Results of correlated effects meta-analysis (Pustejovsky & Tipton, 2022)

Relative effects on outcomes (SMD)	MST (k=23)				FFT (k=20)			
	95% PI		Valid k		95% PI		Valid k	
	LB	UB	k	%	LB	UB	k	%
Out of home placement	-0.72	0.17	17	74%			4	20%
Arrest or conviction	-0.55	0.26	18	78%	-0.39	0.76	8	40%
Delinquency	-1.31	0.77	14	61%			5	25%
Substance abuse	-1.35	1.20	9	39%			4	20%
Peer relations	-1.53	1.91	13	57%			3	15%
Youth behavior/symptom	-1.52	1.26	20	87%	-0.24	0.18	7	35%
Parent behavior/symptom	-0.77	0.45	16	70%			5	25%
Family functioning	-1.08	1.27	15	65%			5	25%
School	-1.92	2.55	8	35%			1	5%
All outcomes combined					-0.37	0.75	15	75%

Prediction intervals (PI) suggest that future studies are likely to find a wide range of positive and negative results

Sources: Littell et al., (2021, 2023)

Confidence in results: GRADE ratings

- **MST:** GRADE ratings of the certainty of evidence for the primary outcomes were ***moderate to low***,
 - meaning that further research is likely to affect confidence in estimates of effects and may change those estimates (Littell et al., 2021).
- **FFT:** GRADE ratings of the certainty of evidence were ***very low*** for all six primary outcomes,
 - meaning that any estimate of effects based on available data is very uncertain (PI for overall -0.37 to 0.75; Littell et al., 2023).
 - **Lacking confidence in evidence for FFT, we conclude that results are not generalizable** beyond the studies in the review.
- Generalizability assessment proceeds, based on the MST case study alone.

Generalizability assessment

- Do *sampling* methods (or sample representativeness) support broader generalizations?
- What is our *confidence* in pooled estimates? (pre-requisite for generalization)
- **What can we learn about generalizability of effects from *heterogeneity, subgroup, and/or moderator analysis?* (to inform the following)**
- Application of *principles of generalized causal inference* (Shadish, Cook, & Campbell, 2002)

Potential sources of heterogeneity (MST)

Effects sizes tend to be larger in studies...

- conducted in the USA vs other countries,
- by MST program developers vs independent teams,
- with higher risks of bias.

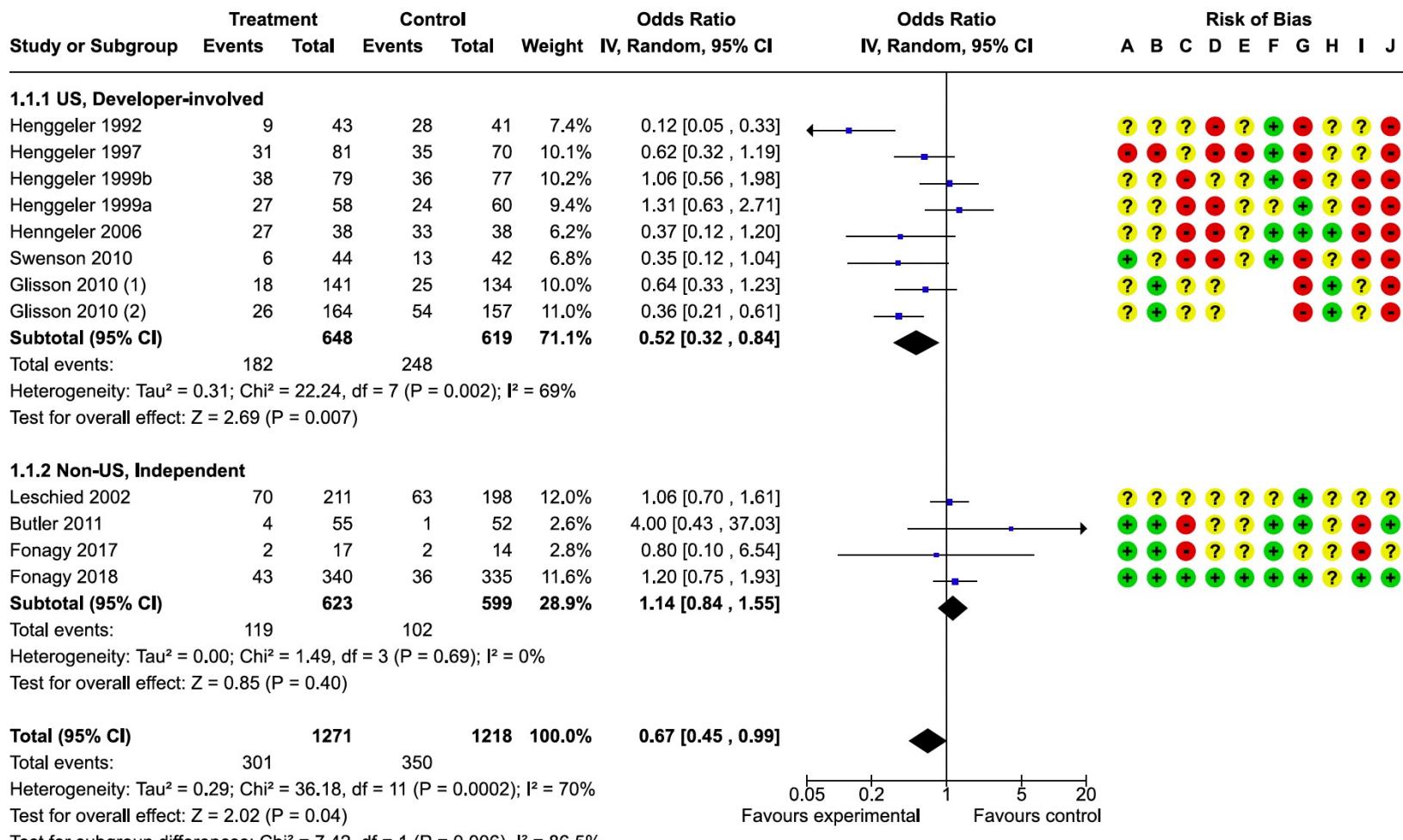
These three moderators are highly confounded

Studies conducted by MST developers are largely in the USA and have relatively high risks of bias.

Not possible to *explain* observed differences in effects between subgroups formed by these moderator variables.

MST effects on out-of-home placements at one year: US developers vs Non-US independents

Comparison 1: Out-of-home placement, Outcome 1: Out-of-home placement, 1 year



Contextual differences in effects: Base rates in control groups

Outcome @ one year	Overall RD	USA		Non-USA			
		MST	Control	RD	MST	Control	RD
Arrest or conviction	-3%	40%	49%	-9%	25%	27%	-2%
Out-of-home placement of youth	-5% *	28%	40%	-12% **	19%	17%	+2%

The diagram consists of two horizontal red arrows. The top arrow originates from the 'Control' value of 49% in the USA MST column and points to the 'Control' value of 27% in the Non-USA MST column. The bottom arrow originates from the 'Control' value of 40% in the USA Control column and points to the 'Control' value of 17% in the Non-USA Control column.

RD = risk difference, * p <0.05, ** p<0.01

Source: Littell, Pigott, et al. (2021)

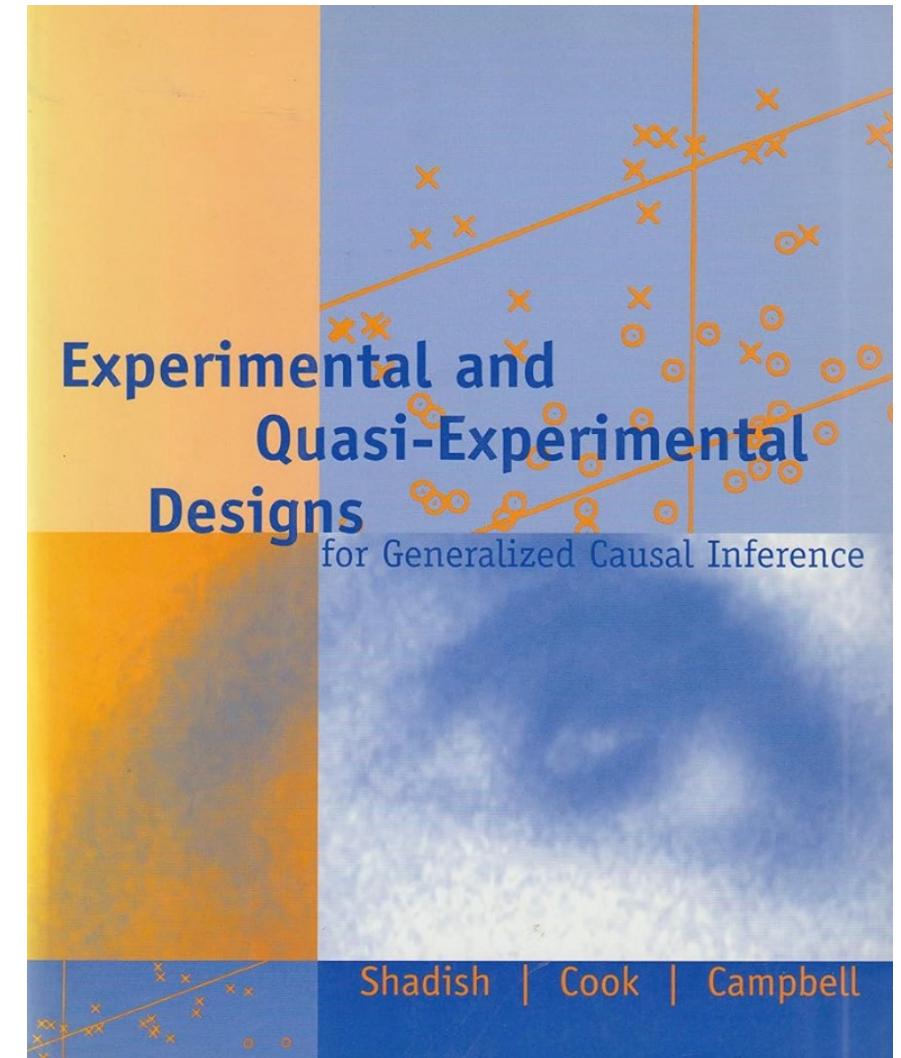
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- **Application of *principles of generalized causal inference* (Shadish, Cook, & Campbell, 2002)**

Principles for generalized causal inference

(Shadish, Cook, & Campbell, 2002)

- Validity is a property of knowledge claims (inferences based on data),
 - not a property of research methods.
- External validity is a property of certain inferences (extrapolation),
 - not a property of probability sampling methods.
- Logic of generalization: a conceptual problem, with empirical referents.



The logic of generalization: A conceptual problem with empirical referents

How can we transfer knowledge developed in

- one set of multi-attribute contexts (studies) to
 - other sets of multi-attribute contexts (targets for generalization)?
-
- “[W]e need something more appropriate than the generalization rhetoric and the solution of it by representative sampling from a universe designated in advance... In this shift, the validity of theoretical interpretation replaces atheoretical generalization...” (Campbell, 1986, p. 73).

Principles for generalized causal inference (Shadish, Cook, & Campbell, 2002)

- 1) Proximal similarity (or surface similarity)
- 2) Ruling out irrelevancies
- 3) Making discriminations
- 4) Interpolation and extrapolation
- 5) Causal explanation

1) Proximal (or surface) similarity

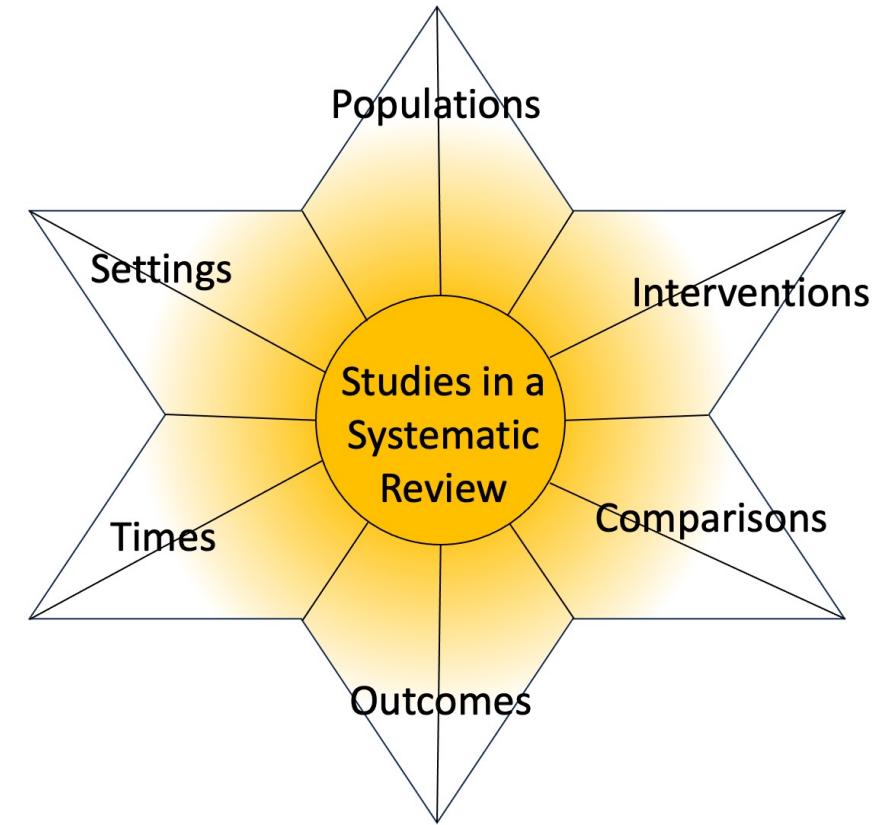
“We generalize most confidently **to applications** where treatments, settings, populations, outcomes, and times are **most similar** to those in the original research” (Shadish, 1995; emphasis added).



Which gradients of similarity are most salient?

PICOTS gradients of similarity:

Populations
Interventions
Comparisons
Outcomes
Times
Settings
Other gradients?



What variables/factors should define each gradient?

N-dimensional comparison space, where N=number of variables/factors on salient gradients

Gradients of similarity for MST?

PICOS gradients of similarity for MST

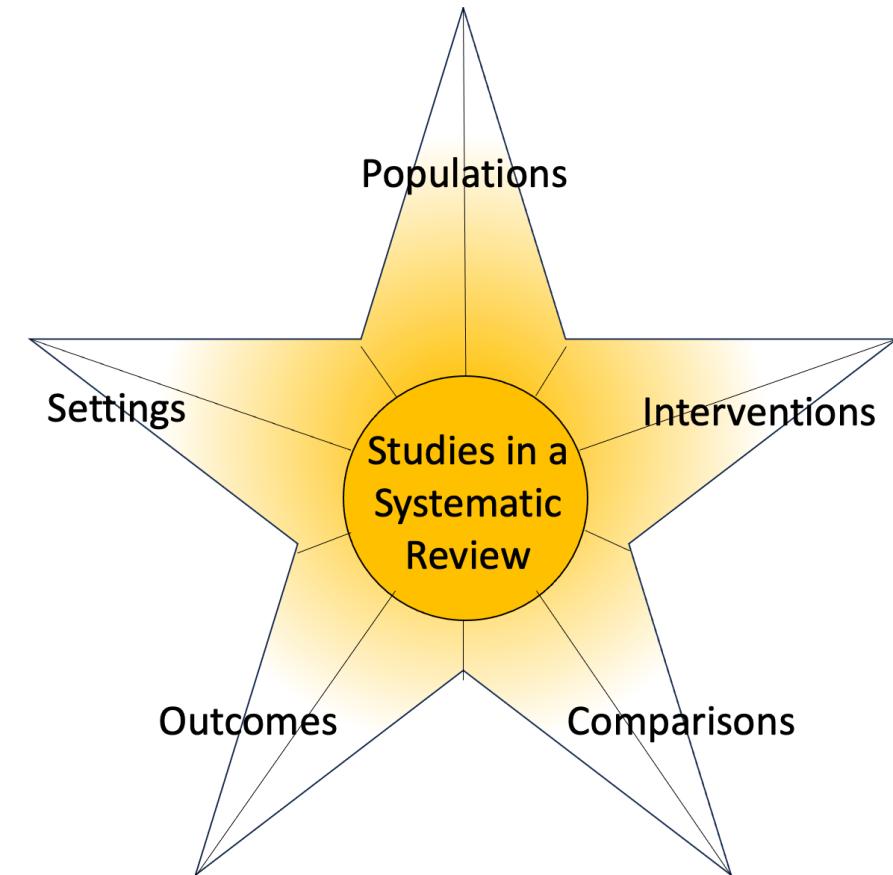
Populations: families of youth with SEB problems

Interventions: short-term, home & community services

Comparisons: varied amounts & types of services

Outcomes: depends on stakeholder goals

Settings: WEIRD countries



WEIRD = Western, Educated, Industrialized, Rich, Democratic

What do we know about these gradients? Study data

- Descriptive data are often not comparable across studies
 - e.g., diverse measures of SES/household income/poverty status; household composition
- Comparable data are superficial or sparse
 - treatment duration, amount
 - participants age, gender, race
- Uneven measurement of outcomes across studies (valid k ranges from 8 to 20 /23)

Descriptive data	MST (k=23)			
	Min	Max	Valid k	(%)
Treatments				
Mean duration (days)	94	231	17	74%
Mean hours of direct contact	21	92	8	35%
Comparisons				
Mean duration (days)	83	380	6	26%
Mean hours of direct contact	23	76	3	13%
Treatment as usual			20	87%
Other active treatments			3	13%
Settings				
USA			16	70%
Other countries			7	30%
Developers' studies			13	57%
Mix of urban, suburban, rural locations			12	52%
Participants				
Mean age (focal youth)	13.4	16.0	22	96%
% male	44%	100%	23	100%
% White	10%	95%	21	91%
% Black	7%	81%	19	83%
Times				
Year enrollment began	1983	2014	17	74%
Relative effects on outcomes (SMD)		95% PI	Valid k	
Out of home placement	-0.72	0.17	17	74%
Arrest or conviction	-0.55	0.26	18	78%
Delinquency	-1.31	0.77	14	61%
Substance abuse	-1.35	1.20	9	39%
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Parent behavior/symptoms	-0.77	0.45	16	70%
Family functioning	-1.08	1.27	15	65%
School	-1.92	2.55	8	35%

Proximal similarity is necessary but insufficient for generalized causal inferences (Shadish et al., 2002)

“Perhaps the principle of proximal similarity merely describes the route to theory-based generalization...” (Campbell, 1986, p. 73).

Need other principles to flesh out generalizability assessment...

2) Ruling out irrelevancies

“We generalize most confidently when a research finding **continues to hold over variations** in persons, settings, treatments, outcome measures, and times that are **presumed to be conceptually irrelevant**” (Shadish, 1995; emphasis added).

Which variations are thought to be conceptually irrelevant?

MST claims that no PICOTS are irrelevant, effects are robust across all PICOTS variations.

- SRMA refutes these claims, by showing that results are inconsistent within and across studies and
- Inconsistent across PICOTS.

3) Making discriminations (Discriminant validity)

“We generalize most confidently when we can show that it is **the target construct**, and not something else, that is necessary to producing a research finding” (Shadish, 1995; emphasis added).

Obstacles:

- MST treatment is confounded with other variables that might account for effects
 - MST cases received more time and attention than control cases
 - MST therapists received more training and supervision than workers who provided services to control cases (Littell, Pigott, et al., 2021).
- MST fidelity measures are confounded with other variables known to predict positive outcomes (therapeutic alliance, client satisfaction, client engagement, early outcomes) and have not been shown to discriminate between MST and other treatments.

4) Interpolation and extrapolation

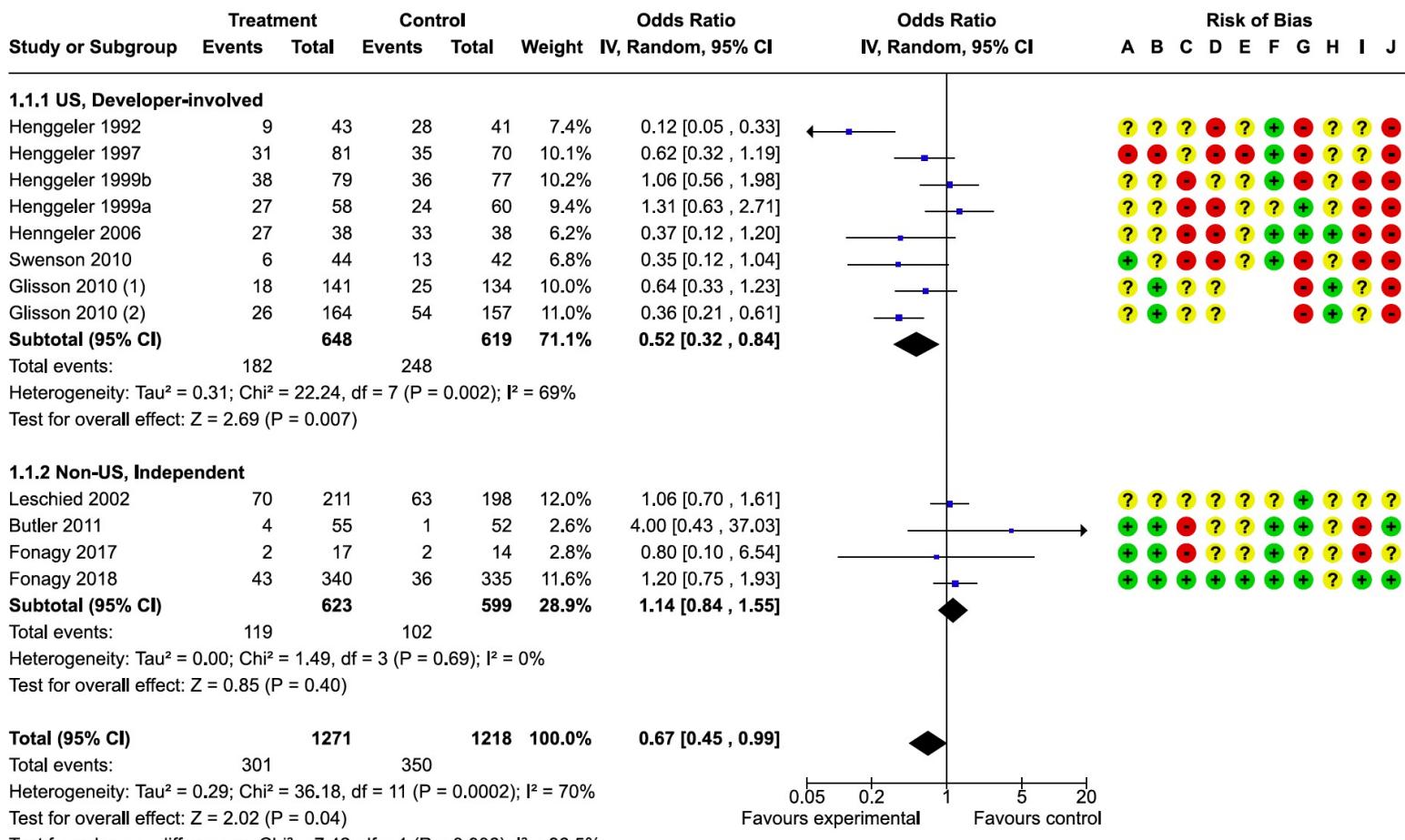
“We generalize most confidently when we can **specify the range** of persons, settings, treatments, outcomes, and times over which the **finding holds more strongly, less strongly, or not at all**” (Shadish, 1995).

Obstacles:

- Moderators of effects of MST (USA/other, control conditions, risks of bias, developers/others) are confounded and
- There are unexplained variations within subgroups (Littell, Pigott, et al., 2021).

MST effects on out-of-home placements at one year: US developers vs Non-US independents

Comparison 1: Out-of-home placement, Outcome 1: Out-of-home placement, 1 year



5) Causal explanation

“We generalize most confidently when we can **specify completely and exactly** (a) which parts of one variable (b) are related to which parts of another variable (c) through which mediating processes (d) with which salient interactions, for then we can transfer only those essential components to the new application to which we wish to generalize”
(Shadish, 1995).

Obstacle: MST theory of change is under-developed, does not fully explain hypothesized effects of treatment, or account for actual (inconsistent) results of studies and SRMAs.

Generalizability assessment

- Do *sampling* methods (or sample representativeness) support broader generalizations?
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- What can we learn about generalizability of effects from *heterogeneity, subgroup, and/or moderator* analysis? (to inform the following)
- Application of *principles of generalized causal inference* (Shadish, Cook, & Campbell, 2002)

Summary: MST generalizability assessment

Criteria	Support for generalized causal inferences	
	Rating	Reasons/Support
Probability/representative sampling	None	Samples are not representative of countries or states with MST programs; MST developer-led studies are over-represented.
Certainty of evidence	Moderate/Low	Risk of bias and GRADE ratings.
Proximal similarity	Unclear	Insufficient descriptive data.
Ruling out irrelevancies	None	Results are inconsistent within and across: studies, USA vs other countries, developers/other investigators, outcome measures, endpoints.
Discriminant validity	None	MST is confounded with amount of service provided (time and attention), worker training and supervision; MST fidelity measures lack face validity, content validity, and discriminant validity.
Interpolation, extrapolation	Unclear	Confounded moderators and unexplained variations within subgroups.
Causal explanation	None	MST theory of change is under-developed, does not fully explain hypothesized effects of treatment, or empirical results of studies and SRMAs.

Summary: FFT generalizability assessment

Criteria	Support for generalized causal inferences	
	Rating	Reasons
Probability/representative sampling	None	Samples are not representative of countries and states with MST programs; developer-led studies are over-represented.
Certainty of evidence	Very Low	Risk of bias and GRADE ratings.
Proximal similarity		Insufficient data
Ruling out irrelevancies		Insufficient data
Discriminant validity		Insufficient data
Interpolation, extrapolation		Insufficient data
Causal explanation		Insufficient data

Generalizability assessment suggests

- Results of MST and FFT are **not widely generalizable**.
- Need better primary studies (with lower risks of bias) that control for factors confounded with treatment (time, attention, training, supervision).
- **Application** of MST results to specific contexts *might* be possible
 - Begin with knowledge of relevant PICOS in local context
 - Identify MST trials most similar to target context(s)
 - Assess credibility of estimates produced by these trials (risk of bias, GRADE)
 - Re-analysis of SRMA data if necessary/possible to estimate likely effects based on selected subgroup of studies (see Shackleford et al., 2021, on dynamic meta-analysis)
 - Obstacle: little statistical power for subgroups analysis in MST review

Common rubrics and rhetoric re: generalization

Use of the **mean effect size**--or a **rating** based on mean ES--as the best available estimate of likely effects.

Often presented without confidence intervals or prediction intervals.



YOUTH ENDOWMENT FUND

WHAT WORKS TO PREVENT VIOLENCE?

YEF Toolkit

A free online resource to help you put evidence of what works to prevent serious violence into action.

VISIT THE TOOLKIT →

About the Toolkit →

<https://youthendowmentfund.org.uk/toolkit/>

Search				
EVIDENCE QUALITY	IMPACT	COST	EVIDENCE QUALITY	ESTIMATED IMPACT ON VIOLENT CRIME
				Moderate
<input type="checkbox"/> Hide approaches with 'Insufficient evidence of impact'				
ADVANCED FILTERS				
THEMES				
PREVENTION TYPES				
SETTINGS				
OUTCOMES				
Mentoring Mentors provide children and young people with guidance and support.		COST £ £ £	EVIDENCE QUALITY 	ESTIMATED IMPACT ON VIOLENT CRIME MODERATE
Multi-Systemic Therapy A family therapy programme for children at risk of placement in either care or custody		COST £ £ £	EVIDENCE QUALITY 	ESTIMATED IMPACT ON VIOLENT CRIME MODERATE
OTHER OUTCOMES Non-US studies suggest that MST is likely to have a low impact on violent crime.				
Parenting programmes Programmes which help parents and their children to develop positive behaviours and relationships.		COST £ £ £	EVIDENCE QUALITY 	ESTIMATED IMPACT ON VIOLENT CRIME LOW
OTHER OUTCOMES HIGH reduction in Behavioural difficulties				
Police in schools Police officers working in schools to prevent crime and violence		COST ?	EVIDENCE QUALITY 	INSUFFICIENT EVIDENCE OF IMPACT ?
Pre-court diversion Diverting children who have committed first-time or low level offences away from the formal youth justice system		COST £ £ £	EVIDENCE QUALITY 	ESTIMATED IMPACT ON VIOLENT CRIME MODERATE

What is “moderate impact”? (in YEF Toolkit)

“The review estimates that MST reduces... offending by 17%.”

<https://youthendowmentfund.org.uk/toolkit/multi-systemic-therapy-2/>

- Estimate derived from our meta-analysis of data on arrests/convictions at one year (Littell, Pigott, et al., 2021).
- Incorrect. The overall risk difference is 3% and it is not statistically different from zero ($p>.05$), but this is not mentioned.
- No confidence interval (or prediction interval) is provided.

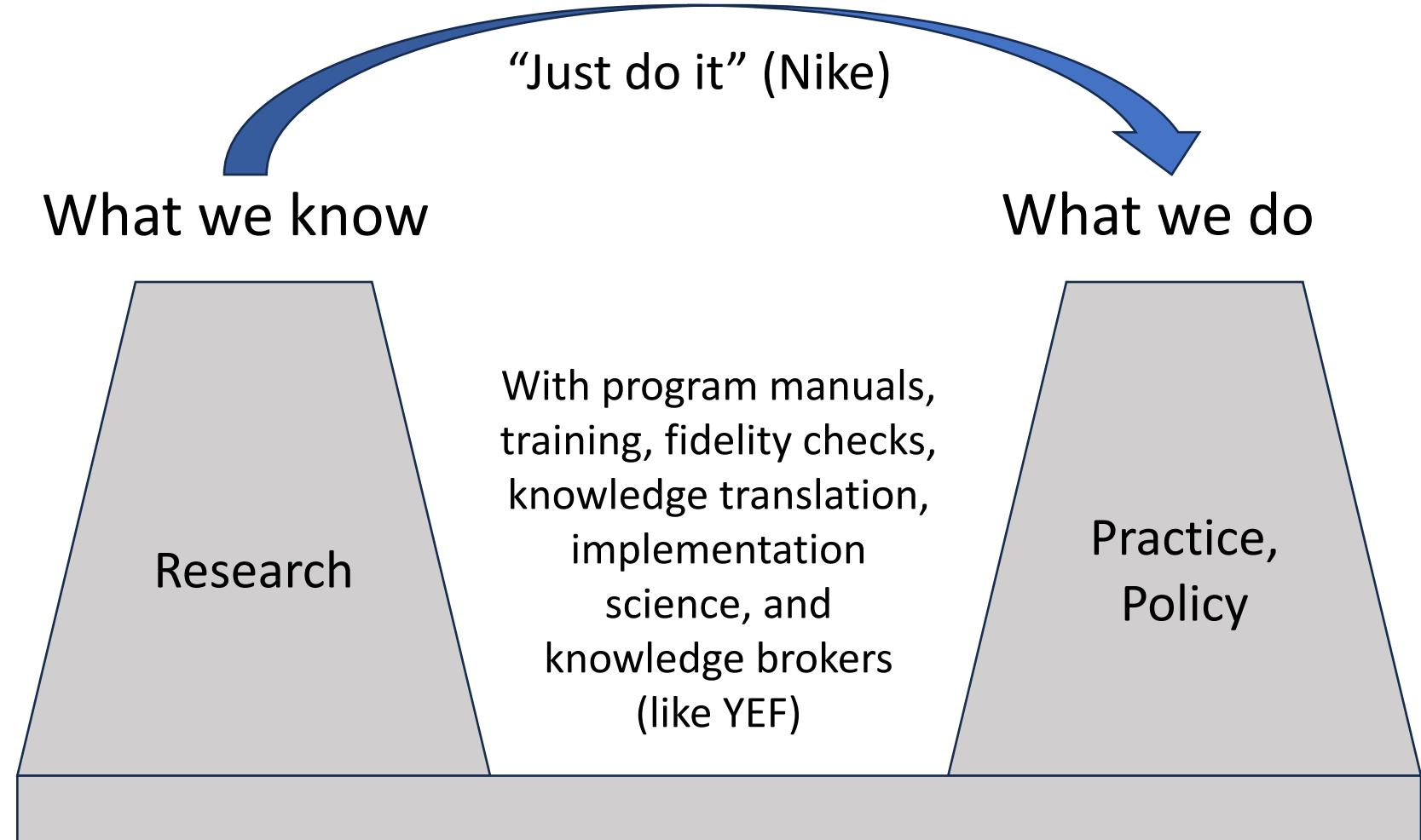
Consistent with APA and SPR guidelines, focus on “positive, pooled effect sizes” without specifying magnitude of ES or whether CIs or PIs can include null/negative effects (Tolin et al., 2015; Gottfredson et al., 2015).

Mean effect sizes are relatively uninformative for purposes of generalization

- Ignore heterogeneity, confidence/credibility of estimates (risks of bias), subgroup differences, moderators...
- Mean effects may have no real **meaning** anywhere in the world.
- When presented without CIs or PIs, point estimates convey **“incredible certitude”** (Manski, 2013).
 - Credible estimates are provided within a range (CI, PI)

Related rhetoric: Bridging the “know-do gap”

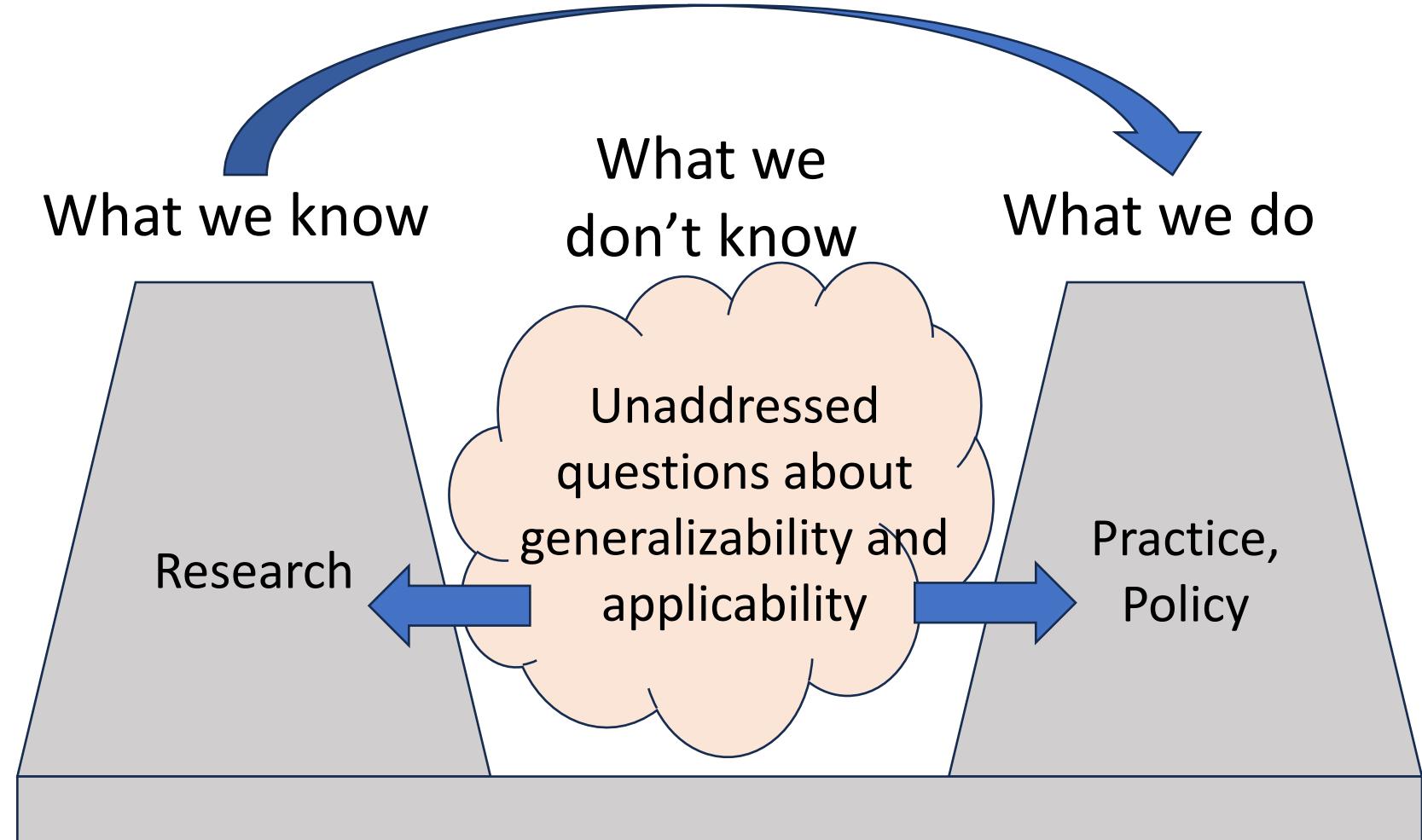
- Knowledge translation
- Implementation science



“Wishful extrapolation” (Manski, 2013)

SRMAs can identify gaps in knowledge and directions for further work.

Generalizability assessment might help.



Conclusions

- Do pooled estimates from SRMAs have greater external validity than study-level effect sizes?
 - Short answer: not necessarily
 - Long answer: Logic of generalization from SRMAs is woefully underdeveloped.
- How can we use SRMAs to inform inferences about generalizability?
 1. Test generalizability claims
 2. Use subgroup/moderator analyses to identify limits on generalizability
 3. Apply principles of generalized causal inference to SRMA data
 4. Identify directions for further primary research to address unanswered questions about generalizability
- More attention to the logic of generalization is needed.

Discussion

Thank you!

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