

Knowledge mobilization and lessons for communicating meta-analytic results

Katie Fitzgerald
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AERA SRMA SIG
8 December 2023

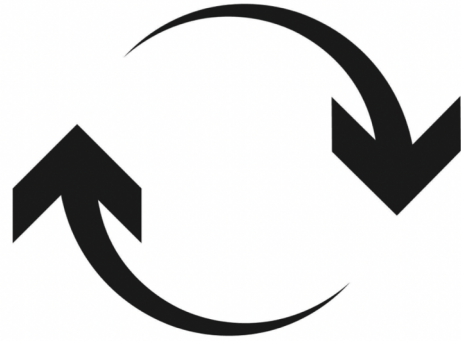
Elizabeth Tipton
Northwestern University

David Khella, Avery Charles
Azusa Pacific University

2022

The Meta-Analytic Rain Cloud Plot: A New Approach to Visualizing Clearinghouse Data

Kaitlyn G. Fitzgerald & Elizabeth Tipton



+ New MARC plot updates!

2023

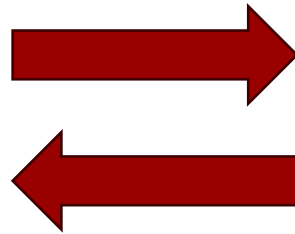
A Knowledge Mobilization Framework: Toward Evidence-Based Statistical Communication Practices in Education Research

Kaitlyn G. Fitzgerald & Elizabeth Tipton

Evidence Use & Knowledge Mobilization



Research Evidence



Educational practice

Shouldn't assume evidence is used and useful

Our corner of the problem



We're trying to communicate effect sizes, statistical uncertainty, meta-analytic results



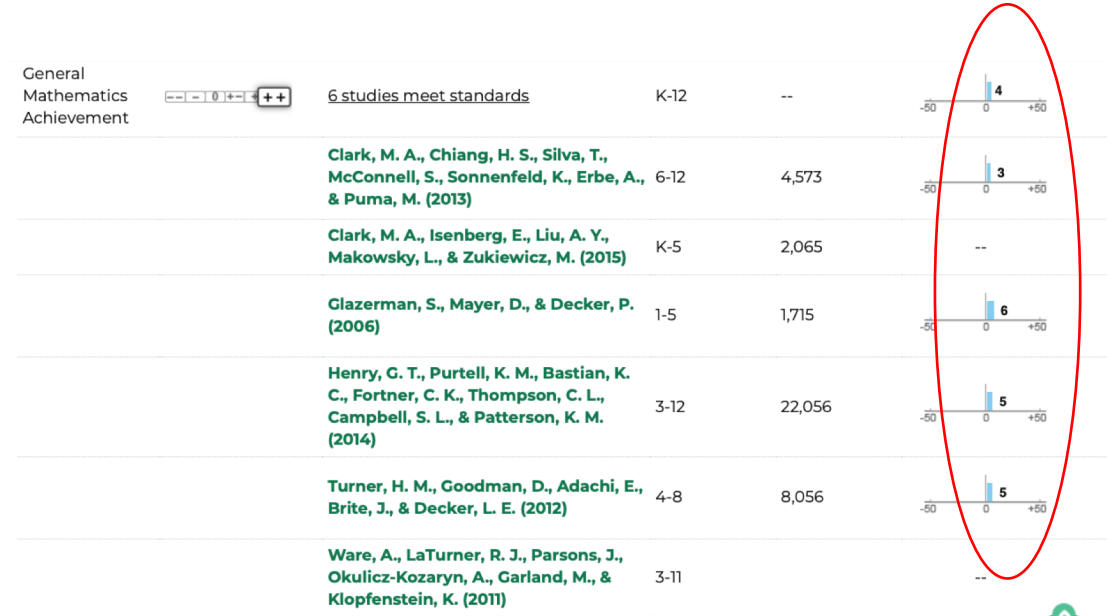
People have poor statistical reasoning skills; minimal evidence on meta-analytic reasoning



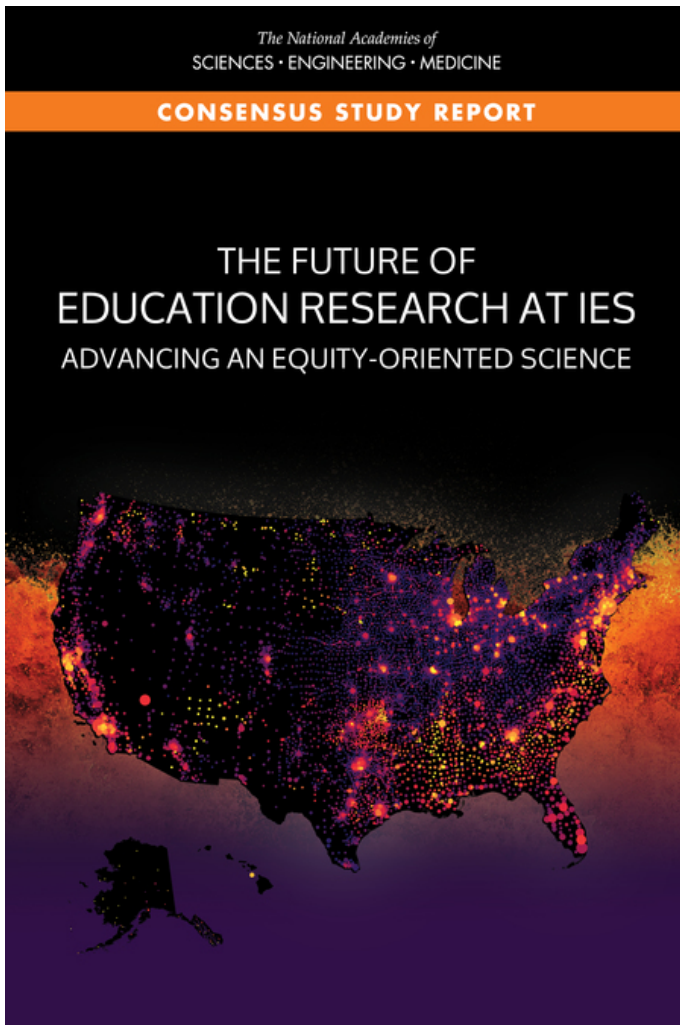
Common visualizations don't align with data viz best practices



How do people reason about the evidence we put in front of them? How can we improve?



National Academies Report (2022)



Knowledge Mobilization as one of five types of needed research

“how schools and decision-makers identify problems and develop solutions; which interventions, curricula, and programs are currently used in schools; **how to get promising evidence into their hands; how educational leaders harness that evidence to guide action; and what conditions support educational leaders to use research more centrally and substantively in their decision making.**”

([Bolding added]; National Academies of Sciences et al., [2022](#); Farley-Ripple et al., [2018](#); Jackson, [2022](#))

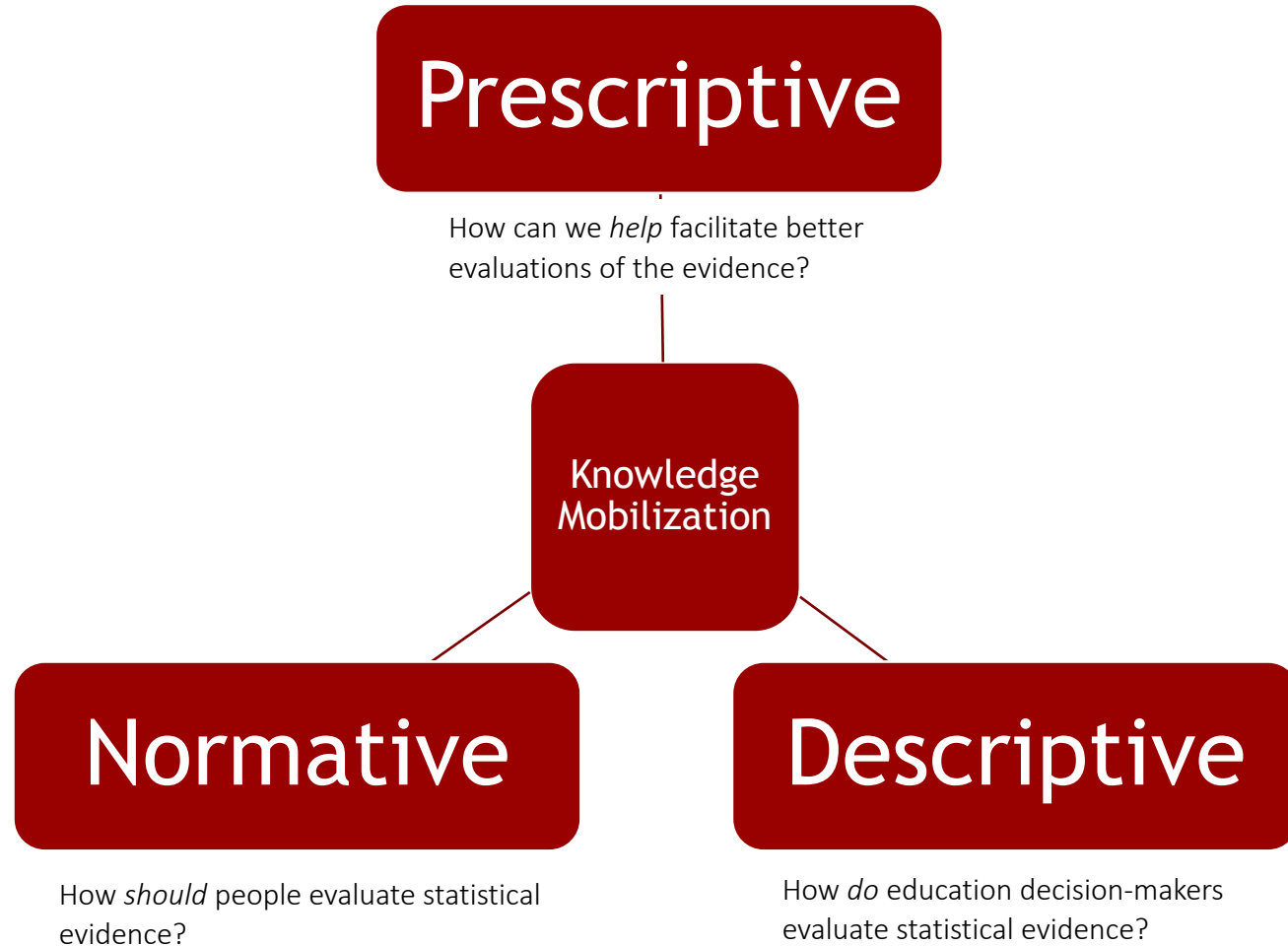
“Strategies to mobilize knowledge [should] be studied directly”

“IES should prioritize research on research use itself” (Conaway, 2021).

*How might we structure these
knowledge mobilization studies?*

Goal: more effective, evidence-based statistical communication practices
in education

Organize Knowledge Mobilization into three facets...



We need to...

Examine *norms* embedded in evidence we communicate

Descriptively understand how decision-makers reason about this evidence as well as their varied decision-making needs

Prescriptively develop and evaluate communication strategies that facilitate better use of evidence by decision-makers

Case study: What Works Clearinghouse Evidence

Outcome domain ⓘ	Effectiveness rating ⓘ	Studies meeting standards ⓘ	Grades examined ⓘ	Students ⓘ	Improvement index ⓘ
Algebra		5 studies meet standards	8-PS	6,854	
		Cabalo, J. V., Jaciw, A., & Vu, M.-T. (2007)	8-PS	344	--
		Campuzano, L., Dynarski, M., Agodini, R., & Rall, K. (2009)	8-9	270	--
		Pane, J. F., Griffin, B. A., McCaffrey, D. F., & Karam, R. (2014)	8-12	5,738	
		Ritter, S., Kulikowich, J., Lei, P., McGuire, C., & Morgan, P. (2007)	9	255	
		Wolfson, M., Koedinger, K., Ritter, S., & McGuire, C. (2008)	9-12	247	

IMPORTANTLY: gaps between intended use and actual use of an information display are not always a result of decision-maker misunderstanding. Such gaps can also result when researchers misunderstand the information needed for decision-making.

Normative:

How should people reason about a collection of studies?

What's the appropriate way to make sense of the 6 lines of research presented here?

Prescriptive:

What are effective strategies and means of communication to bridge the gap?

What info should be included, how should it be displayed?

Descriptive:

How do decision-makers reason about and interpret this information?

Is this information relevant to their decision-making needs?

Thesis: Knowledge Mobilization is an invitation to be more evidence-based in our own practices, and we think this framework can help

So what evidence should we turn to? And where do we need to generate new evidence?

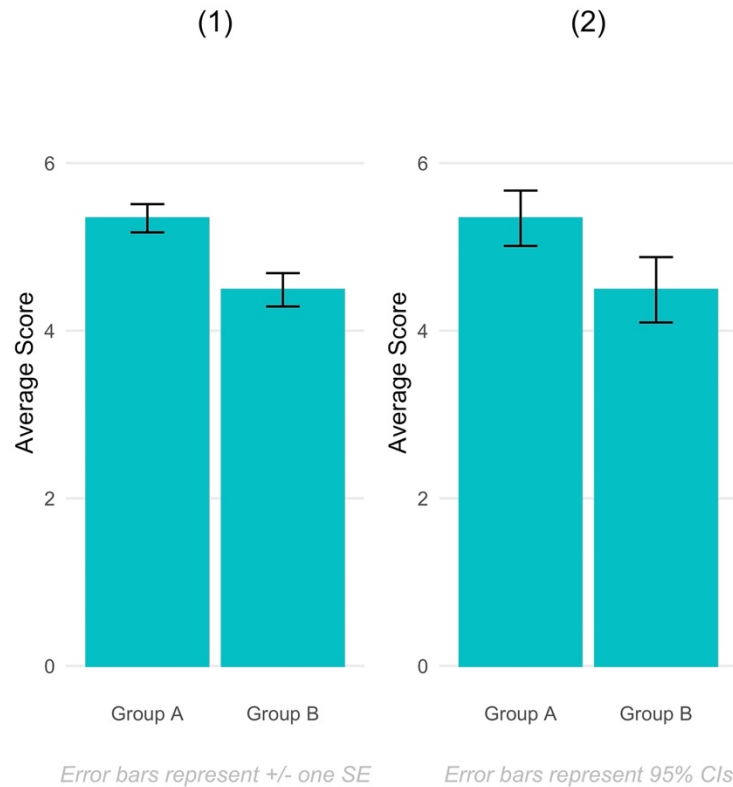


Lessons from Data Viz, Cog Sci, HCI

Beware of the curse of expertise!

Message sent \neq message received

Descriptive – lessons from Data Viz, Cog Sci, HCI



Caution against:



Error bars for uncertainty

Bar plots for effect sizes

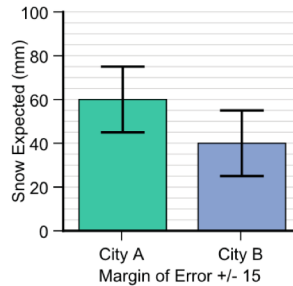
Prescriptive – lessons from Data Viz, Cog Sci, HCI

2142

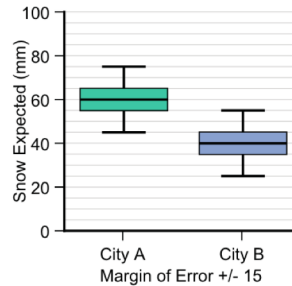
IEEE TRANSACTIONS ON VISUALIZATION AND COMPUTER GRAPHICS, VOL. 20, NO. 12, DECEMBER 2014

Error Bars Considered Harmful: Exploring Alternate Encodings for Mean and Error

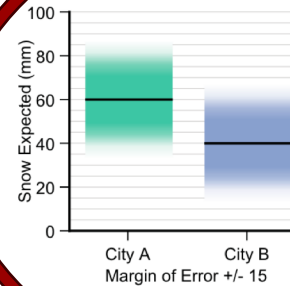
Michael Correll *Student Member, IEEE*, and Michael Gleicher *Member, IEEE*



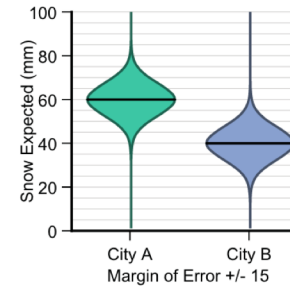
(a) **Bar chart** with error bars: the height of the bars encodes the sample mean, and the whiskers encode a 95% t-confidence interval.



(b) **Modified box plot**: The whiskers are the 95% t-confidence interval, the box is a 50% t-confidence interval.



(c) **Gradient plot**: the transparency of the colored region corresponds to the cumulative probability density function of a t-distribution.

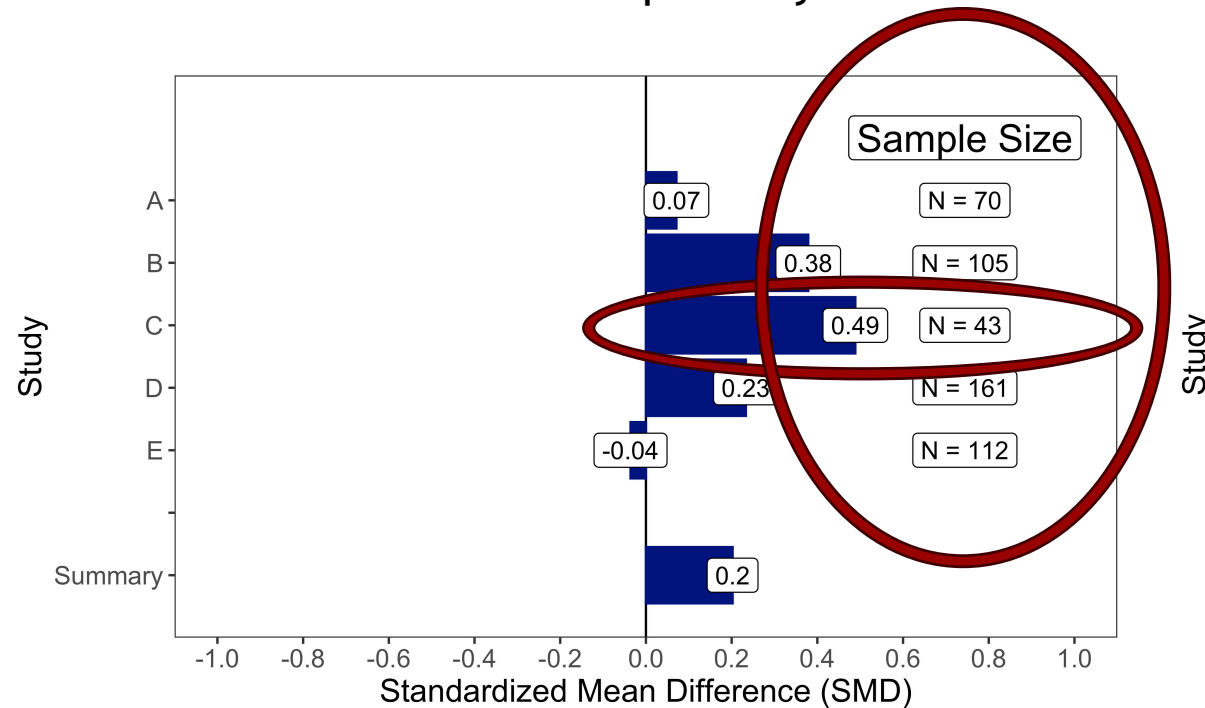


(d) **Violin plot**: the width of the colored region corresponds to the probability density function of a t-distribution.

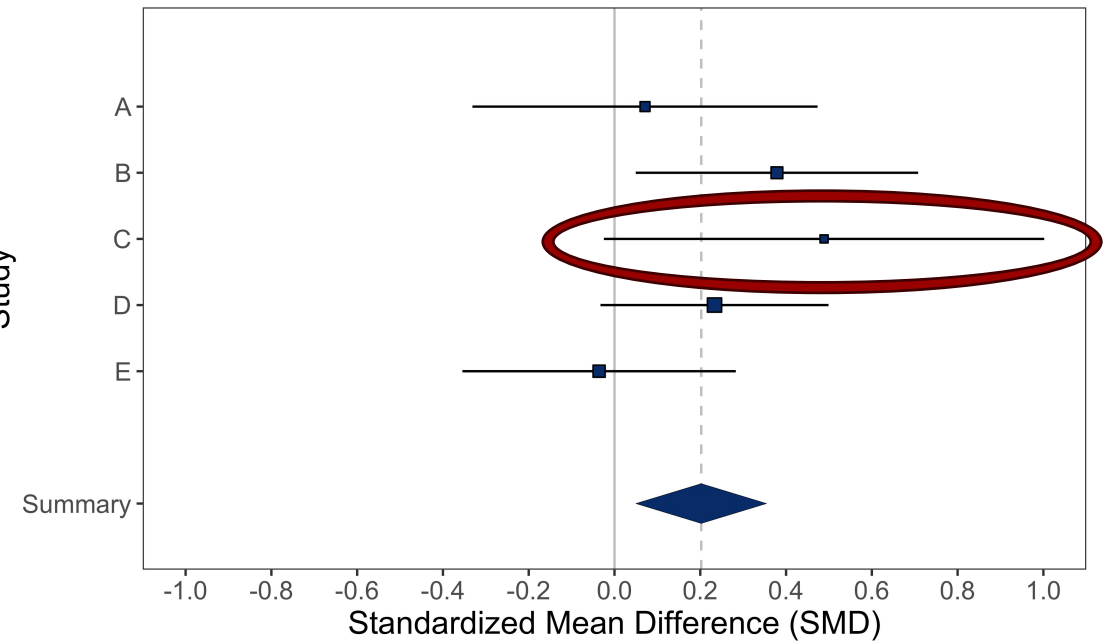
More effective

What about meta-analysis?

Effect sizes as bar plots - yikes!



CI bars for uncertainty - yikes!



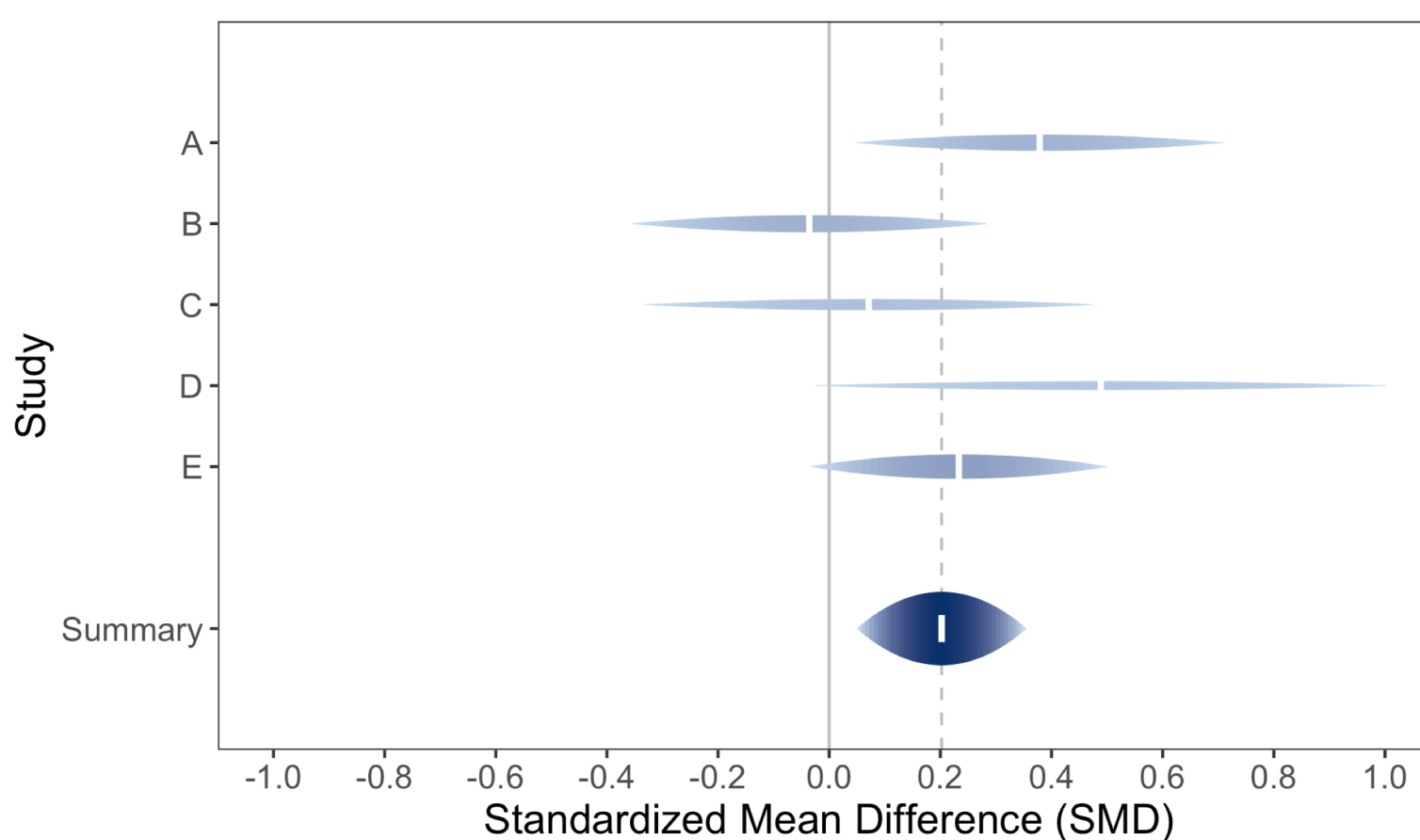
Fitzgerald & Tipton (2022)



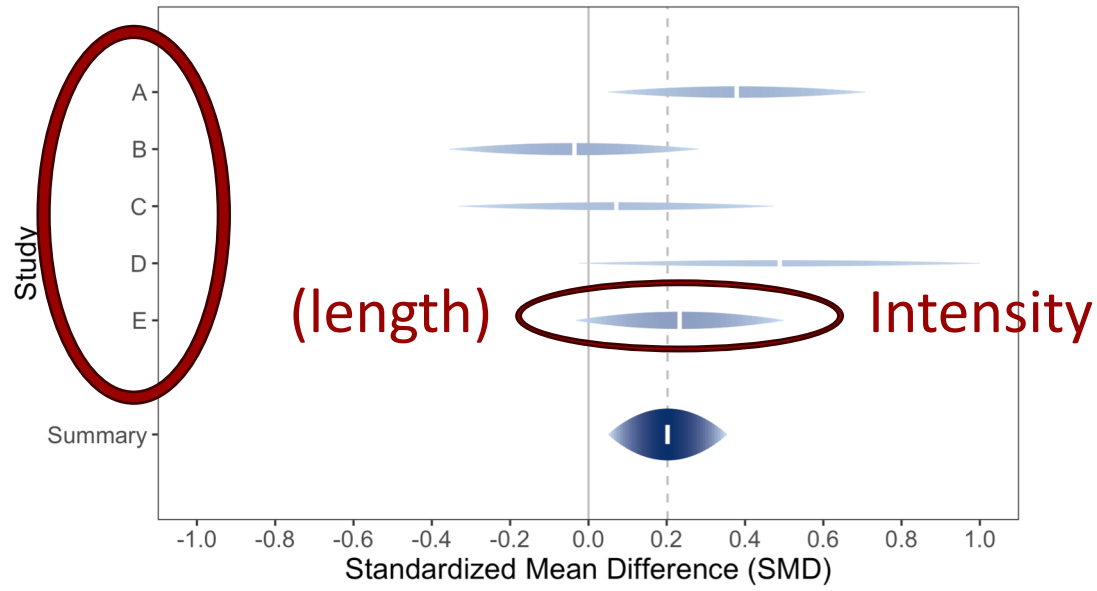
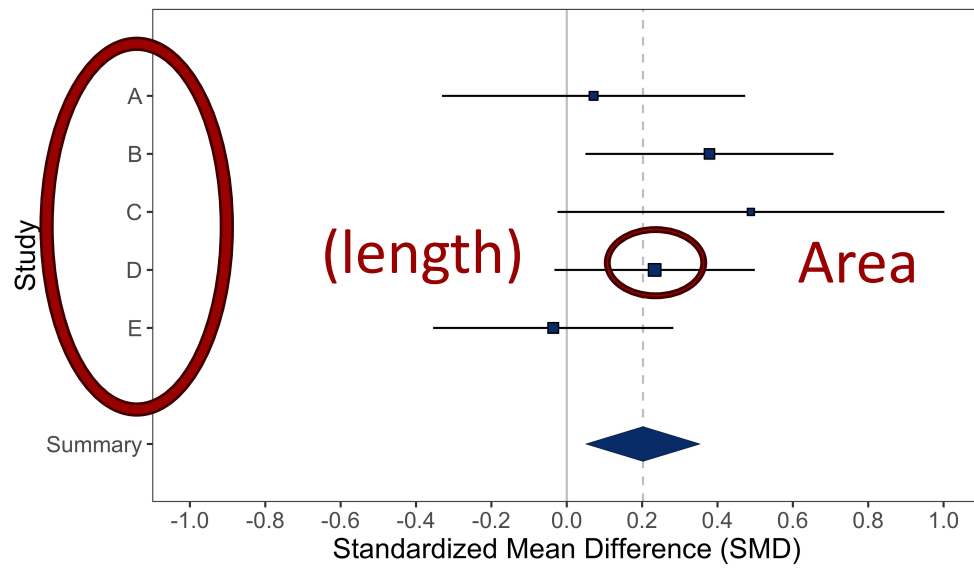
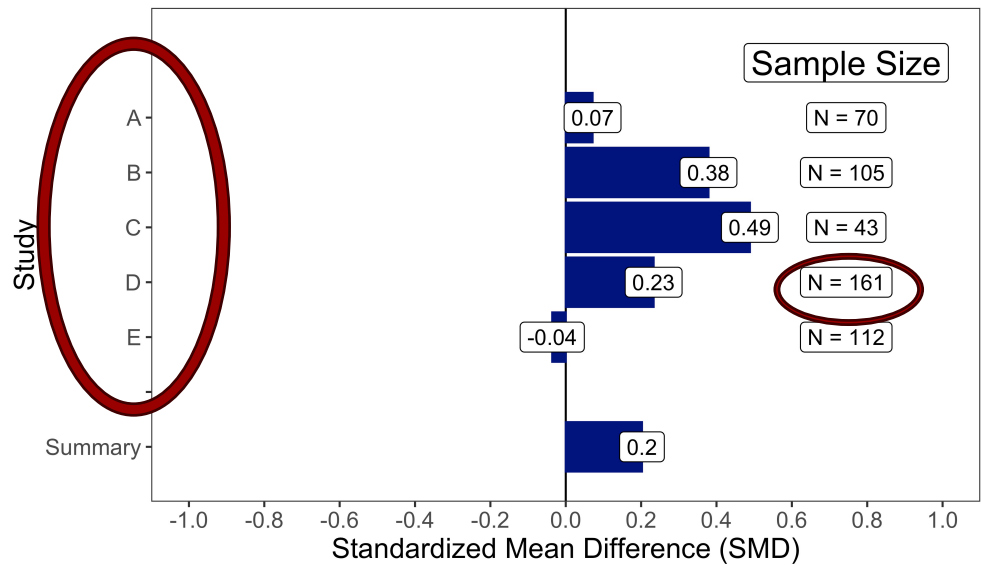
Caution against:

Bar plots & forest plots for meta-analytic data

The rainforest plot seems promising?



Curse of expertise!
Complex encodings



Key to meta-analytic reasoning:
 More precise effects get more weight

Franconeri, S. L., Padilla, L. M., Shah, P., Zacks, J. M., & Hullman, J. (2021). The science of visual data communication: What works.

Absolute precision ranking for seeing a single ratio

Visual estimation of the 1:7 ratio (moving toward bottom)

Position

Length

Area

Angle

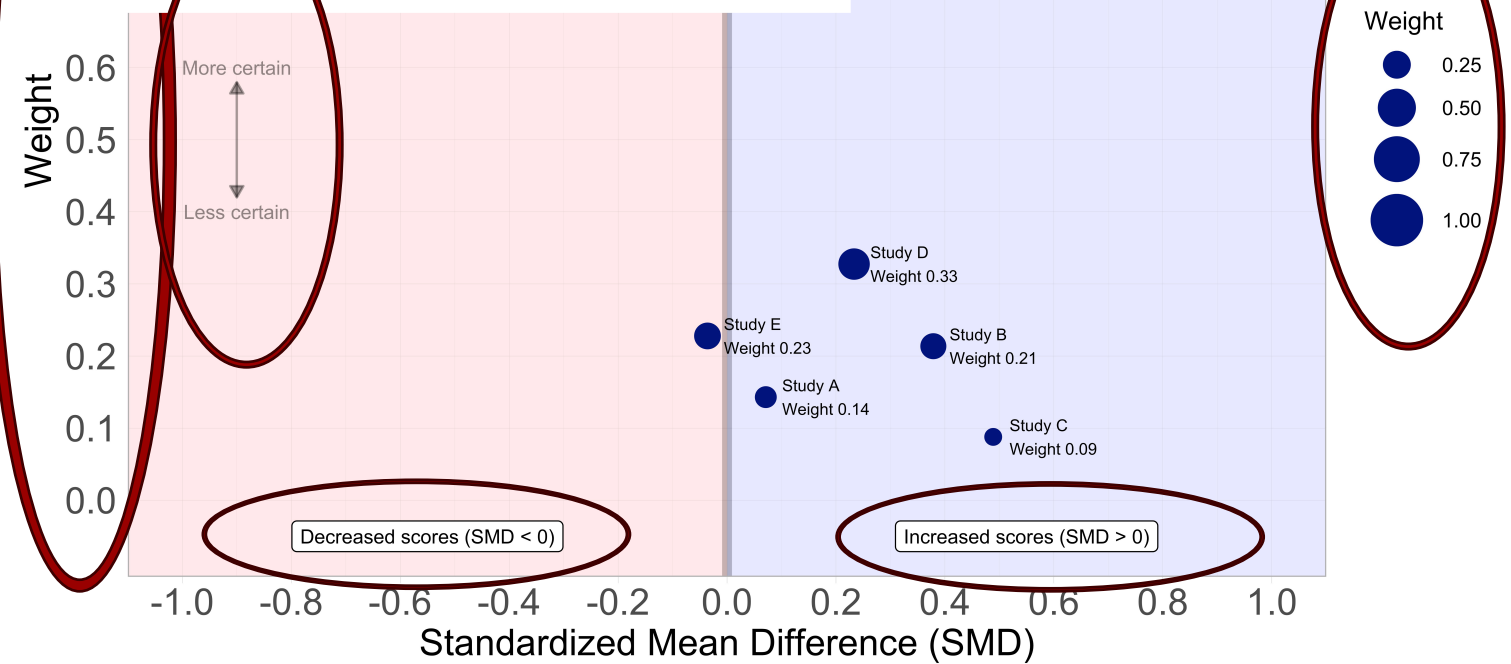
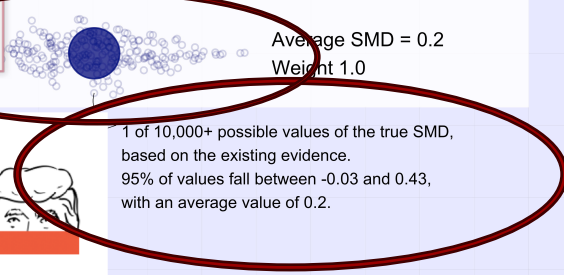
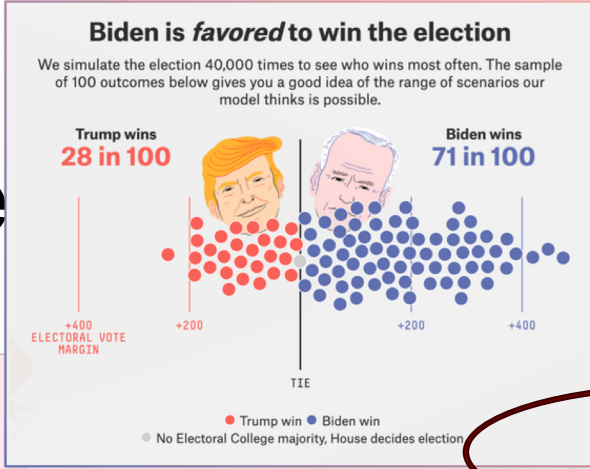
Intensity

Highest ↑

↓ Lowest

Me

Forest Plot (MARC) Plot



Recommend:

Make meta-analytic weight salient

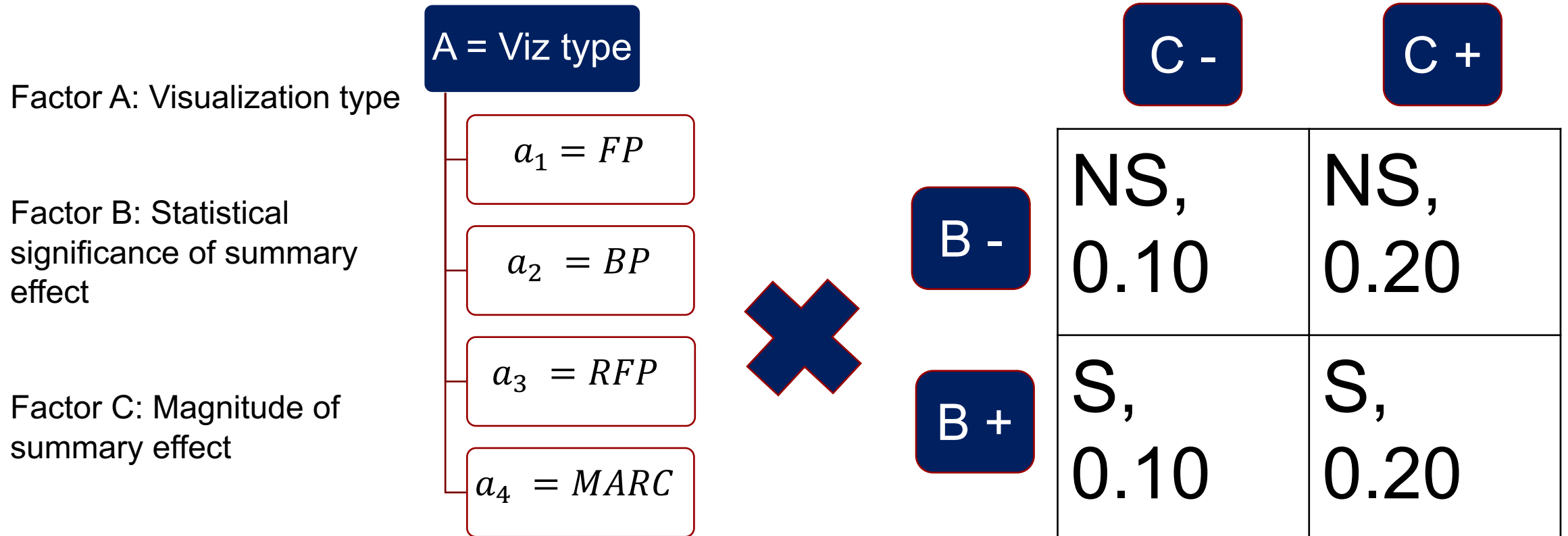
Utilize y-axis

Simple encodings

Continuous (and individual outcomes) display of uncertainty

Use annotations to guide interpretation

Experimental design ($4 * 2^2$)



Participants

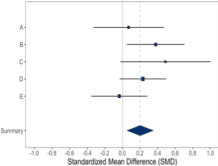


EDUCATION
PRACTITIONERS
N = 83



EDUCATION
RESEARCHERS
N = 94

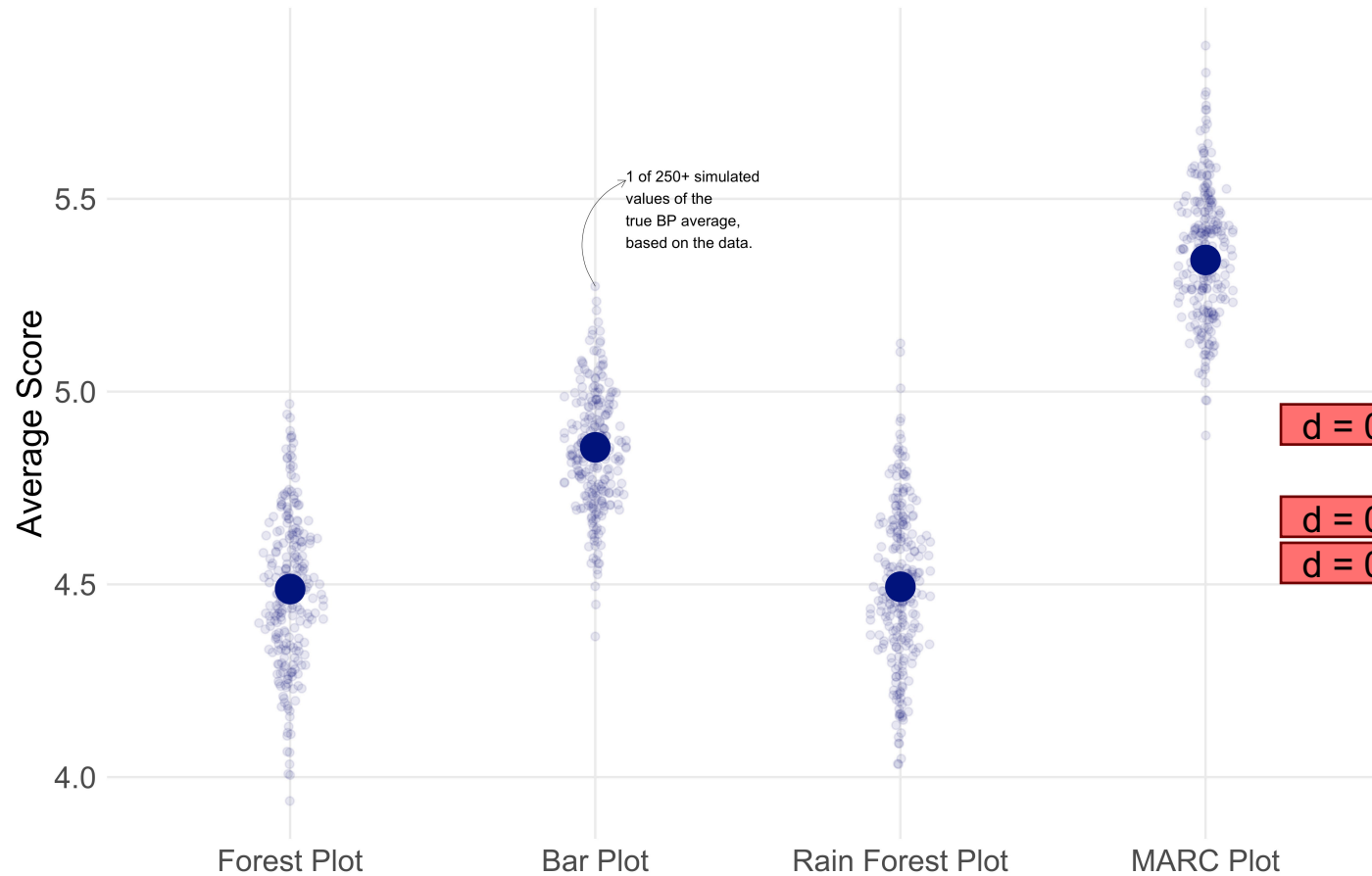
Can practitioners accurately interpret the meta-analytic data?

Visualization	n	Q1 Trust Most	Q2 Most Weight	Q3 Least Certain	Q4 Largest SMD	Q5 Avg SMD	Q6 Best estimate	Q7 Sufficient evidence
	82	0.512	0.573	0.683	0.866	0.780	0.598	0.476
	83	0.759	0.554	0.687	0.904	0.831	0.663	0.458
	81	0.580	0.580	0.617	0.827	0.802	0.667	0.420
	82	0.720	0.951	0.890	0.866	0.805	0.610	0.500

Which study was most accurate
in determining

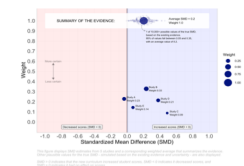
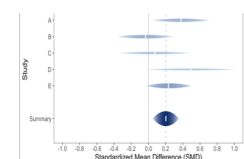
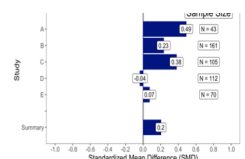
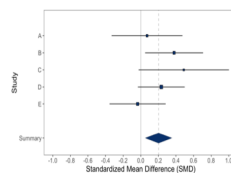
Positional encodings work

MARC Plots perform better

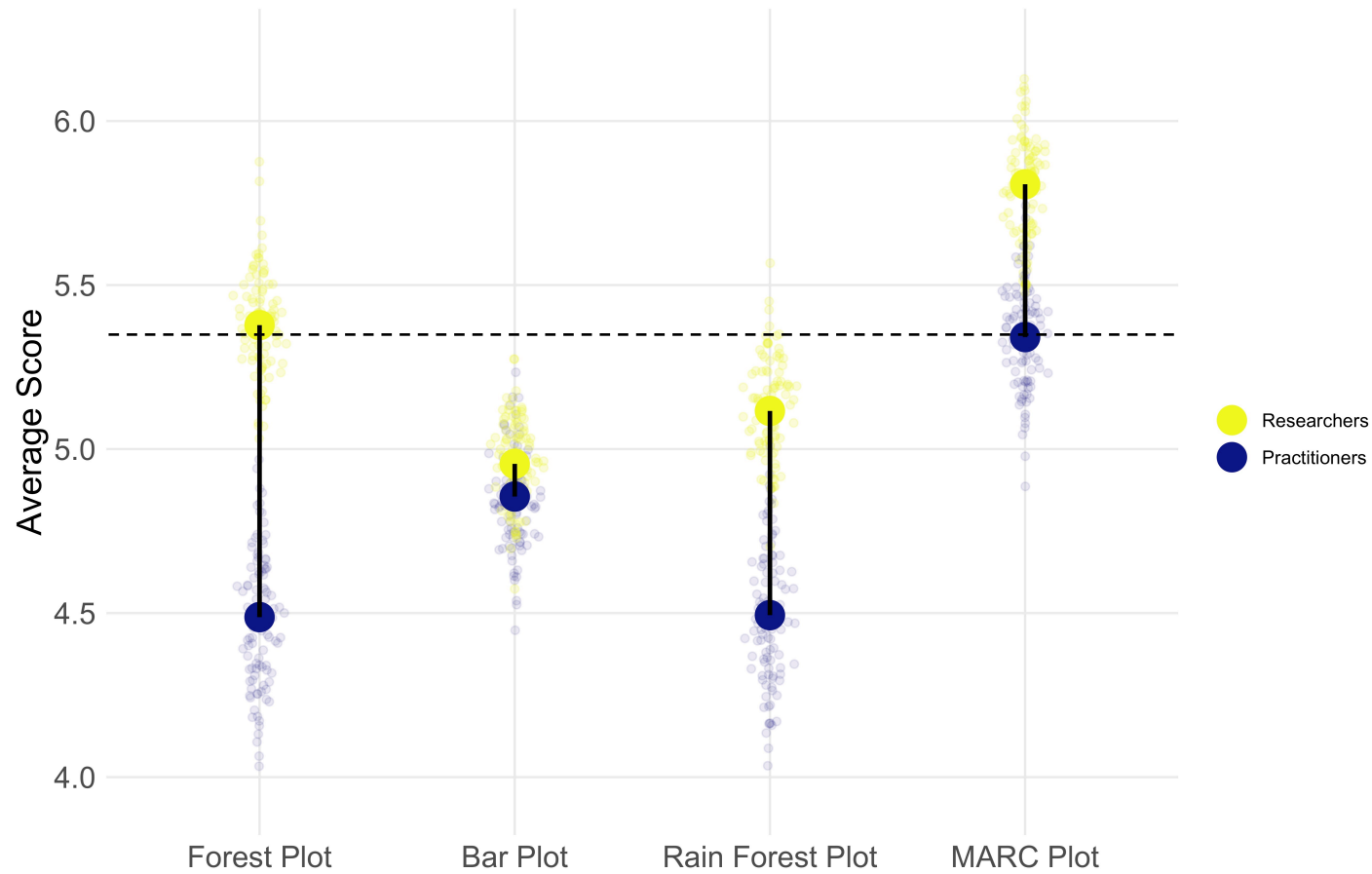


d = 0.76
d = 0.43
d = 0.76

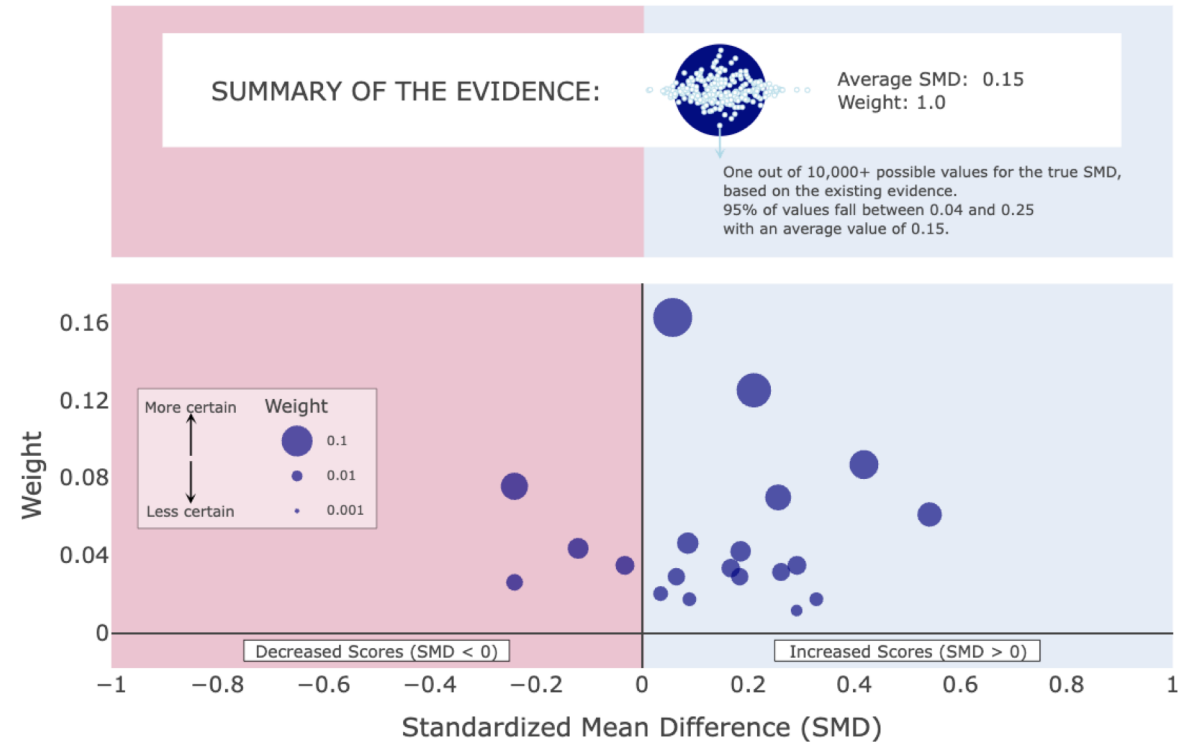
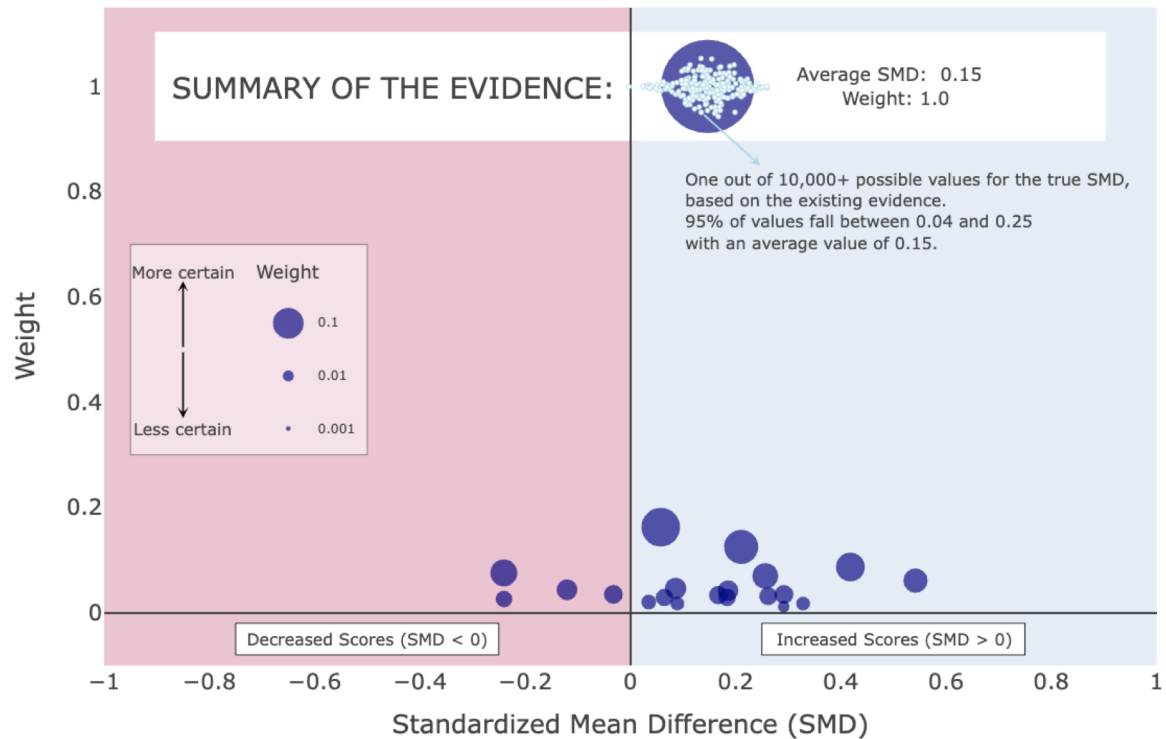
Contrast	Difference Estimate	Lower	Upper	Adjusted P-value
BP-FP	0.368	-0.084	0.819	0.153
RFP-FP	0.006	-0.448	0.460	1.000
MARC-FP	0.854	0.401	1.306	0.000
RFP-BP	-0.362	-0.814	0.091	0.167
MARC-BP	0.486	0.035	0.937	0.029
MARC-RFP	0.848	0.394	1.302	0.000



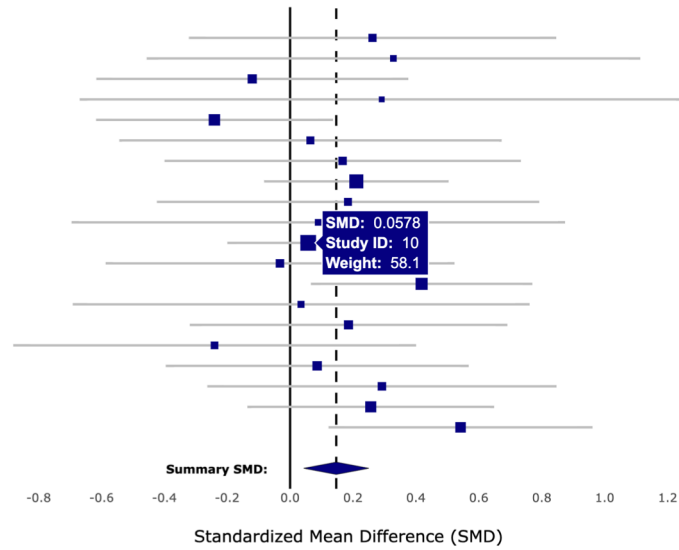
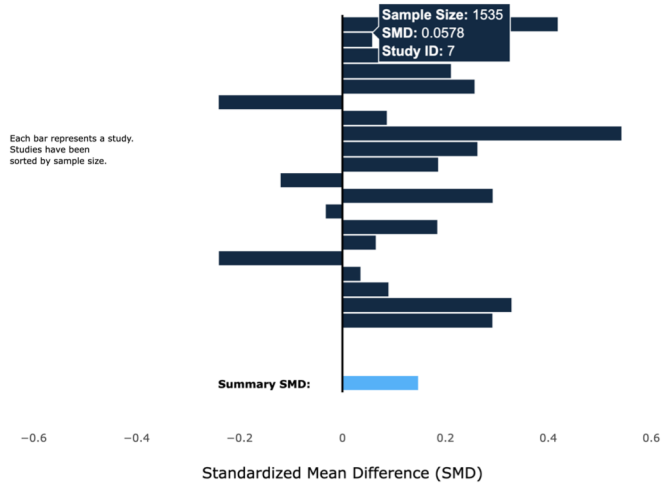
Researchers vs. Practitioners



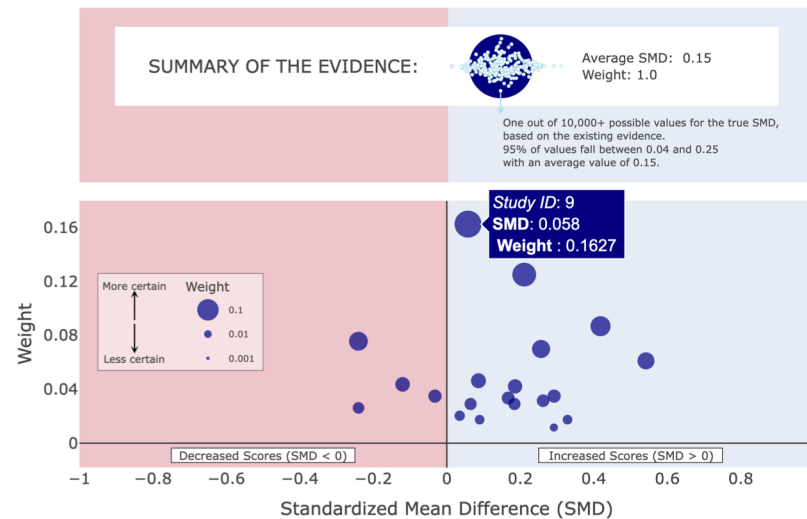
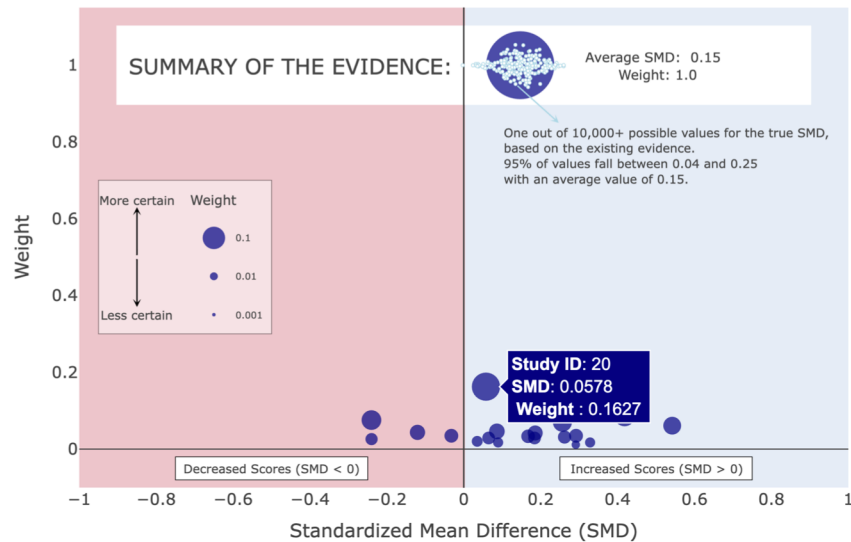
Concerns about large k



4*4 factorial design



k
10
20
50
100



Advantage of MARC(v2) persists for large k

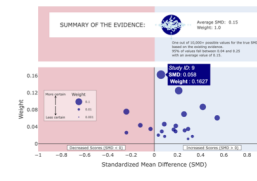
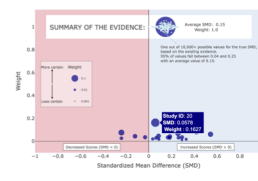
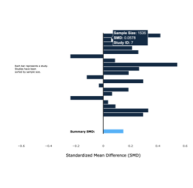
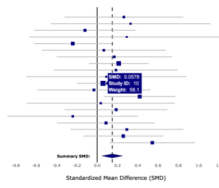


Forest Plot

Bar Plot

MARCv1

MARCv2



Contrast	Difference Estimate	Lower	Upper	Adjusted P-value
BP-FP	-0.694	-1.002	-0.387	0.000
MARCv1-FP	0.063	-0.240	0.365	0.951
MARCv2-FP	0.367	0.064	0.670	0.010
MARCv1-BP	0.757	0.452	1.062	0.000
MARCv2-BP	1.061	0.755	1.367	0.000
MARCv2 -MARCv1	0.304	0.004	0.605	0.045

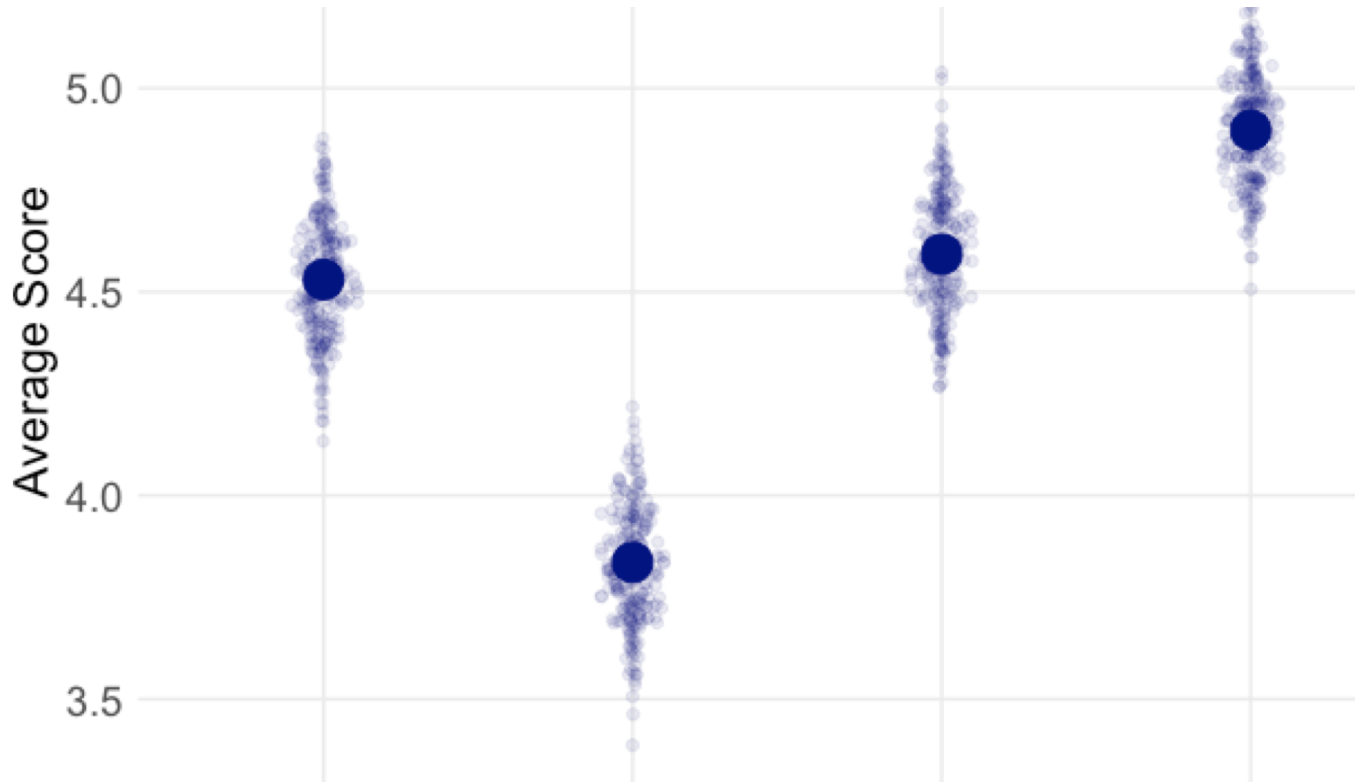
d = 0.36

d = 1.03

d = 0.30

Advantage of MARC(v2) persists for large k

Forest plot seemed to improve w/ the hover text

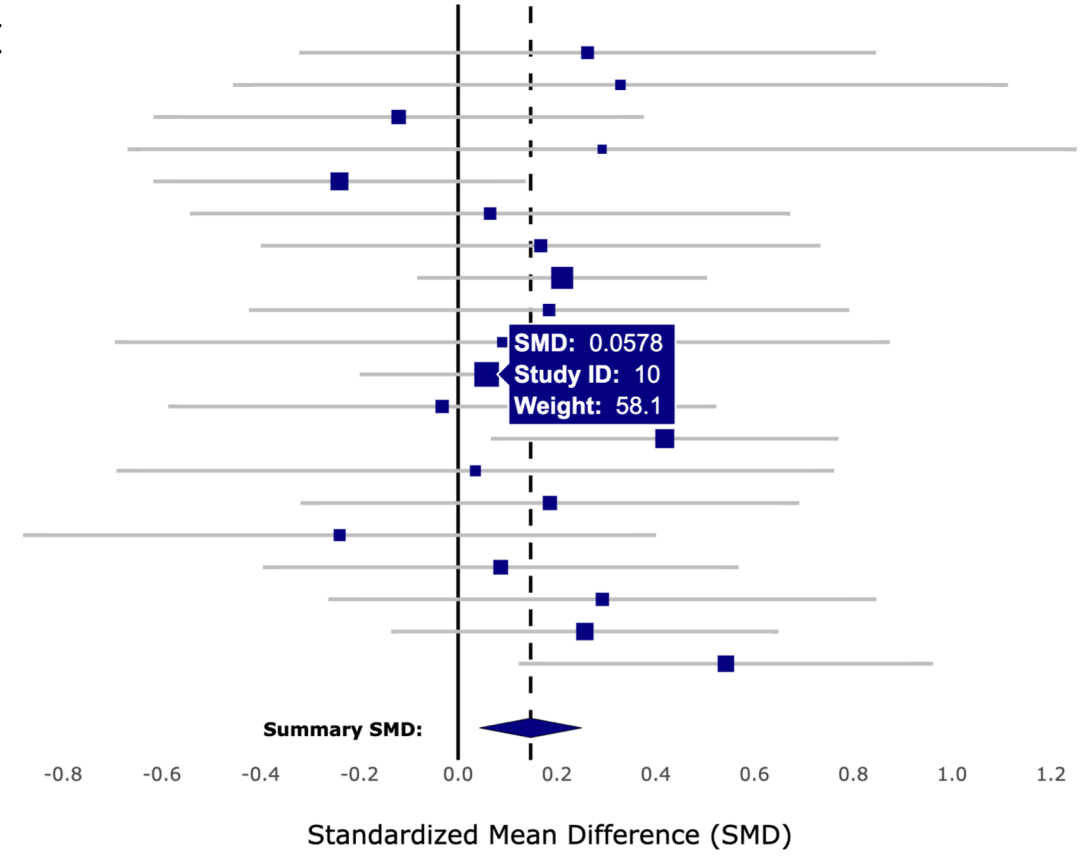
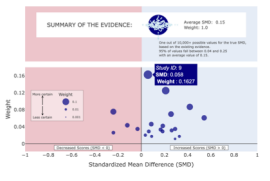
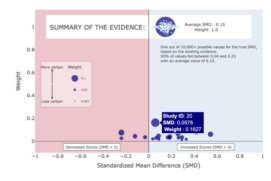
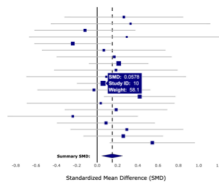


Forest Plot

Bar Plot

MARCv1

MARCv2



Summary SMD:

SMD: 0.0578
Study ID: 10
Weight: 58.1

Standardized Mean Difference (SMD)

Advantage of MARC(v2) persists for large k

Forest plot seemed to improve w/ the hover text

Sample size as poor proxy for uncertainty in CRTs

Average Score

5.0

4.5

4.0

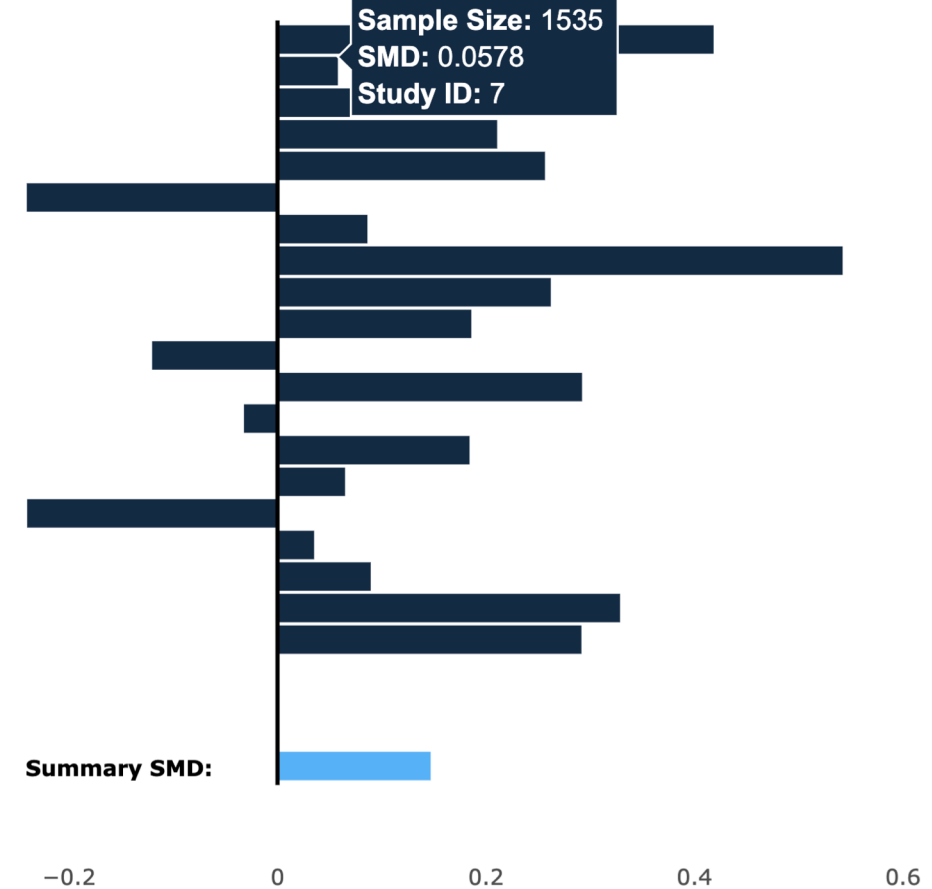
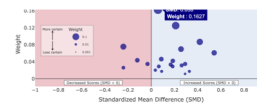
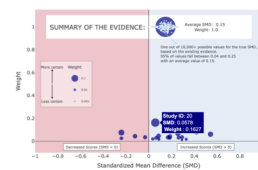
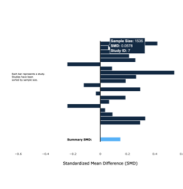
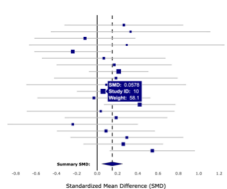
3.5

Forest Plot

Bar Plot

MARCV1

Each bar represents a study.
Studies have been
sorted by sample size.



Standardized Mean Difference (SMD)

Future directions

- R package on CRAN
 - Bare bones version currently available on GitHub 😊
 - <https://github.com/kgfitzgerald/MARCViz>
- Encoding other study characteristics. How to help people reason about subgroup effects and moderators?
 - Need descriptive, normative, and prescriptive work here!
- Comparison of multiple interventions
 - More realistic to decision-making process



Takeaways

Beware of the curse of expertise

Let's examine our own norms and evaluate our own practices

We need (more) evidence on how decision-makers engage with meta-analytic evidence & their decision-making needs

We need healthy feedback loops between normative, descriptive, prescriptive work – an integrated science – to establish best practices for mobilizing knowledge

Thanks!

Email: kfitzgerald@apu.edu

Twitter: @fitzgerald_kg

MARCV2 code: <https://github.com/kgfitzgerald/MARCViz>



What visualization / evidence communication scenarios would you like to see tackled?

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Descriptive – examples from education

Educational Researcher



Impact Factor: **8.2** /

 Open access |   | Research article | First published online January 12, 2021

How Should Educational Effects Be Communicated to Teachers?

[Hugues Lortie-Forgues](#) , [Ut Na Sio](#), and [Matthew Inglis](#) [View all authors and affiliations](#)

[Volume 50, Issue 6](#) | <https://doi.org/10.3102/0013189X20987856>

Find: the metric on which evidence is presented greatly influences teachers' level of engagement with the evidence as well as their perception of the effectiveness of the intervention.



Caution against:

Months of progress as an effect size

Prescriptive – examples from education

Evidence-Based Decisions and Education Policymakers

Nozomi Nakajima *

November 2021

Find: Strong preference for external validity compared to internal validity. Policymakers do update their beliefs in response to research evidence, but that the effect is large and persistent only when the **explanation provided** for how the evidence was generated is **brief and accessible**.