Improving the Design and Use of Meta-analyses of Career Interventions

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Overview

- Questions asked in meta-analyses of career interventions: Let’s focus on variation

- Benefits of theory in meta-analysis

- (M)UTOS framework for generalizability

- Examples are based on career decision making self efficacy studies from Ryan (1999)

Questions asked in career meta-analyses

Early meta-analyses of interventions typically ask…

- Do career interventions work? (Spokane & Oliver found $\bar{d}$ = 0.85, later estimates lower)

- What affects how they work? Do moderators like duration and type explain variation in study outcomes?

It is less common to examine and depict the <u>estimated variance</u> due to study features.

Questions asked in career meta-analyses (An example)

Ryan (1999) found 8 treatment effects for career decision making self efficacy.

- The mean was 0.21 under fixed effects
- Effects were heterogeneous
- We do not know how variable they were

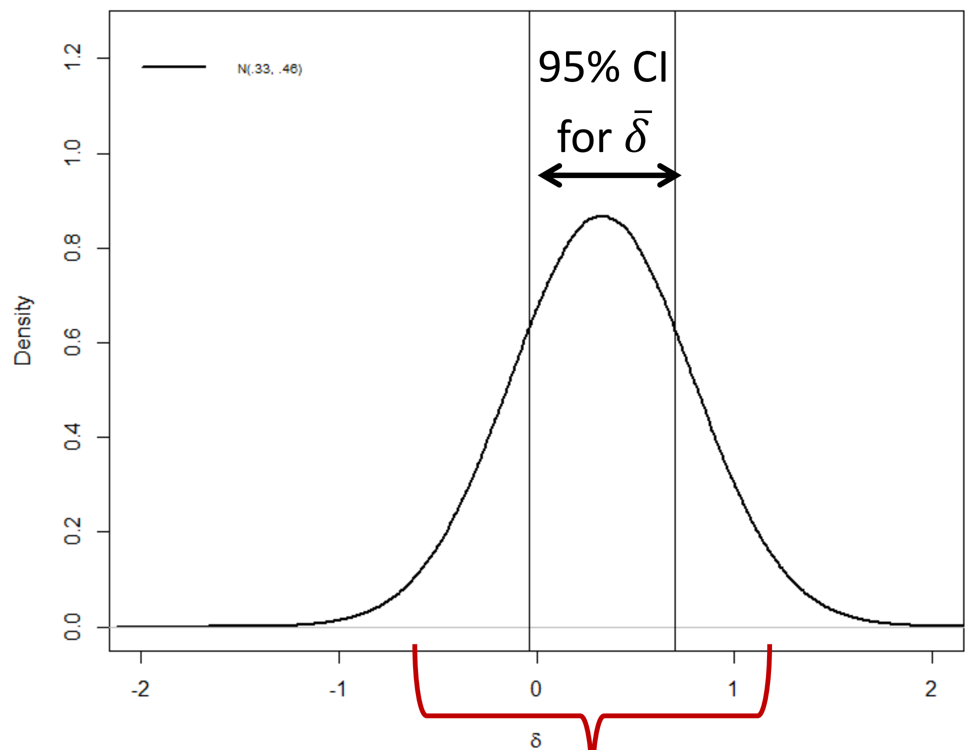
Let's find out: We will assume the population of effects is normal.

Questions asked in career meta-analyses

The random-effects mean is 0.33, with SD $s_\delta = 0.46$.

The mean is not different from zero.

76% of true effects would be positive.



95% would fall between -0.6 and 1.2.

Benefits of theory in meta-analysis

- Using theory (Becker, 1994, 1996, 2009) to drive meta-analyses of career-intervention effects can buy us…
  - Models for outcomes, with more powerful tests
  - Ways to know what has **not** been studied
  - Ways of directly assessing aspects of our theories
  - Ways of assessing generalizability of results, and asking how much more information is needed

(M)UTOS framework for generalizability

What is MUTOS? Cronbach (1982) proposed a theory of generalizability for evaluation studies, with four components:

U -> u:	Populations and samples of Units (or participants)
T -> t:	Populations and samples of Treatments
O -> o:	… of Observing operations (measures)
S -> s:	… of Settings

I add M (and m) for Methods, thus: MUTOS.

Theory and (M)UTOS

Theory can suggest important UTOS features, or prioritize them. For example different theories may identify different key components of effective treatments.

We may not find all desired UTOS populations in the literature, if some have not been studied (e.g., minorities or disabled clients).

Specifying UTOS before the meta-analysis forces us to see "what we don't know," rather than simply narrowing our questions or just reporting what we find.

(M)UTOS framework for generalizability

M is different because we do not want to generalize to a *study* with particular methods, we want to generalize to the world of practice.

We often "hope" the m's do not relate to outcomes, but rather reflect Cook's (1991) "heterogeneous irrelevancies" which support generalizability.

That is, we'd like the results to not depend on how the studies were done.

How do we use (M)UTOS? (Becker, 1996; Becker & Aloe, 2016)

- Specify potential populations by defining MUTOS, using relevant theory
- Classify study features using MUTOS
- Evaluate diversity in m’s, u’s, t’s, o’s, and s’s
- Assess overall heterogeneity of effects, as above
- Evaluate empirical variation in results for MUTOS components
- Assess connections to desired domain of application, *UTOS

Evaluate diversity in m’s, u’s, t’s, o’s, and s’s to gauge potential to generalize

- Assess *number of features* per component and *degree of diversity* in features (variety of levels).
- The more diverse and numerous the features, the greater the potential to generalize. If features do not vary, *we cannot tell* whether we can generalize broadly.

- Ryan’s CDMSE studies used three measures. Only one was known to my experts. Other measures exist.
- Judgment: These outcomes are not diverse or fully representative, limiting potential generalizability across outcomes.

Evaluate extent of variation in results

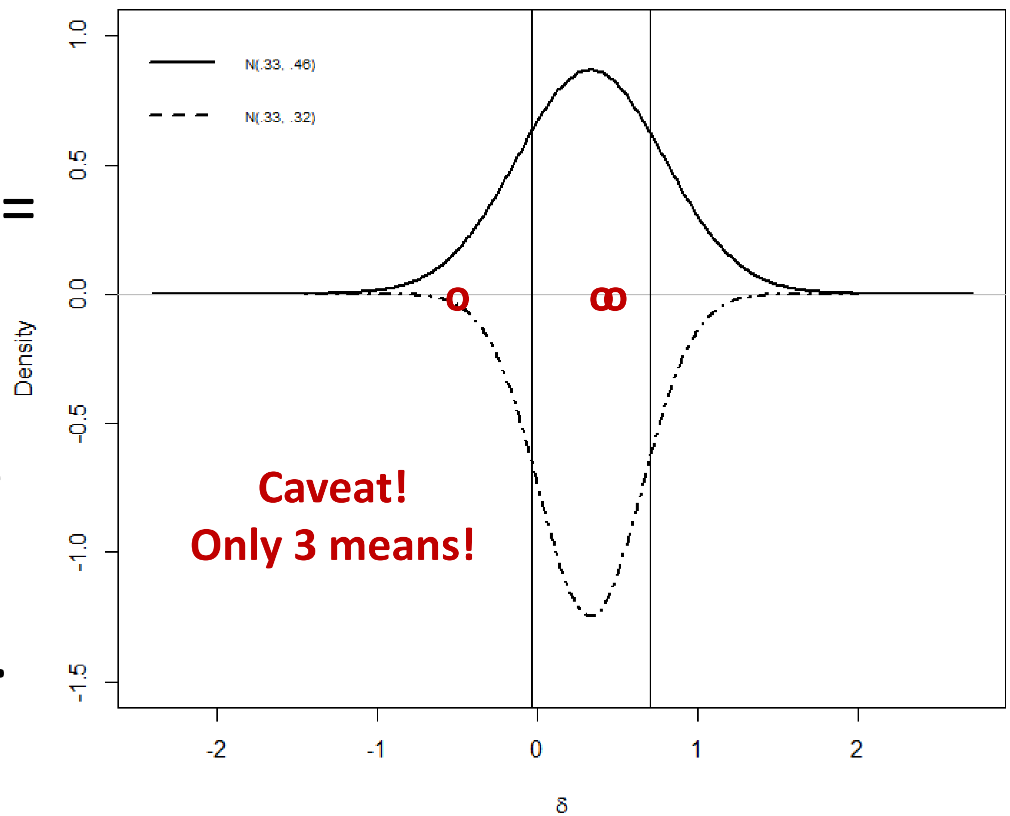
- Analyze overall variation, as above. If none, we can generalize across all studied conditions. Ryan’s results varied significantly, and widely, so do not generalize simply.
- Assess variation due to mutos features. The more a feature impacts the effects, the less we can generalize across levels of the feature.
- “Measure used” relates to the size of the effect ($Q_B(2) = 26.8$, $p < .0001$), and explains essentially all variance among effects from Ryan.
- New!! We now estimate the variance of the group means.

Evaluate extent of variation in results

The flipped distribution shows variation due to measure. The distribution of the measure means is shown with the dot-dashed line.

- Between-measures variance is half that of the full population (SD = .32), but still large.

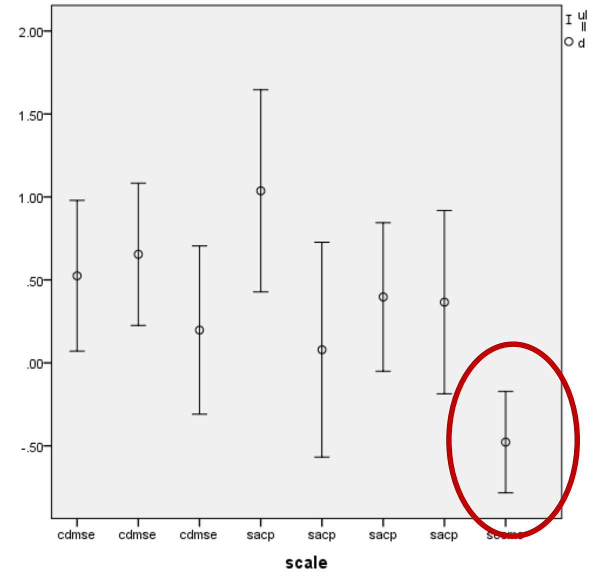
- Judgment: It is not safe to generalize the mean effect across measures.



Evaluate extent of variation in results

We should also do standard analyses. This forest plot reveals a discrepant study.

- It was the only study using the Self-Estimated Career Management Competencies scale!

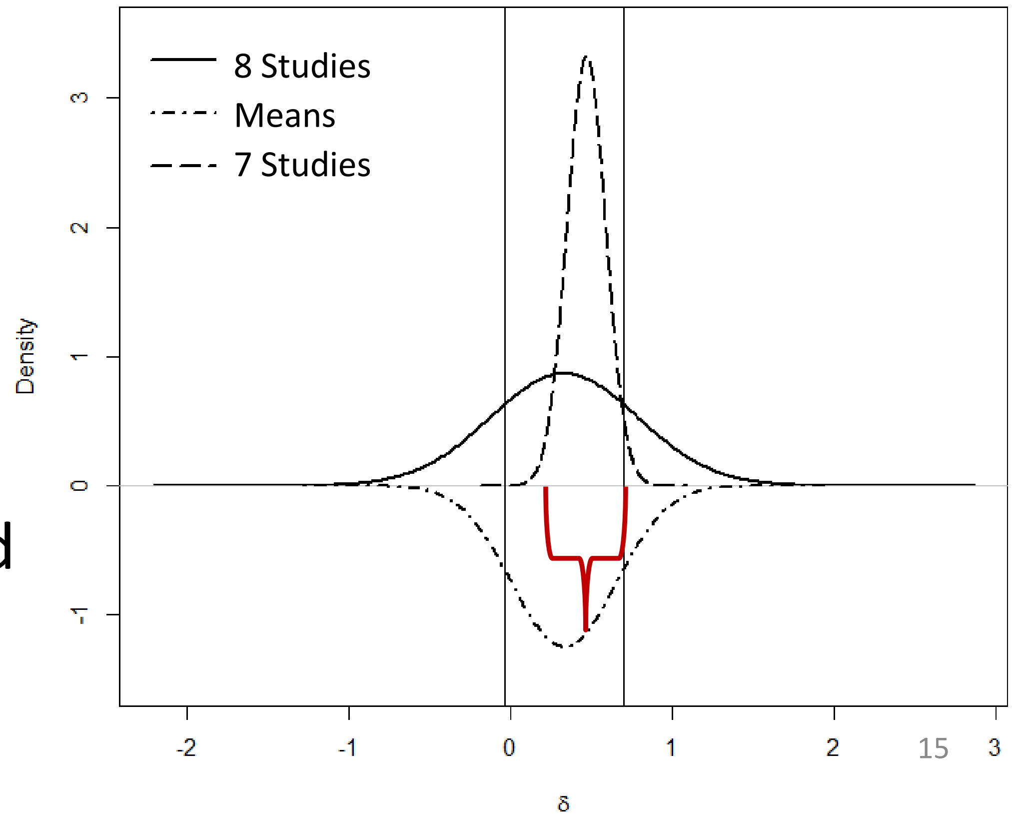


- The SECMC asks respondents to make normative statements like “What quartile on CDMSE do you fall within?”.
- A sensitivity analysis will omit this study.

Evaluate extent of variation in results

- The new overall distribution is shifted and narrower; its mean is 0.47 and it is homogeneous.
- Nearly all population effects are expected to be positive; 95% are between 0.23 and 0.71.

- Judgment: Without the quirky measure, we can generalize the mean effect across the other observed measures.
- Caveat! Other unstudied measures may show different results.



Connect to *UTOS

- Finally we identify situations in which we want to apply the results (Cronbach's *UTOS).

- We compare them to the studied utos, and judge whether the accumulated evidence applies. An app like this one, with some added features, could help:

  http://shinyserver.byu.edu/family_therapy/

Summary

- Theory, combined with a framework for generalizability, can help meta-analysts identify what is not known, as well as what is.
- Focusing on variation in effects helps us assess whether we can make simple, broad statements about effects.
- Features that are represented diversely, and do NOT relate to effect size, mean results can be safely generalized across levels of those features. This is good news for generalization!

Summary

- The field of career interventions has good meta-analyses, but they have been largely empirically driven.
- Your mission, should you choose to accept it, is to pursue meta-analyses guided by theory, that focus on variation!
- Good luck SVP (and these slides will NOT self-destruct in five seconds)! Contact me at bbecker@fsu.edu
- Thank you!

The role of theory in meta-analysis

Studies of career decision making self-efficacy from Ryan (1999)

Authors	Year	n^T	n^C	g	Scale
Garis & Harris-Bowlsbey	1984	47	15	1.05	SACP
Healy & Mourton	1984	74	99	-0.48	SECMC
Fukuyama et al.	1988	39	38	0.53	CDMSES
Tempestini, Horan & Good	1988	55	11	0.08	SACP
Garis & Niles	1990	87	25	0.40	SACP
Niles & Garis	1990	51	17	0.37	SACP
Luzzo & Taylor	1993	44	44	0.66	CDMSES
Luzzo, Funk & Strang	1996	30	30	0.20	CDMSES

Note: Measures included the Career Decision Making Self Efficacy Scale (CDMSES), the Self-Assessment of Confidence and Progress in Educational/Career Planning (SACP), and the Self-Estimated Career Management Competencies scale (SECMC).

Sample sizes for treated and control samples are n^T and n^C, and g is the uncorrected standardized mean difference from Ryan (1999).

- How can this be done?

- Planning meta-analyses using theory (i.e., for problem formulation, data analysis, etc.); I will present a framework in support of this approach.

- In analyses, such as by way of model-driven meta-analysis (AKA linked meta-analysis), with meta-analytic path modeling (meta-SEM).

Questions asked in career meta-analyses

"How" and "why" questions are usually asked later; simple moderator analyses do not fully characterize intervention processes.

Analyzing moderators separately ignores potential confounding and interactions among them.

Rubin's "regression surface" models can be used for predicting optimal results – say an intervention with each of Ryan's five ingredients, and with other key features (e.g., 5 sessions). That is, we don't stop at just the model.

Scholars already use theory in meta-analysis

- Model-driven meta-analysis has been used since the 1990s. Sheu et al. (2010) looked at social cognitive theory in the frame of Holland's themes

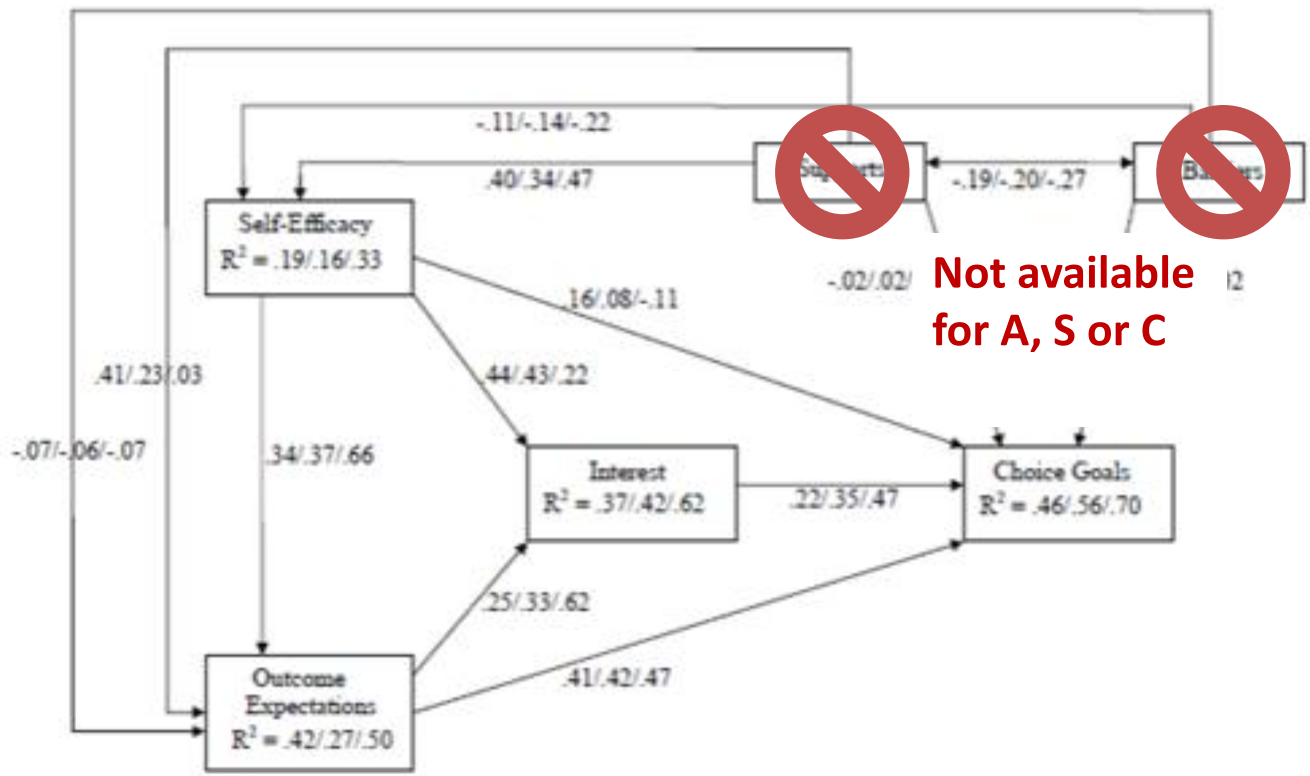


Fig. 2. Parameter estimates of the 6-variable model (3B) in the Realistic (R), Investigative (I), and Enterprising (E) Themes. Standardized path coefficients and R^2 are presented in the order R, I, and E. Absolute values of path coefficients >.04 are significant at the .05 level.

Rubin argued for predicting optimal results – say an intervention with all five ingredients, and with other features (e.g., 5 sessions).

A possible model would be

$$d_i = b_0 + \underbrace{b_1X_1 + \dots + b_5X_5}_{\text{Each ingredient is modeled with a dummy variable for its presence}} + b_6X_6\ e_i$$

Number of sessions as well

Other features can be included.

(M)UTOS framework for generalizability

Units: Differences in populations of participants (old vs. young; clinical patients vs. students using campus counseling centers, etc.). U defines populations of interest.

Treatments: Collection of treatments of interest and the ways they vary: duration, type, how implemented….

Observing operations: How outcomes are observed, e.g., type of scales, measure features, reliability, etc.

(M)UTOS framework for generalizability

Settings: Cronbach originally did not vary setting, because his framework was for one study. Across studies S can reflect populations of locations, dates of study, types of schools, and the like.

M reflects varying methods, such as sample type, analysis used, type of control group(s), matching or randomization, and number and type of control variables.