

AERA SRMA-SIG Online Seminar

Friday the 13th & Single Case Experimental Designs:

Allegedly Unlucky Encounters for Meta-Analysts

John Ferron, PhD & Megan Kirby, PhD
13 November 2024



Acknowledgements

Methods Guide for Effect Estimation and Synthesis of Single-Case Studies

January 16, 2024

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Disclaimer

This report was supported by the Institute of Education Sciences, U.S. Department of Education, through Grant R324U190002 to the University of Oregon. The opinions expressed are those of the authors and do not represent views of the Institute or the U.S. Department of Education.

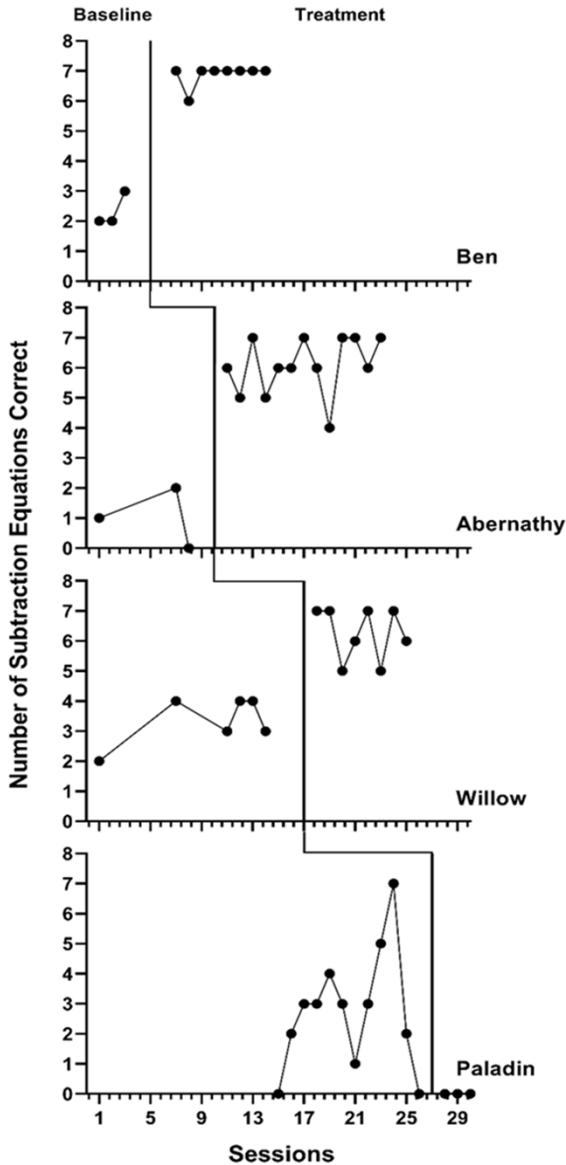
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Single Case Experimental Designs



Used by:

Professionals & researchers
Education, psychology, organizational behavior management, medicine

To study:

The effects of an intervention on an individual participant

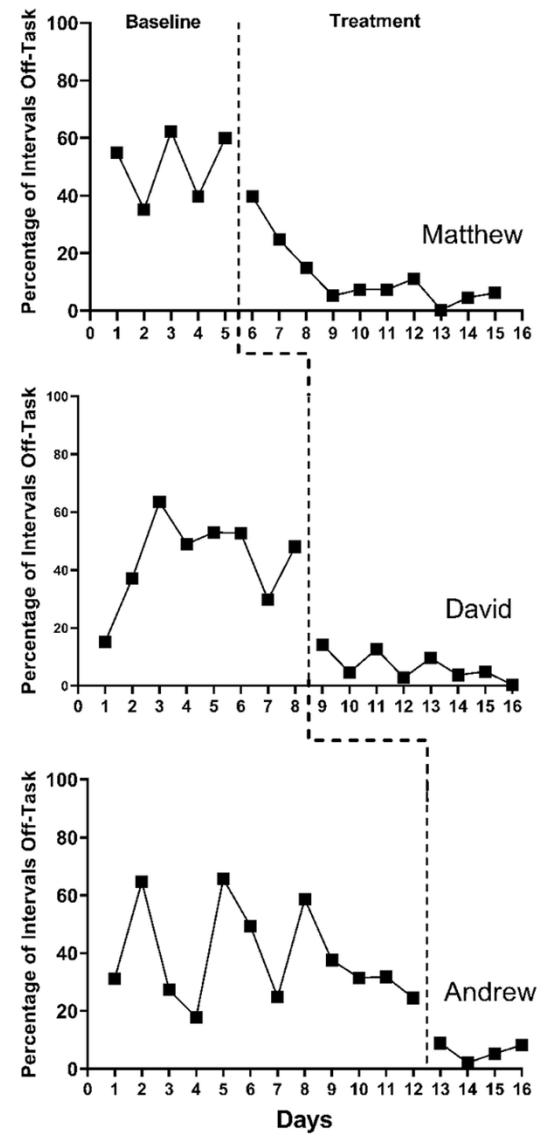
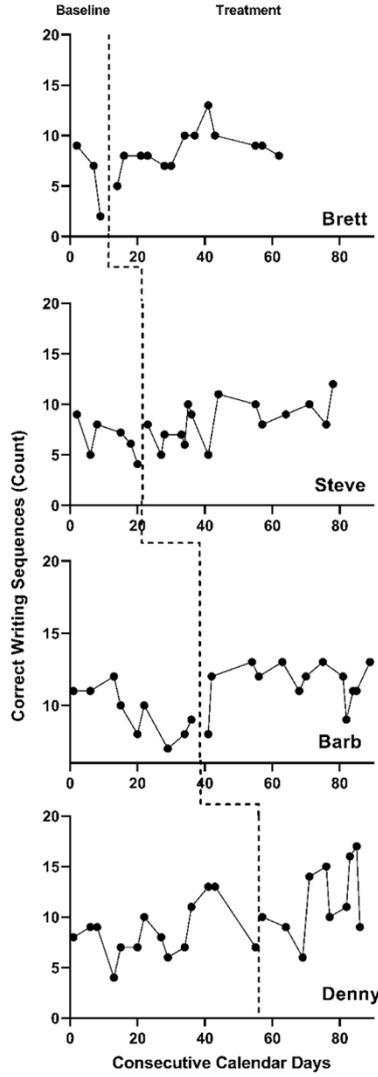
For:

Studying special populations
Developing new interventions
Practitioner led research
Focusing on individuals

Raw Participant Data

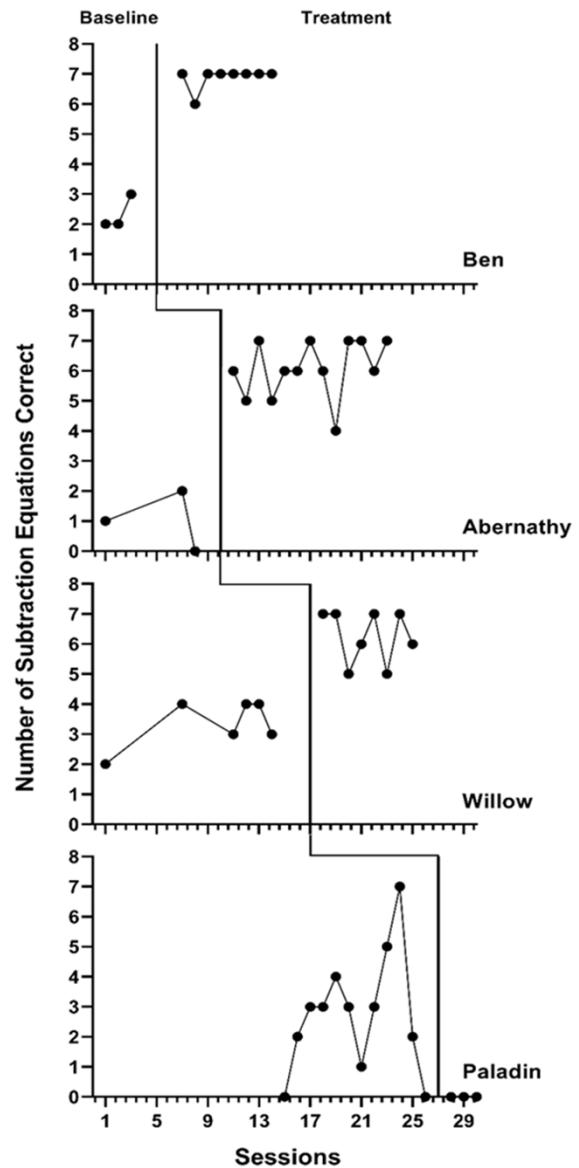
Individual cases
Common outcomes
Time

Number of Correct Writing Sequences on the Sentence Construction Probes (Rodgers et al., 2020)



Graphical Analysis of Outcomes

Case, L. P., Harris, K. R., & Graham, S. (1992). Improving the mathematical problem-solving skills of students with learning disabilities: Self-regulated strategy development. The Journal of Special Education, 26, 1-19.



Dilemma in the Single Case Community

Are supplemental statistics necessary?

"We lose data about the individual when we summarize a graph with a single value."

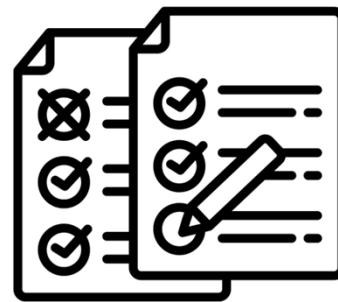
"Why aren't they including our studies?"

It's likely that a SCED study will not be eligible for inclusion in a meta-analysis if only visual analysis is conducted.

Choosing from 3 General Approaches



Design-
Comparable
Effect Sizes?



Case Specific
Effect Sizes?
(e.g., NAP, TauU,
SMDW, LRR, PoGO)



Multilevel
Modeling?

Single-Case and Group Designs

Design-Comparable
Effect Sizes

Study
Types

Single-Case Designs

Type(s) of
Outcomes

Common Across Cases
(interest in variation of
effects across cases
and time)

Multilevel Modeling of
Raw Data

Different Across Cases
(interest in variation of
effects across cases)

Case-Specific
Effect Sizes

Synthesizing Effect Evidence from Single- Case Research

Design-Comparable Effect Sizes

Choosing between the options for Between-Case Standardized Mean Differences

"What would the standardized mean difference effect size be if one could somehow perform a between-group randomized experiment based on the same population of participants, intervention protocol, and outcome measures?"

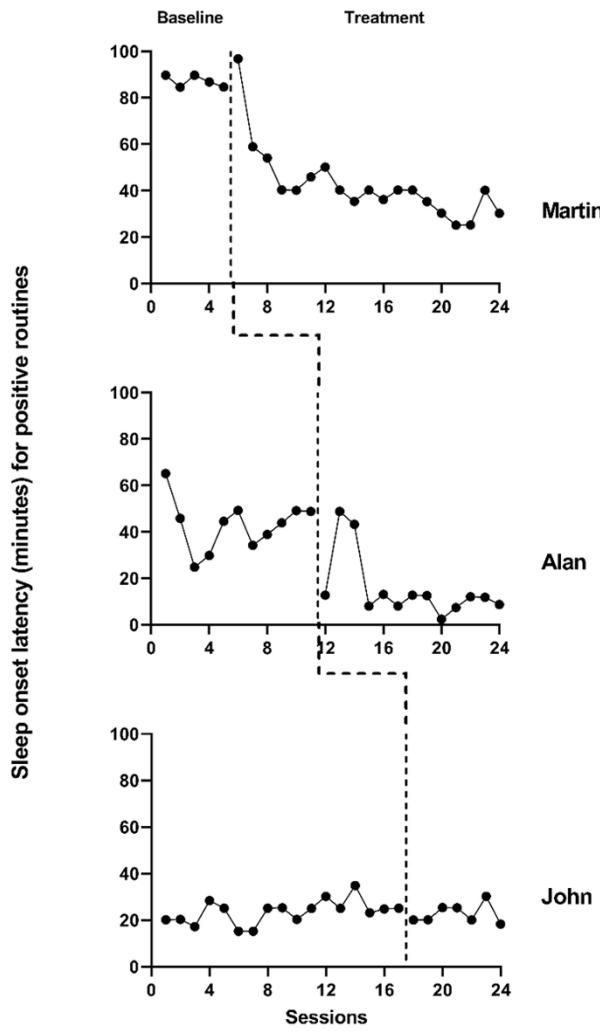
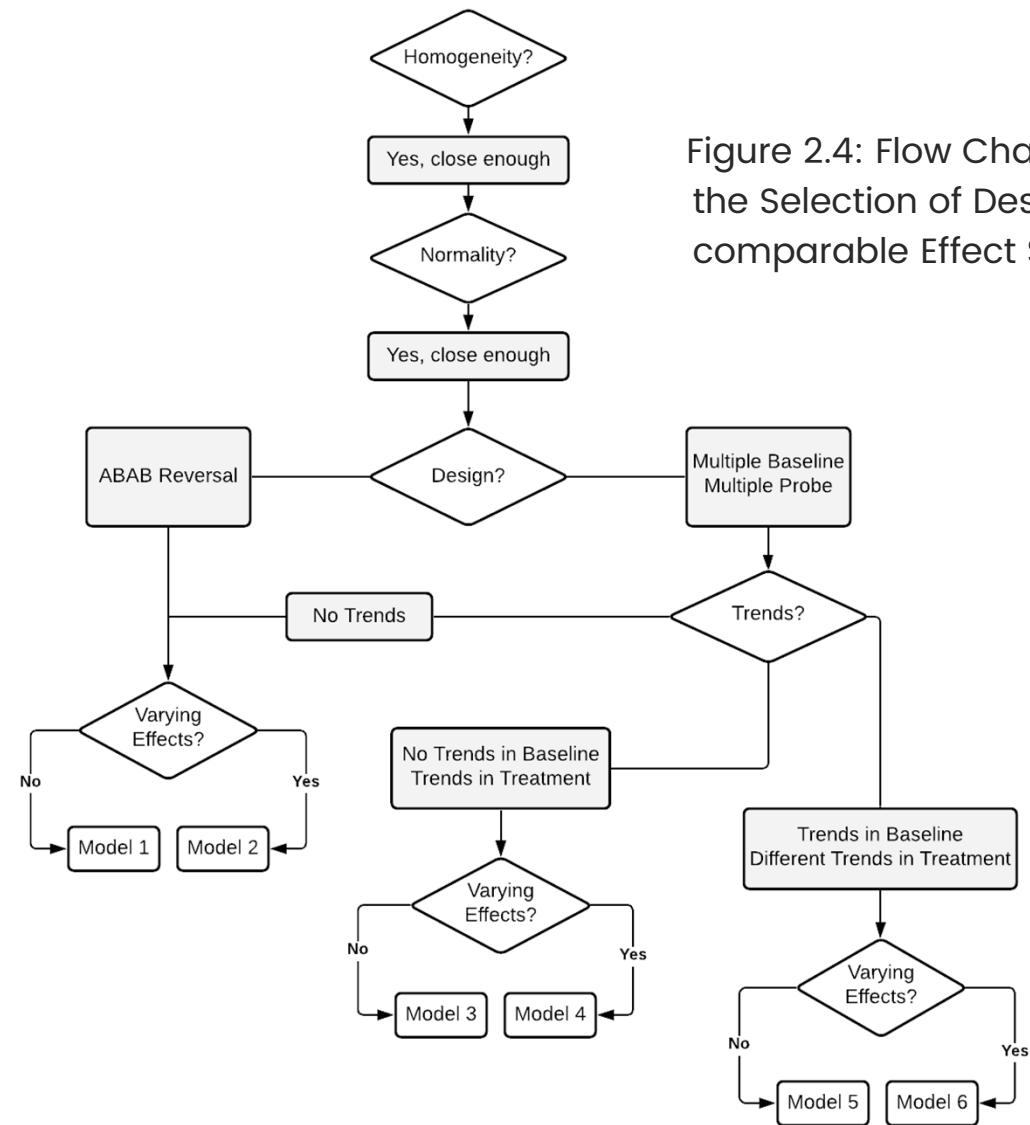


Figure 4.1: Multiple Baseline Data for Martin, Alan, and John (Delemere & Dounavi, 2018)



	A	B	C	D	E
1	Case iden	Phase ide	Session n	Outcome variable	
2	Ben	b	1	2.0	
3	Ben	b	2	2.0	
4	Ben	b	3	3.0	
5	Ben	b	4		
6	Ben	b	5		
7	Ben	b	6		
8	Ben	i	7	7.0	
9	Ben	i	8	6.0	
10	Ben	i	9	7.0	
11	Ben	i	10	5.0	
12	Ben	i	11	7.0	
13	Ben	i	12	5.0	
14	Ben	i	13	6.0	
15	Ben	i	14	7.0	
16	Abernathy	b	1	1.0	
17	Abernathy	b	2		
18	Abernathy	b	3		
19	Abernathy	b	4		

DCES Calculations

scdhlm application

[https://jepusto.shinyapps.io/
scdhlm/](https://jepusto.shinyapps.io/scdhlm/)

(Pustejovsky et al., 2021)



Between-case standardized mean difference estimator

scdhlm Load Inspect Model Effect size Syntax for R

What data do you want to use?

- Use an example
- Upload data from a .csv or .txt file
- Upload data from a .xlsx file

Upload a .xlsx file

Browse... DCES Models 1-2.xlsx Upload complete

File has a header?

Select a sheet

Case Harris for App rev2

1. Please specify the study design.

Multiple Baseline/Multiple Probe

2. Please select the variable containing each type of information.

Case identifier

Case_identifier

Phase identifier

Phase_identifier

Session number

Session_number

Outcome variable

Outcome_variable

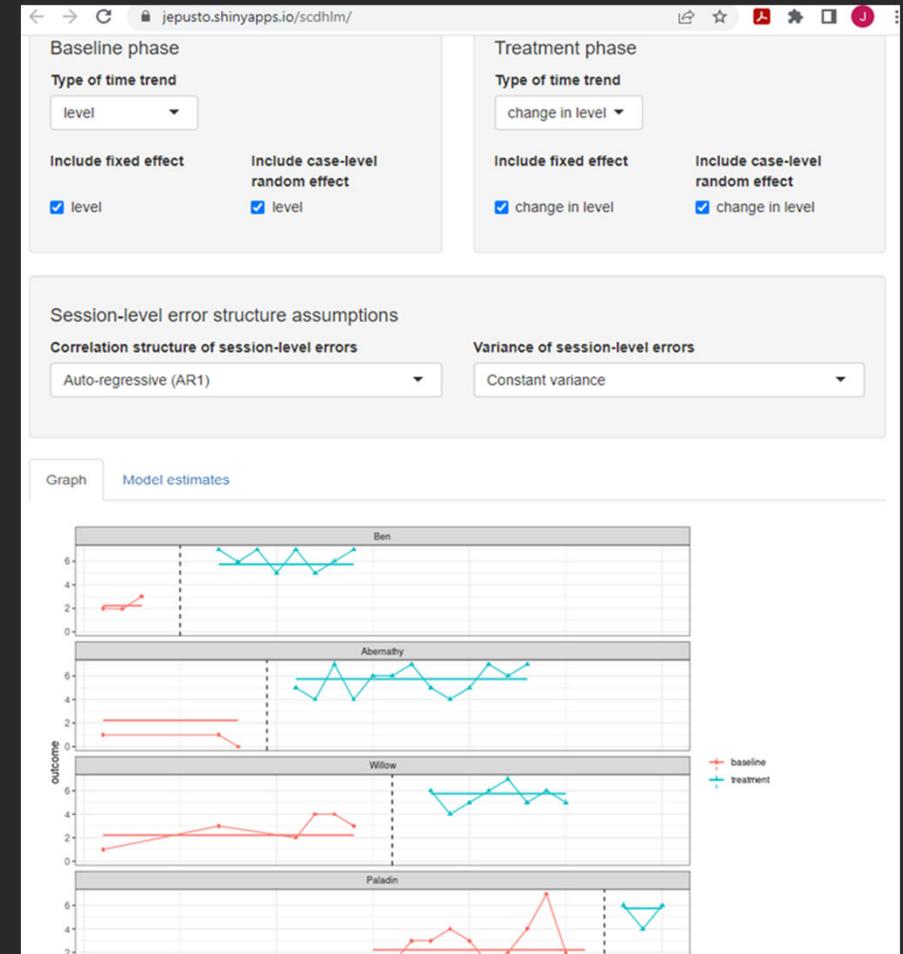
3. Please specify the baseline and treatment levels.

Baseline level

b

Treatment level

i



Effect size estimates and auxilliary information

CI coverage level (%)

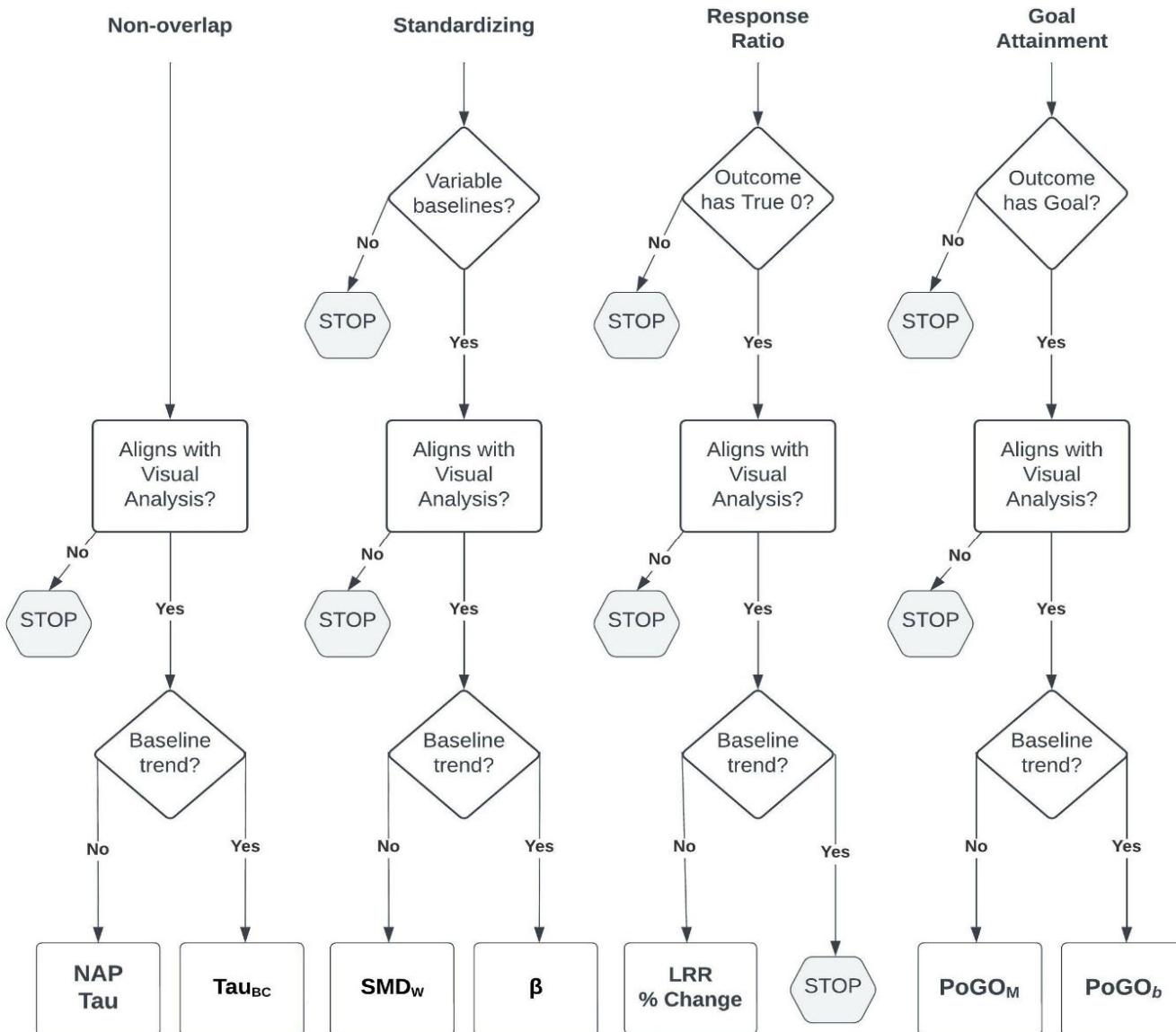
BC-SMD estimate	Std. Error	95% CI (lower)	95% CI (upper)	Degrees of freedom	Auto-correlation	Intra-class correlation	Study design	Estimation method	Baseline specification
2.5719	0.4548	1.6467	3.4970	33.1820	0.1969	0.0000	Multiple Baseline/Multiple Probe	Restricted Maximum Likelihood	F:0 R:0

Download

DCES Calculation

(scdhlm web-based app)

Case Specific Effect Sizes



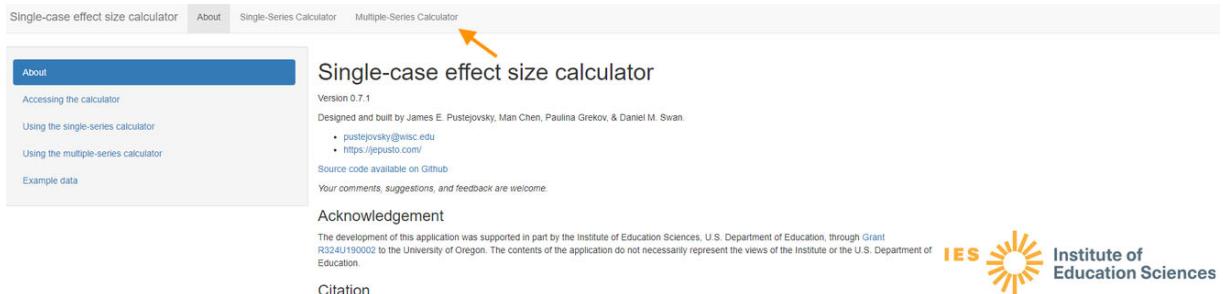
Non-overlap
Standardizing
Response Ratio
Goal Attainment

Case Specific Effect Sizes

Concern	PND	PEM	ECL	NAP (Tau)	TauU	TauBC	SMD (g)	B	LRR	PoGO
Outliers	:frowny:	:smile:	:neutral:	:smile:	:neutral:	:neutral:	:neutral:	:neutral:	:smile:	:neutral:
Baseline length	:frowny:	:smile:	:smile:	:smile:	:frowny:	:smile:	:smile:	:smile:	:smile:	:smile:
SE estimation*	:frowny:	:frowny:	:frowny:	:neutral:	:frowny:	:frowny:	:neutral:	:neutral:	:neutral:	:neutral:
Baseline trends**	:frowny:	:frowny:	:neutral:	:frowny:	:neutral:	:neutral:	:frowny:	:neutral:	:frowny:	:neutral:
Ceiling effects	:frowny:	:frowny:	:frowny:	:frowny:	:frowny:	:frowny:	:smile:	:smile:	:smile:	:smile:
Baselines of 0	:smile:	:smile:	:smile:	:smile:	:smile:	:smile:	:frowny:	:frowny:	:frowny:	:smile:
Outcome scale: No true 0	:smile:	:smile:	:smile:	:smile:	:smile:	:smile:	:smile:	:smile:	:frowny:	:smile:
Outcome has no goal	:smile:	:smile:	:smile:	:smile:	:smile:	:smile:	:smile:	:smile:	:smile:	:frowny:
Computational accessibility	:smile:	:smile:	:neutral:	:smile:	:smile:	:smile:	:smile:	:neutral:	:smile:	:neutral:

*no smiles, because even those that have standard errors rely on tenuous assumptions

**no smiles, because even those that have trend adjustments rely on tenuous assumptions



Single-case effect size calculator About Single-Series Calculator Multiple-Series Calculator

About

Accessing the calculator

Using the single-series calculator

Using the multiple-series calculator

Example data

Single-case effect size calculator

Version 0.7.1

Designed and built by James E. Pustejovsky, Man Chen, Paulina Grekov, & Daniel M. Swain.

- pustejovsky@wisc.edu
- <https://jepusto.com/>

Source code available on [Github](#)

Your comments, suggestions, and feedback are welcome.

Acknowledgement

The development of this application was supported in part by the Institute of Education Sciences, U.S. Department of Education, through Grant R324U190002 to the University of Oregon. The contents of the application do not necessarily represent the views of the Institute or the U.S. Department of Education.

Citation

IES Institute of Education Sciences

Single-Case Effect Size Calculator

(Pustejovsky et al., 2023)

Web-based app

[https://jepusto.shinyapps.io/
SCD-effect-sizes/](https://jepusto.shinyapps.io/SCD-effect-sizes/)

Video demonstration of the Single-Series
Calculator:
[https://www.youtube.com/watch?v=V_r9
MEX9LwY](https://www.youtube.com/watch?v=V_r9MEX9LwY)



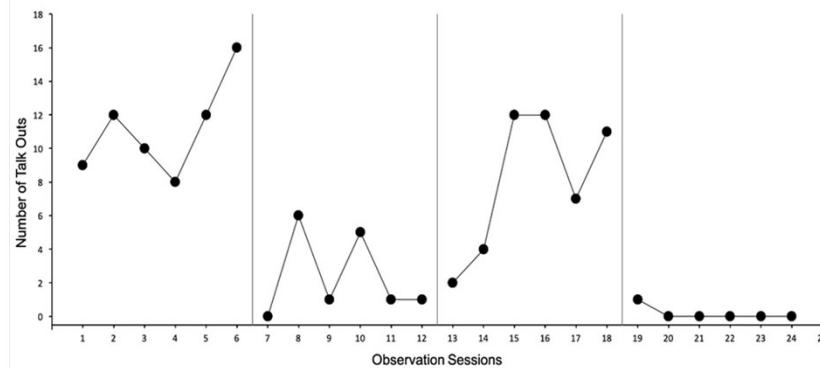
SingleCaseES R package

[https://jepusto.github.io/
SingleCaseES/](https://jepusto.github.io/SingleCaseES/)

Video demonstration of the Multiple-Series
Calculator:
[https://www.youtube.com/watch?v=DSW7
wuFG7og](https://www.youtube.com/watch?v=DSW7wuFG7og)



Crozier, S., & Tincani, M.J. (2005). Using a modified social story to decrease disruptive behavior of a child with autism. Focus on Autism and Other Developmental Disabilities, 20, 150-157.



Data input

Enter data values, separated by commas, spaces, or tabs.

Phase A
9 12 10 8 12 16

Phase B
0 6 1 5 1 1

Show graph

Effect sizes

Non-overlap

Parametric

Effect size index
NAP

Direction of improvement
decrease

Confidence level
95

Digits
2

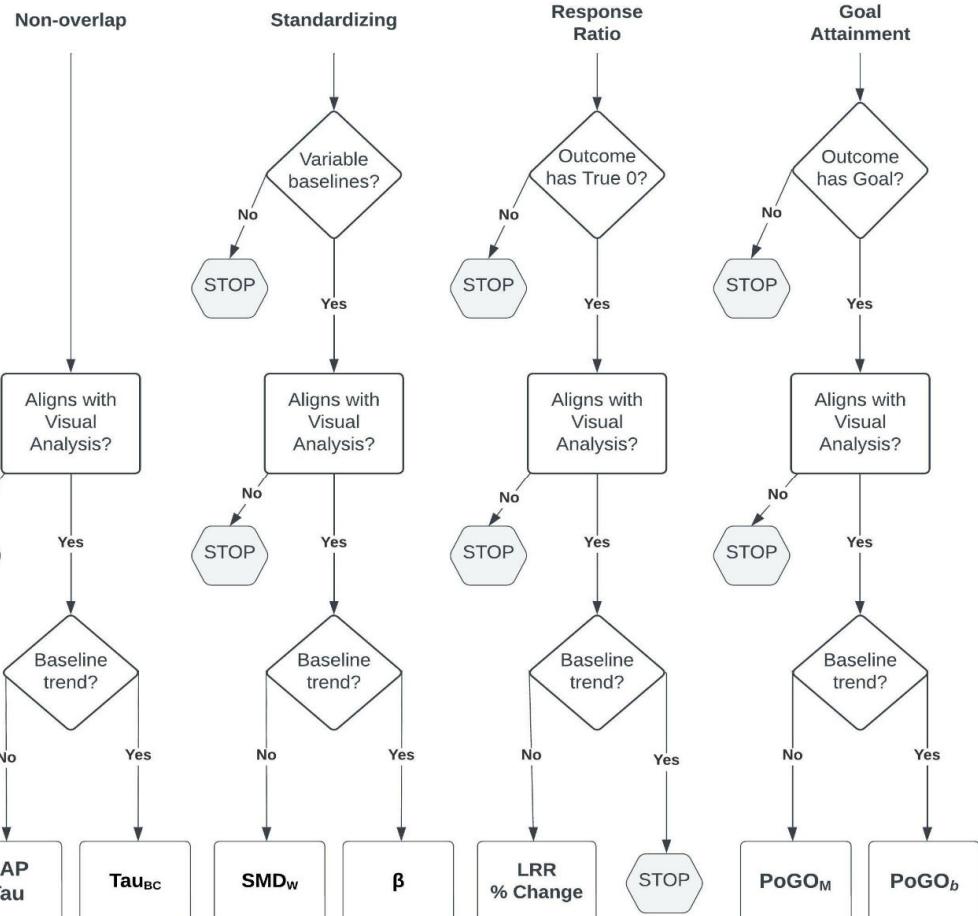
Non-overlap of All Pairs

Effect size estimate: 1.00
Standard error: 0.02
95% CI: [1.00, 1.00]

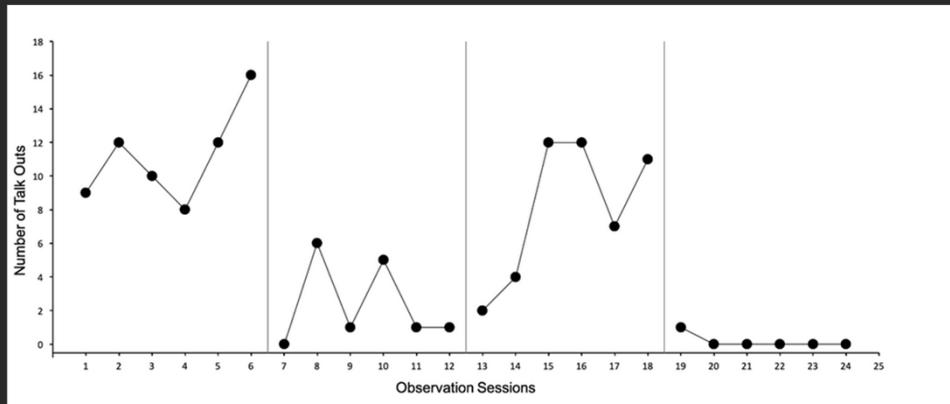
Note: SE and CI are based on the assumption that measurements are mutually independent (i.e., not auto-correlated).

Show methods and references

Illustrative Example



Summary of Effect Sizes from Crozier & Tincani (2005)



Phase Change: A1 to B1

NAP = 1.00
SMDW = 2.60
LRR = -1.48
% Change = -77
PoGO = 79.1

Phase Change: B1 to A2

NAP = .89
SMDW = 1.91
LRR = 1.16
% Change = 219
PoGO = 64.2

Phase Change: A2 to B2

NAP = 1.00
SMDW = 1.52
LRR = -3.40
% Change = -97
PoGO = 97.9

Multilevel Modeling of Raw Data

Choosing between the options
for multilevel models of SCED

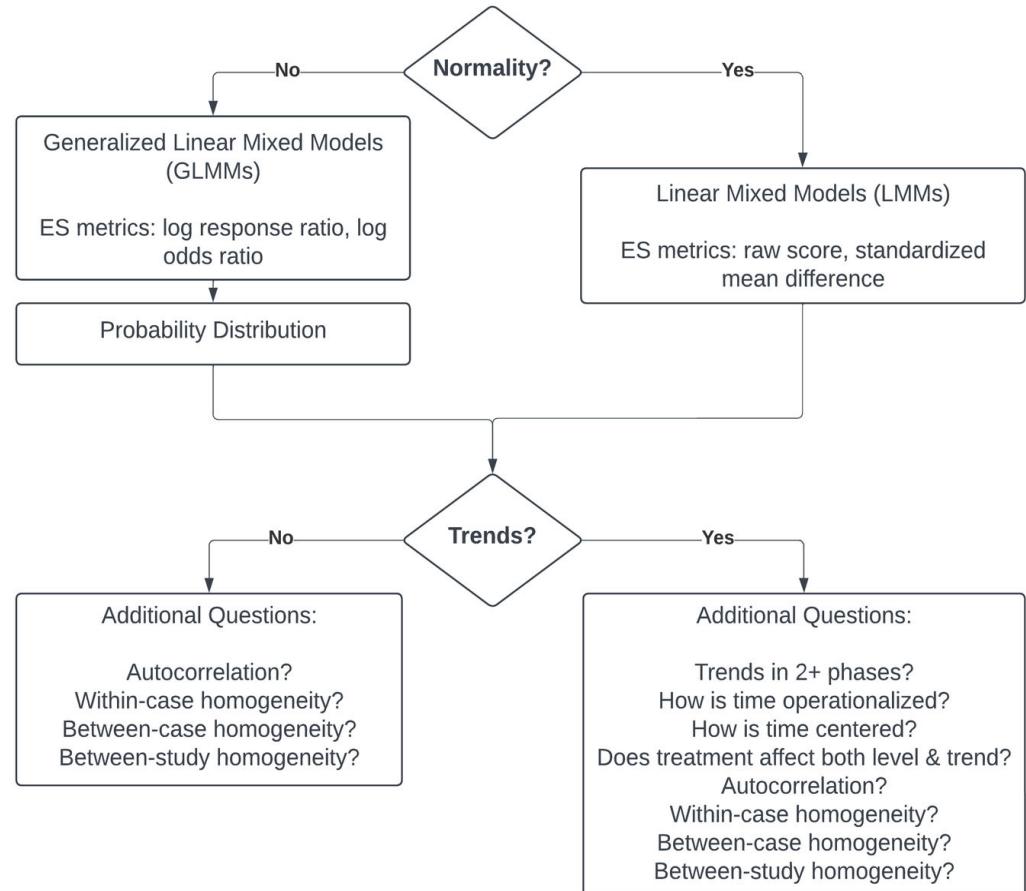


Figure 6.2: Flow Chart for the Selection of Multilevel Modeling Approach

Multilevel Modeling Options for Synthesis of SCED Studies

MultiSCED application
(Declercq et al., 2020)
<http://34.251.13.245/MultiSCED>

Your preferred application
R, SAS, etc.

Three-level model

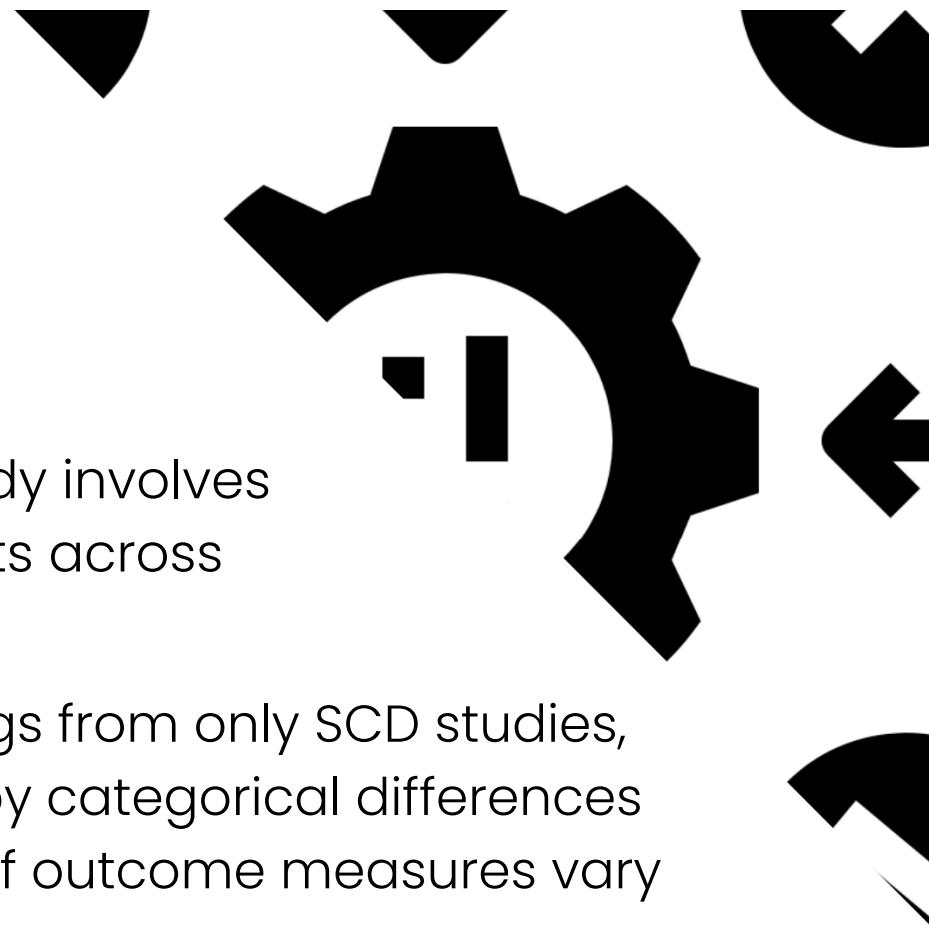
Used in the full meta-analysis.

$$\text{CWSpM}_{ijk} = \beta_0 + \beta_1 \text{Time}_{ijk} + \beta_2 \text{Intervention}_{ijk} + \beta_3 (\text{Intervention} \times \text{Time})_{ijk} + e_{ijk}$$

$$\begin{cases} \beta_{0jk} &= \theta_{00k} + u_{0jk} \\ \beta_{1jk} &= \theta_{10k} + u_{1jk} \\ \beta_{2jk} &= \theta_{20k} + u_{2jk} \\ \beta_{3jk} &= \theta_{30k} + u_{3jk} \end{cases}$$

$$\begin{cases} \theta_{00k} &= \gamma_{000} + v_{00k} \\ \theta_{10k} &= \gamma_{100} + v_{10k} \\ \theta_{20k} &= \gamma_{200} + v_{20k} \\ \theta_{30k} &= \gamma_{300} + v_{30k} \end{cases}$$

It's all about context.



Design-Comparable: Purpose of the study involves the comparison and averaging of effects across single-case and group designs

Case Specific: Aim is to synthesize findings from only SCD studies, exploring variation in treatment effects by categorical differences or individual participant characteristics, If outcome measures vary across studies,

MLM: Analyzing a set of SCEDs that use very similar outcome measures, and the aim is to study effects over time within and between cases.



Preprints are preliminary reports that have not undergone peer review.
They should not be considered conclusive, used to inform clinical practice,
or referenced by the media as validated information.

A Meta-Analysis of Reading Interventions for Students with Emotional/Behavioral Disorders

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Research Article

Keywords: Meta-analysis, emotional disorder, behavioral disorder, reading intervention, reading outcome

Posted Date: December 1st, 2024

DOI: <https://doi.org/10.21203/rs.3.rs-5362938/v1>

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Additional Declarations: No competing interests reported.



Journal of Autism and Developmental Disorders
<https://doi.org/10.1007/s10803-023-08212-2>

ORIGINAL PAPER



Contents lists available at [ScienceDirect](#)

Early Childhood Research Quarterly



journal homepage: www.elsevier.com/locate/ecresq



Review

Embedded instruction for young children with disabilities: A systematic review and meta-analysis of single-case experimental research studies

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ARTICLE INFO

Keywords:
Inclusion
Embedded instruction
Young children with disabilities
Evidence-based practice
Meta-analysis

ABSTRACT

Embedded instruction is a recommended practice to support development and learning of young children with disabilities in inclusive early childhood settings and natural environments. The number of individual studies investigating the impact of embedded interventions on child learning outcomes has increased in recent years. In the current systematic review and meta-analysis, we examined the methodological quality, characteristics, and effects of single-case experimental research studies focused on embedded instruction to determine whether the evidence from these studies suggests embedded instruction is effective for young children with disabilities. We evaluated rigor of the studies using What Works Clearinghouse (2017) instrument and quality indicators of single-case experimental research, and calculated treatment effect estimates using Tau-U. A total of 10 single-case experimental research studies with 21 participants published between 1993 and 2017 met the inclusion criteria and were included in this systematic review and meta-analysis. The studies were conducted by seven different research groups with no overlapping authorship at seven different institutions across two countries. The mean treatment effect of embedded instruction on child learning outcomes across the 10 studies was .80. This systematic review and meta-analysis provide sufficient evidence to consider embedded instruction as an evidence-based practice for young children with disabilities and to support its continued use in enhancing the development and learning of young children with disabilities in inclusive early childhood settings. Implications for future research and practice are discussed.

Some Concrete Examples

Recent syntheses using DCES and Case Specific effect size estimation methods

Individual Participant Data Meta-Analysis Including Moderators: Empirical Validation

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^aUniversity at Albany-SUNY, Albany, NY, USA; ^bPrinceton University, Princeton, NJ, USA

ABSTRACT

We have entered an era in which scientific evidence increasingly informs research practice and policy. As there is an exponential increase in the use of single-case experimental designs (SCEDs) to evaluate intervention effectiveness, there is accumulating evidence available for quantitative synthesis. Consequently, there is a growing interest in techniques suitable to meta-analyze SCED research. One technique that can be applied is individual patient data (IPD) meta-analysis. IPD is a flexible approach, allowing for a variety of modeling options such as modeling moderators to explain intervention heterogeneity. To date, no methodological research has been conducted to evaluate the statistical properties of effect estimates obtained by using IPD meta-analysis with the inclusion of moderators. This study is designed to address this by conducting a large-scale Monte Carlo study. Based on the results, specific recommendations are provided to indicate under which conditions the IPD meta-analysis including moderators is suitable.

KEYWORDS

Individual patient meta-analysis; meta-analysis; moderators; Monte Carlo simulation study; simulation studies; single-case experimental design



A Systematic Review and Meta-Analysis of Single Case Experimental Design Play Interventions for Children with Autism and Their Peers

Megan Fedewa¹ , Laci Watkins¹, Lucy Barnard-Brak¹, Yusuf Akemoglu²

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Abstract

This systematic review and meta-analysis examined interventions targeting play skills of children with autism spectrum disorder (ASD) involving typically developing (TD) peers. The objectives of this work are to (a) identify and describe the characteristics and components of interventions aimed at improving play skills in children with ASD and their TD peers, (b) examine the role of peers in interventions, (c) evaluate intervention effects, and (d) identify potential moderating variables that may influence intervention outcomes. Twenty single-case experimental design (SCED) studies published between 2000 and 2020 were included and summarized. The majority of interventions produced significant effects, further supporting the inclusion of TD peers in interventions targeting play skills for children with ASD. Recommendations for future research and practice are discussed.

Keywords Autism spectrum disorder · Peers · Play · Intervention

Play is essential to childhood development. The development of play skills is linked to increased social communication skills, cooperative behavior, and joint attention (Shire et al., 2020). Play develops in a natural progression among typically developing (TD) children. Beginning around age two, play skills progress from parallel play (playing independently beside another) to more social play (communicating

while communicating about play, proposing a script, assigning roles, etc.) (Howes, 1988; Howes & Matheson, 1992). Complex cooperative or social play is critical to development and is understood as a merger between two crucial areas: cognitive development and socioemotional development (Jordan, 2003).

Children with autism spectrum disorder (ASD) often

have difficulty with play skills, particularly social play (communicating about play, proposing a script, assigning roles, etc.) (Howes, 1988; Howes & Matheson, 1992).

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Children with autism spectrum disorder (ASD) often

MLM Examples



Multilevel Meta-Analysis of Single-Case Experimental Designs Using Robust Variance Estimation

Man Chen and James E. Pustejovsky

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Abstract

Single-case experimental designs (SCEDs) are used to study the effects of interventions on the behavior of individual cases, by making comparisons across multiple measures of an outcome across different intervention conditions. In research areas where SCEDs are prevalent, there is a lack of methods to synthesize results across multiple studies. One approach to synthesis uses a multilevel meta-analysis (MLMA) model to describe the distribution of effect sizes across studies and across cases within studies. However, MLMA relies on having accurate sampling variances of effect size estimates for each case, which may not be possible due to auto-correlation in the raw data series. One possible solution is to combine MLMA with robust variance estimation (RVE), which provides better estimation of uncertainty even if the sampling variance of the effect size estimate is inaccurate. Another possible solution is to focus on MLMA and use simpler, ordinary least squares (OLS) methods with RVE. This study evaluates the performance of effect size estimators and methods of synthesizing SCEDs in the presence of auto-correlation, for several different effect size metrics, via a Monte Carlo simulation designed to emulate the features of real data series. Results demonstrate that the MLMA model with RVE performs properly in terms of bias, consistency, and confidence interval coverage, estimating overall average log response ratios. The OLS estimator combined with RVE performs the best in terms of overall average Tau effect size. None of the available methods perform adequately for meta-analysis of within-case standardized mean differences.

Translational Abstract

Single-case experimental designs (SCEDs) are used to investigate the effects of interventions for individual participants (or cases), through comparison of outcomes measured under different intervention conditions. Effect size metrics are quantitative indices for describing the strength of intervention effects and can be used to summarize results across multiple studies. One approach to synthesis is to use a multilevel meta-analysis (MLMA) model. Because outcomes in SCEDs are collected repeatedly over time for each case, it is possible that outcomes that are closer in time tend to be more similar to each other compared to outcomes from more distant time points, leading to auto-correlation. The MLMA relies on an assumption that might be violated due to auto-correlation. One possible solution is to combine MLMA with robust variance estimation (MLMA-RVE), which provides better estimation in the presence of auto-correlation. Another possible solution is to use simpler OLS methods along with RVE (OLS-RVE). In this study, a Monte Carlo simulation was conducted to evaluate the performance of several commonly used effect size indices and methods of summarizing SCEDs when auto-correlation is present. The simulation results demonstrate that the MLMA-RVE performs well for the log response ratio effect size index. The OLS-RVE provides good performance for the Tau effect size index. None of the available methods produce adequate performance for the within-case standardized mean difference index.

Keywords: meta-analysis, single-case experimental designs, log response ratio, nonoverlap of all pairs, within-case standardized mean difference

Supplemental materials: <https://doi.org/10.1037/met0000510.sup>

Meta-Analysis of Single-Case Design Research: Application of Multilevel Modeling

Mikyung Shin, Stephanie L. Hart, and Michelle Simmons

Department of Education, Center for Learning Disabilities, West Texas A&M University

This study describes the benefits and challenges of meta-analyses of single-case design research using four-level multilevel modeling through open-source R code. The demonstration uses data from multiple-baseline or multiple-probe across-participant single-case design studies ($n = 21$) on word problem instruction for students with learning disabilities published between 1975 and 2023. Researchers explore changes in levels and trends between adjacent phases (baseline, intervention, intervention vs. maintenance) using the mixed model. The findings conclude that word problem solving of students with learning disabilities based on the complexity of the word problem (matrices, multiplication, division, mixed-word problem, and generalization questions). These moderating effects differed across adjacent phases. These findings extend previous literature on meta-analyses methodology by describing how multilevel modeling can be used to compare the impacts of time-varying predictors within and across cases when analyzing single-case design studies. Future researchers may want to use this methodology to explore the roles of time-varying predictors as well as case or study-level moderators.

Thank you!

Questions? Comments?

Methods Guide for Effect Estimation and Synthesis of Single-Case Studies

January 16, 2024

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Disclaimer

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Visit: <https://jepusto.github.io/SCD-Methods-Guide/>