

The state of single-case synthesis: Premises, tools, and possibilities

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- This work has been shaped by many collaborators, although the views expressed are my own (as are any errors!).



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Positionality

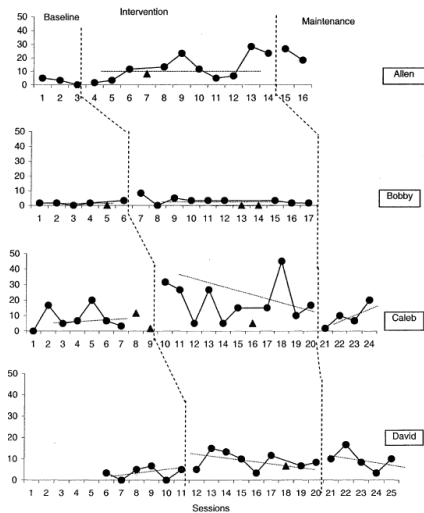
- Trained as statistician.
- Interested in single-case methodology as a toolset for investigating research contexts where other methodologies are infeasible or unsuitable.
- Scholarship focuses on meta-analysis methods, social science applications.
- No experience as interventionist or primary researcher.

Overview

- Premises of synthesis
- Currently available tools for single-case synthesis
- Theoretical possibilities and directions

PREMISES

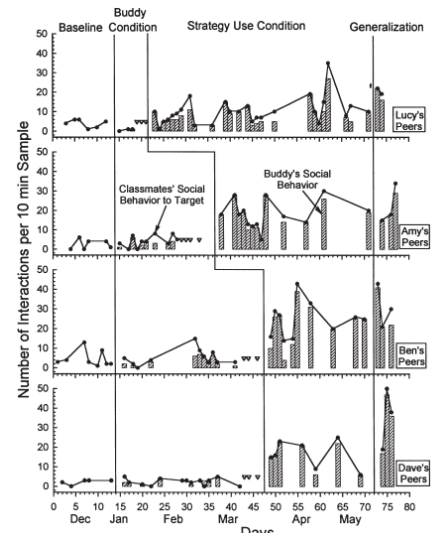
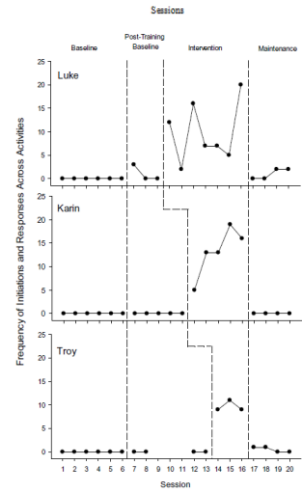
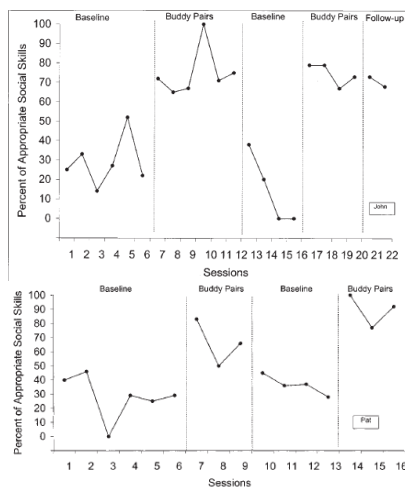
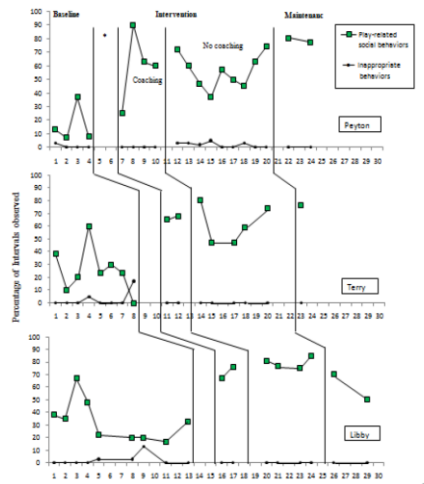
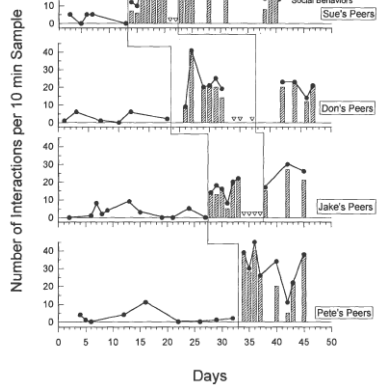
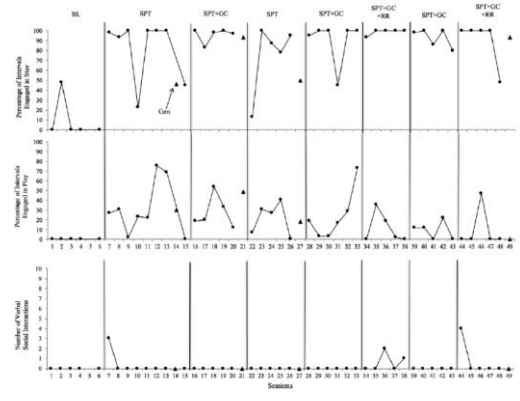
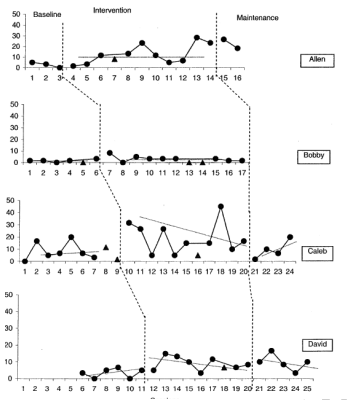
Research synthesis for informing evidenced-based practice



- SCED can provide evidence about intervention effects *for individual participants*.
- But single SCEDs provided limited basis for *generalization* to other participants or contexts.
- Combining evidence from multiple studies can provide a firmer basis for generalization about effects of intervention.

Synthesis of SCEDs

- Summarize magnitude of intervention effects.
- Characterize *variation* in effect magnitude.
- Identify *systematic predictors* of effectiveness.



Roadblocks for analysis of SCED data

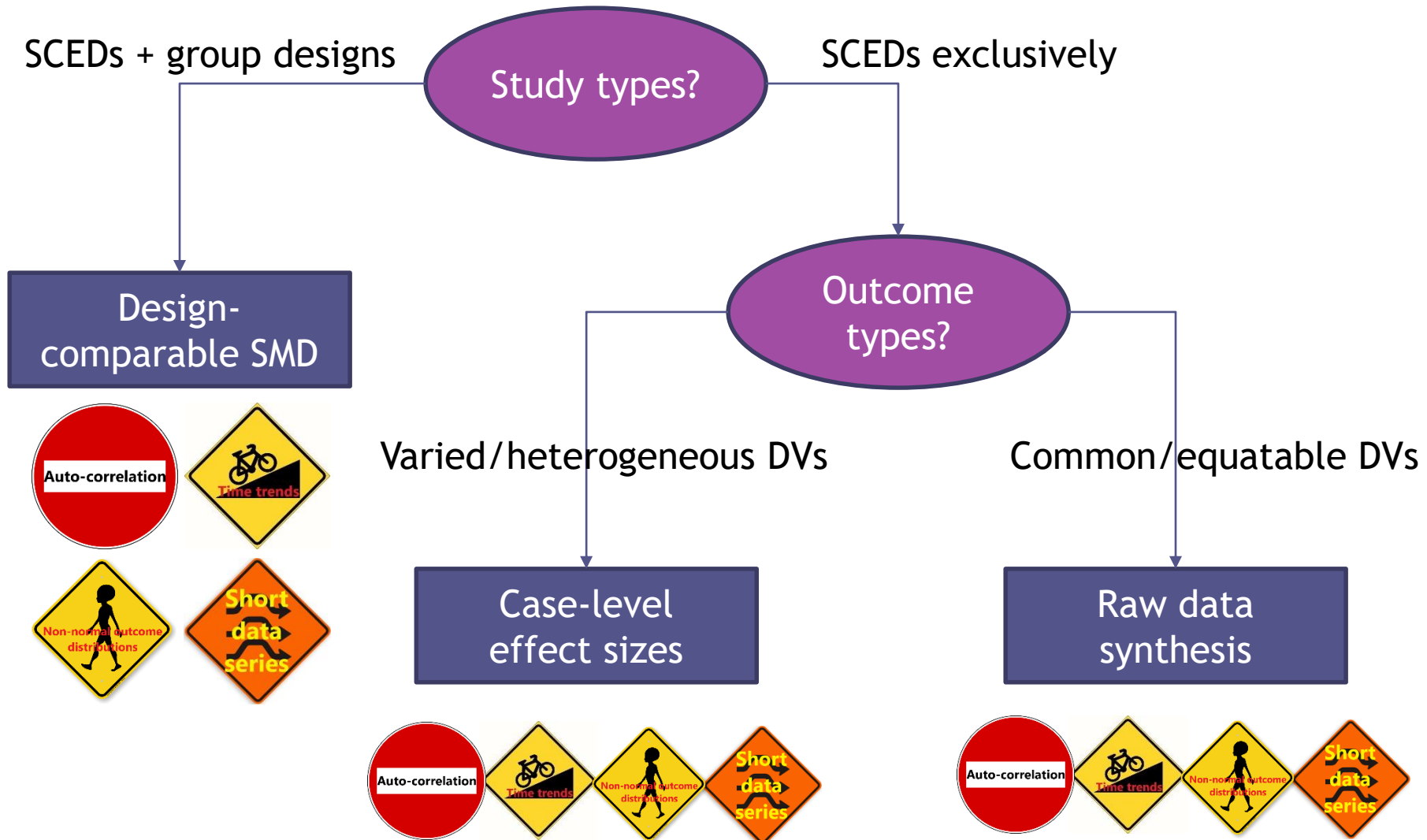


CURRENT TOOLS

Three broad approaches to synthesis

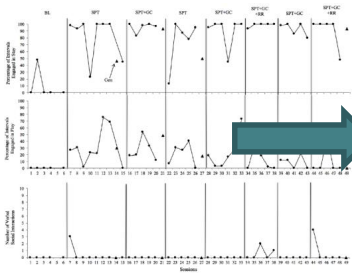
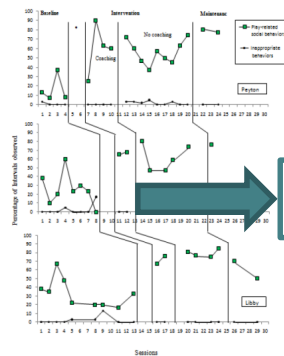
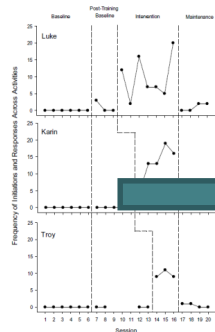
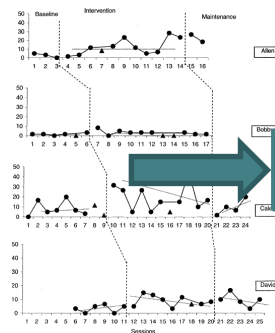
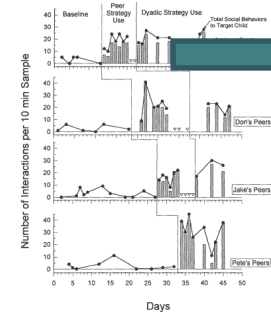
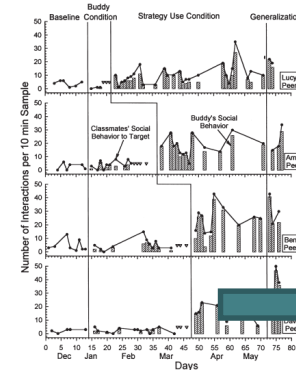
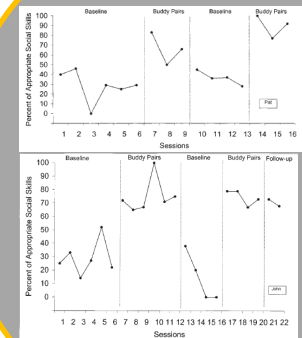
1. Meta-analysis of study-level summary effect sizes
(design-comparable standardized mean differences)
2. Meta-analysis of case-level effect sizes
3. Raw data synthesis

Synthesizing single-case research



Study-level summary effect sizes

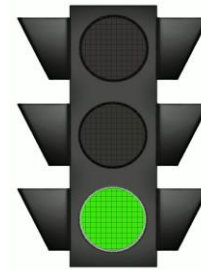
- Between-case standardized mean difference (a.k.a. design-comparable effect size)
- Single-number summary of average intervention effect.


 d_1, SE_1

 d_3, SE_3

 d_2, SE_2

 d_4, SE_4

 d_5, SE_5

 d_6, SE_6


Study-level summary effect sizes

- Goal: Provide a summary effect size in a metric that is theoretically comparable to ES from a between-group design.
 - Can then use conventional meta-analysis methods for synthesis.

- Roadwork completed:
 - ✓ Models account for autocorrelation
 - ✓ Can model time trends



- scdhlm web-app and R package
(<https://www.jepusto.com/software/scdhlm/>)

Study-level summary effect sizes



- Current limitations:
 - Only one available metric (SMD), based on models with normally distributed errors.
 - Requires designs with **3+ participants** in order to estimate between-person variation in outcome (for scale).
 - Limited available designs:
 - Across-participant multiple baseline/multiple probe.
 - Replicated treatment reversals (ABAB).
- Chen and colleagues propose extensions for BC-SMD to:
 - Multiple baselines across behaviors, replicated across participants.
 - Clustered multiple baseline designs.
 - Multivariate across-participant multiple baseline designs.

Case-level effect sizes



PND

PAND

IRD

LRR

POGO

PEM

NAP

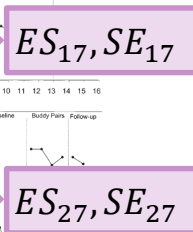
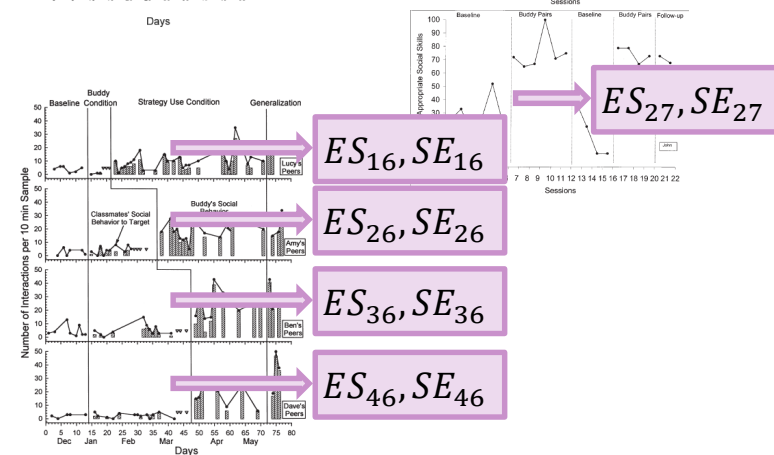
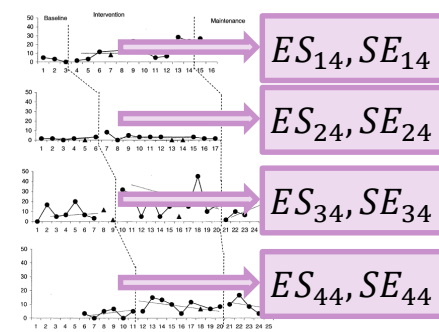
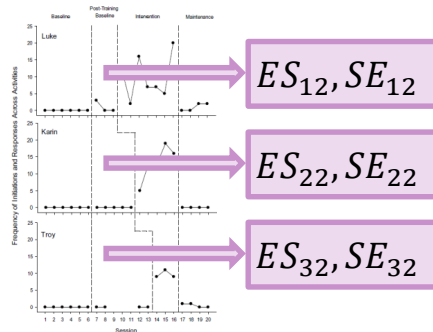
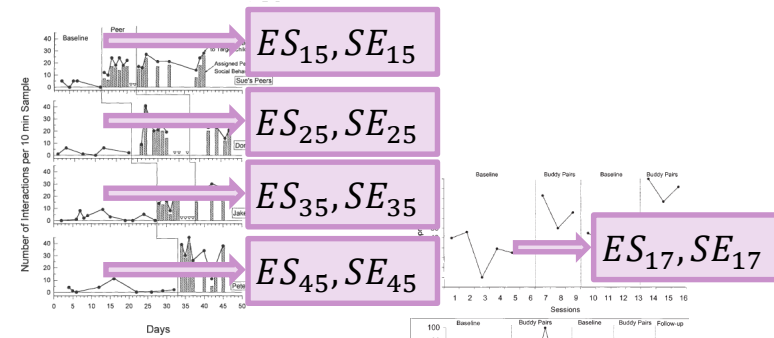
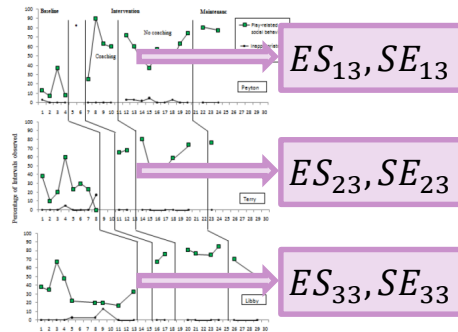
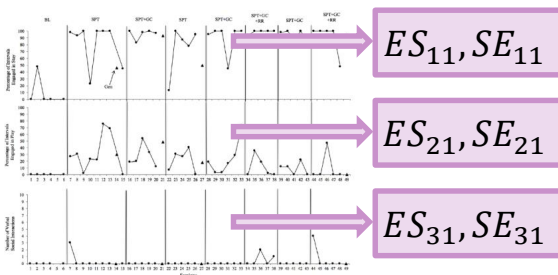
Tau(AB)

SMD(within)

Tau-U

Case-level effect sizes

- Single-number summary of intervention effect *for each case*.



Case-level effect sizes

- Goal: Compare results across participants and SCED studies *that use various outcome measures*.
 - Examine heterogeneity of effects within and between studies.
 - Examine individual-level predictors of effects.
- Many available ES metrics, some appropriate for non-normal outcome distributions.
 - But most available metrics only describe level change.
- SingleCaseES web-app and R package (<https://www.jepusto.com/software/SingleCaseES/>)



Meta-analysis of case-level effect sizes



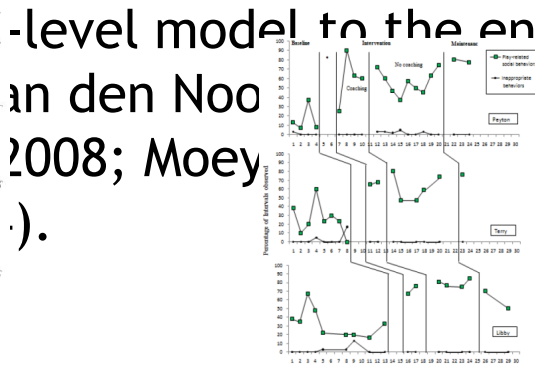
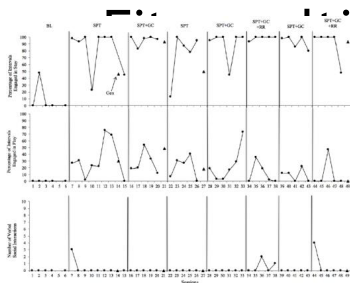
- Because of short data series, strategy for meta-analysis depends on the effect size metric (Chen & Pusto, In Press).

Metric	Strategy	Non-normal outcomes	Auto-correlation	Time trends
Log response ratio	Multi-level meta-analysis			
Within-case SMD	Simple average			
Non-overlap of All Pairs	Simple average			
Tau(AB)	Simple average			

Raw data synthesis

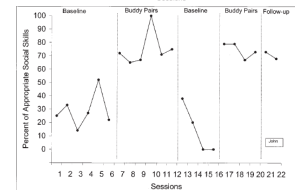
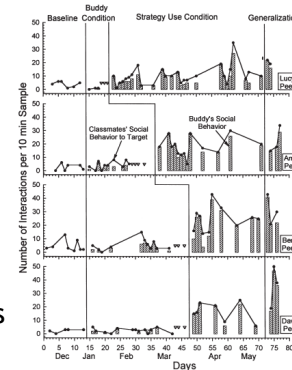
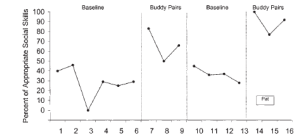
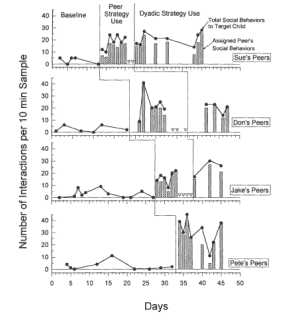
- Combine the raw data from multiple participants & studies.
 - This requires common DVs or DVs that can be meaningfully equated.

Three-level model to the entire
 van den Noortgate, W. (2008); Moeyaert, M., et al. (2013).



- Moeyaert, M., Ugille, M., Ferron, J. M., Beretvas, S. N., & Van den Noortgate, W. (2013). The three-level synthesis of standardized single-subject experimental data: A monte carlo simulation study. *Multivariate Behavioral Research*, 48(5), 719-748. <http://doi.org/10.1080/00273171.2013.816621>
- Moeyaert, M., Ugille, M., Ferron, J. M., Beretvas, S. N., & Van den Noortgate, W. (2014). Three-level analysis of single-case experimental data: Empirical validation. *The Journal of Experimental Education*, 82(1), 1-21. <http://doi.org/10.1080/00220973.2012.745470>

- Van den Noortgate, W., & Onghena, P. (2008). A multi-level meta-analysis of single-subject experimental design studies. *Evidence-Based Communication Assessment and Intervention*, 2(3), 142-151. <http://doi.org/10.1080/17489530802505362>



Raw data synthesis

- Goal: Develop a model that describes the distribution of outcomes (and effects) across studies, cases, & phases.
 - Examine heterogeneity of effects within and between studies.
 - Examine individual-level predictors of effects.
 - Examine temporal variation in effects.

- Roadwork completed:

- ✓ Models can account for autocorrelation
- ✓ Can develop models with time trends
- ✓ Can handle short data series

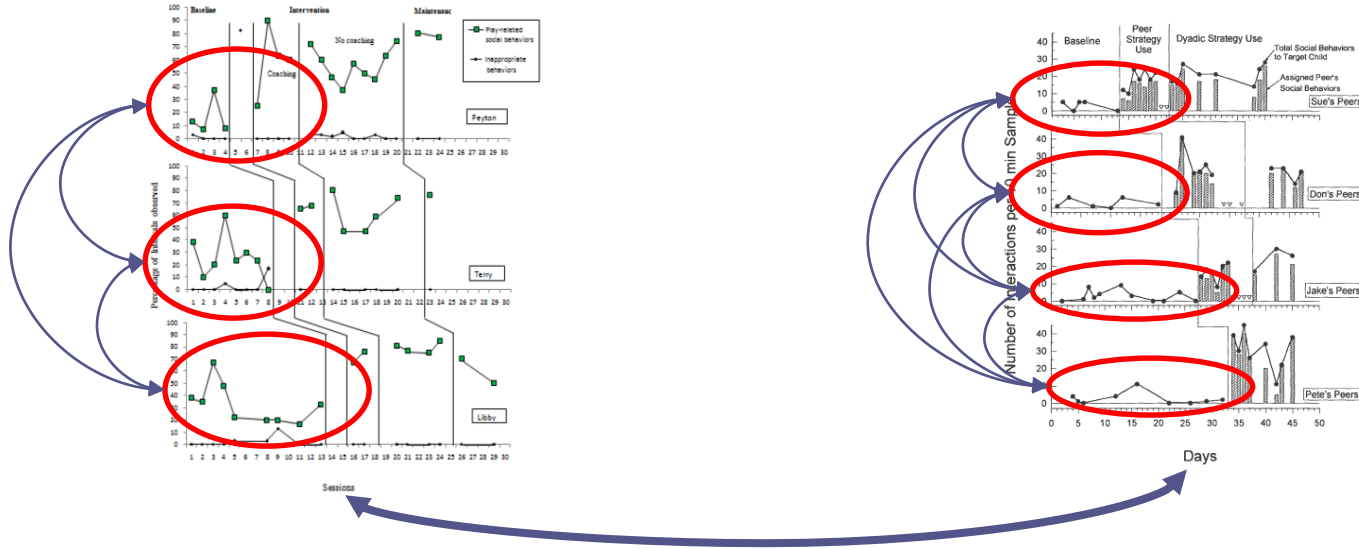


- MultiSCED web-app

(<https://ppw.kuleuven.be/single-case>)

Raw data synthesis: Assumptions

- Features of baseline data series (levels, slopes, variability) are *similar across cases and studies*.



- Timing of intervention start/end is *unrelated to outcome pattern* (levels, slopes, variability).

Raw data synthesis



- Current limitations:
 - Available methods limited to raw mean difference or within-case SMD metrics.
 - Available models are mostly based on normally distributed errors
- Declercq and colleagues (2020) investigate models for count outcomes.

THEORETICAL POSSIBILITIES AND DIRECTIONS

Three broad approaches to synthesis

	Goal/level of analysis	ES metrics	Assumptions
Study-level summary effect sizes	Study	BC-SMD	Hierarchical model of each study
Case-level effect sizes	Case	Many	Case-specific
Raw data synthesis	Time-point	Raw mean difference, within-case SMD	Hierarchical model across studies

Level of analysis, ES metric, and assumptions are *theoretically distinct* and (possibly) *orthogonal dimensions*.

Theoretical possibilities

Assumptions

ES metric	Study-level analysis	Case-level analysis	Time-point-level analysis
Raw mean difference		X	X
Standardized mean difference (within)		X	X
Standardized mean difference (between)	X		
Response ratio		X	
Odds ratio		X	
Non-overlap		X	
...			

Level of analysis

- Level of analysis should be determined by research aims/research questions.
 - What sources of variation are of interest?
- Higher level of analysis is more reductive, but also simpler to explain.

Effect size metric choice

- ES metric needs to be meaningful and interpretable for the set of interventions and dependent variables identified for synthesis.
- Dependent variable and form of intervention effect should be primary considerations.

Assumptions

- Currently, little recognition of the connection between study procedures and statistical/meta-analytic modeling assumptions.
 - How do response-guided design practices affect assumptions (Joo et al., 2018; Swan et al., 2020)?
- Both substantive SCED researchers and methodologists need to work on *clarifying and scrutinizing our assumptions*.
- Need better tools for *investigating model fit*, building confidence in statistical summaries of SCED research.

Joo, S.-H., Ferron, J. M., Beretvas, S. N., Moeyaert, M., & Van den Noortgate, W. (2018). The impact of response-guided baseline phase extensions on treatment effect estimates. *Research in Developmental Disabilities, 79*, 77-87. <https://doi.org/10.1016/j.ridd.2017.12.018>

Swan, D. M., Pustejovsky, J. E., & Beretvas, S. N. (2020). The impact of response-guided designs on count outcomes in single-case experimental design baselines. *Evidence-Based Communication Assessment and Intervention, 1-26*. <https://doi.org/10.1080/17489539.2020.1739048>

Which combinations are needed?

	ES metric	Study-level analysis	Case-level analysis	Time-point-level analysis
Raw mean difference			X	X
Standardized mean difference (within)			X	X
Standardized mean difference (between)	X			
Response ratio			X	
Odds ratio			X	
Non-overlap			X	
...				

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Illustrative use case for BC-SMD

- Calder and colleagues (2020, 2021) studied an explicit grammar instruction intervention for children with developmental language disorder.
- 2020: multiple baseline across nine participants
 - Summary effect sizes after 9 weekly intervention sessions.
 - $d = 1.45, SE = 0.54$ for expressive morphosyntax.
 - $d = -0.04, SE = 0.54$ for grammaticality judgements.
- 2021: crossover randomized trial
 - $N = 21$ participants
 - $d = 1.97, SE = 0.11$ for expressive morphosyntax.
 - $d = 0.06, SE = 0.06$ for grammaticality judgements.

Calder, S. D., Claessen, M., Ebbels, S., & Leitão, S. (2020). Explicit grammar intervention in young school-aged children with developmental language disorder: An efficacy study using single-case experimental design. *Language, Speech, and Hearing Services in Schools*, 51(2), 298-316. https://doi.org/10.1044/2019_LSHSS-19-00060

Calder, S. D., Claessen, M., Ebbels, S., & Leitão, S. (2021). The efficacy of an explicit intervention approach to improve past tense marking for early school-age children with developmental language disorder. *Journal of Speech, Language, and Hearing Research*, 64(1), 91-104. https://doi.org/10.1044/2020_JSLHR-20-00132