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Comparing the percentage of non-overlapping data approach and the hierarchical linear modeling approach for synthesizing single-case studies in autism research

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ABSTRACT

We examined the performance of two approaches for synthesizing single-case experimental data: the percentage of non-overlapping data (PND) approach and the hierarchical linear modeling (HLM) approach. The comparison was performed by analyzing an empirical dataset on behavioral interventions for reducing challenging behavior in persons with autism by means of the two approaches. We compared the findings of both approaches for analyzing the outcomes of the behavioral interventions as well as for identifying moderating variables. With respect to the analysis of the interventions' outcomes, similar positive results were found based on both approaches. With respect to the moderating variables, *Functional analysis/assessment* and *Availability of follow up data* were found to be statistically significant moderators by means of the PND as well as the HLM approach. The variables *Intervention type*, *Availability of generalization attempts*, *Design type*, and *Availability of inter-rater reliability data* were also found to be statistically significant moderators by means of the PND approach. The PND approach seems overly liberal in identifying statistically significant predictors in comparison to the HLM approach.

1. Introduction

A considerable number of empirical studies on interventions in persons with autism rely on single-case experimental designs (SCEDs) (e.g., Bulkeley, Bundy, Roberts, & Einfeld, 2013; Ganz et al., 2011; Matson, Turygin, Beighley, & Matson, 2012; Reynhout & Carter, 2011; Wang, Cui, & Parrila, 2011). SCEDs are often used to evaluate the effect of an intervention for a single person or a small number of persons, although they can also be used for studying a large number of participants (e.g., Geller, Paterson, & Talbott, 1982). In an SCED involving a single participant, the intervention (e.g., a social stories intervention) can be considered as one of the levels of the independent variable, which is manipulated by the experimenter, and the effect can be evaluated by a dependent variable (e.g., prosocial behavior), which is measured repeatedly for this single person over time.

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1.1. Analyzing individual study data

Traditionally, single-case researchers have been using visual analysis for evaluating behavior change, by means of inspecting graphed SCED data for changes in level, variability, trend, latency to change, and overlap between phases in order to judge the reliability and consistency of treatment effects (Horner, Swaminathan, Sugai, & Smolkowski, 2012; Kazdin, 2011). It is concluded that the changes in behavior across phases result from the implemented treatment and are indicative of improvement when the changes in level, trend, and/or variability are in the desired direction and when they are immediate, readily discernible, and maintained over time (Busse, Kratochwill, & Elliott, 1995). However, when there is a long latency between manipulation of the independent variable and change in the dependent variable, when level changes across conditions are small and/or similar to changes within conditions, and when trends do not conform to those predicted following manipulation of the independent variable, demonstration of a functional relationship between the independent and dependent variable is compromised (Horner et al., 2005; Kazdin, 2011).

A group of SCED effect size measures that closely relates to visual analysis are nonoverlap statistics, such as the percentage of non-overlapping data (PND; Scruggs, Mastropieri, & Casto, 1987), the percentage of data points exceeding the median of baseline phase (PEM; Ma, 2006), and the percentage of all nonoverlapping data (PAND; Parker, Hagan-Burke, & Vannest, 2007). These nonoverlap statistics are all nonparametric effect size measures. In addition to nonparametric SCED effect size measures, parametric effect size measures for analyzing and interpreting SCED data have been developed, such as standardized mean difference (SMD) and regression-based effect size measures. Examples are the SMD effect size measure developed by Hedges, Pustejovsky, and Shadish (2012), the piecewise regression approach of Center, Skiba, and Casey (1985–1986), the regression approach of White, Rusch, Kazdin, and Hartmann (1989), the regression approach of Allison and Gorman (1993), and hierarchical linear modeling (HLM; Van den Noortgate & Onghena, 2003a,b).

Next to the use of descriptive statistics (including parametric and nonparametric effect size measures), inferential statistical techniques can be used for analyzing SCED data (including parametric and nonparametric significance tests). Parametric significance tests traditionally used for analyzing group-comparison studies, such as *t*- and *F*-test, are often not appropriate to analyze SCEDs because assumptions of normality are frequently violated for SCED data, SCED data are often autocorrelated, and these tests are insensitive to trends that occur within a phase (Houle, 2009; Smith, 2012). Parametric approaches that are more appropriate to analyze SCED data are for instance generalized least squares regression analysis (Maggin et al., 2011b), interrupted time series analysis procedures such as ITSACORR (Crosbie, 1993, 1995), piecewise regression analysis (Center et al., 1985–1986), and HLM (Van den Noortgate & Onghena, 2003a,b). Of those parametric approaches, the HLM approach is considered one of the most promising parametric approaches for analyzing SCED data (Gage & Lewis, 2014; Kratochwill et al., 2010; Van den Noortgate & Onghena, 2008; Wolery, Busick, Reichow, & Barton, 2010).

Furthermore, nonparametric significance tests have been recommended for analyzing SCEDs, because they are valid without making distributional assumptions (e.g., Kruskal–Wallis test, Wilcoxon–Mann–Whitney test, randomization test for raw data). An advantage of the randomization test for raw data over the Kruskal–Wallis and Wilcoxon–Mann–Whitney test is that it allows deriving a *p* value without degrading the observed scores to ranks (Onghena & Edgington, 2005). However, the randomization test can only be validly used when the measurement occasions are randomly assigned to the experimental conditions before the start of the experiment, which might not be possible or desirable for all SCEDs (Heyvaert & Onghena, 2014; Onghena & Edgington, 2005).

1.2. Meta-analyzing SCED data

Within the present evidence-based practice movement, researchers, practitioners, and policymakers increasingly rely on research syntheses and meta-analyses to render guidelines for best practice (Beretvas & Chung, 2008; Shadish & Rindskopf, 2007). Important merits of SCED meta-analytic research over individual SCED studies include: a higher statistical power to detect effects, more accurate effect size estimations, the ability to make more convincing generalizations to a larger population, and the ability to identify sources of heterogeneity and to test moderators to explain detected between-study variation. Whereas the analysis of individual SCED studies can be accomplished using visual and/or statistical methods, the synthesis of a large number of SCEDs in a meta-analysis necessitates the use of statistical methods (Smith, 2012).

One frequently used approach for conducting a meta-analysis of SCED studies is to calculate the (weighted) average of the effect sizes of all SCED studies included in the meta-analysis. For instance, nonoverlap effect size measures such as PND, PEM, or PAND are calculated for individual SCED studies and are afterwards aggregated over all SCED studies included in the meta-analysis. Many meta-analyses of SCEDs published in the field of autism research are conducted by aggregating nonoverlap effect sizes. For most of these meta-analyses the PND effect size is used (e.g., Bellini & Akullian, 2007; Campbell, 2003; Preston & Carter, 2009; Tincani & Devis, 2010). In Section 1.3 we will discuss in detail how the PND approach can be used for meta-analyzing SCED data.

More advanced approaches for conducting meta-analyses of SCED studies are for instance the Busk and Serlin's (1992) approaches and the HLM approach proposed by Van den Noortgate and Onghena (2003a,b, 2008). In the field of autism research, recently several meta-analyses of SCEDs have been conducted that used the HLM approach (e.g., Vanderkerken, Heyvaert, Maes, & Onghena, 2013; Wang et al., 2011; Wang, Parrila, & Cui, 2013). In Section 1.4 we will discuss in detail how the HLM approach can be used for meta-analyzing SCED data.