

Explaining variance and identifying predictors of children's communication via a multilevel model
of single-case design research: Brief report

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Abstract

The purpose of this study was to explain the variability in data collected from a single-case design study and to identify predictors of communicative outcomes for children with developmental delays or disabilities ($n = 4$). Using SAS® University Edition, we fit multilevel models with time nested within children. Children's level of baseline communication and teachers' frequency of strategy use when directed at the children predicted their outcomes. These results indicate that children's initial level of communication predicted their communicative outcomes and also that positive associations exist between teachers' implementation of evidence-based communication strategies when they are directed toward children with disabilities and the children's communicative outcomes. Implications for research and practice are provided.

Keywords: single-case intervention research, multi-level modeling, inclusive environments, professional development, communication development

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Communication and language skills in children's early years affect learning as well as the formation of relationships [1]. Further, infant interaction abilities are strongly linked to infant social-emotional [2] and cognitive [3] development. In the preschool years, language development is also strongly associated with social development [4], with language delays often co-existing with behavior problems [5]. In addition, early language development is related to school readiness [6], to later academic and social success [3], and, more specifically, to reading development [7]. Indeed, delays and differences in language development in early childhood may undermine social relationships and school success for years.

Despite the critical importance of early language skills, there is variability in the degree to which early childhood teachers use strategies that positively influence language development [8-12]. That is, adults may not always intentionally and deliberately use language strategies that promote child initiations and responses and may not always engage in conversations that include high-quality language input by adults [13]. Thus, a research to practice gap in early childhood is widely recognized [14], especially with respect to evidence-based (EB) language strategies [11]. Finding ways for early childhood teachers to gain access to professional development (PD) that will allow them to effectively implement EB strategies in language and communication skills remains a challenge in the field.

PD focused on supporting teachers' implementation of EB strategies should be focused on a set of practices, implemented collaboratively with the teacher, grounded in the teachers' practice, and linked to desired outcomes [15]. Growing evidence demonstrates that training supplemented with coaching is more effective in creating long-lasting change than training workshops alone [16, 17]. Technology can play an important role in providing effective PD. As example, Bug-In-Ear (BIE) technology has been used for over 60 years to support professionals' acquisition of applied skills [18]. Current research suggests that using this technology to coach

teachers increases their implementation of EB strategies and decreases their use of less effective practices [19, 20].

Highlighting the importance of effective PD is the assumption that children's development will be enhanced by teachers' increased use of EB strategies [21]. Studies have reported positive associations between teachers' attendance in PD that resulted in a change in their instructional practices and children's language and literacy outcomes [17, 22], although the effects on children may not be immediate or easily detected [22]. To better detect children's communicative outcomes as a result of a PD designed to improve educators' use of EB communication strategies, we utilized multilevel modeling to conduct a secondary analysis of data collected for a single-case intervention design (SCID) study. The SCID study examined the effects of BIE coaching on early childhood teachers' use of EB strategies and associations between the PD and children's expressive communication for four teacher-child dyads [23]. Functional relations were determined from the educator-level data by examining data within- and between-phases and documenting three demonstrations of an effect [24]. Because child outcomes were secondary in nature we did not examine causal links between the PD and child outcomes, but rather associations between the two variables (see figures 1-4).

For the original study, the associations between the PD and child-level outcomes were examined based upon the six features of visual analysis for SCID research [24, 25]. The main challenges in determining an association between the variables were the overlap of data and variability in children's outcomes during the intervention phase. Although there were mean improvements for all children from the baseline to the intervention phase, there were drastic differences in children's rate of communication within the intervention phase from one session to the next. For example, Dion's mean rate of communication per min was 3.19 ($SD = 1.68$), whereas Dion's mean rate of communication was 6.83 per min ($SD = 3.66$) during the intervention phase (see figure 1). These data indicate that the variability in children's

communication during intervention was twice as much as in baseline, which helps justify why we sought to explain the variability in children's outcomes using multilevel modeling.

Insert figures 1, 2, 3, and 4 about here

Although visual analysis did not indicate strong relations between the PD and children's outcomes, we decided to use multi-level modeling to further examine outcomes because of the burgeoning evidence of the effectiveness of this method in analyzing SCID data [26-28]. Thus, the purpose of this paper was to use multilevel modeling to explain the variation and identify predictors in children's communicative outcomes. We accounted for the hypothesized moderator of teachers' use of EB communication strategies, as well as contextual factors at the child (e.g., initial communication) and classroom (e.g., number of children in the group) level that we hypothesized were obscuring the results observed via traditional visual analysis procedures. For level-1 predictors, we hypothesized that the number of children in the group would be negatively associated with outcomes [29] and the frequency that teachers used the strategies with target children would be positively associated [30]. For level-2 predictors we hypothesized that children with higher initial levels of communication would experience greater outcomes than children with lower levels [31]. We also predicted better outcomes for children with developmental delays (DD) than children with autism spectrum disorders (ASD) [32].

Methods

Participants included four 2-year-old children with DD or ASD who attended inclusive early childhood centers in a city in the Southeast. Three children (Dion, Braxton, Doston; pseudonyms) were male, one female (Mya; pseudonym). Doston was African-American and the other children were bi-racial (Caucasian and African-American). At the start of the study, Dion, Braxton, and Doston were significantly delayed in their expressive communication, whereas Mya communicated within the low-average range of communication for her age.

The teachers' PD intervention focused on communication strategies (imitation, expanding language, modeling language, reinforcement, following the child's lead, offering

choices, wait time) that have a strong empirical base of effectiveness in enhancing children's communication. The original study [23] used a multiple-baseline across strategies design that was replicated across the four teacher-child dyads. Three strategies were selected by teachers and taught one at a time by the first author via 15- to 30-min didactic trainings. Then, BIE coaching was provided daily for about 20-min until visual analysis procedures indicated a functional relation. At this time, the first author randomized the start-point of the next phase [33]. The original study [23] provides more information on the PD, EB strategies, and SCID methods.

Three-min video-recorded observations of small-group play activities were coded by trained research staff to identify the frequency with which teachers used their three targeted EB communication strategies (e.g., imitation) correctly, whether the strategies were directed at the target child, the number of children participating in each play session, and children's mean weighted expressive communication per min (for information on weighting [23]). Kappa (κ) was calculated to record inter-observer agreement for 30% of each dyad's sessions. κ equaled 1.0 for identifying whether the communication strategies were directed at the target child and the number of children in each group. κ ranged from .63 to .73 for teachers' use of their targeted communication strategies and .42 to .70 for children's communication. The lower range of children's agreement resulted from loud environments during the observation sessions (e.g., crying), which made it difficult to hear the children's verbal communication on video recordings.

Recent simulation studies have indicated that multilevel modeling is an appropriate technique for analyzing SCID data when the primary focus is on the fixed effects associated with time-varying predictors, such as our treatment variable and our hypothesized mediator (child-directed EB communication strategies). Although the use of multilevel models with SCID data leads to biased variance estimates and limited power in the tests for the fixed effects of level-2 variables, when the model is correctly specified the fixed effect estimates are unbiased and the inferences about them are accurate if restricted maximum likelihood estimation is used with the Kenward-Roger small sample size adjustments for inferences [27, 28]. Consistent with

recommendations from these and other methodologists [34], we used multilevel modeling with restricted maximum likelihood (REML) estimation and the Kenward-Roger method of inference.

Results and Discussion

The primary purpose of this study was to explain the variation in children's communication using multilevel models to examine the effects of our PD intervention and the potential mediation of these effects by the number of child-directed communication strategies used correctly. For Dion the rate of communication per min varied across measurement occasions from 0 to 18.7 with a mean of 6.0 ($SD = 3.7$). For Braxton there tended to be fewer communications with values ranging from 0 to 6 with a mean of 1.3 ($SD = 1.3$), whereas for Mya there were more communications with values ranging from 1.3 to 25.7 with a mean of 14.1 ($SD = 5.9$). Finally, for Doston the range was 0 to 11.7 with a mean of 3.8 ($SD = 3.1$).

We developed our base model by considering two competing variance structures, and three potential control variables [baseline level of communication ($M = 4.01$, $SD = 3.36$, grand mean centered so $M = 0$), type of disability (DD = 0; ASD = 1), and number of children in the group ($M = 4.35$, $SD = 1.60$, grand mean centered so $M = 0$)], each of which is unrelated to the manipulated treatment variable, but potentially related to the outcome (rate of communication). We then added variables to our base model in a series of theory-driven steps [35] to examine the effect of our intervention [*phase* coded baseline phase = 0 and treatment phase = 1] and the mediation of this effect through the number of EB communication strategies used with the child ($M = 3.93$, $SD = 3.92$, grand mean centered so $M = 0$).

Initially, we estimated an unconditional model that was complex in terms of the variance structure (random variation across participants, within-person variances and autocorrelations that were allowed to vary across phases and participants) and compared it to a simpler variance structure that assumed a common within-person variance and autocorrelation for all participants and phases. The model that assumed heterogeneity in the within-participant variances (AIC = 723.3, BIC = 712.8) fit statistically significantly better [$\chi^2(14) = 91.1$, $p < .05$] than the simpler

model that assumed homogeneity of the within-participant variances (AIC = 786.4, BIC = 784.6), and thus the more complex variance model was adopted (see Model A in Table 1). This finding supports outcomes from simulation studies indicating that autocorrelation and heterogeneity of variance should be considered when using multilevel modeling for SCID analyses [26-28, 34].

Next we considered the addition of three potential control variables, one at a time and in combination. Baseline communication showed a significant positive association with our outcome whether considered individually ($\beta = 1.09, p < .0001$) or in the context of the other potential control variables ($\beta = 1.21, p = .0023$). No significant relationship was found between the outcome and type of disability ($\beta = -3.26, p = .58$ when considered individually and $\beta = 0.75, p = .40$ when entered with other controls) or number of children ($\beta = -0.22, p = .17$ when considered individually and $\beta = -0.19, p = .23$ when entered with other controls). Thus, only baseline communication was retained as a variable in our base model (see Model B in table 1).

In Model C (see Table 1), our treatment variable, *phase*, was added. On average, the rate of communication per min was 1.67 more in the treatment phases than the baseline phases ($p = .033$). We expected that the intervention effect would be mediated by the number of child-directed EB communication strategies, more specifically, that the intervention would increase the number of child-directed EB communication strategies, which in turn would lead to more child communication. To test this mediation hypothesis, we estimated a multilevel model where the number of child-directed EB communication strategies served as the dependent variable and found there were more child-directed EB strategies in the treatment phases than the baseline phases ($\beta = 1.46, p < .0001$). Next we entered the number of child-directed EB communication strategies as an additional variable in the multilevel model (see Model D). In this model, the effect of the child-directed EB communication strategies was found to be positive and statistically significant ($\beta = 0.20, p = .0046$), whereas the direct effect of *phase* was not statistically significant ($\beta = 1.47, p = .15$). These results are consistent with our mediation hypothesis and suggest that the PD increased the teachers' use of child-directed EB strategies,

thereby enhancing children's communication. This finding was obscured when we examined the data via visual analysis procedures and suggests that multilevel model provides an effective method for analyzing SCID data and determining an intervention's direct and indirect effects.

Insert table 1 about here

In Model E (see Table 1) we examined whether the effect of the number of child-directed EB communication strategies depended on the baseline level of communication by adding the interaction of these variables to the model. The positive interaction, which was statistically significant ($\beta = 0.07$, $p = .0041$), suggests that the positive effect of the number of child-directed EB communication strategies ($\beta = 0.36$, $p < .0001$ when level of baseline communication is at the mean) is more pronounced when there are higher levels of baseline communication. To get a better sense of the strength of this interaction and the effect of child-directed EB strategies, consider three children: one that is 1 *SD* below the mean in baseline communication, one that is at the mean, and one that is 1 *SD* above the mean. If we consider the predicted increase in the rate of communication per min as we move from the mean number of EB communication strategies to 1 *SD* above the mean (a change of 3.92 strategies), the predicted increases for the three children are 0.43, 1.42, and 2.40 communications per min, respectively. These data provide evidence indicating that the EB communication strategies have differential effects on children's communication, namely that the strategies are more beneficial for children with higher levels of initial communication. Moreover, future research should examine if there are similarly differential effects on children's communication based upon the specific strategies used.

The *post-hoc* nature of the research is the major limitation of the study, because these studies provide weaker evidence than *a priori* developed research studies. Therefore, to mitigate the drawbacks of conducting *post-hoc* analyses, future researchers should plan to conduct examinations of SCID data using multilevel modeling to study an intervention's effectiveness and other potential mediators and predictors. Nonetheless, this study provides evidence of the benefits of using multilevel models to analyze SCID data. The results of this

study indicate that teachers direct more EB strategies toward children with DD and ASD after receipt of PD aimed to enhance teachers' correct use of EB strategies in their classrooms. Additionally, the findings provide insight regarding the reason child-level outcomes may be difficult to identify in studies examining effects of teachers' PD [21]. Namely, our results suggest that children's outcomes may vary based upon the frequency with which teachers direct EB strategies toward them, as well as the interaction between teachers' use of EB strategies and children's initial levels of communication. Although these outcomes should not be extended beyond the population examined, they provide valuable information to aid future researchers in analyzing the relations between teachers' PD, learning opportunities provided to children with disabilities, and children's developmental outcomes.

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Table 1

Model Comparisons

	Model A	Model B	Model C	Model D	Model E
FIXED EFFECTS					
Intercept	5.60 (2.24)	4.81* (0.40)	4.04* (0.52)	4.50 (1.06)	5.08* (0.60)
Baseline Communication		1.09* (0.12)	1.26* (0.13)	1.29 (0.22)	1.25* (0.11)
Phase			1.67* (0.69)	1.47 (0.96)	0.04 (0.78)
Child EBCS				0.20* (0.07)	0.36* (0.08)
Child EBCS * Baseline Communication					0.07* (0.02)
BETWEEN-CASE VARIANCES					
Intercept	19.5 (16.3)	0	0	1.6 (3.0)	0
WITHIN-CASE VARIANCES					
Child 1 Baseline	21.2 (28.4)	3.9 (4.0)	3.0 (2.5)	5.6 (9.2)	3.0 (2.5)
Child 1 Intervention	13.7 (4.2)	22.3 (8.3)	18.3 (6.4)	13.9 (6.0)	23.4 (9.2)
Child 2 Baseline	1.3 (1.3)	1.2 (1.2)	2.5 (3.3)	7.3 (10.5)	1.3 (1.5)
Child 2 Intervention	2.0 (0.6)	2.0 (0.6)	2.1 (0.7)	2.1 (0.7)	1.9 (0.6)
Child 3 Baseline	46.8 (54.9)	47.8 (56.1)	49.5 (57.5)	45.5 (52.5)	34.4 (33.8)
Child 3 Intervention	41.4 (14.2)	40.4 (13.8)	31.2 (9.6)	25.5 (7.4)	19.6 (5.6)
Child 4 Baseline	2.9 (1.7)	3.2 (1.8)	2.9 (1.8)	2.9 (1.8)	2.8 (1.6)
Child 4 Intervention	11.7 (3.4)	11.0 (3.0)	10.9 (2.9)	9.2 (2.8)	8.3 (2.3)
AUTOCORRELATIONS					
Child 1 Baseline	.95 (.07)	.71 (.37)	.61 (.42)	.80 (.38)	.58 (.44)
Child 1 Intervention	.17 (.29)	.53 (.17)	.42 (.21)	.24 (.37)	.58 (.16)
Child 2 Baseline	.85 (.17)	.84 (.18)	.92 (.11)	.97 (.04)	.85 (.19)
Child 2 Intervention	.31 (.21)	.30 (.20)	.35 (.23)	.17 (.21)	.21 (.21)
Child 3 Baseline	-.90 (.14)	-.89 (.14)	-.88 (.16)	-.88 (.15)	-.80 (.24)
Child 3 Intervention	.39 (.19)	.37 (.20)	.19 (.21)	.09 (.20)	-.01 (.20)
Child 4 Baseline	-.21 (.50)	-.06 (.40)	-.40 (.40)	-.34 (.42)	-.26 (.42)
Child 4 Intervention	.38 (.17)	.34 (.17)	.33 (.17)	.38 (.18)	.37 (.17)
MODEL FIT					
AIC	723.3	713.9	706.5	703.6	694.1
BIC	712.8	704.1	696.7	693.2	684.3

Note. Estimates are provided with standard errors; EBCS = evidence-based communication strategies; * = $p < .05$, significance only indicated for fixed effects.

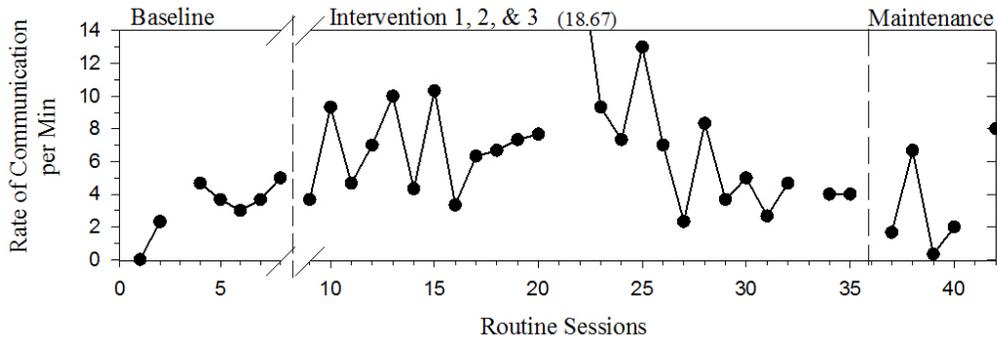


Figure 1: Dion's Weighted Expressive Communication per Min

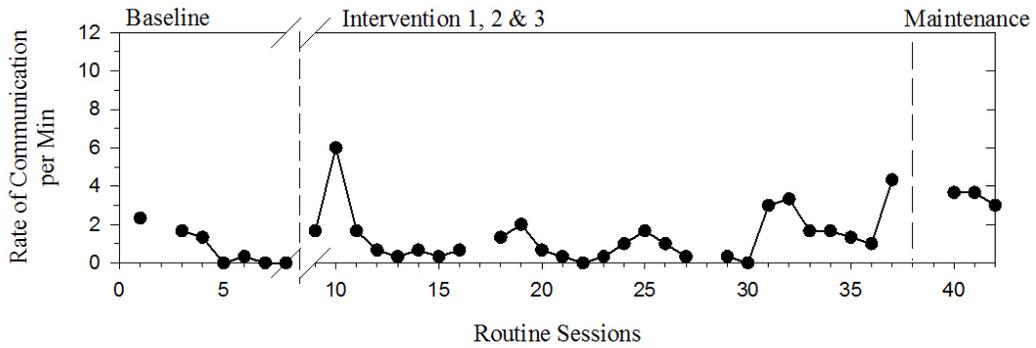


Figure 2: Braxton's Weighted Expressive Communication per Min

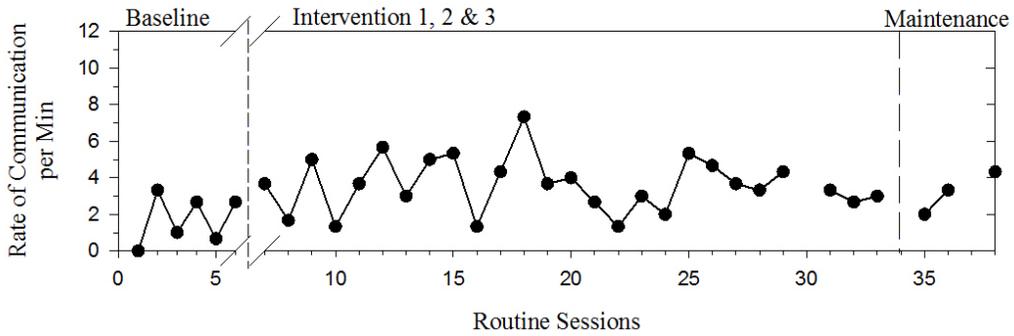


Figure 3: Mya's Weighted Expressive Communication per Min

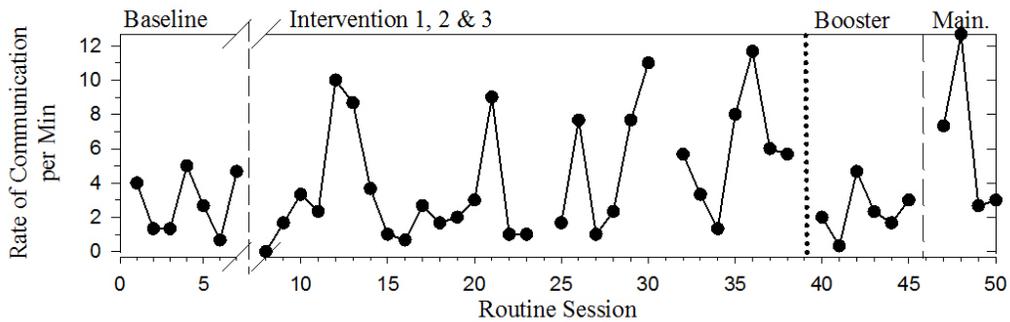


Figure 4: Doston's Weighted Expressive Communication per Min