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Statistical Analysis and Interpretation in a Follow-Up Study of Prelingually Deaf Children Implanted Before 5 Years of Age

Michael J. Strube

Department of Psychology, Washington University, St. Louis, Missouri

Abstract

Problems—One important challenge in the follow-up study was the need to develop composite measures that were highly reliable and equally representative of communication skills measured at two distinct developmental periods. A second challenge was the need to partition variance in the outcome variables among conceptually important sets of variables in an attempt to identify unique and significant predictors and to identify likely pathways of influence. A final challenge was the need to preserve sample size in the presence of attrition from the initial data collection period and missing data.

Solutions—Primary analyses were based on principal components analysis to form composite measures of highly correlated variables followed by hierarchical multiple regression to determine the contribution of predictor sets ordered to reflect important causal assumptions and conceptual questions. The principal components analyses resulted in unidimensional, highly reliable composite measures of communication skill, educational environment, and information processing. The hierarchical multiple regression analyses allowed partitioning variance to isolate the unique contributions made by particular variables or sets of variables. Importantly, these analyses also allowed inferences about pathways of influence from early predictors to later outcomes. Multiple imputation was used to construct complete data sets, preserving power and consistency across the numerous analyses.

Summary—Collectively, the chosen statistical analyses provide a pragmatic and parsimonious solution to the challenges posed by the data collected in this study. The analyses allowed clear conclusions about the major predictors of early and late communication skill in this sample and identified likely pathways through which early child, family, and educational environment variables have their influence.

OVERVIEW OF THE STUDY

The longitudinal study described in this monograph examined the high school communication skills of a sample of prelingually deaf children implanted before 5 yrs of age and first assessed when they were in elementary school (Geers 2003). A major goal of the follow-up study was to determine how early child, family, and educational environment characteristics affect later communication skill. In this article, I describe the major statistical approach taken with the follow-up data. Similar to its predecessor (Strube 2003), this article focuses on the major goals of the analyses and the types of information those analyses provide, with an emphasis on interpretation rather than underlying statistical theory.

NEW DATA, NEW PROBLEMS

The follow-up study yielded outcome variables representing the communication skills of the sample when they were in high school, an average of 8 yrs after initial data were collected. The major approach taken to the follow-up analyses duplicated that used with the initial assessment: principal components analyses to produce reliable composite measures of communication skill followed by hierarchical multiple regression analyses to identify the predictive role played by conceptually important sets of variables. The rationale for this approach is described in detail elsewhere (Strube 2003) and will not be repeated here. Instead, I will focus on the new challenges posed by the follow-up data and the solutions that we used.

Three problems in particular required attention in the follow-up data analyses. First, the measurement of similar communication skills over time required the development of equally valid and reliable composite measures for each assessment period (e.g., speech perception measured in elementary school and in high school). Second, the longitudinal nature of the design provided an opportunity to explore multiple pathways of influence from early predictors to later communication skill, but the nonexperimental nature* of the study required careful planning of statistical control and thoughtful partitioning of outcome variance. Third, attrition from the initial sample along with missing data for those who participated in the follow-up threatened the power of the statistical analyses. In the sections that follow, I describe how each problem was addressed and I provide guidance to the interpretation of the resulting analyses.

DIFFERENT MEASURES, SAME CONSTRUCTS

One important goal in this study was to examine communication skills over time and to determine whether the relative standing of participants on early outcomes persisted into high school. A key challenge, however, was that the measures used to assess a particular skill (e.g., speech perception) in elementary school were different from the measures used to assess that skill in high school. To draw sensible inferences about relations over time, it was important to construct measures that were similar in their measurement quality (e.g., reliability and unidimensionality). To achieve this goal, we used principal components analysis (Gorsuch 1983; Duntzman 1989; Johnson 1998)[†] to provide economical summary scores for the major sets of outcome variables. The sets were chosen with the goal of providing conceptually defensible collections of measures that were parallel over time, unidimensional in structure, and highly reliable.

A principal components analysis is designed to provide a linear combination that is a good representation or summary of the original variables. The analysis proceeds by standardizing

*Because participants could not be randomly assigned to “conditions” (e.g., device, duration of deafness, and SES), this research is nonexperimental, and some of the predictors are correlated, sometimes substantially so.

[†]Preliminary analyses examined the use of factor analysis, which takes as a key assumption that not all the variance in the variables can be accounted for by linear combinations (Cliff 1987; Johnson 1998; Fabrigar et al. 1999). Importantly, a confirmatory approach (Brown 2006) can be taken with factor analysis, which can offer some assurance that, for example, a unidimensional model provides a good reconstruction of the data. The small sample, however, challenged the use of these procedures. Given that our data reduction goals are easily met using principal components analysis, this was the primary reason the approach was chosen.

In addition to the major analyses described in the text, other analyses conducted to insure the integrity of the conclusions being drawn and to explore other features of the data. For example, regression diagnostics (Fox 1991; Hamilton 1992; Berry 1993) were conducted to determine whether conclusions were influenced by unusual cases and to determine whether major assumptions (e.g., heteroskedasticity) were met. We also explored the possibility of nonlinear relations as well (cf. Cohen et al. 2003); very few such relations were found. Finally, the previously described analyses focused entirely on simple linear relations between predictors and outcome that did not depend on levels of other predictors, that is, *main effect* models. Nonetheless, we explored the possibility that some variables might modify the strength of the relation between another predictor and outcome—that is, an *interaction* (Jaccard et al. 1990; Aiken & West 1991). These too were found to be relatively rare.

the variables to remove differences in scale and then deriving weighted linear combinations that satisfy two simple rules: (a) all linear combinations of the measures must be statistically independent of each other and (b) each linear combination must account for as much of the original variability as it can. By following these two rules, principal components analysis replaces the original set of variables with a smaller number of variables (ideally just one) that contains most of the information in the original variables. The quality of a principal component—the degree to which it captures information in the original collection of measures—is indexed by the *eigenvalue*. The eigenvalue is the variance of the principal component. Because the original variables are rescaled to have variances of 1.00, the eigenvalue for a principal component can be compared with this single-measure variance as a way of determining its informativeness. When a principal component has an eigenvalue that greatly exceeds 1.00, it contains much more information than any single item from the original set—it allows a single new combination of the variables to replace the larger number of original variables. At a minimum, principal components should be considered useful for further analyses if they have eigenvalues >1.00 (Cliff 1987, 1988). This insures that only principal components that are as informative as any single original measure are retained. But, the more the eigenvalue exceeds 1.00, the better, so an adjunct to the “eigenvalues greater than 1.00” rule is to examine the pattern of eigenvalues to gauge their relative size. This approach, called the “scree test” (see Gorsuch 1983), determines if one or a few of the principal components stand out as especially important. In the scree test, the eigenvalues are displayed in descending order and a clear break in the pattern is sought, especially the location where the eigenvalues begin to depart noticeably from a value of 1.00. The test gets its name from the resemblance of the plot to that of a cliff and the rubble that accumulates at the bottom of the cliff (called scree). Only those principal components that rise noticeably above the rubble are considered important.

Using this procedure, we developed composite variables for the major sets of variables in this study (i.e., educational environment, information processing, and communication skill). Figure 1 illustrates the eigenvalue plot for the speech perception principal components. For both measurement periods, there is a single dominant source of information in the collection of measures, and a single linear combination captures it very well. Indeed, by dividing the eigenvalue by the total number of measures (four in each measurement period for speech perception), we get the proportion of original score variance that is accounted for by the principal component. Over 80% of the variance in the collection of speech perception measures at each time period is captured by just a single linear combination.

Another important piece of information from a principal components analysis is the extent to which the original variables are correlated with the new linear combination—the principal component *loadings*. The loadings show how well the original variables are accounted for by the principal component and indicate whether some variables are more highly related to the new composite than others (i.e., define it more clearly or are weighted more heavily). The loadings for the speech perception variables are listed in Table 1 of Geers et al. (in press) and range from 0.85 to 0.94. Clearly, each of the original variables correlates substantially with its principal component. In combination with the finding that only a single component underlies these measures, the principal components analysis suggests that a substantial simplification is possible—the original variables can be replaced with a single new variable without substantial loss of information.

Principal components analyses of the other outcome variable sets revealed similar conclusions—the multiple variables in each set could be replaced by a single new variable. The percentages of variance that these new linear combinations accounted for ranged from 69% for Sign Enhancement to 85% for the Language measures assessed in high school (see Table 2 of Geers et al. in press). Composite variables can be judged by their reliability as

well. Estimates of the principal component reliabilities (Armour 1974) are listed in Table 2 of Geers et al. (in press) and indicate highly reliable summary variables.

ACCOUNTING FOR VARIANCE AND PATHWAYS OF INFLUENCE

The principal component scores and a select number of individual variables were used in hierarchical multiple regression analyses (Hamilton 1992; Cohen et al. 2003; Kleinbaum et al. 2008). One key goal in the longitudinal follow-up was to establish the role played by early measures in the communication skills assessed in high school. Hierarchical multiple regression provides a reasonable approach to answering such questions because it allows partitioning variance in the outcome variable and allocating it to sets of predictors ordered in conceptually sensible ways. To illustrate, I will use an abbreviated example that is described in more detail in the final article in this monograph (Geers et al. in press). Table 1 summarizes a hierarchical multiple regression of the high school speech perception composite, which is predicted by the sign enhancement composite, the verbal rehearsal speed composite, and the elementary school speech perception composite. The predictors were entered into the analysis sequentially, according to their assumed causal priority. Table 1 shows the standardized regression coefficients and squared semi-partial correlations for the predictors at each of the three steps of the analysis.

The results for step 1 indicate that the Sign Enhancement Ratio is positively and significantly related to Speech Perception CI-HS. The value of the standardized regression coefficient indicates that a 1SD increase in Sign Enhancement Ratio produces a 0.41SD increase in Speech Perception CI-HS. The squared semi-partial correlation (sr^2) indicates the proportion of variance in the outcome that is accounted for by the predictor. In this case, Sign Enhancement Ratio accounts for 15% of the variability in Speech Perception CI-HS. At step 2, Verbal Rehearsal Speed is added to the regression model. It is negatively and significantly related to Speech Perception CI-HS, with each 1SD increase in Verbal Rehearsal Speed associated with a -0.39 SD decrease in Speech Perception CI-HS. Above and beyond the influence of Sign Enhancement Ratio, Verbal Rehearsal Speed accounts for an additional 11% (sr^2) of the variance in Speech Perception CI-HS. Notice that at step 2, the influence of Sign Enhancement Ratio is still significant but it is reduced ($\beta = 0.29$ at step 2 compared with $\beta = 0.41$ at step 1). This reflects the fact that Sign Enhancement Ratio and Verbal Rehearsal Speed are correlated (-0.37 , Table 2 of Geers et al. in press) and so some of their influence on Speech Perception CI-E is potentially redundant. In the multiple regression analysis, the *unique* contribution of each is indicated by the β and sr^2 values.

At step 3, Speech Perception CI-E is added to the regression model. It makes a significant and positive contribution to the prediction of Speech Perception CI-HS, indicating that a 1SD increase in Speech Perception CI-E is associated with a 0.92SD increase in Speech Perception CI-HS. Above and beyond the influence of Sign Enhancement Ratio and Verbal Rehearsal Speed, Speech Perception CI-E accounts for an additional 33% of the variance in Speech Perception CI-HS. Note that at step 3, Sign Enhancement Ratio and Verbal Rehearsal Speed are not significantly related to Speech Perception CI-HS independently of Speech Perception CI-E. In other words, when all three predictors are considered simultaneously, only Speech Perception CI-E has a unique influence on Speech Perception CI-HS. The influences of Sign Enhancement Ratio and Verbal Rehearsal Speed are redundant with Speech Perception CI-E. This may seem to imply that Sign Enhancement Ratio and Verbal Rehearsal Speed are not important predictors, but as I will show shortly, these results actually reveal important information about pathways of influence.

The partitioning of variance that occurs in hierarchical multiple regression is illustrated in Figure 2. The major elements of the analysis—the outcome variable and the three steps of

the analysis (S_1 , S_2 , and S_3)—are represented by circles in the left panel. The extent to which the predictor (or predictors if more than one is entered on a particular step) is related to the outcome is represented by the overlap of each predictor circle with the outcome circle. Likewise, the extent to which the predictors are redundant or correlated is represented by overlap among the predictor circles. Some of the variance in the outcome accounted for by predictors is unique and not shared by other predictors (A, D, and F), but some is redundant and reflects the correlations among predictors (B, C, and E). The allocation of the shared variance is determined by the order in which the variables are entered into the analysis. Variables entered earlier are allocated variance shared with variables entered later. This is illustrated in the right panel of Figure 2. The predictor entered on step 1 (S_1) is allocated all the overlap it shares with the outcome (A, B, and C). The predictor that enters on step 2 (S_2) is allocated just that part of its overlap with the outcome that is not shared with the first predictors (D and E). The predictor that is entered last (S_3) is allocated that part of its overlap with the outcome that is not shared with either of the previously entered predictors (F). Returning to the example from Table 1, the sr^2 values for each predictor on the step it enters (highlighted in gray) correspond to the sr^2 values in the right panel of Figure 2. The sr^2 values for all predictors on the last step (surrounded by a box in Table 1) correspond to the unique proportions of variance accounted for in the outcome. These correspond to areas A, D, and F in the left panel of Figure 2.[‡]

The variance partitioning that hierarchical multiple regression provides is especially powerful when determining pathways of influence. To illustrate, I will use several of the tables from the final article in this monograph (Tables 2 to 4 and 8 in Geers et al. in press). The important information is summarized in Figure 3, which shows the standardized regression coefficients (and simple correlations in parentheses) for the assumed causal relations among Sign Enhancement Ratio, Verbal Rehearsal Speed, Speech Perception CI-E, and Speech Perception CI-HS. Moving from left to right in the figure, each ellipse beginning with Verbal Rehearsal Speed represents an outcome variable from a multiple regression analysis with all variables to the left of that outcome as predictors. So, for example, the pathway from Sign Enhancement Ratio to Verbal Rehearsal Speed ($\beta = -0.31$) indicates that increases in Sign Enhancement Ratio are significantly and negatively related to Verbal Rehearsal Speed (from Table 3, step 2, in Geers et al. in press). When Speech Perception CI-E is treated as an outcome, both Sign Enhancement Ratio ($\beta = 0.33$) and Verbal Rehearsal Speed ($\beta = -0.47$) are significant predictors (from Table 4, step 3, in Geers et al. in press). An important conclusion to draw here is that Sign Enhancement has two pathways of influence. One is direct and operates independently of Verbal Rehearsal Speed. The other is indirect and operates *through* Verbal Rehearsal Speed. Moreover, the magnitude of these two pathways can be compared. The magnitude of the direct path is simply the size of the standardized regression coefficient (0.33), indicating that a 1SD increase in Sign Enhancement Ratio is associated with a 0.33 increase in Speech Perception CI-E. The magnitude of the indirect path is estimated by taking the product of the standardized regression coefficients ($-0.31 \times -0.47 = 0.15$). In both cases, the effect of an increase in Sign Enhancement Ratio is an increase in Speech Perception CI-E, but the direct route is nearly double the magnitude of the indirect route. The total effect of Sign Enhancement Ratio on Speech Perception CI-E is the sum of the direct and indirect effects: $0.15 + 0.33 = 0.48$.

When Speech Perception CI-HS is treated as the outcome variable, the only significant predictor is Speech Perception CI-E. Neither Sign Enhancement Ratio nor Verbal Rehearsal Speed has a significant independent (direct) effect, which is indicated in Figure 3 by the

[‡]The sizes of the overlap areas in Figure 2 are illustrative and not intended to match the magnitude of the sr^2 values in Table 1.

dotted paths. The important conclusion to draw here is that the influences of Sign Enhancement Ratio and Verbal Rehearsal Speed on Speech Perception CI-HS operate indirectly through Speech Perception CI-E. Stated differently, Sign Enhancement Ratio and Verbal Rehearsal Speed have their influences early on Speech Perception CI-E, and those influences then persist over time.[§]

MISSING DATA

A final challenge in the follow-up data was the attrition from the original sample (62% participated in the follow-up) and the presence of missing data in the follow-up measures. Together, these had the potential to reduce the effective sample size and threaten the power of the statistical analyses. Although only 1% of the variable values were missing in the follow-up data, 38% of the variables and 9% of the cases had at least one missing value. Missing data can be handled in a variety of ways, but most of the common and traditional approaches (case deletion, pairwise deletion, mean substitution, and regression-based substitution) are flawed and can introduce serious biases into the analyses (see Schafer & Olsen 1998). Instead, modern missing data solutions rely on using data that are present to provide plausible estimates for the missing values while retaining an appropriate element of randomness to account for the uncertainty that goes into the estimation process. These methods, known as multiple imputation (Rubin 1996; Sinharay et al. 2001; Schafer & Graham 2002), begin by generating multiple data sets (10 is considered sufficient), each with plausible estimated values, but varying randomly across data sets. Then, the chosen statistical analysis (e.g., hierarchical multiple regression) is conducted with each data set. The parameter values (e.g., regression coefficients) within an analysis are estimated in the usual way and have SEs that reflect within-set sampling variability. But, importantly, the parameter values vary across sets in ways that correctly account for the uncertainty that went into the missing value estimation. The final parameter estimates are aggregated across the multiple analyses, and the SEs take into account both the within-set variability and across-set variability.

For the 62% of the original sample who had data available in the follow-up, we used multiple imputation to preserve that sample size and to include complete information across analyses. Ten imputed data sets were created using Markov Chain Multiple Imputation. The principal components analyses, correlation analyses, and hierarchical multiple regression analyses I have described were conducted on each data set. The parameter estimates reported represent the aggregated values from the multiple analyses, with SEs appropriately reflecting within-set and across-set variability.

SUMMARY

The analysis of any complex data set, especially one that includes a longitudinal element, presents special challenges and requires balancing the demands of statistical rigor with ease

[§]Other parameters are sometimes reported with multiple regression analyses, depending on the features of the data that are to be emphasized. Table 1 contains *standardized regression coefficients*, representing the change in the outcome variable in SD units that corresponds with a 1SD change in the predictor. This metric is easy to understand and was chosen for that reason. The regression coefficients can be reported in the original metric of the variables, which was the choice made in the previous monograph. The choice is largely a matter of preference—whether one prefers working in the metric of the original predictors or in SD units. The two coefficients share the same significance test so the choice is largely one of exposition. Table 1 likewise reports one type of “variance accounted for” estimate—the squared semi-partial correlation. This is the proportion of variance in the outcome that is uniquely accounted for by a particular predictor. An alternative is the *squared partial correlation coefficients*. The difference is that the latter is the proportion of variance in the outcome not accounted for by other predictors that is accounted for the predictor of interest. Both the partial and semi-partial correlations “correct” the simple bivariate correlation for the influence of other predictors; they simply correct it in somewhat different ways. These share the same test of significance as the regression coefficients and so simply provide alternative ways of representing the statistical control that multiple regression provides.

of interpretation, simple communication, and acknowledgment of data limitations.|| The approaches I have described in this article provide a pragmatic compromise among these multiple aims.

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||As I described elsewhere (Strube 2003), there are numerous ways to approach the general goals of the analyses. A number of these (e.g., confirmatory factor analysis, structural equation modeling, and path analysis with reliability correction) were explored with the follow-up data but were ultimately abandoned in favor of the approaches described in the text. The major limitation to using these more sophisticated approaches was the small sample size in combination with relatively large numbers of predictors and complex causal models. These sometimes produced intractable estimation problems that prevented a common approach being taken for all the data analysis goals.

Note also that strict measurement and construct equivalence (Meredith 1993; Widaman & Reise 1997; Meredith & Teresi 2006; Bontempo & Hofer 2007) across time cannot be established in this study because different measures were necessarily used at different ages. Rather, selection of measures that tapped equivalent constructs was guided by expert consensus, and the reliability and unidimensionality of those constructs were established statistically.

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Fig. 1. Eigenvalues for the principal components analyses of speech perception measures.

Fig. 2.
Variance proportions for stages of the hierarchical multiple regression.

Fig. 3.
Pathways of influence for predictors of speech perception.

TABLE 1
Prediction of speech perception CI-HS from sign enhancement, verbal rehearsal speed, and speech perception CI-E

Predictor	Step 1		Step 2		Step 3	
	β	sr^2	β	sr^2	β	sr^2
Sign Enhancement Ratio	0.41	0.15	0.29	0.07	-0.03	<0.01
Verbal Rehearsal Speed			-0.38	0.11	0.05	<0.01
Speech Perception CI-E					0.92	0.33

Bold regression coefficients are statistically significant ($p < 0.05$). To keep the example simple, the table does not show an initial step in which performance IQ, sex, family size, SES, and duration of deafness were entered. Results in the table nonetheless have the influence of these predictors removed.