Analysis of Reading Skills Development From Kindergarten Through First Grade: An Application of Growth Mixture Modeling to Sequential Processes

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ANALYSIS OF READING SKILLS DEVELOPMENT FROM KINDERGARTEN THROUGH FIRST GRADE: AN APPLICATION OF GROWTH MIXTURE MODELING TO SEQUENTIAL PROCESSES[1]

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Abstract

Methods for investigating the influence of an early developmental process on a later process are discussed. Conventional growth modeling is found inadequate but a general growth mixture model is sufficiently flexible. The growth mixture model allows prediction of the later process using different trajectory classes for the early process. The growth mixture model is applied to the study of progress in reading skills among first-grade students.

1 Introduction

This paper outlines how general growth mixture modeling can be used to study achievement and learning progress. The work is motivated by a study of reading development among children from kindergarten to first grade. Section 2 presents the data and the substantive problem, Section 3 discusses random coefficient growth modeling, and Section 4 present how random coefficient growth modeling in a latent variable framework can be used to relate the growth factors of two growth processes. Section 5 extends the latent variable framework so that multiple classes of development can be studied.

[1] We thank Noah Yang for helpful research assistance.

2 The Substantive Problem

2.1 The Reading Study

The research questions originated from the study Detecting Reading Problems by Modeling Individual Growth (Francis, 1996), also referred to as the EARS study (Early Assessment of Reading Skills). EARS collected data in a modified longitudinal time-sequential design involving about 1000 children. The children were measured four times a year from kindergarten to Grade 2. In Grades 1 and 2, measures included spelling, word recognition, and reading comprehension. In kindergarten, skills that are considered precursor skills to reading development were measured, such as alphabetic awareness, orthographic and phonemic awareness, and visual motor integration. Standardized reading comprehension tests were administered at the end of first and second grade. The background variables gender, SES, and ethnicity were collected.

Francis (1996) focused on the early detection and identification of reading disabled children. In this context, he formulated three research hypotheses: (1) Kindergarten children will differ in their growth and development in precursor skills; (2) the rate of development of the precursor skills will relate to the rate of development and the level of attainment of reading and spelling skills, and individual growth rates in reading and spelling skills will predict performance on standardized tests of reading and spelling; (3) the use of growth rates for skills and precursors will allow for earlier identification of children at risk for poor academic outcomes and lead to more stable predictions regarding future academic performance.

2.2 General Issues

Conventional growth modeling of individual differences in development can in principle use growth trajectory features such as the rate of learning as statistically-based measures of progress. There is a general problem, however, of measuring and modeling student progress over an extended period of time. As the EARS study illustrates, the underlying construct under study in a developmental process is changing and evolving due to maturation of subjects. Reading skills are relevant in first grade but not in kindergarten. In kindergarten, reading precursor skills are of interest, but lose their relevance in first grade.

This exposes the Achilles' heel of growth modeling, namely the assumption that the outcome variable has a constant scale or metric and a stable meaning over time. If it does not, conventional growth modeling is not meaningful. Item Response Theory offers a limited solution to this problem by allowing the formation of scale scores based on different test forms that change over time but have overlapping items. But constructs of interest in a longitudinal study are naturally changing and evolving over time in more fundamental ways, and to capture this, a more radical solution is necessary.

Changing meaning of the outcome does not make growth modeling impossible. Instead, conventional growth modeling needs to be developed methodologically to suit the research problem. Developmental processes that evolve over time need to be studied in the context of multi-stage growth and multiple processes. There is a need to investigate modeling methodology that can describe how one growth process leads into the next process. It is of interest to see how relationships between trajectories of early growth processes relate to failure/success in later growth processes.

The solution proposed in this paper is essentially to turn the problem into an opportunity. Different developmental phases have different expressions of a construct and should not be forced onto the same scale. Instead, a multi-stage analysis approach should be taken where the different phases are viewed as sequential processes, one leading to another, and are analyzed jointly. This study will focus on how an early process influences a later process as exemplified by how the development of phonemic awareness during kindergarten influences the development of word recognition in first grade. A special focus is on modeling that provides a prediction of a first-grade development by kindergarten development.

3 Growth Modeling

Research hypotheses regarding achievement and learning are often formulated in terms of individual development over time and tested using repeated measurements on groups of individuals. With a developmental perspective, the interest is not so much in the level of a certain outcome at a particular time point as it is in the growth trajectory across multiple time points. Learning outcomes typically show natural systematic growth over time. There may be an initial phase of rapid increase followed by a later phase of leveling out.

The starting level, the rate of increase, and the leveling out are of interest in studying learning theories. The focus is on characterizing the individual variation in development and describing it in terms of its antecedents and consequences.

Standard statistical techniques for repeated measures data use random coefficient modeling to describe individual differences in development. This is carried out using software such as BMDP5V, SAS PROC MIXED, and MIXOR using the mixed linear model (see, e.g., Jennrich & Schluchter, 1986; Laird & Ware, 1982; Lindstrom & Bates, 1988), or MLn and HLM drawing on hierarchical linear (multilevel) modeling (see, e.g., Bryk & Raudenbush, 1992; Goldstein, 1995). From a modeling point of view, these approaches are essentially the same. Although it is possible to model multivariate outcomes using these techniques (see, e.g., MacCallum, Kim, Malarkey, & Kiecolt-Glaser, in press; Thum, 1997), applications typically focus on longitudinal development of a univariate outcome variable. Antecedents of individual variation are modeled as time-invariant covariates while time-specific antecedents are modeled as time-varying covariates.

Developmental theories can be better modeled if the analysis methodology can allow trajectory shapes to be of primary focus rather than measurements at specific time points. This means that analysis methodology is needed to describe trajectory shapes not only as outcomes, but also as predictors, as mediators, and, in intervention studies, as the performance of a control group to which the trajectories of the intervention group are compared. Multiple processes, each with its own set of trajectories, for which the interplay and dependencies of the processes are of key interest should also be allowed. The trajectories should be able to have multiple indicators at each time point to reduce measurement error influence and to capture several aspects of the developing construct.

Given this broader research perspective, it is advantageous to perform repeated measures analysis in a more general framework than the mixed linear model or multilevel model. Latent variable structural equation modeling offers such a general framework. While repeated measures analysis of a single outcome variable is obtained as a special case of latent variable structural equation modeling, the generalizations discussed above are possible in the latent variable structural equation modeling framework. This is because the random coefficients are represented as latent variables where the latent variables can have regression relations among themselves and where the latent variables can also represent constructs as outcomes that have multiple indicators. Using psychometric growth modeling introduced by Meredith and Tisak (1990) as a starting point, Muthén and Curran (1997) give an overview of latent variable work related to longitudinal modeling as well as mixed linear modeling and hierarchical linear modeling work and provide an up-to-date account of the potential of latent variable techniques for longitudinal data suitable for developmental studies. As pointed out in Muthén and Curran (1997), once the mixed linear model is put into the latent variable structural equation modeling framework, many general forms of longitudinal analysis are possible including mediational variables influencing the developmental process; ultimate (distal) outcome variables influenced by the developmental process; multiple developmental processes for more than one outcome variable; sequential-cohort and treatment-control multiple-population studies; and longitudinal analysis for latent variable constructs in the traditional psychometric sense of factor analytic measurement models for multiple indicators. The latent variable framework also accommodates missing data (see. e.g., Arminger & Sobel, 1990; Muthén, Kaplan, & Hollis, 1987), categorical and other non-normal variable outcomes (see, e.g., Muthén, 1984, 1996), and techniques for clustered (multilevel) data (see, e.g., Muthén, 1994, 1997; Muthén & Satorra, 1995).

4 Multi-Stage Growth Modeling of Reading Skills Development Using a Conventional Latent Variable Framework

A first attempt at multi-stage modeling of sequential processes uses the conventional latent variable framework for growth modeling. It is suitable for relating multiple outcome variables to each other. The case of a single outcome variable will be discussed first.

4.1 Growth Modeling With a Single Outcome Variable

Consider a certain outcome variable y_j which is measured repeatedly. For individual i at time t, we may formulate the following linear growth model for this outcome variable

$$y_{ijt} = \eta_{ij1} + (a_t - a_0)\, \eta_{ij2} + \varepsilon_{ijt};\ t = 1, 2, \ldots, T. \quad (1)$$

Here $\eta_{ijk}\,(k = 1, 2)$ are latent variables, or growth factors, representing the random coefficients of the growth process, the individually-varying intercepts and slopes, respectively. Furthermore, a_t denotes a time-related variable such as age, a_0 is an anchor point (such as mean age), and ε_{ijt} is a residual. The model may be elaborated by adding time-varying covariates to (1) representing educational inputs or other factors influencing the learning at different time points.

The modeling in (1) can be used to address the first research hypothesis of Francis (1996): Kindergarten children will differ in their growth and development in precursor skills. The amount of variation in development is captured by the variance of the growth factors η_{ij1} and η_{ij2}. This variation can be explained by background variables observed for the children, such as gender, SES, and ethnicity. A child's developmental status at a given time is of interest when transitioning to a new phase of learning. Here, developmental status refers to the value predicted by the growth curve, not including the time-specific term ε_{ijt} in (1). For instance, if a_0 represents the end of kindergarten, η_{ij1} represents the developmental status at that time. The child's progress over time adds further useful information. A measure of progress is obtained by η_{ij2}, the linear growth rate for individual i. This describes how the individual reached the kindergarten end point. A child may have been close to that level throughout the year or may have experienced rapid growth up to that level. Given an estimated growth model for a sample of individuals, a specific individual's status and growth rate may be estimated by Bayesian methods; in psychometrics this is termed factor score estimation. This describes the essence of how conventional growth modeling can be used to study progress.

4.2 Growth Modeling with Multiple Processes

The novel growth modeling feature to be considered is relating the random coefficients of the later process to those of the earlier process. This addresses the second research hypothesis of Francis (1996): The rate of development of the precursor skills will relate to the rate of development and the level of attainment of reading and spelling skills, and individual growth rates in reading and spelling skills will predict performance on standardized tests of reading and spelling.

Phonemic awareness can be taken as an example of a precursor skill. Consider the influence of phonemic awareness on first-grade word recognition. Using the subscripts p and w to replace the generic j subscript in the growth model of (1), these outcome variables will be denoted y_{ipt} and y_{iwt} with the corresponding subscripts for the η factors. The intercept and slope equations for the growth coefficients of the first-grade process regressed on those of the kindergarten process may then be written as,

$$\eta_{iw1} = \alpha_1 + \beta_{11}\,\eta_{ip1} + \beta_{12}\,\eta_{ip2} + \zeta_{i1}, \qquad (2)$$

$$\eta_{iw2} = \alpha_2 + \beta_{21}\,\eta_{ip1} + \beta_{22}\,\eta_{ip2} + \zeta_{i2}. \qquad (3)$$

Here, the β coefficients represent the strength of the dependencies on past performance and acquired skills in transitioning to a new skill. It is assumed that phonemic awareness development predicts word recognition development, emphasizing the importance of the β transition parameters.

As an additional sequential link, the standardized reading and spelling test scores at the end of first grade can be regressed on the growth coefficients of the first-grade process. Letting the reading and spelling scores be denoted y_r and y_s, respectively,

$$y_r = \alpha_r + \beta_{r1}\,\eta_{iw1} + \beta_{r2}\,\eta_{iw2} + \zeta_{ir}, \qquad (4)$$

$$y_s = \alpha_s + \beta_{s1}\,\eta_{iw1} + \beta_{s2}\,\eta_{iw2} + \zeta_{is}. \qquad (5)$$

Products of β coefficients in (2), (3) and in (4), (5) translate progress on precursor skills into predictions of ultimate outcomes on the standardized reading and spelling tests. Background characteristics of the child may have an influence on the dependent variables in all four of these equations.

Assembling the observed variables into the vector $\mathbf{y}_i = (y_{ip1}, \ldots, y_{ipT}, y_{iw1}, \ldots, y_{iwT}, y_{ir}, y_{is})'$ and considering the latent variable vector $\eta_i = (\eta_{ip1}\,\eta_{ip2}\,\eta_{iw1}\,\eta_{iw2}\;y_{ir}, y_{is})'$, (1) may be fitted into the measurement part of a structural equation model,

$$\mathbf{y}_i = \nu + \Lambda\eta_i + \varepsilon_i\,. \qquad (6)$$

Equations (2) - (5) may be fitted into the structural part of a structural equation model,

$$\eta_i = \alpha + B\eta_i + \Gamma \mathbf{x}_i + \zeta_i , \tag{7}$$

where $\mathbf{x}$ represents background variables. The model may be estimated by maximum-likelihood under normality assumptions using standard structural equation modeling software (see, e.g., Muthén & Curran, 1997).

4.3 Results

The growth model in (1), (2) and (3) was applied to the growth processes of kindergarten phonemic awareness and Grade 1 word recognition. Linear growth was found to hold for both processes. A sample of n = 410 children had complete data on the four kindergarten measures and the four Grade 1 measures, and the analyses are based on these children. To capture the phonemic awareness level at exit from kindergarten, the intercept factor is defined at time point 4. Similarly, the word recognition intercept factor is defined at time point 4 in Grade 1.

The maximum-likelihood estimate of the mean of the phonemic awareness slope factor is 0.21. The variance of the intercept and slope factors are 0.64 and 0.02. Both values are significantly different from zero. Their relative size shows the typical feature of much higher level variation than growth rate variation. The correlation between the intercept and slope is high, 0.72. The estimates of the four β coefficients in the growth factor equations (2) and (3) are given in Table 1.

The standardized β coefficients are (going row-wise in the table) 0.70, –0.07, –0.24, and 0.30. This indicates that for word recognition level at the end of Grade 1 (i.e., the W intercept), the phonemic awareness level at the end of kindergarten (P intercept) is more important than the kindergarten growth rate (P slope).

Table 1

Estimates of the Relations Between the Growth Factors (Standard Errors in Parentheses)

Dependent variable	P intercept	P slope
W intercept	0.79 (0.07)	-0.41 (0.40)
W slope	-0.05 (0.02)	0.32 (0.11)

The amount of variation in the W intercept accounted for by the kindergarten growth factors is 42%. The Grade 1 growth rate (W slope) is best predicted by the kindergarten slope (P slope). In this case, however, only 4% of the variation is accounted for.

5 General Growth Mixture Modeling

This section describes shortcomings in the analysis of sequential processes using growth modeling in a conventional latent variable framework. An alternative, extended growth model analyzed in a more general latent variable framework is presented.

5.1 Shortcomings of the Growth Model

The growth model allows for individual differences in development. In this way, the estimated model gives not only an estimated mean curve but also estimates the variation in individual curves as a function of the growth factors. This model allows curves for different individuals to be very different. Nevertheless, the model is restrictive in that it does not recognize that the sample of children may be heterogeneous so that different subgroups may follow different models. This restriction is particularly limiting when attempting to predict a later process from an earlier process.

The use of growth factors as predictors is complicated by the fact that the meaning of a growth factor may be different at different levels of another growth factor. Consider for example the hypothesis that a high kindergarten phonemic awareness intercept and slope interact to influence good Grade 1 word recognition development. The intercept is defined at the kindergarten exit point, so a high positive slope value means that the child has been at considerably lower levels earlier in kindergarten. This rapid growth can in principle be either good or bad. The rapid growth may be good because the child shows potential for rapid learning that may carry over to Grade 1. For example, a low starting point in kindergarten may be due to detrimental home circumstances, but the child grows because its aptitude for reading is good. The rapid growth may be bad because the child has not been at the kindergarten exit level for long and therefore may have had limited learning opportunities during kindergarten. It is conceivable that these two alternatives have different plausibility at different kindergarten exit levels. If this is the case, the influence of the interaction between kindergarten intercept and slope is not monotonic and needs a special modeling approach. An approach of this type will now be presented.

5.2 Multiple-Class Growth Modeling

The heterogeneity of the growth will be captured by a categorical latent variable with K latent classes, $\mathbf{c}_i = (c_{i1}, \ldots, c_{iK})'$, where $c_{ik} = 1$ if individual i falls in class k and zero otherwise. The latent variable model in (6) and (7) will be modified as

$$\mathbf{y}_i = \nu + \Lambda\, \eta_i + \varepsilon_i\,, \tag{8}$$

and

$$\eta_i = \mathbf{A}\,\mathbf{c}_i + \mathbf{B}\eta_i + \Gamma\,\mathrm{x}_i + \zeta_i\,, \tag{9}$$

where the kth column of $\mathbf{A}$ contains the intercepts α_k for η for latent class k. This is a finite mixture model similar to what has been proposed by Verbeke and Lesaffre (1996) and Muthén and Shedden (1998). Maximum-likelihood estimation under normality assumptions can be carried out using the EM algorithm. A useful side product of the analysis is estimated posterior probabilities for each individual's class membership.

In the context of growth modeling the finite mixture model above will be referred to as a general growth mixture model. Mixture modeling can be viewed as a form of cluster analysis. Many researchers have attempted to cluster longitudinal measures to capture different classes of trajectories. In the present study, a "confirmatory" clustering approach will be taken, where parameter restrictions are imposed based on a priori hypotheses about growth. Different prespecified growth shapes can be captured by letting some of the parameters of $\mathbf{A}$ be fixed.

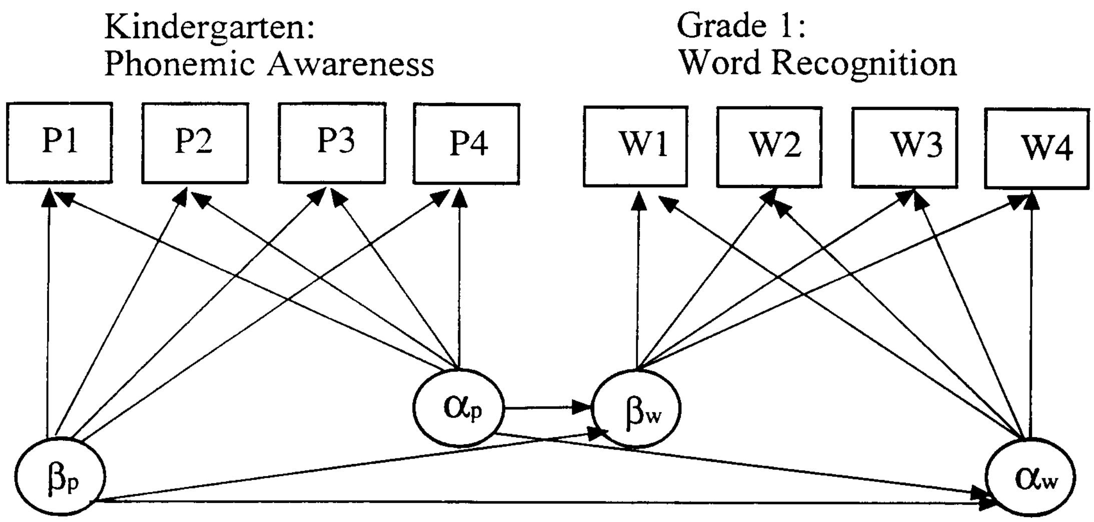
Applied to the prediction of first-grade word recognition growth using kindergarten phonemic awareness growth, $\mathbf{y}_i = (y_{ip1}, \ldots, y_{ip4}, y_{iw1}, \ldots, y_{iw4})'$ and $\eta_i = (\eta_{ip1}, \eta_{ip2}, \eta_{iw1}, \eta_{iw2})'$. The covariates $\mathbf{x}$ in (9) are not included. In (9), the first two rows of $\mathbf{A}$ contain the means of the phonemic awareness intercept and slope, whereas the last two rows contain the means of the word recognition intercept and slope.

To study the possibly non-monotonic interaction between the kindergarten intercept and slope discussed earlier, a set of trajectory classes are specified for phonemic awareness. The trajectory classes are obtained by fixing the **A** mean of the phonemic awareness intercept and slope to different values. Six classes are chosen to represent variation in both intercept and slope values for phonemic awareness development in kindergarten; they will be described below. Given the high number of classes, it is assumed that relatively little within-class variation remains in these growth factors. The variation is instead represented by the latent classes. Because of this, the latent class variable is taken as the predictor of first-grade development of word recognition, and **B** in (9) is zero. This is expressed by (9) where the six columns of **A** capture the across-class differences in means. The last two rows of **A** contain the word recognition intercept and slope means. Their estimated values are of primary interest in the analysis. The model is shown in path diagram form in the bottom part of Figure 1, where as a comparison the top part represents the conventional growth model estimated in Section 4.

The six prespecified trajectory classes for phonemic awareness are shown in the left-hand panel of Figure 2. Each line is plotted at the mean values of the phonemic awareness intercept and slope for the class. Each class allows variation around this line as a function of variation in the intercept and slope. As seen in Figure 2, the six classes consist of three pairs, where members of a pair have the same mean for the phonemic awareness intercept η_{ip1}, the level at the kindergarten exit point. Three intercept mean values are considered, the kindergarten exit mean and the mean plus and minus one standard deviation. Each pair has a trajectory with a high positive slope and a trajectory with a low positive slope. The value of the high slope is chosen so that the trajectory level at the starting point of kindergarten is the same as for the trajectory class with a low slope ending up one standard deviation below it. This high slope value corresponds approximately to a slope value one standard deviation above the mean of the slope as estimated from the single-class model in the previous section. The value of the low slope is chosen so that it is approximately one standard deviation below the mean as estimated from the single-class model.

5.3 Multiple-Class Results

Table 2 shows the prespecified means for the phonemic awareness intercept and slope for the six classes and also the estimated class probabilities. It is seen



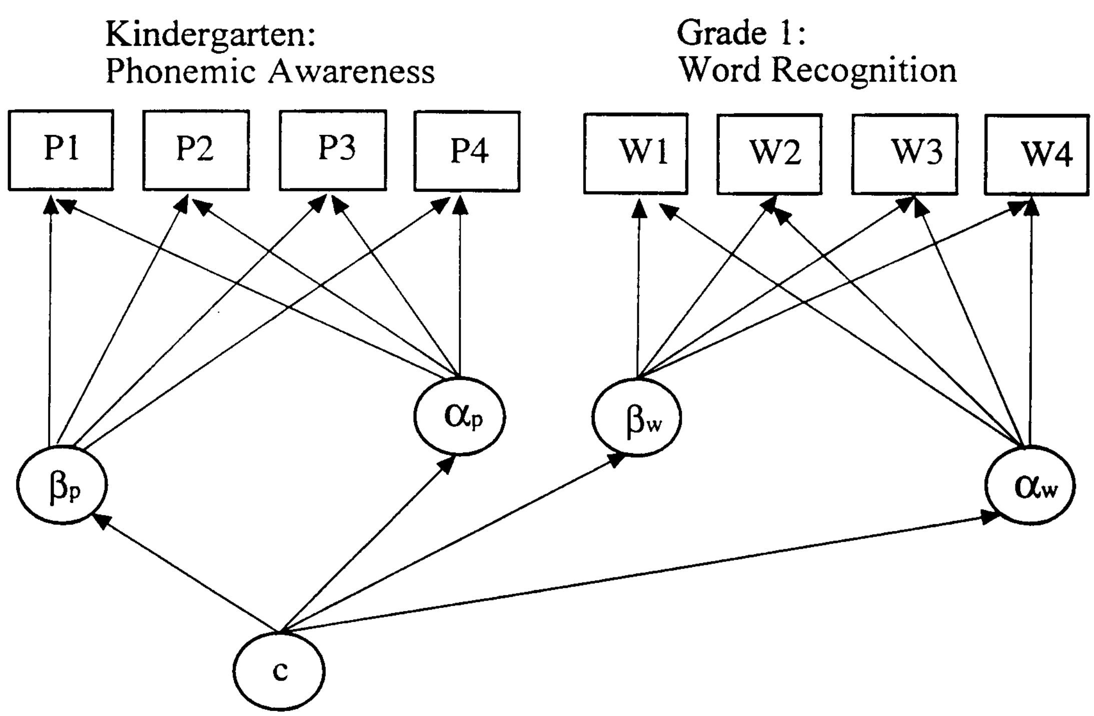


Figure 1. Path diagram.

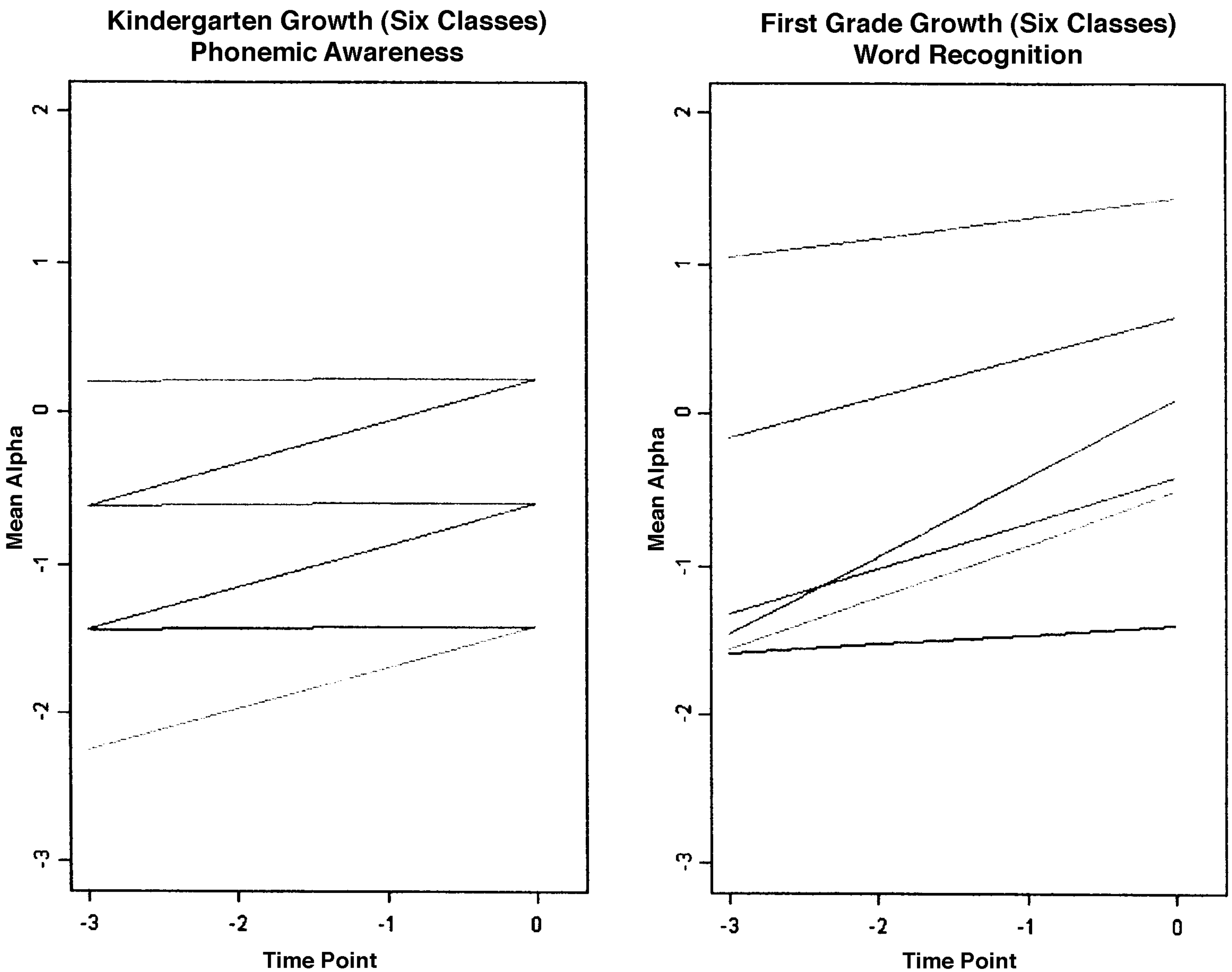


Figure 2. Prespecified trajectory classes.

that Class 1, showing little kindergarten growth and a low level at exit from kindergarten, contains 19% of the children. Class 2, showing rapid kindergarten growth but the same low level at exit from kindergarten, contains 12% of the children. Class 3 and Class 4 contain children with average level at exit from kindergarten having little and rapid growth, respectively. Class 5 and Class 6 contain children with high level at exit from kindergarten having little and rapid growth, respectively.

Table 3 shows the estimated word recognition intercept and slope means for the six classes. The corresponding estimated trajectories are shown in the right-hand part of Figure 2.

Table 2

Fixed Values for the Kindergarten Phonemic Awareness Intercept and Slope Means and the Estimated Class Probabilities

	Intercept	Slope	Probability
Class 1	-1.42	0.01	.19
Class 2	-1.42	0.28	.12
Class 3	-0.60	0.01	.13
Class 4	-0.60	0.28	.21
Class 5	0.22	0.01	.05
Class 6	0.22	0.28	.31

Table 3

Estimated Values for the First-Grade Word Recognition Intercept and Slope Means (Standard Errors in Parentheses)

	Intercept	Slope
Class 1	-1.40 (.06)	0.06 (.02)
Class 2	-0.52 (.13)	0.35 (.03)
Class 3	-0.42 (.14)	0.30 (.03)
Class 4	0.10 (.08)	0.52 (.02)
Class 5	1.43 (.06)	0.13 (.03)
Class 6	0.64 (.07)	0.27 (.01)

Table 3 and Figure 2 show that children in Class 1 continue to do poorly during first grade in terms of word recognition development. Children in Class 1 do better than children in Class 2 in terms of their word recognition development in first grade. This responds to the earlier discussion about whether rapid growth up to a certain level is better than having been at that level longer. These results indicate that at this kindergarten exit level, rapid growth is preferable for good first-grade development of word recognition. Children in Class 3 and Class 4 have an average level at exit from kindergarten. Their first-grade development shows that also at this level, rapid growth up to this level is preferable to having been at this level longer. In fact, the slow-growing children of Class 3 have almost the same first-grade development as the fast-growing children in Class 2. At the high exit level from kindergarten, however, the picture is reversed. The slow-growing children in Class 5 have a significantly better first-grade development than the rapidly growing children in Class 6.

The results from the multiple-class analysis may be contrasted with those of the conventional, single-class analysis in Section 4. In the single-class analysis, the slope of the phonemic awareness development was not found to be a significant predictor of the word recognition intercept at exit from Grade 1. In contrast, the multiple-class analysis shows that the phonemic awareness slope is an important determinant of word recognition level at exit from Grade 1. This is particularly well illustrated by comparing word recognition development for Class 1 and Class 2.

6 Conclusions

The general growth mixture modeling approach was found to be a useful tool for studying the relationship between two sequential processes. It avoided the complexity of predicting growth in the later process by the growth factors of the earlier process. Instead, a latent class variable with classes corresponding to prespecified growth shapes was used to predict growth in the later process.

Application to predicting first-grade word recognition development by kindergarten phonemic awareness development resulted in several interesting findings. In particular, it was found that among children with low phonemic awareness scores at the end of kindergarten, those who had shown little growth during kindergarten continued to do poorly in terms of word recognition during first grade. An estimated 19% of the children in this sample showed this type of development. The children who had started out lower but had grown rapidly up to this low phonemic awareness level at the end of kindergarten performed significantly better in terms of word recognition during first grade. An estimated 12% showed this type of development.

This line of research has important implications for preventive interventions and choice of treatment, that is, different methods of teaching reading. Children belonging to different trajectory classes may respond differently to a given treatment and the modeling can be used to better assess treatment-aptitude interactions. The modeling can also be used to design different treatments for children belonging to different trajectory classes.

In future research it is of interest to use an estimated model of this type to attempt to classify individuals already at the end of kindergarten. This would be a useful approach to identify children who are at risk for reading failure before they go through first grade. The statistical question to be studied is with which reliability such a classification can be made and to what extent background information is useful for increasing the classification reliability.

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