Application of Piecewise Hierarchical Linear Growth Modeling to the Study of Continuity in Behavioral Development of Baboons (*Papio hamadryas*)

María Victoria Hernández-Lloreda, Fernando Colmenares, and Rosario Martínez-Arias
Universidad Complutense de Madrid

In behavioral science, developmental discontinuities are thought to arise when the association between an outcome measure and the underlying process changes over time. Sudden changes in behavior across time are often taken to indicate that a reorganization in the outcome–process relationship may have occurred. The authors proposed in this article the use of piecewise hierarchical linear growth modeling as a statistical methodology to search for discontinuities in behavioral development and illustrated its possibilities by applying 2-piece hierarchical linear models to the study of developmental trajectories of baboon (*Papio hamadryas*) mothers’ behavior during their infants’ 1st year of life. The authors provided empirical evidence that piecewise growth modeling can be used to determine whether abrupt changes in development trajectories are tied to changes in the underlying process.

The conceptualization and measurement of change, whether the developing traits under study are morphological, physiological, behavioral or psychological, remains a challenging area. The contents of a developing individual’s behavioral repertoire and the rate at which the various behaviors are used change over time. This general characteristic of behavioral development raises the question as to the nature of the processes that guide and control the development of behavior over an individual’s lifetime. Continuity is a key concept but one that has a controversial status in developmental psychology, animal behavior, and evolutionary biology (e.g., Bateson & Martin, 2000; Gould, 2002; Kagan, 1999; Mayr, 2001; Patterson, 1998; Suomi, 1997). In animal behavior, the multiple meanings of continuity have been revised and critically assessed a number of times (e.g., Bateson, 1978; Bateson & Martin, 2000; Hinde & Bateson, 1984; Sackett, Sameroff, Cairns, & Suomi, 1981). In general, discontinuities in behavioral development are thought to arise when the association between an outcome measure (e.g., the level of performance of a behavior pattern) and the underlying process (e.g., the set of internal and external factors that control it) changes across time.

There have been two major approaches to studying and assessing developmental continuity and change. One approach focuses on the issue of stability over time in the rank-order status of individuals for a set of behavior patterns (Berman, 1990a, 1990b; Fairbanks, 1989, 1996; Hernández-Lloreda & Colmenares, 2003; Suomi, Novak, & Well, 1996) or in the rank order of a set of measures that define an individual’s physiological or behavioral profile (Suomi et al., 1996). The major concern with this correlational approach is that evidence for stability (or instability) of between-subjects and within-subject rank orders, respectively, across time should not necessarily be interpreted as evidence for continuity (or discontinuity) in the physiological, psychological, or environmental processes that are hypothesized to control the developing individual’s behavior (e.g., Bateson, 1978; Hernández-Lloreda & Colmenares, 2003; Hinde & Bateson, 1984; Rogosa, Brandt, & Zimowski, 1982; Willett, 1988). For example, changes in rank orders can arise from floor or ceiling effects in the measurements when the rate of development varies across individuals or when a new set of influences becomes temporarily important.

The second approach to characterizing continuity and change in behavioral development involves the fitting of developmental functions or growth curves (Wohlwill, 1973) to the behavioral data and the search for statistically significant patterns of association between the individuals’ behavioral development and their correlates across time (Hernández-Lloreda, Colmenares, & Martínez-Arias, 2003). These development trajectories can be continuous or discontinuous, continuity being seen as a consequence of quantitative change in a single underlying process, whereas discontinuity is attributed to a shift from one process to another. Thus, the occurrence of sudden changes in the status of a given outcome measure over time is often interpreted as an indicator that a major
Hierarchical Linear Growth Modeling: Polynomial and Piecewise Models

The study of behavioral development requires repeated assessment of the status of each subject’s behavior over time. Longitudinal data are hierarchically structured, and the proper analysis of such multilevel information requires a growth modeling approach, which has been developed and mainly used within the field of educational statistics (Bryk & Raudenbush, 1992; Raudenbush, 2001; Rogosa et al., 1982; Willett, 1988). Hierarchical linear regression models, variously labeled multilevel models, random-coefficient models, mixed models, or covariance components models (Raudenbush, 2001), represent a powerful statistical methodology that, when applied to longitudinal data, allows the estimation of a group’s average growth trajectory and each individual’s development trajectory and the analysis of correlates and predictors of individual differences in the parameters of change.

The longitudinal approach to the study of behavioral development typically provides multiple waves of data over an extended period of time. Such growth data very often suggest a curvilinear relation between the status of the behavior and time (i.e., individual’s age). In this context, there are at least two options that can be used to tackle relevant developmental issues. One option is to fit polynomial multilevel models to the data on the status of an individual’s behavior across time. Another option is to break up the curvilinear development trajectory into several separate linear components and then fit piecewise linear hierarchical models. Bryk and Raudenbush (1992) and van der Leeden (1998) pointed out that the latter approach is particularly interesting when one wants to compare development rates during two different periods of time. In this article, we proposed to use both modeling options in a two-step sequence (Figure 1) in order to first identify discontinuities in the outcome measure (i.e., the maximum or minimum of the function) and then to determine if such behavioral discontinuities, whenever they occur, may reflect discontinuities in the outcome–process relationship.

Although higher order multilevel models can be applied, many processes involving an individual’s behavioral development across time can be adequately represented through a two-level hierarchical model, with observations (Level 1 units) nested within subjects (Level 2 units). This involves the specification of a pair of linked statistical models: a Level 1 model for individual development (i.e., within-subject or repeated-observations model) and a Level 2 model for individual differences in development (i.e., between-subjects or individual-level model). This two-level conceptualization of development implies the need for an integrated model in which the individual parameters in the first level become the outcome measures in the second level (Bryk & Raudenbush, 1987, 1992; Goldstein, 2003; Snijders & Bosker, 1999; Willett, 1988).

Polynomial Hierarchical Model

Individual development can be modeled as a polynomial function of time. The general within-subject (Level 1) model has the form

$$Y_{i,t} = \beta_0 + \beta_1 T_{i,t} + \beta_2 T_{i,t}^2 + \ldots + \beta_p T_{i,t}^p + e_{i,t};$$

(1)

It is assumed that $Y_{i,t}$ is the measurement on the dependent or outcome variable for individual $i$ at occasion $t$, is a function of a
systematic growth trajectory or development curve plus random error. The betas are the coefficients of a polynomial function of degree $p$, and $e_i$ is a random error term. The Level 1 predictor variable $T_{it}$ represents the age of individual $i$ at time $t$. The powers $\beta_{g} T_{it}^g, (g = 1, \ldots, p)$ represent transformations of this variable, specifying a linear, quadratic, cubic, or higher order polynomial development function (Bryk, Raudenbush, & Congdon, 1996; Bryk & Raudenbush, 1992; van der Leeden, 1998). Visual inspection of the raw data may provide a first clue about the degree of the polynomial to be fitted. In picking the order of the model, authors generally recommend to maintain a sense of parsimony and avoid high-order polynomials (Montgomery, Peck, & Vining, 2001; Willrett, 1988). Hypothesis tests of the fixed effects of the model eventually decide which terms should be maintained and, therefore, what is the order of the final model.

A key feature of Equation 1 is the assumption that the individual growth parameters (i.e., the beta values) vary across subjects. For a full account of hierarchical linear modeling, including model assumptions, estimation of parameters, hypothesis tests, and proportion of variance accounted for by the models, the reader is referred to Bryk and Raudenbush (1987, 1992), Willett (1988), van der Leeden (1998), Goldstein et al. (1998), Snijders and Bosker (1999), and Goldstein (2003).

Piecewise Hierarchical Model

The variable time now has to be recoded (see Bryk & Raudenbush, 1992) to fit linear models in each period. For a two-piece model, the within-subject Level 1 model is of the form

$$Y_i = \beta_{0i} + \beta_{1i} T_{it} + \beta_{p} T_{it}^p + e_i,$$

where $a_{1i}$ and $a_{2i}$ are coded variables to represent the piecewise regression (Tables 1 and 2 below illustrate how this is done for the examples analyzed here). $\beta_0$ is the intercept of behavior at Interval 1, $\beta_1$ is the growth rate of Period 1, and $\beta_p$ the growth rate of Period 2. The between-subjects or Level 2 model can be a simple random variation model (see below, Equation 5) or a complex variation model (see below, Equation 6) in which the correlates of the growth parameters in each period may either remain the same (e.g., $Z$ in both periods) or vary across periods (e.g., $Z$ in Period 1 and $Q$ in Period 2).

$$\beta_{0i} = \gamma_{00} + u_{0i},$$

$$\beta_{1i} = \gamma_{10} + u_{1i},$$

$$\beta_{p} = \gamma_{p0} + u_{pi}.$$

In Equation 3, the variation in individual development parameters (i.e., $\beta_{0i}, \beta_{1i}, \ldots, \beta_{pi}$) is taken to be a function of differences between individuals in the Level 2 variable $Z$, and the coefficients $\gamma_{0i}, \gamma_{1i}, \ldots, \gamma_{pi}$ stand for the effect of variable $Z$ on the individual development parameters (van der Leeden, 1998).

For the Level 1 random terms $(e_i)$, it is assumed that they are independent and normally distributed with zero mean and variance $\sigma^2$. The Level 2 random terms are assumed to have a joint normal distribution with zero mean, variance $\tau_{qq'}$ and covariance $\tau_{qq''}$ for any pair of random effects $q$ and $q'$. In Equation 2, the parameters $\gamma_{00}, \gamma_{10}, \ldots, \gamma_{p0}$ are known as fixed effects and represent the average development curve over all individuals. The $u_{0i}, u_{1i}, \ldots, u_{pi}$ are random error components denoting the departures of $\beta_{0i}, \beta_{1i}, \ldots, \beta_{pi}$ from these $\gamma_{00}, \gamma_{10}, \ldots, \gamma_{p0}$ coefficients for each individual $i$. More elaborate between-subjects models can be developed if one or several Level 2 predictor variables are added to try to explain part of the variability of the Level 1 beta coefficients. The new between-subjects model can be written as

$$\beta_{0i} = \gamma_{00} + u_{0i},$$

$$\beta_{1i} = \gamma_{10} + u_{1i},$$

$$\beta_{p} = \gamma_{p0} + u_{pi}.$$
Regression.

Their wild counterparts (e.g., Kummer, 1984) have been found to resemble those described for social organization and mating patterns of this colony (see Colmenares, 1992; Colmenares, 2004) housed at the Madrid Zoo, which has been the subject of a long-term research since it was established in 1972 (Colmenares, 2002; Colmenares et al., 2006). All the assumptions were met by our data. We assessed their validity by checking the tenability of the assumptions by means of the analysis of empirical Bayes residuals (Bryk & Raudenbush, 1996). As indicated above, the analyses were done in a two-step sequence. First, we applied polynomial hierarchical linear growth modeling. This allowed us to identify the average development trajectory for each behavior and to detect the occurrence of discontinuities in the outcome measures, that is, the age point at which the developmental function reached the maximum and there was a slope change from positive to negative (Figure 1a). Once such discontinuities had been detected, the second step consisted in fitting, for each behavior, a two-piece linear model to the data involving the two periods of time, that is, before and after the discontinuity in the outcome measure had occurred (Figure 1b). After fitting the final models, we assessed their validity by checking the tenability of the assumptions by means of the analysis of empirical Bayes residuals (Bryk & Raudenbush, 1992; Bryk et al., 1996). All the assumptions were met by our data.

### Method

**Subjects and Housing**

The subjects of this study were 23 infants, including 9 males and 14 females. They were members of the colony of hamadryas baboons (Papio hamadryas) housed at the Madrid Zoo, which has been the subject of a long-term research since it was established in 1972 (Colmenares, 2002; Colmenares & Gomendio, 1988). During the period of study, the colony consisted of 48–61 individuals, organized into five one-male units. The social organization and mating patterns of this colony (see Colmenares, 1992; Colmenares, 2004) have been found to resemble those described for their wild counterparts (e.g., Kummer, 1984).

**Procedure**

We used focal animal sampling methods (Altmann, 1974), observing each infant for four to nine 15-min sessions per fortnight period from birth to 380 days of age. Each 2-week period is referred to as an age interval; thus, each infant’s observations spanned a total of up to 25 age intervals. During the focal-infant sessions, we collected all the occurrences of any social interaction (from a previously established behavioral catalogue) that involved the focal subject and any other member of the colony. Observations were written directly on check-sheets that consisted of 60 partitions, each denoting a 15-s interval.

### Behavioral Measures

The behavioral measures analyzed here for exemplifying the application of piecewise linear growth modeling to the assessment of discontinuity are (a) mother approaches her infant (MapI), operationalized as the rate per hour that the mother approached to within 50 cm of her infant, and (b) mother breaks contact with her infant (MbcI), defined as the rate per hour with which the mother broke body contact with her infant.

### Data Analysis

This study is based on 673 hours of systematic data collection. Each individual’s behavioral records were pooled per age interval. To correct for nonnormality, the two outcome measures analyzed were square-root transformed. Because the data for MbcI contained many zero scores, we added 0.5 to all values, that is, $y = \sqrt{x + 0.5}$ (e.g., Martin & Bateson, 1993). As indicated above, the analyses were done in a two-step sequence. First, we applied polynomial hierarchical linear growth modeling. This allowed us to identify the average development trajectory for each behavior and to detect the occurrence of discontinuities in the outcome measures, that is, the age point at which the developmental function reached the maximum and there was a slope change from positive to negative (Figure 1a). Once such discontinuities had been detected, the second step consisted in fitting, for each behavior, a two-piece linear model to the data involving the two periods of time, that is, before and after the discontinuity in the outcome measure had occurred (Figure 1b). After fitting the final models, we assessed their validity by checking the tenability of the assumptions by means of the analysis of empirical Bayes residuals (Bryk & Raudenbush, 1992; Bryk et al., 1996). All the assumptions were met by our data.

**Step 1: Fitting polynomial hierarchical models.** The kind of polynomial models fitted are described in Equations 1 and 2.

**Step 2: Fitting two-piece hierarchical linear models.** The results thus obtained for the two behavioral measures analyzed indicate that the objective criterion of discontinuity at the behavioral level was fulfilled; therefore, the application of two-piece linear growth models should be worth noting.

---

### Table 1

**Coding Scheme for the Two-Piece Linear Model Fitted to the Data on Mother Approaches Her Infant**

<table>
<thead>
<tr>
<th>Coded variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
<th>17</th>
<th>18</th>
<th>19</th>
<th>20</th>
<th>21</th>
<th>22</th>
<th>23</th>
<th>24</th>
<th>25</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_{1t}$</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
<td>8</td>
</tr>
<tr>
<td>$a_{2t}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
<td>12</td>
<td>13</td>
<td>14</td>
<td>15</td>
</tr>
</tbody>
</table>

**Note.** The discontinuity in the outcome measure occurred at Age Interval 9 (i.e., 4.5 months of age). $a_{1t}$ and $a_{2t}$ = coded variables to represent piecewise regression.

---

### Table 2

**Coding Scheme for the Two-Piece Linear Model Fitted to the Data on Mother Breaks Body Contact With Her Infant**

<table>
<thead>
<tr>
<th>Coded variable</th>
<th>1</th>
<th>2</th>
<th>3</th>
<th>4</th>
<th>5</th>
<th>6</th>
<th>7</th>
<th>8</th>
<th>9</th>
<th>10</th>
<th>11</th>
<th>12</th>
<th>13</th>
<th>14</th>
<th>15</th>
<th>16</th>
<th>17</th>
<th>18</th>
<th>19</th>
<th>20</th>
<th>21</th>
<th>22</th>
<th>23</th>
<th>24</th>
<th>25</th>
</tr>
</thead>
<tbody>
<tr>
<td>$a_{1t}$</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
<td>12</td>
</tr>
<tr>
<td>$a_{2t}$</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>0</td>
<td>1</td>
<td>2</td>
<td>3</td>
<td>4</td>
<td>5</td>
<td>6</td>
<td>7</td>
<td>8</td>
<td>9</td>
<td>10</td>
<td>11</td>
<td>12</td>
<td>12</td>
<td>12</td>
</tr>
</tbody>
</table>

**Note.** The discontinuity in the outcome measure occurred at Age Interval 13 (i.e., 6.5 months of age). $a_{1t}$ and $a_{2t}$ = coded variables to represent piecewise regression.
considering. The variable time was then re-coded for both behaviors, using as the break point the age interval at which the average growth curve reached the maximum (see Tables 1 and 2). The kind of linear models fitted are described in Equations 4, 5, and 6.

For Level 2, we explored two predictors: infant’s sex, which was defined as a dummy-coded variable with values 1 for males and 0 for females, and mother’s reproductive experience, operationalized as number of infants previously reared, from 0 to 10. A way to explore potential variables to be included in the Level 2 model is to compute a simple univariate regression of the empirical Bayes residuals from each of the Level 2 equations on Z variables that might be added to the model. In general, the magnitude of the estimated effect of a given predictor and the associated t ratio are used as criteria for its inclusion in the model. Bryk and Raudenbush (1992, p. 212) advised that in this exploratory stage predictors with t ratios near or less than 1 be excluded from the model.

To run the analyses, we used the software packages HLM for Windows, Version 4.01 (Bryk et al., 1996) and MlwiN, Version 1.00 (Goldstein et al., 1998). There are other more popular software packages that can carry out multilevel modeling, including BMDP, SAS, SPSS, STATA, and SYSTAT; however, these may have some limitations because they are more general. Goldstein (2003, Table 15.1, p. 228) lists up to 20 packages, together with relevant Internet addresses and a brief note describing their basic features. The Centre for Multilevel Modeling, which can be accessed at http://multilevel.ioe.ac.uk, maintains a series of reviews.

Results

Development Trajectories

The rate of performance of MapI can be represented as a third-order polynomial function of infant age (Figure 2a and 2b). All three fixed growth parameters were significantly different from zero and, therefore, they are all necessary for describing the average development curve for MapI ($\gamma_{10} = .53, t_{22}$-ratio = 19.22; $\gamma_{20} = .04, t_{22}$-ratio = 6.59; $\gamma_{30} = .53, t_{22}$-ratio = 19.22; $\gamma_{40} = .04, t_{22}$-ratio = 6.59; $\gamma_{50} = .53, t_{22}$-ratio = 19.22; $\gamma_{60} = .04, t_{22}$-ratio = 6.59; $\gamma_{70} = .53, t_{22}$-ratio = 19.22; $\gamma_{80} = .04, t_{22}$-ratio = 6.59; $\gamma_{90} = .53, t_{22}$-ratio = 19.22; $\gamma_{100} = .04, t_{22}$-ratio = 6.59). Significant individual differences were found only for the coefficient of the first term ($\sigma_{\beta_1} = .00), \chi^2(21) = 57.91, p < .001$.

In regard to the rate of MbcI, this can be represented as a second-order polynomial function of infant age (Figure 2c and 2d). The three fixed parameters were significantly different from zero ($\gamma_{10} = .96, t_{22}$-ratio = 6.59; $\gamma_{20} = .14, t_{22}$-ratio = 5.64; $\gamma_{20} = .01, t_{22}$-ratio = 6.07, $p < .001$ in all cases). Significant individual differences were found for the initial status ($\sigma_{\beta_0} = .21), \chi^2(17) = 27.62, p = .049, and for the coefficients of the first and second terms ($\sigma_{\beta_1} = .01), \chi^2(17) = 39.02, p = .002; (\sigma_{\beta_2} = .00), \chi^2(17) = 40.50, p = .001$.

Discontinuities at the Behavioral Level

Figure 2a shows that, beginning at 1 month of age, the rate of approaches made by mothers (MapI) increased rapidly until it peaked at about four times per hour when the infant attained the age of 4.5 months (Age Interval 9). It then declined smoothly, and finally, toward the end of the infant’s 1st year of life, approaches stabilized at low rates. Figure 2c reveals that the curve for the rate of contacts broken by mothers (MbcI) takes on a bell shape as a function of age. The peak is reached at Age Interval 13 (i.e., 6.5 months of age) when, on average, mothers broke contact with their infants at a mean rate of three times per hour.

Discontinuities in the Outcome-Process Relationship: Individual Differences and Their Predictors Across Periods

The two-piece linear growth model fitted to the data on MapI revealed that, in both periods, the growth rate was significantly different from zero (Period 1: $\gamma_{10} = .16, t_{22}$-ratio = 6.45; Period 2: $\gamma_{20} = .09, t_{22}$-ratio = 7.45, $p < .001$ in both cases), and the
individual differences in growth rates were significant (Period 1: $\sigma^2_{\epsilon_1} = 0.007$, $\chi^2(18) = 51.94, p < .001$; Period 2: $\sigma^2_{\epsilon_2} = 0.001$, $\chi^2(18) = 31.56, p = .025$). Table 3 shows that of the two potential Level 2 predictors explored for inclusion in the model, the variable infant’s sex appeared to be a suitable candidate in both periods, whereas the mother’s reproductive experience was so only in Period 2. However, the inclusion of these variables into the final model revealed that the only predictor of individual differences in growth rate that reached statistical significance was the mother’s reproductive experience (Table 4). Therefore, this was the only predictor variable incorporated in the final model fitted to the data (Table 5), which accounted for 18% of the variation in growth rate in Period 2. Figure 3a plots the average development trajectory for Mapl during the first period in which no individual differences related to the infant’s sex and the mother’s reproductive experience were found, and during the second period, in which, in contrast, the rate of approaches by mothers with low reproductive experience was found to decrease more smoothly than that of mothers with higher reproductive experience.

The two-piece linear growth model fitted to the Mbcl data shows that, in both periods, the mean growth rate was significantly different from zero (Period 1: $\gamma_{10} = .07$, $t_{21}$-ratio = 4.43, $p < .001$; Period 2: $\gamma_{20} = -.06$, $t_{21}$-ratio = -5.12, $p < .001$) and that the individual differences in growth rates were significant only in Period 1 (Period 1: $\sigma^2_{\epsilon_1} = 0.00$, $\chi^2(17) = 29.09, p = .03$; Period 2: $\sigma^2_{\epsilon_2} = .00$, $\chi^2(17) = 20.75, p = .23$). Table 6 shows that of the two potential Level 2 predictors explored for inclusion in the model, only infant’s sex fulfilled the criterion and did so only in Period 1. The inclusion of this predictor variable into the final model reveals that infant’s sex did have a significant effect on the growth rate of Mbcl in Period 1 (see Table 7). In fact, the infant’s sex explained 46% of the variation in growth rate in Period 1. As shown in Figure 3b, the rate of change of this mother-related behavior during the infants’ first 6.5 months is steeper when the latter were males than when they were females. Nevertheless, although the sex differences in the status of this behavior persisted after the behavioral discontinuity, the difference in the rate of change vanished in Period 2.

### Discussion

Many psychologically and biologically meaningful questions about the nature of behavioral development cannot be answered (or even posed in the first place), simply because we have neither dependable empirical data on trajectories of behavioral development nor adequate statistical methods to analyze them. Theoretical and conceptual analyses are necessary indeed for identifying the developmental questions that require attention and for coming up with predictions that can be empirically tested. However, the advance in the understanding of the processes that drive the individuals’ highly diverse patterns of behavioral development will rest ultimately on the quality of the data collected and on the statistical techniques that we can apply to them. Thus, multiple time points of data are required if questions bearing on the time course of behavioral development are tackled, and an adequate growth modeling approach is recommended if one’s goal is to describe the parameters of behavioral change and to analyze the correlates and predictors of individual differences in such parameters (Bryk & Raudenbush, 1987, 1992; Hernández-Lloreda et al.,

### Table 3

<table>
<thead>
<tr>
<th>Level 1 coefficient ($\beta$)</th>
<th>Potential Level 2 predictors</th>
</tr>
</thead>
<tbody>
<tr>
<td>Sex ($t$)</td>
<td>Experience ($t$)</td>
</tr>
<tr>
<td>For Period 1: $\beta_1$</td>
<td>-1.25</td>
</tr>
<tr>
<td>For Period 2: $\beta_2$</td>
<td>1.59</td>
</tr>
</tbody>
</table>

Note: Level 2 predictor variables were infant’s sex and mother’s reproductive experience. Exploratory analysis was done to decide if they should be included in the two-piece hierarchical linear model of growth rate of mother approaches her infant during the infant’s 1st year of life (25 2-week intervals).

### Table 4

Two-Piece Hierarchical Linear Model of Growth Rate for Mother Approaches Her Infant During the Infant’s 1st Year of Life (25-Week Intervals)

<table>
<thead>
<tr>
<th>Fixed parameter</th>
<th>Coefficient</th>
<th>SE</th>
<th>t ratio</th>
<th>df</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period 1 ($\beta_1$)</td>
<td>$\gamma_{10}$</td>
<td>0.17</td>
<td>0.03</td>
<td>6.65</td>
<td>21</td>
</tr>
<tr>
<td>Period 2 ($\beta_2$)</td>
<td>$\gamma_{20}$</td>
<td>-0.08</td>
<td>0.02</td>
<td>-3.66</td>
<td>20</td>
</tr>
<tr>
<td>Effect of sex, $\gamma_{11}$</td>
<td>0.03</td>
<td>0.02</td>
<td>1.29</td>
<td>20</td>
<td>.21</td>
</tr>
<tr>
<td>Effect of experience, $\gamma_{21}$</td>
<td>-0.01</td>
<td>0.00</td>
<td>-2.39</td>
<td>20</td>
<td>.03</td>
</tr>
</tbody>
</table>

Note. Level 2 predictor variables were infant’s sex and mother’s reproductive experience.

### Table 5

Final Two-Piece Hierarchical Linear Model of Growth Rate for Mother Approaches Her Infant During the Infant’s 1st Year of Life (25-Week Intervals)

<table>
<thead>
<tr>
<th>Fixed parameter</th>
<th>Coefficient</th>
<th>SE</th>
<th>t ratio</th>
<th>df</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period 1 ($\beta_1$)</td>
<td>Mean growth rate, $\gamma_{10}$</td>
<td>0.16</td>
<td>0.02</td>
<td>6.20</td>
<td>22</td>
</tr>
<tr>
<td>Period 2 ($\beta_2$)</td>
<td>$\gamma_{20}$</td>
<td>-0.06</td>
<td>0.01</td>
<td>-3.94</td>
<td>21</td>
</tr>
<tr>
<td>Effect of experience, $\gamma_{21}$</td>
<td>-0.007</td>
<td>0.003</td>
<td>-2.61</td>
<td>21</td>
<td>.01</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Random parameter</th>
<th>Variance component</th>
<th>$\chi^2$</th>
<th>df</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Period 1 ($U_i$)</td>
<td>0.007</td>
<td>51.77</td>
<td>18</td>
<td>.00</td>
</tr>
<tr>
<td>Period 2 ($U_j$)</td>
<td>0.001</td>
<td>31.43</td>
<td>17</td>
<td>.02</td>
</tr>
</tbody>
</table>

Note. Includes Level 2 predictor variable mother’s reproductive experience.
that the residual error terms are independent. This leads to ineffi-
cient estimates and a Type I error rate that is much higher than the
nominal alpha level. Compared with these conventional statistical
methods, hierarchical linear growth modeling is a statistical meth-
ology that takes fully into account the nested structure of lon-
gitudinal data, that is flexible with regard to both the design and
the modeling of complex covariance structures, and that allows an
integrated study of average development trajectories and the cor-
relates of the processes underlying individual differences in their
developmental pathways (e.g., Bryk & Raudenbush, 1987, 1992;
Raudensbush, 2001).

Piecewise hierarchical linear growth models represent an alter-
native approach whose application seems worth considering when
the growth trajectory of an outcome measure is found to be
nonlinear (Bryk & Raudenbush, 1992; van der Leeden, 1998).

In animal behavior research, the number of developmental stud-
ies in which multiple waves of data have been collected is notably
low. Even in areas where a fairly large amount of information has
been collected, few attempts have been made to model the develop-
mental trajectories exhibited by the individuals and to account
for the observed individual differences. This is the case, for ex-
ample, for the relatively numerous studies on the development of
primate mother–infant relationships that have been conducted both
in the wild and in captive settings (see Deputte, 2000; Fairbanks,
1996, for recent reviews). Traditional statistical methods applied to
the study of developmental trajectories have included mixed model
analysis of variance (ANOVA; e.g., Maestripieri, 1994; Suomi et
al., 1996) and conventional (simple and multiple) regression anal-
ysis (e.g., Bramblett, 1980; Bramblett & Coelho, 1985; Wasser &
Wasser, 1995). However, these methods suffer from some meth-
odological and/or statistical limitations (e.g., Bryk & Raudenbush,
1987, 1992; Hernández-Lloreda et al., 2003; Hox & Kreft, 1994;
Michel, 2001; van der Leeden, 1998). For example, ANOVA is
rather restrictive regarding the design and the kind of covariance
structures that can be modeled. In addition, traditional regression
analyses, by ignoring the multilevel structure of longitudinal data,
often fail to meet some of the model assumptions, for example,
that the residual error terms are independent. This leads to ineffi-

table 6

<table>
<thead>
<tr>
<th>Potential Level 2 predictors</th>
<th>Fixed parameter</th>
<th>Coefficient</th>
<th>SE</th>
<th>t ratio</th>
<th>df</th>
<th>p</th>
</tr>
</thead>
<tbody>
<tr>
<td>Level 1 coefficient (β)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sex (t)</td>
<td></td>
<td>0.08</td>
<td>0.01</td>
<td>5.50</td>
<td>21</td>
<td>.00</td>
</tr>
<tr>
<td>Experience (t)</td>
<td></td>
<td>-0.04</td>
<td>0.02</td>
<td>-2.21</td>
<td>21</td>
<td>.04</td>
</tr>
<tr>
<td>For Period 1: β₁</td>
<td></td>
<td>-2.16</td>
<td>0.22</td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Table 7

<table>
<thead>
<tr>
<th>Final Two-Piece Hierarchical Linear Model of Growth Rate for Mother Breaking Contact With Her Infant During the Infant’s 1st Year of Life (25-Week Intervals)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fixed parameter</td>
</tr>
<tr>
<td>-----------------</td>
</tr>
<tr>
<td>Period 1 (β₁)</td>
</tr>
<tr>
<td>γ₁₀</td>
</tr>
<tr>
<td>Effect of sex, γ₁₁</td>
</tr>
<tr>
<td>Period 2 (β₂)</td>
</tr>
<tr>
<td>γ₂₀</td>
</tr>
<tr>
<td>Effect of sex, γ₂₁</td>
</tr>
<tr>
<td>Random parameter</td>
</tr>
<tr>
<td>Variance component</td>
</tr>
<tr>
<td>Period 1 (U₁)</td>
</tr>
<tr>
<td>Period 2 (U₂)</td>
</tr>
<tr>
<td>Level 1 error (ε₁)</td>
</tr>
</tbody>
</table>

Note. Includes Level 2 predictor variable infant’s sex.
periods of time, they suffer from the very same problems as the linear regression models already mentioned.

Preliminary inspection of the shape of development trajectories of different individuals reveals that the rate of behavioral change is often far from constant. In other words, the occurrence of sudden changes in the rate, or even in the direction, of change is fairly common. The question that can then be asked is if such changes in behavioral development indeed reflect the occurrence of major reorganizations in the processes that control the developing individual’s behavior. The goal of the present study was to show that piecewise hierarchical linear growth modeling can be useful in the context of searching for discontinuities in behavioral development. Our criterion for starting the search for discontinuities was that the behavioral outcome measure should exhibit a change in the direction of change. In his experimental study of the development of object play in kittens, Bateson (1981) observed that the subjects exhibited a five-fold increase in the rate of object play from 6 to 8 weeks of age and argued that this abrupt change in the rate of object play across time might be an indicator that a developmental discontinuity had occurred. Other methods have been developed to determine the break point objectively (see Pieplow & Ogutu, 2003). These are relevant when one is interested in testing hypotheses regarding the break point. In the present study, however, we did not intend to determine the exact timing of the break point but to compare developmental trajectories across two different periods of time. Thus, the maximum (or minimum) of the polynomial function fitted to the data appeared to be a parsimonious and objective procedure to identify when a discontinuity in the outcome measure has taken place.

Our data set comes from an observational study of 23 baboon mother–infant pairs, from whom 25 time points of data had been collected over the infants’ first year of life. The two-piece linear growth models fitted to the data on MapI and MBcI allowed us to examine the stability of the association between the time course of development of these behaviors and two potential correlates of the underlying process across the two periods, that is, before and after the discontinuity in the outcome measures (Table 8). The findings from this application of piecewise linear modeling show that individual differences in behavioral development can be significant in one period and then nonsignificant in others and that the correlates of the underlying processes can also vary across time. In other words, the statistical method applied here to the analysis of development trajectories does seem to fulfill the goal of finding out discontinuities in behavioral development.

By identifying potential candidates for behavioral discontinuity, this statistical methodology can pave the way for a deeper analysis of the factors that may be involved in the control of the behavioral changes observed across time. Bateson (1981), for example, hypothesized that the behavioral discontinuities that he found in the development of play in cats could be driven by processes associated to weaning. In our own study of baboon mother–infant relationships, there are indications that many of the discontinuities in the outcome measures that were found appeared to be associated with the time when mothers resumed sexual activity after the postpartum amenorrhea period (Hernández-Lloreda & Colmenares, 2003). However, it must be emphasized that the absence of discontinuities in a given outcome measure should not be necessarily taken to imply that behavioral discontinuities are not involved in its development. That is, the finding that the rate of development of a particular behavioral pattern is constant across time is not a proof that the processes controlling its development have not changed over time. Piecewise hierarchical linear modeling could also disclose the occurrence of discontinuities in behavioral development even when the rate (and direction) of change remain stable across time. We conclude, then, that piecewise growth modeling can be useful to determine whether abrupt changes in development trajectories are tied to changes in the underlying process.

Table 8
Summary of the Results Obtained in the Present Study

<table>
<thead>
<tr>
<th>Behavior</th>
<th>Period 1</th>
<th>Period 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>Approaches made by the mother</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual differences</td>
<td>yes</td>
<td>yes</td>
</tr>
<tr>
<td>Sex</td>
<td>no</td>
<td>no</td>
</tr>
<tr>
<td>Experience</td>
<td>no</td>
<td>yes</td>
</tr>
<tr>
<td>Contacts broken by the mother</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Individual differences</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>Sex</td>
<td>yes</td>
<td>no</td>
</tr>
<tr>
<td>Experience</td>
<td>no</td>
<td>no</td>
</tr>
</tbody>
</table>

Note. For each behavior, mother approaches her infant and mother breaks contact with her infant, and for each period, that is, before and after the discontinuity in the outcome measures, we examined whether there were significant individual differences in growth rate and whether the predictor variables infant’s sex and mother’s reproductive experience had a significant effect on growth rate.

References


Received March 17, 2003
Revision received December 14, 2003
Accepted January 13, 2004