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Latent Change Score Modeling of Psychophysiological Data: An Empirical Instantiation Using Electrodermal Responding

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Abstract

We examined latent change score (LCS) modeling as an approach to the analysis of children's skin conductance level (SCL) throughout a stressful task—a simulated inter-adult argument—as it relates to externalizing and internalizing symptoms. LCS is an extension of traditional multi-level modeling (MLM) which allows estimation of proportional growth terms. Children (Age 6 – 12 years; $N = 150$) were from two-parent families. Mothers reported on children's internalizing and externalizing symptoms. Results indicated that the LCS models outperformed the traditional MLM. The use of LCS yielded important novel information regarding profile and pattern of responding for various children and is likely to advance understanding of relations between children's physiological responses and psychopathology symptoms.

Electrodermal responding (EDR) is a widely studied psychophysiological measure considered to be an important index of the activity of the sympathetic nervous system (SNS). Relations between EDR during lab challenges and both externalizing (e.g., Posthumus, et al., 2009) and internalizing (e.g., Najstrom & Jansson, 2006; Thayer, Friedman, & Borkovec, 1996) problems have been examined for some time, typically by averaging EDR across a task. Although researchers continue with this approach, explication of EDR through real-time assessments is critical for providing estimates of how quickly individuals respond, the magnitude of response, and the speed at which individuals return to baseline (recovery). This study introduces latent change score modeling as an innovative statistical method for the examination of real-time changes in EDR and the study of mental health correlates of EDR.

Electrodermal Responding and Children's Adjustment Problems

There is a large literature examining associations between EDR—often measured via skin conductance level (SCL) or non-specific fluctuations in skin conductance—and child internalizing and externalizing symptoms and disorders (Friedman, 2007; Fung, Raine, et al., 2005; Gao, Raine, Venables et al., 2010; Gatzke-Kopp, Raine et al., 2002; Raine, 2002). Many of these studies use the traditional technique of averaging EDR across the duration of tasks (Beauchaine, Gatzke-Kopp, & Mead, 2007; Gray & McNaughton, 2000; Fowles, 2002; Friedman, 2007). Children with attention-deficit/hyperactivity disorder (ADHD) or oppositional defiant disorder (ODD) show fewer skin conductance fluctuations than children without these disorders under baseline and reward (board game) conditions (Beauchaine et al, 2001; Crowell, Beauchaine, et al., 2006). High skin conductance response can buffer

against the effect of parental antisocial behavior on increased child conduct problems (Shannon, Beauchaine, et al., 2007). High SCL has also been associated with behavioral inhibition in children (Scarpa, Raine, Venables, & Mednick, 1997). On the other hand, lower baseline SCL in children is a risk factor for depressive symptoms and lower self-esteem in community samples (El-Sheikh & Arsiwalla, 2010).

Use of Repeated Measures ANOVA

In the past, some researchers have segmented EDR during a task into bins varying from 1 s (Laine et al., 2009) to 10 s (Melzig et al., 2007) to 5 min (Rautkyla et al., 2009) and used repeated measures ANOVA to determine mean differences in EDR between bins. However, multi-level modeling is a superior choice over ANOVA for several reasons. First, the assumptions of repeated measures ANOVA (e.g., sphericity) are commonly violated to a severe extent (Maxwell & Delaney, 2004). Second, repeated measures ANOVA provides inaccurate estimates of growth parameters if there are missing data on repeated measures, unless those missing data meet the highly restrictive case of missing completely at random (MCAR) (Francis et al., 1991). Third, procedures available for addressing these issues in repeated measures ANOVA reduce power or are highly statistically complex (e.g., multiple imputation of missing data) (Singer & Willett, 2003). Fourth, model complexity is limited and cannot accommodate time-varying covariates, associations between change parameters across multiple time series, or coupling between time series.

Alternative Statistical Models of EDR

For this reason, the application of advanced statistical models—especially multilevel models—is becoming increasingly popular among psychophysiologicalists. Beauchaine, Hong, and Marsh (2008) examined trajectories of nonspecific fluctuations in skin conductance over the course of several 30 s rest periods (the rest periods occurred between blocks of repetitive response trials). Aggressive girls showed declines in responding across the baselines, while nonaggressive girls showed increases in responding. Marsh, Beauchaine, and Williams (2008) employed multi-level modeling (MLM) to examine associations between facial expressions of sadness and SCL over the course of a sad movie clip. Time series analyses have also been employed, in particular to examine synchrony between SCL responses and other variables (e.g., DiPietro, et al., 2004; Kettunen & Ravaja, 2000).

Latent change score Modeling

Our aim is to build on these prior studies through the introduction of latent change score (LCS) modeling as a statistical approach to the study of EDR. LCS, also known as latent difference score modeling (Ferrer & McArdle, 2003; Ferrer & McArdle, 2010; Malone et al., 2004; McArdle & Hamagami, 2001; McArdle & Prindle, 2008) is an extension of traditional MLM that is conducted within the structural equation modeling framework. Specifically, LCS parameterizes change as a function of both the traditional linear growth terms (e.g., intercept, slope, quadratic term) and proportional growth (i.e., change from one time point to the next depends on the level at the earlier time point). LCS can be employed with a hierarchical approach in which a baseline (no change) model is compared to a model with only the traditional MLM components (i.e., linear terms) or a model with only proportional growth, which can then be compared to a model including both types of growth. LCS has all of the advantages of traditional MLM: (1) within and between person variance can be modeled; (2) data missing at level 1 can be handled using full information maximum likelihood estimation; and (3) there is no assumption of sphericity or compound symmetry.

LCS also has additional advantages: (1) all statistical components of change can be included simultaneously in the model. It is an empirical question whether both growth components

together result in better estimation of SCL trajectories than either component alone, and this empirical question is the focus of the present study; (2) by parameterizing change using latent change scores, an additional aspect of individual differences in change can be predicted. Specifically, independent variables can be used to predict deviations from linear growth terms. Although LCS is a relatively new statistical model, it has been used successfully in various fields, including clinical psychology (Sbarra & Allen, 2009), gerontology (Pinquart & Schindler, 2007), learning and intelligence research (Ferrer et al., 2007; McArdle et al., 2000), and neuroscience (Raz et al., 2005).

A more detailed overview of LCS is now provided based on McArdle and Hamagami (2001). Additional detailed technical descriptions are available from McArdle and Hamagami (2001) as well as Ferrer and McArdle (2003). In LCS, there is an observed score at each time point (for example, the means of SCL during each of seven 30 s observations), which is modeled as a function of the “true” level of SCL and error in the measurement of SCL (both latent, unmeasured variables):

$$Y_{ti} = y_{ti} + e_{ti} \quad (1)$$

In equation (1), the capitalized Y_{ti} is the observed score on variable y for person i at time t , y_{ti} is the latent “true” value of variable y for person i at time t , and e_{ti} is the error in measurement of variable y for person i at time t . The latent “true” SCL levels are modeled as a function of the latent “true” SCL level at the prior time point and some degree of change. This change is also a latent score, and is the difference between SCL level at the prior time point and SCL level at the current time point: it is the latent change score:

$$\Delta y_{ti} = y_{ti} - y_{t-1,i} \quad (2)$$

That is, Δy_{ti} is the difference between y at time t and y at the previous assessment ($t - 1$). And so,

$$y_{ti} = y_{t-1,i} + \Delta y_{ti} \quad (3)$$

In other words, the value of y at time t is the value of y at the previous time point plus the change from the previous time point to the current one. Change in the observed variable is modeled through these latent differences: proportional change is modeled by permitting the latent change scores to be a function of the prior SCL level, whereas constant change/linear growth is modeled by permitting the latent change scores to be a function of an intercept and linear slope. The equation for such a model would be written as:

$$\begin{aligned} \text{Level 1: } \Delta y_{ti} &= \alpha_s * s_i + \alpha_q * q_i + \beta * y_{t-1,i} \\ \text{Level 2: } s_i &= \pi_0 + e_{i0} \\ q_i &= \pi_1 + e_{i1} \end{aligned} \quad (4)$$

Where at level 1, Δy_{ti} is the latent change score for person i at time t , α_s is how many units of time have passed, s_i is the linear slope, or amount of change per unit of time, α_q is how many squared units of time have passed, q_i is the quadratic term, or the effect of time squared, β is the proportional growth term (association between y_t and y_{t-1}) and $y_{t-1,i}$ is the value of y at the prior time point for person i at time t . At level 2, the linear slope and quadratic terms for person i are estimated as a function of the mean linear slope (π_0) or mean quadratic term (π_1) for the sample, plus the difference between the individual's term and the

mean (e_{i0} or e_{i1}). There is no intercept in this model, because where no time has passed, Δy_{it} is undefined. However, LCS models do provide an estimate of the value of y_{i0} , the intercept, which has a mean and a variance. The quadratic component is not necessary in equation (4), and higher order functions can also be included, if data have been measured at a sufficient number of time points. The LCS approach is illustrated in Figure 1. Because it is the latent differences rather than the observed scores that are a function of the slope, the factor loadings for the linear slope (α in equation 4) are all constrained to 1 (i.e., one unit of time has passed for each latent change score). Constraints on the factor loadings for the quadratic component are made such that if the traditional factor loadings on an observed variable are taken (the linear loadings squared--1, 4, 9, 16, 25, etc), the difference between them is the factor loading for the LCS (e.g., $4 - 1 = 3$, $9 - 4 = 5$, $16 - 9 = 7$, etc.). The proportional growth terms, β , can be constrained to be equal across time, or they can differ across time. However, they do not differ across individuals; they are path coefficients rather variables, and therefore cannot be predicted. LCS models can be fit with any standard structural equation modeling software.

Independent variables can be used to predict the traditional linear growth terms. This is because the linear growth terms are latent variables with estimated means and variances. To include a predictor that varies only between persons, this predictor would be entered into the level 2 models:

$$\begin{aligned} \text{Level 1: } \Delta y_{it} &= \alpha_s * s_i + \alpha_q * q_i + \beta * y_{t-1,i} \\ \text{Level 2: } s_i &= \pi_{s0} + \pi_{sx0} * x_i + e_{s0} \\ q_i &= \pi_{q1} + \pi_{qx1} * x_i + e_{q1} \end{aligned} \quad (5)$$

The coefficients π_{sx0} and π_{qx1} represent the association between x and the linear slope and quadratic terms, respectively. To include a predictor that varies within persons, this variable would be entered into the level 1 equation. An important advantage of LCS is that independent variables can also be used to predict the latent change scores. These estimates would provide information about whether the independent variables have an impact on change over time beyond that which is due to the linear growth terms. For example, whether change from T1 to T2 is determined by the independent variable in addition to the T1 value and the intercept, slope, etc.

The Present Study

The present study is designed to demonstrate the usefulness of LCS for the estimation of real-time changes in children's SCL. We hypothesized that these trajectories will be irregular in shape, and therefore characterized by traditional linear growth terms and by proportional change (Andreassi, 2007). We examined these trajectories in response to an inter-adult argument (El-Sheikh, Keller, & Erath, 2007). A secondary goal was examination of children's internalizing and externalizing symptoms as predictors of SCL trajectories. Consistent with the findings of Beauchaine et al (2008), we hypothesized that higher externalizing symptoms would be associated with decreasing trajectories of SCL. It was also hypothesized that trajectories characterized by pronounced response and minimal recovery would be associated with internalizing symptoms (Kagan et al., 1987). Finally, we considered child sex as a predictor of trajectories, and also as a moderator of relations between SCL and child symptoms of maladjustment. Also consistent with Beauchaine et al (2008), we proposed that the association between externalizing symptoms and decreasing SCL would be stronger for girls.

Method

Participants

Participants were drawn from a larger study and were recruited through community groups, birth records, and advertisements. Families were eligible to participate if they included a child between the ages of 6 and 12 years and two parents were living in the home. Multiple children per family participated in the broader study, and one child per family was randomly selected for the current study to avoid problems with dependent observations. Although multi-level modeling (including LCS) uses full information maximum likelihood to estimate missing data at level 1 (i.e., the repeated measure), software programs that perform multi-level modeling require data missing at level 2 or higher to be handled before estimation. Given that there were only small amounts of missing data (< 10%), listwise deletion was used to handle missing data at level 2.

The resulting sample consisted of 76 boys and 75 girls ($N = 151$), 67% European American, 27% African American, and smaller percentages of other ethnicities. Families were predominantly middle class or upper middle class (92%). Several papers have been published with this data set, which is from a larger study of the effects of parental problem drinking on child development. The papers that have included child skin conductance data have all averaged skin conductance level for each task or baseline (Cummings et al., 2007; El-Sheikh, 2005; El-Sheikh, 2007; El-Sheikh et al., 2009; El-Sheikh, Keller, & Erath, 2007; Whitson & El-Sheikh, 2003).

Procedures

This study was conducted with the approval of the institution's internal review board, and informed consent and assent were obtained. Parents (91% were mothers, the remainder were fathers) and children visited a university laboratory where parents completed questionnaires of children's adjustment and children's SCL was assessed during a baseline condition (3 min) and in response to an argument. During baseline, children were asked to sit down quietly and relax (Papillo & Shapiro, 1990).

Following the baseline, children listened to a 3-min audiotaped argument between a man and woman, broadcast through speakers into the laboratory (El-Sheikh, 2005; El-Sheikh, Erath, & Keller, 2007). Children were not informed that it was a recording and were led to believe that the argument was occurring outside the room between a couple. Two argument themes (i.e., in-laws and leisure activity issues) were used, and children were randomly assigned to theme. The arguments were characterized by verbal expressions of anger, which were similar in valence throughout the three min of each argument (i.e., arguments did not have a peak in intensity) and across both argument scenarios. No significant differences in SCL during the two argument themes were observed.

Measures

Skin Conductance—Assessment of SCL followed recommended approaches (Scherbo et al., 1992). Ag/AgCl skin conductance electrodes filled with BioGel (an isotonic NaCl electrode gel) were attached to the volar surfaces of the distal phalanges of the child's nondominant hand. A constant sinusoidal (AC) voltage was used to avoid biasing electrodes. The electrodes allowed a gel contact area of 1 cm in diameter. A 16-channel A/D converter was used to digitize and amplify signals. SCL was assessed continuously throughout the baseline and argument at a rate of 1,000 readings per s using James Long Company (Caroga Lake, NY) software. The SCL range was 0 to 25 μS and the SCL resolution was 0.000763 μS . Data are reported in μS . For LCS modeling, the data were divided into 30 s bins during the 3-min argument (i.e., six data points) and SCL was averaged within each bin. The last 30

s of the baseline condition was used as the first bin in order to determine changes from baseline. Thus, a total of 7 bins were modeled.

Child Internalizing and Externalizing Symptoms—A parent completed Internalizing and Externalizing scales of the Child Behavior Checklist (CBCL; Achenbach, 1991). The CBCL has excellent psychometric properties. The Internalizing subscale includes items assessing child Withdrawal (e.g., would rather be alone than with others) and Anxious/Depressed (e.g., complains of loneliness). The Externalizing scale includes Delinquency (e.g., lying or cheating) and Aggression (e.g., Cruelty, bullying, or meanness to others) subscales. To provide greater specificity of results, and consistent with other studies of SCL and child symptoms of maladjustment (e.g., Beauchaine, Hong, & Marsh, 2008), subscales were used for analyses. The following percentages of children had T scores in the borderline or clinical range ($T > 67$): 5.4% for Withdrawn, 6.7% for Anxious/Depressed, 6% for Delinquent, and 4% for Aggression.

Analyses

LCS models were fit in a hierarchical fashion. First, a traditional multilevel model was fit to determine the significance of linear and quadratic growth parameters. These models correspond to theoretical propositions of how the SNS—and EDR in particular—changes in response to stress (increases, decreases, or initial increases followed by recovery). Second, a traditional proportional growth model was fit without the multi-level growth components. Proportional growth models take into account and are consistent with the law of initial values (Andreassi, 2007; Benjamin, 1967). These models were nested within a full LCS model with both proportional growth and the multi-level linear growth components. Model fit was compared to determine whether the inclusion of both forms of growth resulted in a significantly improved model fit. These comparisons were based on the difference in model χ^2 between the two nested models, in which the difference in the χ^2 is itself a χ^2 (denoted $\Delta\chi^2$) with degrees of freedom equal to the difference in degrees of freedom between the two models. A significant $\Delta\chi^2$ indicates that the more complex model is a significantly better fit for the data. Based on recommendations (e.g., Browne & Cudek, 1993), models were considered an acceptable overall fit for the data if they met at least two of the following three criteria: RMSEA $< .08$; CFI $> .95$; and SRMR $< .010$. Analyses were performed with Mplus 5.1 (Muthén & Muthén, 2008) and syntax is available from the first author upon request.

Results

Preliminary Analyses

Means and standard deviations are presented in Table 1. Initial analyses considered relations between children's maladjustment symptoms and SCL using the traditional practice of averaging across the tasks. SCL reactivity was computed as the difference between baseline SCL and SCL during the argument. Multiple regression models were used in which the baseline SCL and SCL reactivity were included as predictors of the CBCL subscales. Results indicated no significant associations.

Unconditional LCS Models of SCL Argument

Unconditional LCS models—models without predictors of individual differences in trajectories—were next fit to the data. Results are presented in Table 3. The linear growth model (Table 2, Model 2) was a significant improvement over the intercept-only model (Table 2, Model 1), $\Delta\chi^2(2) = 113.80, p < .001$. The model with quadratic growth (Table 2, Model 3) was a significant improvement over the linear growth model (Table 2, Model 2), $\Delta\chi^2(2) = 147.51, p < .001$. Adding a cubic growth term resulted in a model that was

undefined and is not presented. Thus, traditional MLM resulted in an estimated quadratic trajectory for SCL during the argument task (Table 2, Model 3). The inclusion of proportional growth in Model 4 yielded a model that was a significantly better fit than the traditional MLM (Table 2, Model 3), $\Delta\chi^2(6) = 94.04, p < .001$. An additional comparison was made between the model with only proportional growth (not shown) and Model 4. The full LCS model was significantly better than the proportional growth only model, $\Delta\chi^2(4) = 301.41, p < .001$.

According to Model 4, children were estimated to have SCL of 13.88 μS ($p < .001$) at baseline, which increased by 6.896 μS ($p < .001$) at the start of the task and then increased by even larger amounts every additional 30 s (i.e., quadratic growth), $B = 0.70, p < .001$. Further, higher levels of SCL at a given time point predicted less change over the next 30 s of the task (i.e., proportional growth, law of initial values), $B_s = -.53$ to $-1.03, p < .001$. There was significant variance in the intercept (variance = 47.33, $p < .001$), linear slope (variance = 10.91, $p < .01$), and quadratic term (variance = .11, $p < .05$). The resulting mean trajectory is presented in Figure 2. The trajectory resulting from the traditional multi-level model is also included in this figure, and shows the ability of LCS to model more complex trajectories. According to the LCS model, children showed a large increase in SCL during the first 30 s of the argument; SCL subsequently remained stable throughout the rest of the argument. The less well-fitting traditional MLM model estimates a more gradual increase in SCL peaking much later in the task and then declining rather than remaining stable.

Conditional LCS models of SCL during the Argument

Models were next fit in which sex, measures of children's symptoms of maladjustment, and interactions between the two were entered as predictors of the constant growth terms (intercept, slope, quadratic terms) and the latent change scores. To reduce model complexity, prediction of latent change scores was excluded from models where associations were not significant, and only one assessment of child maladjustment symptoms was considered at a time. In one case (where Anxious/Depressed was the predictor), prediction of the intercept was fixed to zero to identify the model. As a result, models have differing degrees of freedom.

Findings are summarized in Table 3. Maternal reports of children's Aggression were related to quadratic growth, $B = .02, p < .05$, and change between 2 min and 2:30 min, $B = .01, p < .05$. Trajectories for children higher (+1 SD) and lower (-1 SD) in aggression are presented in Figure 3A, and indicate that children lower in aggression decrease in SCL throughout the argument, reaching the lowest point between 2:00 to 2:30 min into the task (a 9% decrease in SCL). Children higher in aggression show increases in SCL throughout the task, with a pronounced initial response to the argument and increases in SCL over the course of the argument, reaching the highest point 2:00 to 2:30 min into the task (a 16% increase).

Maternal report of delinquency was related to change in children's SCL between 2 min and 2:30 min (see Table 3). Trajectories for children higher and lower in delinquency are presented in Figure 3B. The pattern is similar to the pattern observed for aggression. The key finding was that SCL toward the end of the argument was significantly greater for children higher in delinquency compared to children lower in delinquency, $B = .02, p < .05$.

Maternal report of children's Anxious/Depressed symptoms was a significant predictor of the quadratic term (see Table 5), $B = .01, p < .01$. Trajectories for children higher and lower in Anxious/Depressed symptoms are presented in Figure 3C. Results indicate that both more Anxious/Depressed and lower Anxious/Depressed children exhibited an initial increase in SCL through the first min of the argument. No additional increases in SCL were observed for children with lower Anxious/Depressed (SCL leveled off at the 1:00 min mark).

Children higher in Anxious/Depressed symptoms showed increasing SCL throughout the course of the argument.

Discussion

We examined an extension of multi-level modeling—LCS—as a statistical approach for the analysis of EDR data. Our hypothesis that SCL trajectories would be better estimated by LCS than traditional MLM models was supported. The full LCS model was a significantly better fit for the SCL data than were traditional MLM models or traditional proportional growth models. LCS yielded several important findings from the unconditional models: (1) real-time changes in SCL follow irregular trajectories that are best characterized by both constant and proportional growth; (2) On average, SCL response is most pronounced in the first 30 s to 1 min of the task; (3) In some cases, recovery to baseline begins during the task. Findings highlight the advantage of LCS for investigations of trajectories of physiological responses; traditional latent growth curve modeling or autoregressive models cannot provide an equally variegated estimate of trajectories. The inclusion of the proportional growth terms highlights the importance of the law of initial values (Benjamin, 1967): statistical models should take into account how SCL at a given time point will affect the amount of change over time.

During the argument, children on average experienced a moderate increase in SCL within the first 30 s, which remained stable throughout the argument. This may be due to the ongoing nature of the stressor, as levels of negative affect were similar throughout the argument, and uncertainty about whether the argument may escalate. The argument does not call for any specific response from the child. Thus, children would experience an initial increase in SCL and plausibly maintain that level of SCL throughout the disagreement in preparation for any necessary action. Obviously, this explanation is tentative pending further empirical investigations. Findings are somewhat consistent with other EDR studies. Beauchaine, and colleagues (2008) provide figures of observed mean trajectories in skin conductance response that also show pronounced changes in the first parts of a computerized repetitive response task, at least for boys with high aggression scores ($T > 70$).

However, conclusions based on LCS are somewhat different than those that would be made from traditional MLM. The best MLM models for the data estimated more gradual increases in SCL in response to the argument. This is somewhat in contrast to current understanding of the rapid reaction of the autonomic nervous system (Porges, 2007), which is more accurately estimated by the full LCS models. The traditional MLM models also estimated a peak SCL level later in the task than the better-fitting LCS model, suggesting that SCL maximum levels occur in the middle of stressors and then subsequently decline at a fairly rapid rate. The better-fitting LCS models indicated that maximum levels occur very rapidly after the onset of the argument and then remain stable. Such trajectories are again more consistent with theory of autonomic stress reactivity (Porges, 2007).

Children higher in aggression, delinquency, or anxious/depressed did not show stabilized levels of SCL after the first min of the argument. Rather, these children exhibited increases in SCL throughout the duration of the argument, while children with fewer symptoms showed stable or decreasing SCL. In the case of aggression and delinquency, the differences were especially dramatic. Others have found that clinical levels of aggression are associated with declining trajectories in skin conductance response over the course of a computerized repetitive response task (Beauchaine, Hong, & Marsh, 2008), and lower SCL reactivity has frequently been observed for children with ADHD, conduct disorder and oppositional defiant disorder (Beauchaine et al, 2001; Crowell, Beauchaine, et al., 2006; Shannon et al., 2007). Our observed response trajectories may indicate that children who have non-clinical

behavior or emotional problems perceive the argument as more threatening and become increasingly hypervigilant and prepared for a fight or flight response. Because the majority of children in this community sample were not suffering from clinical levels of externalizing or internalizing problems, inferences about clinical problems cannot be made.

Limitations

Findings should be interpreted in the study's context and limitations. The study design was cross-sectional and conclusions about directionality of effects between SCL and children's externalizing and internalizing behaviors are not possible. In addition, the sample was community-recruited with low rates of clinically significant adjustment problems. Hence, it is not evident whether findings would generalize to clinical populations. It is not clear why sex differences in trajectories of SCL did not emerge. Prior research on sex differences has been inconsistent. While some researchers report greater EDR for girls (McManis et al., 2001), others find no sex differences in EDR (El-Sheikh, 2007; Gao et al., 2007). Child sex differences in relations between EDR and psychopathology have also been reported (Isen, Raine, et al., 2010), including research employing MLM (Beauchaine, Hong, & Marsh, 2008). Future research is needed to further clarify the role of child sex.

LCS as a statistical approach also has limitations. Like most longitudinal designs, this model requires attention to the timing of assessments. Assessment with shorter or longer bins may yield different findings. Like traditional multi-level modeling, full information maximum likelihood estimation cannot be used to handle data missing at the between-person level. The most common approach to handling between-person missing data is listwise deletion. This approach assumes data are missing completely at random. Multiple imputation can be used as an alternative approach and makes the more relaxed assumption that data are missing at random.

Specification of models should include starting values. Starting values are initial estimates of what the model coefficients will be. They can be based on theory, prior research findings, or estimates from simpler models (e.g., repeated measures ANOVA, regression, traditional MLM models—as was the case for the present study). Many psychophysiological researchers will be unfamiliar with the practice of determining starting values. However, starting values simply provide a place for the iterative estimation procedure to start. As long as the researcher is able to provide a starting value that is in the “ballpark” based on simpler models, estimation will run smoothly and accurately. Results of models with different starting values can also be compared.

Although the models appear very complex (Figure 1), they estimate relatively few parameters and may have few degrees of freedom. For example, the most complex unconditional model fit had only 12 parameter estimates and 19 degrees of freedom. This is because most of the paths depicted in Figure 1 are fixed to those values that render the estimated coefficients interpretable. On the one hand, this is an advantage because models can be fit to somewhat smaller sample sizes than more complex models (sample sizes lower than 100 are not recommended, however, and sample sizes greater than 200 are preferred; Kline, 2005). On the other hand, degrees of freedom are not determined by sample size, but by the difference between the number of possible and actual parameter estimates. Thus, simpler models have lower power than more complex models.

Proportional growth terms are represented by path coefficients rather than latent variables, and therefore their means and variance terms cannot be estimated. Similarly, between person differences in proportional growth terms cannot be predicted in the same way that between person differences in linear growth terms can be predicted. However, LCS does include latent variables representing change between each adjacent time point, and individual

differences in these latent change scores can be predicted (as has been shown in the current study).

In summary, this study demonstrates the feasibility of LCS for investigating trajectories of children's physiological responses during various lab challenges. Furthermore, it highlights associations between children's externalizing and internalizing behaviors and their SCL trajectories during the session. It is our hope that these findings would encourage future methodological advances including the use of LCS and other advanced longitudinal methods in developmental psychobiology and psychophysiology.

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Figure 1.
The Latent change score Model.

Figure 2.
Mean Estimated Trajectories of Change in SCL Throughout the Course of the Argument Task.

Figure 3.
Trajectories of Change in SCL during the Argument as a Function of Maladjustment Symptoms

Table 1

Means and Standard Deviations

Variable	<i>M</i>	<i>SD</i>
Baseline 1	13.92	6.91
SCL 1 st 30 s Argument	14.11	6.85
SCL 2 nd 30 s Argument	14.15	6.81
SCL 3 rd 30 s Argument	14.15	6.80
SCL 4 th 30 s Argument	14.17	6.77
SCL 5 th 30 s Argument	14.17	6.76
SCL 6 th 30 s Argument	14.18	6.75
Child Withdrawal	54.85	6.57
Child Anxious/Depressed	54.83	6.36
Child Delinquency	53.72	5.18
Child Aggression	53.55	5.80

Note: All SCL scores are in microSiemens; Child Withdrawal, Anxious/Depressed, Delinquency and Aggression scores are T scores.

Table 2

Results from LCS Modeling for SCL Change During the Course of the Argument

	Model 1	Model 2	Model 3	Model 4
X ²	638.97***	525.17***	377.66***	283.62***
Df	29	27	25	19
CFI	.893	.913	.938	.954
RMSEA	.374	.351	.307	.305
SRMR	.03	.014	.003	.003
ΔX^2		113.80***	147.51***	94.04***
Intercept	14.49***	14.22***	13.93***	13.88***
Var(Intercept)	46.381***	46.93***	47.35***	47.33***
Linear Slope		0.02*	0.13***	6.90***
Var(slope)		0.02***	.09***	10.91**
Quadratic			-.02***	.70***
Var(quadratic)			.01***	.11*
Proportional Growth on 1 st 30 s Argument				-.53***
Proportional Growth on 2 nd 30 s Argument				-.63***
Proportional Growth on 3 rd 30 s Argument				-.73***
Proportional Growth on 4 th 30 s Argument				-.83***
Proportional Growth on 5 th 30 s Argument				-.93***
Proportional Growth on 6 th 30 s Argument				-1.03***

Note: Model 1 = baseline model with no change (intercept only); Model 2 = model with only linear change over time; Model 3 = model with quadratic change over time; Model 4 = model with quadratic change and proportional growth. Proportional growth on each 30 s segment reflects the relation between it and the prior 30 s.

*
 $p < .05$;

**
 $p < .01$;

 $p < .001$.

Table 3

Conditional Models of SCL During the Argument

	Aggression	Delinquency	Withdrawal	Anxious/Depressed
X ²	286.64***	289.42***	293.39***	292.83***
df	28	28	31	34
CFI	.955	.954	.954	.955
RMSEA	.248	.249	.238	.225
SRMR	.002	.002	.002	.064
Intercept				
Intercept	13.14***	13.12***	13.02***	13.88***
Female	11.72	1.60	1.69	0
Maladjustment Sx	.24	.12	-.15	0
Female x Maladj.	-.19	-.14	.07	0
Residual Variance	45.94***	46.51***	46.11***	47.33***
Linear Slope				
Intercept	6.69***	6.69***	6.56***	7.02***
Female	5.23	.65	.69	-.86
Maladjustment Sx	.12	.01	-.07	-.01
Female x Maladj.	-.09	-.06	.03	.01
Residual Variance	10.93**	11.11**	10.75**	11.16**
Quadratic				
Intercept	.69***	.67***	.67***	.72***
Female	.84	.05	.06	.16
Maladjustment Sx	.02*	.01	-.01	.01**
Female x Maladj.	-.02	-.01	.01	-.01
Residual Variance	.11*	.11*	.11*	.11*
Change in 1 st 30 s				
Proportional G.	-.54***	-.54***	-.53***	-.54***
Change in 2 nd 30 s				
Proportional G.	-.64***	-.64***	-.64***	-.64***
Change in 3 rd 30 s				
Proportional G.	-.74***	-.74***	-.73***	-.74***
Change in 4 th 30 s				
Proportional G.	-.84***	-.84***	-.83***	-.84***
Change in 5 th 30 s				
Proportional G.	-.94***	-.94***	-.93***	-.94***
Female	.39	-.01		
Maladjustment Sx	.01*	.02*		
Female x Maladj.	-.01	-.01		

	Aggression	Delinquency	Withdrawal	Anxious/Depressed
Change in 6 th 30 s				
Proportional G.	-1.04 ***	-1.04 ***	-1.03 ***	-1.04 ***

Note: Columns refer to models in which the column label is the measure of Maladjustment Sx included in the model; Female, Maladjustment Sx, and the interaction between them were found to predict latent change scores in two cases; prediction was therefore excluded where possible to reduce model complexity. Predictions of the intercept were fixed to zero in the Anxious/Depressed model for identification purposes. Proportional G refers to the association between change in SCL and the prior level of SCL.

*
 $p < .05$;

**
 $p < .01$;

 $p < .001$.