

# A latent change score approach to understanding dynamic autonomic coordination

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## Abstract

Children's self-regulation is a core adaptive system in child development. Physiological indices of regulation, particularly the autonomic nervous system (ANS), have garnered increased attention as an informative level of analysis in regulation research. Cardiography supports the simultaneous examination of both ANS branches via measures of pre-ejection period (PEP) and respiratory sinus arrhythmia (RSA) as indicators of sympathetic and parasympathetic activity, respectively. However, despite their heavily intertwined functions, research examining autonomic coordination across sympathetic and parasympathetic systems is scarce. Moreover, extant efforts have favored static, mean level reactivity analyses, despite the dynamic nature of ANS regulation and the availability of analytic tools that can model these processes across time. This study drew on a sample of 198 six-year-old children from a diverse community sample (49.5% female, 43.9% Latinx) to examine dynamic autonomic coordination using bivariate latent change score modeling to evaluate bidirectional influences of sympathetic and parasympathetic activity over the course of a challenging puzzle completion task. Results indicated that children evidenced reciprocal sympathetic activation (i.e., PEP attenuation and RSA withdrawal) across the challenge task, and these regulatory responses were characterized by a temporally leading influence of PEP on lagging changes in RSA. The current findings contribute to our understanding of children's autonomic coordination while illustrating a novel analytic technique to advance ongoing efforts to understand the etiology and developmental significance of children's physiological self-regulation.

## KEYWORDS

autonomic nervous system, coordination, latent change score models, parasympathetic, regulation, sympathetic

## 1 | INTRODUCTION

Patterns of physiological regulation (e.g., reactivity and recovery in response to life's challenges) are heavily implicated in psychological adjustment (Beckmann & Kellmann, 2004; Blair, 2010; Phillips & Shonkoff, 2000). Prior research has shown that multiple biological indices of self-regulation (e.g., heart rate, cortisol, skin conductance) are related to a wide

range of adaptive outcomes (e.g., behavior, secure attachment, and physical health; Berry, Blair, Ursache, Willoughby, & Granger, 2014; Hagan, Roubinov, Adler, Boyce, & Bush, 2016). In particular, the autonomic nervous system (ANS) has garnered increased research attention because it permits time-sensitive, dynamic analyses of physiological regulation, and cardiography can support the investigation of both sympathetic (i.e., fight/flight) and parasympathetic

(i.e., rest/digest) influences on ANS regulation. Despite the intertwined and dynamic nature of sympathetic and parasympathetic regulation, however, prior studies have primarily focused on one branch of the ANS using static, mean-level indicators of physiological regulation during a single task (e.g., aggregating sympathetic *or* parasympathetic activity values across a challenge), rather than dynamic, multi-level indicators (e.g., patterns of change in sympathetic *and* parasympathetic activity across a challenge). Thus, the current study addressed the need for dual and dynamic investigations of both sympathetic and parasympathetic branches of the ANS using multi-level modeling to evaluate patterns of activation within and across sympathetic and parasympathetic regulatory systems as they work in tandem to influence adaptive responses to stress (i.e., autonomic coordination).

## 1.1 | The autonomic nervous system

The ANS encompasses the sympathetic excitatory system and the parasympathetic inhibitory system, which are fundamental to mobilizing adaptive responses to stress (e.g., smooth muscles, respiration, heart rate; McEwen, 2007). Theoretically, activities of the sympathetic and parasympathetic branches of the ANS complement one another (Jänig & McLachlan, 1992). At rest, sympathetic activation may be relatively low, which, in tandem with a comparatively elevated inhibitory influence from the parasympathetic nervous system, allows the body to maintain a readiness for response mobilization (Esler & Kaye, 2000).

In contrast to evidence that an optimal resting state comprises a system that is ready to mobilize a response (i.e., parasympathetic dominance), there is no evidence to support a universally adaptive ANS response to challenge. Indeed, research suggests that the appropriate response likely varies by challenge context (Davis, Brooker, & Kahle, 2020). For example, in response to a challenge that warrants behavioral mobilization, such as a startling stimulus, an appropriate response may be characterized by activation in the sympathetic system in tandem with a decrease in parasympathetic activation to release its inhibitory influence on the sympathetic system and support action. A recent study utilizing such a task found that children's sympathetic activation and parasympathetic withdrawal in response to a startling stimulus predicted higher ratings of adaptability and fewer attention problems (Rudd & Yates, 2018). Conversely, in response to a challenge that requires sustained attention, such as a difficult memorization task, an appropriate response may be characterized by a decrease in sympathetic system activation in tandem with an increase in the parasympathetic system's inhibitory influence to constrain the sympathetic nervous system and enhance the organism's capacity to sustain a calm focus. Although no studies measuring both branches

of the ANS have employed tasks requiring sustained attention, studies of parasympathetic activity in isolation often find augmentation in response to focused attention challenges and some suggest that these responses may be associated with better outcomes (Davis, Quiñones-Camacho, & Buss, 2016; Hastings et al., 2008). However, studies have also documented parasympathetic withdrawal in response to attention-engaging tasks (Griffiths et al., 2017; Overbeek, van Boxtel, & Westerink, 2014), which points to additional complexity underlying these processes.

Multiple biological measures index sympathetic *or* parasympathetic activity (e.g., salivary alpha-amylase for sympathetic activity, pupil dilation for parasympathetic activity), but the cardiac system is unique because it affords the unique opportunity to examine both branches of ANS regulation as they operate in tandem to modulate heart rate. Pre-ejection period (PEP; a measure of sympathetic activity) is a systolic time interval representing the elapsed duration from the beginning of electrical cardiac stimulation until the ejection of blood from the left ventricle (Berntson, Lozano, Chen, & Cacioppo, 2004). A shorter PEP time interval represents sympathetic activation, which is accompanied by increases in heart rate. Respiratory sinus arrhythmia (RSA; a measure of parasympathetic activity) represents the naturally occurring variation in heart rate as a function of respiration (Porges, 2007). A higher RSA level reflects parasympathetic activation, which is associated with decreases in heart rate. Despite widespread recognition of the coordinated regulatory actions of the sympathetic and parasympathetic branches of the ANS broadly, and as indexed by PEP and RSA in particular, theoretical perspectives offer divergent opinions regarding the nature of autonomic coordination.

## 1.2 | Theories of autonomic coordination

Berntson was among the first to conceptualize cardiac coordination in development, arguing that sympathetic and parasympathetic systems function along two dimensions that define *the autonomic space* and operate with varying degrees of coordination to regulate responses therein (Berntson & Cacioppo, 2004; Berntson, Cacioppo, & Quigley, 1991; Berntson, Cacioppo, Quigley, & Fabro, 1994). Although Berntson posited that cardiac systems operate in either reciprocal/nonreciprocal (i.e., opposing activation vs. coactivation/coinhibition) or coupled/un-coupled fashion (i.e., correlated vs. uncorrelated activity, such as when activation in one system is accompanied by no change in the other system), autonomic space theory does not position either ANS branch as more or less likely to take the lead in this regulatory dance. Indeed, higher order central nervous system afferents to brain stem nuclei are thought to regulate autonomic responses, and some researchers suggest that these

mechanisms independently influence autonomic coordination (Smith, Thayer, Khalsa, & Lane, 2017).

In contrast to Bernston's emphasis on the *degree* of coordination between systems, Porges' (2001, 2007, 2009) polyvagal theory emphasizes the *direction* of coordination by positioning the parasympathetic system as the driving force of ANS regulation (Porges & Furman, 2011). Indeed, Porges (2007) conceptualizes RSA as an index of parasympathetically mediated vagal control that supports sympathetic mobilization during challenge when withdrawn, and inhibits the excitatory activity of the sympathetic branch of the ANS as a "vagal brake" when augmented (Porges, Doussard-Roosevelt, Portales, & Greenspan, 1996). Porges' theory implies that the parasympathetic system initially reacts to challenge and is met by sympathetic response when the challenge cannot be regulated by parasympathetic innervation alone. In this view, the intensity of the challenge determines whether ANS regulation features single system activation or dual-system coordination.

Although Porges' polyvagal theory, and its attendant presumption of parasympathetic dominance in ANS regulation, has gained the most traction in the field, Bernston and others remain critical of its postulates (Berntson, Cacioppo, & Grossman, 2007; Grossman & Taylor, 2007). For example, evidence suggesting that shifts in sympathetic activity can influence measures of parasympathetic indicators (Berntson et al., 2007) counter Porges' theory. Indeed, it may be that autonomic coordination is best captured by a combination of these theoretical perspectives, much like our understanding of ANS reactivity generally. In line with research suggesting that physiological responses may vary by task demands (Davis et al., 2020), features of the challenge context (e.g., social, cognitive, and emotional characteristics) may influence both the degree and direction of sympathetic and parasympathetic activation. Further, in line with Porges' polyvagal theory of a socially attuned vagus (2001, 2007, 2009), reactivity patterns during a socially engaging dyadic task may be influenced most strongly by parasympathetic activity. Conversely, a more arousing task, such as a startling challenge, may be guided most strongly by sympathetic activity. Ongoing debates about temporal and causal patterns of autonomic coordination highlight the need to evaluate both sympathetic and parasympathetic systems to capture the multifaceted nature of ANS regulation fully.

### 1.3 | Studies of autonomic coordination

Despite extant theory demonstrating the importance of regulatory dynamics between and within systems (Cacioppo, Gardner, & Berntson, 1997; Flam & Powell, 2009; Gottlieb & Halpern, 2002), integrative investigations of sympathetic and parasympathetic influences on physiological regulation

are scarce. Moreover, the few studies that have examined both sympathetic and parasympathetic regulatory processes have typically measured each branch of the ANS in separate physiological systems, such as skin conductance and RSA (El-Sheikh et al., 2009; Philbrook, Erath, Hinnant, & El-Sheikh, 2018) or salivary alpha amylase and RSA (Keller & El-Sheikh, 2009). Findings from these and other studies have yielded conflicting results suggesting that patterns of autonomic coordination, as well as their developmental significance, may vary as a function of the indices used to assess each facet of the ANS (Erath & El-Sheikh, 2015; Gatzke-Kopp & Ram, 2018; Gordis, Feres, Olezeski, Rabkin, & Trickett, 2010; Quas et al., 2014).

A few studies have examined autonomic coordination within the cardiac system using either person-oriented profile-based conceptualizations of autonomic coordination (Alkon, Boyce, Davis, & Eskenazi, 2011; Salomon, Matthews, & Allen, 2000) or interactive, continuous analytic approaches (Clark, Skowron, Giuliano, & Fisher, 2016; Rudd & Yates, 2018; Suurland, van der Heijden, Huijbregts, Van Goozen, & Swaab, 2017). These studies have revealed interesting developmental patterns (e.g., coordinated profiles of regulatory activity appear to increase across the first five years of life; Alkon et al., 2011, 2014) and adaptive implications of autonomic coordination (e.g., children who had interactive patterns of sympathetic and parasympathetic co-activation or coinhibition in response to interpersonal stress as infants show higher levels of physical aggression than those who evidenced reciprocal autonomic coordination; Suurland et al., 2017).

Together, prior studies suggest that autonomic coordination develops over time and may facilitate positive adaption in childhood. Thus, efforts to examine the coordination between autonomic systems may provide a deeper understanding of development and adaptation than studies of single system regulation. That said, extant studies examining both autonomic systems remain limited by their use of static analytic approaches to capture what is fundamentally a dynamic interplay between sympathetic and parasympathetic systems. Following the tenets of a dynamic systems theory of development, which holds that development is best understood by examining processes of organization rather than outcomes alone (Thelen, 2005), establishing the temporal pattern of activation across sympathetic and parasympathetic systems represents a necessary first step toward capturing the true nature of ANS regulation.

### 1.4 | Dynamic strategies to study autonomic regulation

Over the past five years, a handful of researchers have begun to employ dynamic analytic strategies to capture

real-time regulatory processes more fully, albeit within a single branch of the ANS (Fisher, Reeves, & Chi, 2016; Gates, Gatzke-Kopp, Sandsten, & Blandon, 2015; Helm, Sbarra, & Ferrer, 2014). Cross-lagged panel studies have examined RSA within romantic dyads (Helm et al., 2014), but no studies have done so with PEP, nor have any studies documented intra-individual patterns of autonomic coordination between PEP and RSA. Although cross-lagged panel analyses have numerous strengths, including the ability to assess reciprocal and directional influences on changes between constructs while controlling for autoregressive effects, they ignore growth over time since only covariances, but not mean structures, are modeled (Hamaker, Kuiper, & Grasman, 2015). Growth curve studies have examined independent trajectories of RSA (Cui, Morris, Harrist, Larzelere, & Criss, 2015; El-Sheikh, Keiley, & Hinnant, 2010; Miller et al., 2013; Patriquin, Lorenzi, Scarpa, & Bell, 2014; Porges & Furman, 2011), and, to a lesser degree, PEP (Kahle, Miller, Lopez, & Hastings, 2016), but none to our knowledge have employed parallel growth curve modeling to assess autonomic coordination between PEP and RSA over time. Despite the strengths of growth modeling procedures, these models cannot account for the influence of previous states on subsequent growth (i.e., autoregressive effects) within or across systems.

Although dynamic modeling approaches in single system investigations constitute a marked improvement over the static measures that feature prominently in extant studies of autonomic coordination, they remain unable to answer key questions about underlying patterns of coordination across a challenge task. Extant research on autonomic coordination has focused on the *quantity* or *degree* of coordination within a given a challenge response (e.g., profiles based on absolute levels of average change), however, there remains a need to assess the *quality* or *pattern* of ANS responses (i.e., PEP-RSA dynamics across a single challenge episode) to fully characterize autonomic coordination. As a dynamic system, the temporal relation *between* sympathetic and parasympathetic influences may yield as much or more information than understanding the magnitude of response *within* any one system in isolation (Thelen, 2005).

In the few studies that have explored autonomic coordination dynamically, Gatzke-Kopp and colleagues utilized multilevel modeling approaches to explore the degree of autonomic coordination across multiple 30-s epochs and whether coordination varied across context (Gatzke-Kopp, Benson, Ryan, & Ram, 2020; Gatzke-Kopp & Ram, 2018). In a study of 5-year-old children employing emotion eliciting videos, researchers found stronger autonomic coordination in the context of an approach-oriented film and weaker coordination in the context of avoidance-oriented emotion elicitation (Gatzke-Kopp & Ram, 2018). Additional results revealed that individual-level differences accounted for very

little variance in children's PEP and RSA coordination, suggesting that coordination itself may depend on the challenge context, rather than trait-like individual differences. In a more recent study examining whether autonomic coordination is moderated by prefrontal cortical activation and/or affective states, Gatzke-Kopp and colleagues (2020) found that children tended to react to a cognitive inhibitory control and affective manipulation task with coordinated ANS activation. Moreover, although this coordination was not significantly moderated by cortical activation, it was moderated by affective state, such that children were more likely to evidence coordinated PEP and RSA responses during the frustration inducing portion of the task. These studies examined the degree of coordination broadly, including both reciprocal sympathetic activation and reciprocal parasympathetic activation, rather than evaluating directional responses, or the pattern of autonomic coordination.

In addition to ongoing efforts to understand whether autonomic coordination is the expected response to a laboratory challenge, understanding the pattern of coordination with regard to whether PEP and RSA respond in tandem, or whether one system takes temporal precedence across time in a dynamic way, will provide advance our understanding of ANS coordination and its adaptive implications. Specifically, elucidating the underlying temporal dynamics of autonomic coordination can help to reconcile differing theories of ANS regulation regarding whether or when one branch may evidence primary or leading action in response to challenge (Berntson et al., 1994; Porges, 2009).

To assess temporal coordination, this investigation employed bivariate latent change score (BLCS) models as a novel and dynamic analytic approach to evaluate autonomic coordination between children's PEP and RSA across a four-minute problem-solving task, while accounting for relations between epoch-to-epoch changes in one autonomic branch and epoch-to-epoch changes in the opposing branch. These models provide a comprehensive framework to model both within-person change across the task and between-person variability in change by combining the strengths of autoregressive cross-lagged panel analyses and growth models to support the investigation of directional dynamics between regulatory systems over time (Ferrer & McArdle, 2010; McArdle & Grimm, 2010). Further, BLCS models allow for modeling complex patterns of change by incorporating both a constant and proportional change component, which may be particularly important for understanding the overall rate of change and deviations in the rate of change across the coordination processes, respectively. By assessing within- and between-person differences in change, dynamic relations within a latent change model can be characterized as temporally "leading" or "lagging," such that values of the "leading" indicator significantly predict changes in the "lagging" indicator. Coupling parameters determine whether performance on one

indicator accounts for subsequent change in performance on a second indicator to represent “leading” or “lagging” temporal dynamics.

As applied to the study of autonomic coordination, a BLCS approach reveals temporal patterns between PEP and RSA regulatory dynamics and, by extension, evaluates competing theories of autonomic coordination. For example, if the data support a unidirectional coupling model wherein PEP takes on the “leading” role, it is likely that, in the present context, the sympathetic system was the primary responder and parasympathetic responses followed in direction and magnitude, which would be consistent with elements of Berntson and colleagues' (2007) suppositions about autonomic dynamics. Alternately, if the data support a unidirectional coupling model wherein RSA takes on the “leading” role, it is likely that the parasympathetic system acts similarly to Porges' (2007) theory by serving as the first responder to challenge, with sympathetic responses occurring secondarily to meet additional demands. In a fully coupled model, wherein PEP and RSA are both leading influences on one another, it is likely that both sympathetic and parasympathetic inputs are active across the entirety of the task, which would be a melding of these current theories.

Importantly, despite the value of applying dynamic models to study autonomic coordination, any interpretations of these data must consider three prominent issues. First, extant measurement techniques remain limited in their capacity to capture real-time fluctuations in these systems. For example, to preserve the reliability of PEP and RSA estimates, researchers must examine autonomic reactivity across 30-epochs, despite the reality that the dynamics likely operate on much shorter, but as yet unreliable to extract, time frames. Thus, efforts to interpret these research findings must fit the epoch-level data and hypotheses. Second, as noted earlier, the degree and form of autonomic coordination will be shaped by the unique features of the challenge at hand. Thus, any findings warrant further evaluation to assess replicability across diverse challenge contexts. Finally, causal interpretations of apparent lead-lag temporal relations are ill-advised in light of strong evidence that higher order neural afferents likely shape these observed downstream relations.

Although the current study was the first to apply a BLCS model to the study of autonomic coordination, research on other psychological constructs using this approach supported the feasibility of this analytic model and informed the current model-fitting procedures (Ferrer & McArdle, 2010; Malone et al., 2004; Quinn, Wagner, Petscher, & Lopez, 2015; Toth, Sturge-Apple, Rogosch, & Cicchetti, 2015). For example, in a study examining the dynamics between vocabulary knowledge and reading comprehension from first to fourth grade, Quinn and colleagues (2015) utilized BLCS models to evaluate competing theories of unidirectional (i.e., vocabulary knowledge leading changes in reading comprehension

versus reading comprehension leading changes in vocabulary knowledge) and bidirectional coupling (i.e., both indicators having a leading influence on one another). Results supported a unidirectional model with a leading influence of vocabulary knowledge on growth in reading comprehension. Extending to the ANS, prior studies of autonomic regulation and coordination suggest meaningful patterns of within-system regulation across a single task (Kahle et al., 2016; Miller et al., 2013) and support the likely utility BLCS models for elucidating temporal patterns of autonomic coordination.

## 1.5 | Current study

This study advanced and integrated two growing edges of contemporary research efforts in the field of ANS regulation research. First, although the ANS has long been described as a system wherein sympathetic and parasympathetic inputs work together to modulate responses to stress, most research in this area has examined each system in isolation. Second, prior studies that have examined autonomic coordination have typically focused on mean-level changes across tasks, or across time within a task, which has limited our understanding of the dynamic interplay between PEP and RSA during a stress response. To address these gaps, this study implemented BLCS modeling as a novel and dynamic statistical approach to evaluate unidirectional and bidirectional coupling models of sympathetic and parasympathetic activity over the course of a challenging puzzle completion task in a large sample of six-year-old children.

First, we hypothesized that, on average, children would evidence coordinated ANS regulation in response to the challenging puzzle task (Gatzke-Kopp et al., 2020; Gatzke-Kopp & Ram, 2018). However, based on previous literature suggesting task-specific patterns of ANS regulation across arousing versus engaging challenges (Davis et al., 2016; Skowron, Cipriano-Essel, Gatzke-Kopp, Teti, & Ammerman, 2014), as well as across tasks entailing varying levels of social, cognitive, and emotional demands (Davis et al., 2020; Roos et al., 2017), we remained agnostic as to whether the coordinated regulatory pattern would be characterized by reciprocal sympathetic activation (i.e., PEP attenuation and RSA withdrawal) or reciprocal parasympathetic activation (i.e., PEP elongation and RSA augmentation).

Second, in addition to coordinated ANS regulation, we expected to find significant coupling between PEP and RSA across the challenge task (i.e., correlated patterns across both systems). Given conflicting theories and the paucity of prior research on autonomic coordination, we evaluated three potential coupling patterns between PEP and RSA. First, PEP may lead RSA change across time, supporting suppositions of the multidetermined nature of RSA responses (Berntson et al., 2007). Second, RSA may lead PEP change across time

as suggested by Porges' (2001, 2007, 2009) Polyvagal theory. Third, there may be full-coupling such that both PEP and RSA dynamically and reciprocally lead and follow changes in one another across the task. In addition, we were open to the possibility that the analyses may not support any single model, with relations best characterized by uncoupled change such that PEP and RSA function independently from one another. This uncoupled pattern would be consistent with autonomic space principles that acknowledge the ability of these systems to act independently from one another (Berntson et al., 1994).

## 2 | METHOD

### 2.1 | Participants

Participants were 198 children (49.5% female;  $M_{age} = 6$  years and 1 month,  $SD = 2.51$  months) who completed a laboratory assessment of self-regulation and stress physiology as part of an ongoing longitudinal study of child development. The current sample was ethnically/racially diverse (43.9% Latinx, 25.3% multiracial, 18.7% African American/Black, 12.1% European American/White), and representative of the surrounding community from which it was drawn (U.S. Census Bureau, 2011). All participating caregivers were female (91.9% biological mothers, 3.0% foster/adoptive mothers, and 5.0% grandmothers or other female kin caregivers). The majority of caregivers were married (61.6%) or in a committed relationship (18.8%), and just over half were employed (55.6%). Education levels were variable (e.g., 12.4% of caregivers did not finish high school, 10.0% had a high school diploma or GED; 19.6% earned a 2-year or technical degree; 8.4% had earned a 4-year-degree; 5.6% had an advanced degree). The average family SES score using the Hollingshead (1975) Four-Factor Index of Social Status was 33.41 ( $SD = 12.31$ ), which corresponds to semi-skilled employment (e.g., sales clerk).

### 2.2 | Procedures

Children and their primary caregivers were recruited to participate in “a study of children's learning and development” via flyers posted in community-based child development centers and preschool programs in Southern California. Potential participants were screened by phone to ensure that the child was (a) between 3.9 and 4.6 years of age at the time of the wave 1 assessment ( $M_{age\_w1} = 4$  years and 1 month,  $SD = 2.82$  months), (b) proficient in English, and (c) not diagnosed with a developmental disability or delay. Dyads completed a three-hour laboratory assessment, which consisted of measures with the child, the caregiver, and the caregiver and

child interacting. Physiological regulation during challenge tasks was first assessed when the children were 6-years-old, which is the sample used in this study. Caregivers were compensated with \$25/hour for their participation, and each child received a small gift. Written informed consent was obtained from the legal guardian at the beginning of each laboratory visit. All procedures were approved by the University's Human Research Review Board.

### 2.3 | Measures

*ANS Regulation* was assessed using measures of the child's PEP and RSA during a resting baseline and a challenging puzzle task. Four spot electrodes were placed on the child's neck and torso to collect impedance and respiratory measures, and three spot electrodes were placed on the right clavicle, left lower rib, and right abdomen to obtain electrocardiogram (ECG) measures. Following a five-minute calibration period, the dyad was asked to complete a three-minute, non-challenging sorting exercise (i.e., sorting foam pieces by color) while seated at a table; this provided a resting baseline for the challenge task, which involved vocalization and hand movements. Immediately following the resting measure, dyads completed a problem-solving challenge in which the child was presented with the tree and dog puzzles from the Wechsler Intelligence Scale for Children—III object assembly task (Wechsler, 2002), and instructed to try their best to complete both puzzles before the examiner returned in four minutes. Caregivers were instructed to let the child complete as much of the puzzles as they could on their own, but to provide guidance if they thought their child needed assistance.

ANS data were collected using Mindware MW1000A ambulatory cardiography ([www.mindwaretech.com](http://www.mindwaretech.com)) via Kendall Medi-Trace #133 spot electrodes. PEP data were extracted and scored using the IMP 3.0.3 analysis program and the  $dZ/dt$  waveforms were used to obtain impedance-derived PEP measures quantified as the time interval in milliseconds from the onset of the ECG Q-wave to the B point of the  $dZ/dt$  wave (Berntson et al., 2004). RSA data were filtered, extracted, and scored using Mindware's HRV 3.0.10 analysis program. This technique utilizes the Mindware software algorithms to calculate the variance in R-R wave intervals. RSA scores were calculated using the interbeat intervals on the ECG reading, respiratory rates derived from the impedance (i.e.,  $dZ/dt$ ) signal, and a specified RSA bandwidth range for 6-year-olds of 0.15 to 0.80 Hz (Bar-Haim, Marshall, & Fox, 2000). The respiratory frequency band adhered to the gold standard recommendations at the time of original data collection and cleaning, however, given recent concerns about potential mis-specification of RSA values based on respiratory frequency bands (Shader et al., 2018), we assessed whether

this band accurately captured respiratory rates in the current sample. Of the 198 children in the current study, 12 evidenced one epoch outside the specified frequency band, 2 evidenced two epochs outside this range, and no cases had more than two epochs with mis-specified RSA bands. Thus, respiratory frequency bands were mis-specified in 1.1% of the epoch-level data and appeared as anomalous epochs randomly distributed across cases, rather than systematic variation within a child. Moreover, the appearance of these mis-specified epochs varied across the broader task, suggesting that sudden changes in respiratory rate likely reflected random alterations in body-posture or vocalization across the task (Grossman & Taylor, 2007; Houtveen, Groot, & De Geus, 2005).

Consistent with prior studies (Alkon et al., 2011; Boyce et al., 2001), data were extracted in 30-s epochs across the four-minute challenge yielding a total of eight PEP and eight RSA values for each child. Although the ANS is a dynamic system that entails moment-to-moment transactions that likely fluctuate within a 30-s period, extant techniques for rendering estimates of PEP and RSA become increasingly unreliable within the anatomical time frame of this system. A handful of studies have used shorter epochs (e.g., 15 s; Miller et al., 2013), but, given the novelty of our analytic approach, we opted to retain well-validated, reliable measures, including the standard epoch measurements of 30-s used in most prior research.

Data cleaning procedures for PEP and RSA included visual inspection of each epoch for errors or abnormalities in the B-points and R-peaks, respectively. For RSA, extensively trained research assistants manually edited R-peaks, which were then checked and finalized by the first author. PEP was cleaned using the finalized RSA epochs, and were also visually inspected by trained research assistants. If B points were not accurate, the assistants flagged the case for inspection by the first author who then manually edited as necessary. Further procedures included screening each epoch for outliers (i.e.,  $>3 SD$ ) and deleting a child's data if more than 25% of their epochs were missing due to computer malfunction, electrode conduction problems, or outliers.

## 2.4 | Analytic plan

All analyses were completed in Mplus version 7.1 (Muthén & Muthén, 2013). Data were examined for outliers, as well as univariate and multivariate normality. Only participants who completed the physiological assessment at age 6 were included in these analyses ( $N = 198$ ). Physiological data were considered missing in instances where there was a computer malfunction ( $n = 11$ ), electrode conduction problems ( $n = 2$ ), PEP outliers ( $n = 3$ ), RSA outliers ( $n = 1$ ), or task administration errors ( $n = 2$ ). Full information maximum likelihood

estimation (FIML; McArdle, 1994) was used to address missing data.

BLCS models, which allow for modeling complex change trajectories as both within-person change across time and between-person variability in change, assessed temporal autonomic coordination. Importantly, these models assume linear trends in the primary study variables across time. To confirm the appropriateness of modeling linear PEP and RSA reactivity patterns in our data, haystack plots probed sample characteristics of both PEP and RSA across the four-minute challenge task. Results suggested that linear trends were most evident in the current sample and supported our evaluation of linear models.

Model fit was assessed sequentially as described by Grimm, Ram, and Estabrook (2006). Growth models for both PEP and RSA were modeled separately to compare fit across four possible models of change. The first model was a *no change model*, which posited no change across the challenge task. Second, we evaluated a *constant change model*, which posited linear growth, akin to the slope factor in growth curve analysis, within each regulatory system (i.e., PEP or RSA). The third model was a *proportional change model* wherein growth was positioned as a function of previous levels of regulation such that the proportional change component captured how change in the system between adjacent measurements depended on the variable level at the preceding time point. Finally, the fourth model was a *dual-change model* that incorporated both linear and proportional change components to capture the extent to which constant change was limited or amplified by the same or the other variable's level at the preceding time point.

Following the evaluation of separate univariate models for PEP and RSA, a bivariate model evaluated coupling effects in the coordination of PEP and RSA across the challenging puzzle task. First, a *no coupling model* fixed all coupling parameters for PEP and RSA to zero and served as a baseline that posits no cross-variable or time-sequential associations. Next, two separate unidirectional models were fit, such that change in PEP predicted change in RSA (i.e., *sympathetic lead model*) or change in RSA predicted change in PEP (i.e., *parasympathetic lead model*). Finally, a *full coupling model* jointly estimated PEP and RSA to evaluate whether PEP and RSA each predicted change in the other autonomic branch.

Chi-square difference tests evaluated comparative fit across each pair of nested models (Satorra & Bentler, 2001). However, given that the likelihood ratio test is influenced by sample size (Browne & Cudeck, 1992), additional practical fit indices were examined, including the Tucker Lewis Index (TLI; Tucker & Lewis, 1973), Comparative Fit Index (CFI; Bentler, 1990), and Root Mean Square Error of Approximation (RMSEA; MacCallum, Browne, & Sugawara, 1996). Good model fit was indicated by TLI and CFI values  $> .95$ , and RMSEA  $< .08$  (Hu & Bentler, 1999). In addition, the Akaike Information Criterion (AIC; Shibata, 1976) and the Bayesian

Information Criterion (BIC; Schwarz, 1978) were used to assess fit across non-nested models, with lower values indicating better fit (Grimm et al., 2006).

### 3 | RESULTS

Means and standard deviations for the eight 30-s epochs of PEP and RSA across the four-minute challenge task, as well as bivariate correlations are presented in Table 1. PEP and RSA evidenced strong within-system correlations, and generally moderate and positive cross-system correlations across the challenge task. Within-system correlations were significant for both PEP and RSA between the resting and challenge episodes, with similarly positive, but moderate, cross-system correlations.

#### 3.1 | Univariate models

Competing models were fit separately for PEP and RSA to assess single-system growth trajectories across the challenge task. Model fit was evaluated using multiple indices given suggestions that assessing agreement across practical fit indices may yield a more balanced evaluation of model fit than any singular criterion (Chen, Curran, Bollen, Kirby, & Paxton, 2008; Lai & Green, 2016).

Fit statistics for univariate PEP models are presented in Table 2. The practical fit indices indicated that the constant change model of PEP fit the data better than the no change and proportional change models, such that change across the task was better described with linear rather than proportional change terms. A subsequent comparison of nested models revealed that the univariate dual change model of PEP fit significantly better than both the constant change model, which removed the proportional change component from the dual change model,  $\Delta\chi^2(1) = 9.698$ ,  $p < .001$ , and the proportional change model, which removed the constant change component from the dual change model,  $\Delta\chi^2(3) = 39.394$ ,  $p < .001$ . Together, these analyses converged to support dual change as the best univariate model for PEP, as both constant change and proportional change were required to model PEP change across the challenge task appropriately.

Parameter estimates from the univariate dual change model of PEP are presented in Figure 1. The average initial PEP score during the first epoch was significantly different from zero ( $M_{PEP} = 99.830$ ,  $p < .001$ ), and there was significant variation in initial mean values indicating individual differences in starting values for PEP. There was significant and negative linear growth in PEP ( $G_{PEP} = -2.947$ ,  $p = .018$ ) across the challenge task, but there was no significant between-person variation in growth across the task ( $\sigma_{PEP} = 1.689$ ,  $p = .216$ ). In other words, children evidenced

a progressive attenuation of PEP across the task (i.e., sympathetic activation) in similar ways. The proportional change component was significant and negative ( $\beta_{PEP} = -0.032$ ,  $p = .003$ ), indicating a slowing of PEP activation across the challenge.

Fit statistics for univariate RSA models are presented in Table 3. The practical fit indices indicated that the constant change model of RSA fit the data better than the no change and the proportional change models, such that change across the task was better described with linear rather than proportional change terms. A subsequent comparison of nested models revealed that the univariate dual change model of RSA fit significantly better than both the constant change model, which removed the proportional change component from the dual change model,  $\Delta\chi^2(1) = 22.831$ ,  $p < .001$ , and the proportional change model of RSA, which removed the constant change component from the dual change model,  $\Delta\chi^2(2) = 18.053$ ,  $p < .001$ . Mirroring the PEP univariate findings, these analyses converged to support dual change as the best univariate model for RSA, as both constant change and proportional change were required to model RSA change across the challenge task appropriately.

Parameter estimates from the univariate dual change score model of RSA are presented in Figure 2. The average initial RSA score during the first epoch was significantly different from zero ( $M_{RSA} = 6.696$ ,  $p < .001$ ), and there was significant variation in initial mean values indicating individual differences in starting values of RSA. There was significant and negative linear growth in RSA ( $G_{RSA} = -0.219$ ,  $p < .001$ ) across the challenge task, as well as significant variation in patterns of growth across the task ( $\sigma_{RSA} = 0.003$ ,  $p = .005$ ). In other words, on average, children exhibited a pattern of declining RSA (i.e., parasympathetic withdrawal) across the task, and there were significant individual differences in these patterns. The proportional change component was significant and negative ( $\beta_{RSA} = -0.036$ ,  $p < .001$ ), indicating a slowing of RSA withdrawal across the challenge.

#### 3.2 | Bivariate models

Competing models of bivariate interactions between PEP and RSA were fit to explore the dynamics of autonomic coordination by modeling both indicators simultaneously. These models included coupling parameters to evaluate the extent to which activation in one autonomic branch predicted subsequent changes in the other branch. Covariances were also estimated between PEP and RSA slopes and intercepts. Bivariate model fit comparisons are presented in Table 4. Difference tests revealed a significant increase in fit from the uncoupled to the unidirectional coupled PEP model,  $\Delta\chi^2(2) = 10.171$ ,  $p = .006$ . However, comparison of the uncoupled model to the unidirectional coupled RSA model



**TABLE 1** Descriptive statistics and bivariate correlations among study variables

	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17
1. RSA <sub>Rest</sub>	–																
2. RSA <sub>1</sub>	.79***	–															
3. RSA <sub>2</sub>	.79***	.78***	–														
4. RSA <sub>3</sub>	.76***	.74***	.81***	–													
5. RSA <sub>4</sub>	.78***	.72***	.73***	.77**	–												
6. RSA <sub>5</sub>	.77***	.73***	.73***	.72**	.76***	–											
7. RSA <sub>6</sub>	.73***	.67***	.71***	.68**	.71***	.73***	–										
8. RSA <sub>7</sub>	.75***	.65***	.69***	.63**	.65***	.70***	.66***	–									
9. RSA <sub>8</sub>	.72***	.64***	.69***	.62**	.61***	.63***	.58***	.71***	–								
10. PEP <sub>Rest</sub>	.21**	.18**	.15*	.22**	.16*	.06	.08	.10	.10	–							
11. PEP <sub>1</sub>	.19**	.16*	.13	.18*	.14	.05	.04	.09	.16*	.74***	–						
12. PEP <sub>2</sub>	.16	.13	.09	.18*	.15*	.04	.03	.01	.09	.77***	.64***	–					
13. PEP <sub>3</sub>	.19*	.18*	.14	.21**	.21**	.08	.07	.08	.11	.74***	.80***	.71***	–				
14. PEP <sub>4</sub>	.16*	.13	.09	.18*	.17*	.06	.02	.07	.11	.82***	.69***	.75***	.76***	–			
15. PEP <sub>5</sub>	.20*	.13	.12	.23**	.17*	.07	.04	.06	.18*	.74***	.66***	.73***	.70***	.78***	–		
16. PEP <sub>6</sub>	.15*	.11	.05	.16*	.17*	.04	.04	.03	.13	.73***	.65***	.69***	.76***	.75***	.71***	–	
17. PEP <sub>7</sub>	.11	.13	.06	.15*	.14	.03	.02	–.03	.07	.75***	.64***	.66***	.68***	.72***	.65***	.76**	–
18. PEP <sub>8</sub>	.16*	.16*	.09	.18*	.18*	.10	.07	.04	.05	.72***	.53**	.62***	.57***	.64***	.54**	.64**	.69***

\**p* < .05; \*\**p* < .01; \*\*\**p* < .001.

TABLE 2 Univariate PEP model fit comparisons

	$\chi^2$	df	RMSEA	CFI	TLI	AIC	BIC
1. No change	152.049	41	<0.001	0.913	0.940	9,074.667	9,084.440
2. Constant change	100.005	38	0.001	0.951	0.964	9,028.623	9,048.168
3. Proportional change	129.701	40	<0.001	0.929	0.951	9,054.319	9,067.349
4. Dual change	90.307	37	0.005	0.958	0.968	9,020.925	9,043.728
<b>Nested comparisons</b>		$\Delta\chi^2$		$\Delta df$		<i>p</i>	
Constant change to dual change		9.698		1		<.001	
Proportional change to dual change		39.394		3		<.001	

Abbreviations: AIC, Akaike information criterion; BIC, Bayesian information criterion; CFI, comparative fit index; RMSEA, root mean square error of approximation, TLI, Tucker Lewis index.

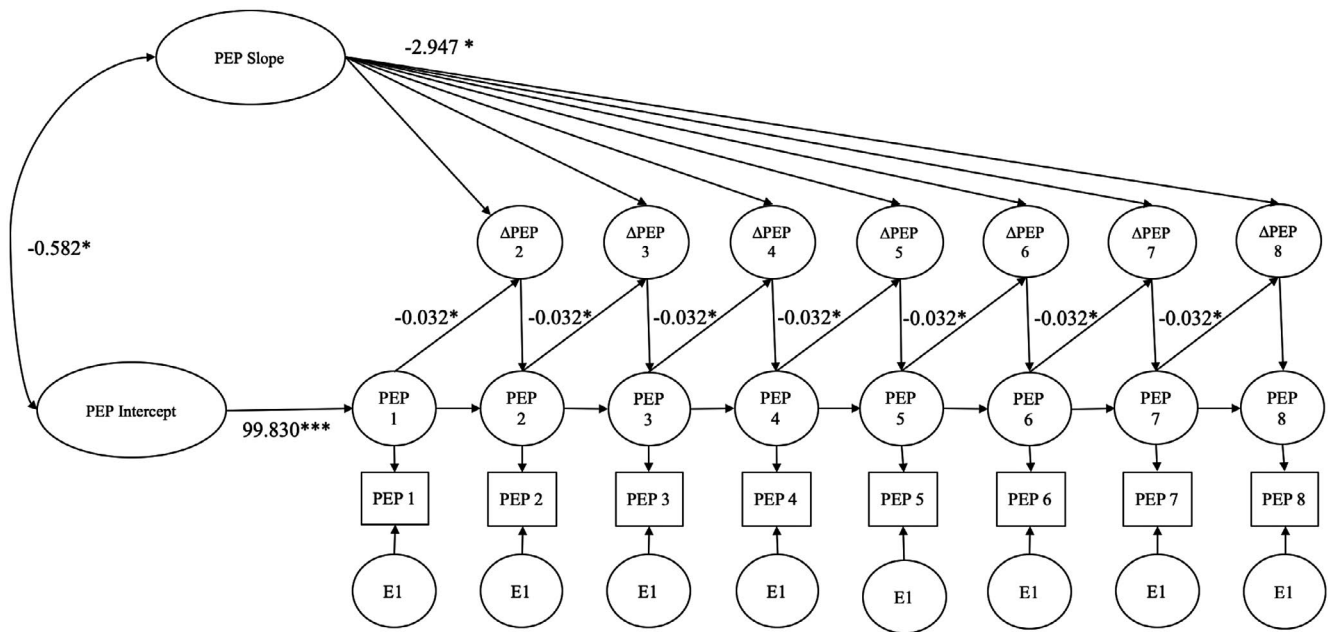


FIGURE 1 Univariate PEP dual change model. Dual change score model for PEP. Diagram with path coefficients for the dual change score model of PEP. Paths with no coefficient are fixed to 1. \**p* < .05; \*\**p* < .01; \*\*\**p* < .001

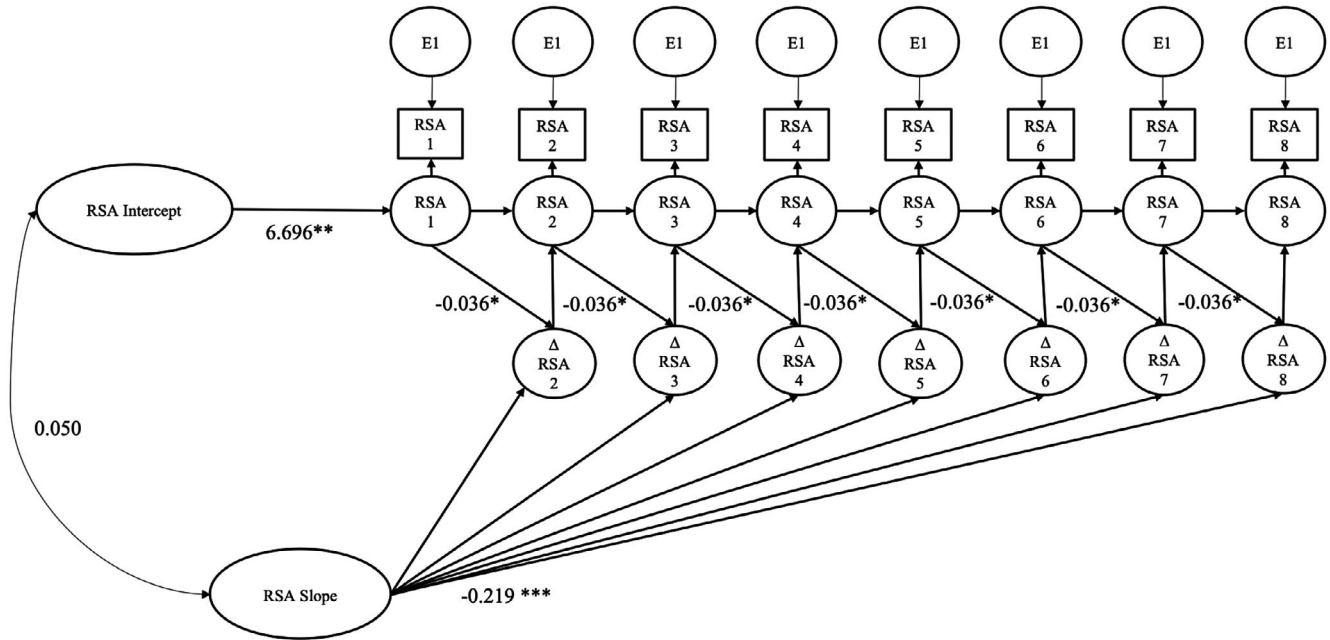
TABLE 3 Univariate RSA model fit comparisons

	$\chi^2$	df	RMSEA	CFI	TLI	AIC	BIC
1. No change	144.844	41	<0.001	0.922	0.946	3,639.911	3,649.745
2. Constant change	121.555	38	<0.001	0.937	0.954	3,623.785	3,643.453
3. Proportional change	140.249	40	<0.001	0.924	0.947	3,638.504	3,651.616
4. Dual change	100.553	37	<0.001	0.952	0.964	3,604.778	3,627.725
<b>Nested comparisons</b>		$\Delta\chi^2$		$\Delta df$		<i>p</i>	
Constant change to dual change		22.831		1		<.001	
Proportional change to dual change		18.053		2		<.001	

Abbreviations: AIC, Akaike information criterion; BIC, Bayesian information criterion; CFI, comparative fit index; RMSEA, root mean square error of approximation, TLI, Tucker Lewis index.

did not reveal a significant increase in fit,  $\Delta\chi^2(1) = 0.393$ , *p* = .530. Moreover, a comparison of the fit indices across the two non-nested unidirectional coupling models indicated that the unidirectional coupled PEP model evidenced better

fit than the unidirectional coupled RSA model. Finally, a nested comparison of a fully coupled bidirectional model and the unidirectional coupled PEP model did not demonstrate a significant increase in fit,  $\Delta\chi^2(1) = 1.008$ , *p* = .315. Thus,



**FIGURE 2** Univariate RSA dual change model. Dual change score model for RSA. Diagram with path coefficients for the dual change score model of RSA. Paths with no coefficient are fixed to 1. \* $p < .05$ ; \*\* $p < .01$ ; \*\*\* $p < .001$

**TABLE 4** Bivariate model fit comparisons

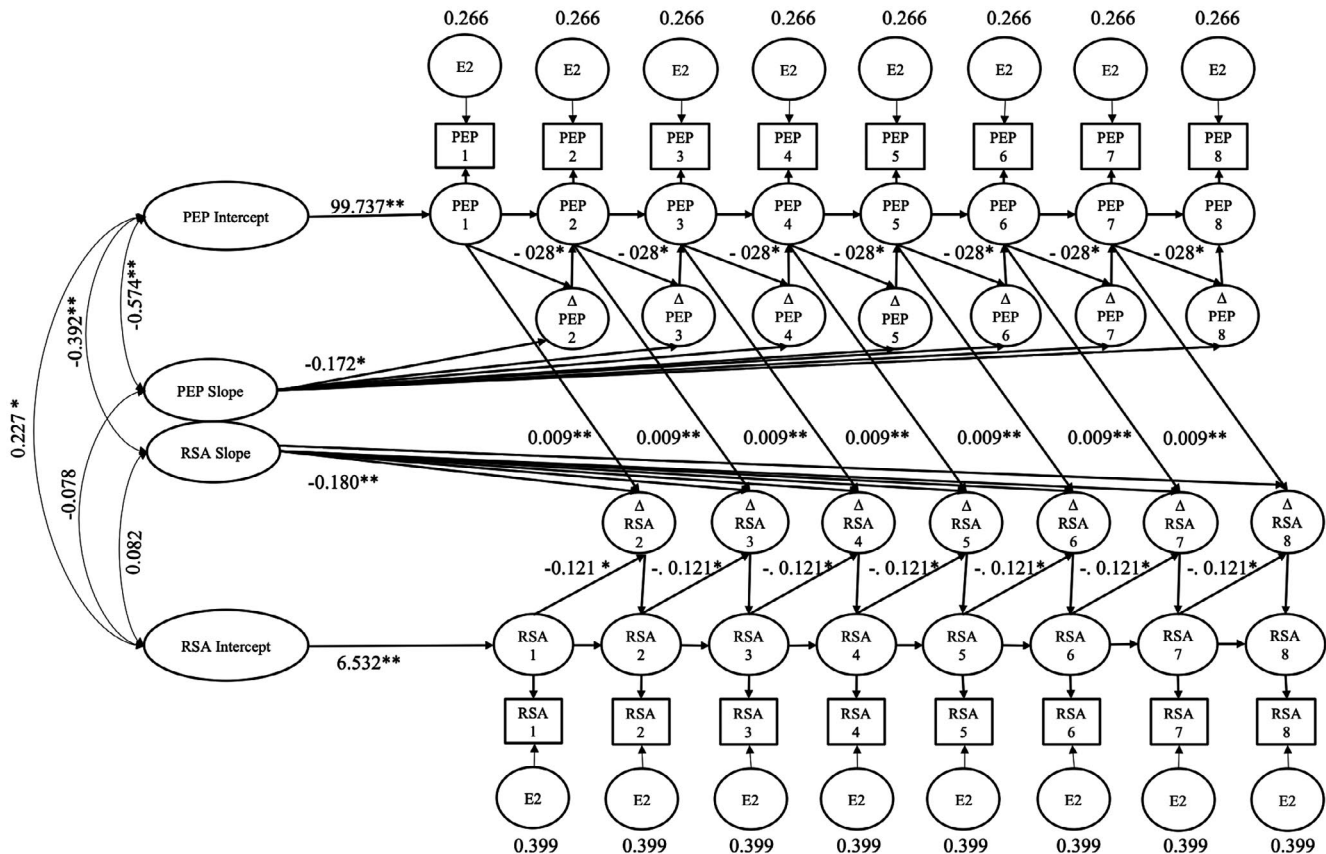
	$\chi^2$	<i>df</i>	RMSEA	CFI	TLI	AIC	BIC
1. Uncoupled	281.646	134	0.001	0.934	0.949	12,660.014	12,719.112
2. Unidirectional PEP influence	271.475	132	0.001	0.946	0.951	12,653.842	12,719.507
3. Unidirectional RSA influence	281.253	133	0.005	0.943	0.948	12,656.816	12,719.197
4. Bidirectional coupling	270.467	131	0.001	0.946	0.951	12,654.835	12,723.783
<b>Nested comparisons</b>		$\Delta\chi^2$		$\Delta df$		<i>p</i>	
Uncoupled to unidirectional PEP		10.171		2		.006	
Uncoupled to unidirectional RSA		0.393		1		.530	
Unidirectional PEP to bidirectional		1.008		1		.315	
Unidirectional RSA to bidirectional		10.786		2		.006	

Abbreviations: AIC, Akaike information criterion; BIC, Bayesian information criterion; CFI, comparative fit index; RMSEA, root mean square error of approximation, TLI, Tucker Lewis index.

the more parsimonious unidirectional coupled PEP model wherein changes in PEP temporally lead subsequent lagging changes in RSA emerged as the final best-fitting model.

Parameter estimates for the unidirectional coupling model of PEP to RSA are displayed in Figure 3. The moderate negative correlation between the slope and intercept of PEP ( $r = -.574$ ,  $p = .003$ ), suggests that higher levels of initial PEP were associated with greater decreases in PEP (i.e., increased sympathetic activation) across the challenge. However, the correlation between the slope and intercept of RSA was not significant ( $r = .082$ ,  $p = .230$ ). In addition, a moderate positive correlation between the slopes of PEP and RSA ( $r = .392$ ,  $p = .004$ ) was consistent with reciprocal activation patterns (e.g., PEP

shortening and RSA withdrawal or PEP lengthening and RSA augmentation). A positive correlation between the intercept of PEP and the intercept of RSA ( $r = .227$ ,  $p = .006$ ) indicated that higher initial PEP values (i.e., lower sympathetic activation) were associated with higher initial RSA values (i.e., higher parasympathetic activation). The negative correlation between the intercept of PEP and the slope of RSA ( $r = -.468$ ,  $p < .001$ ) indicated that a higher initial value in PEP, which connotes a longer PEP interval and lower sympathetic activation, was associated with decreases in RSA (i.e., parasympathetic withdrawal) across the task. The correlation between initial RSA values and PEP slope was not significant. The significant and positive coupling parameter from PEP to RSA of .009



**FIGURE 3** Bivariate dual change model. Linear change coefficients, variances, and covariances are not presented for clarity. \* $p < .05$ ; \*\* $p < .01$ ; \*\*\* $p < .001$

standardized units indicated that PEP levels predicted subsequent negative growth in RSA. Specifically, a child whose PEP interval was one standard deviation higher than the group mean would evidence declines in RSA that were .009 standard deviations faster from one epoch to the next epoch across the challenging task.

## 4 | DISCUSSION

This study examined the autonomic coordination of PEP and RSA regulation using BLCS models to evaluate the temporal patterning of sympathetic and parasympathetic activity across a challenging puzzle task. The results of univariate models examining separate, within-system regulation demonstrated that both PEP and RSA were best-described by dual-change models, such that a combination of linear growth and proportional changes best characterized responses across the challenge task. Dynamic assessments of PEP and RSA coordination supported a reactivity pattern of sympathetic activation and parasympathetic withdrawal (i.e., reciprocal sympathetic activation), as well as a unidirectional coupling model wherein changes in PEP antedated subsequent changes in RSA across eight 30-s epochs during the four-minute challenge. These results suggest that, at least at the level of

30-s epochs, sympathetic activity can take temporal precedence in patterns of ANS regulation (Berntson et al., 2007; Obrist, 2012), with RSA (and attendant parasympathetic responses) following to accommodate sympathetic activation in some contexts. Consistent with patterns of sympathetic activation leading parasympathetic withdrawal across the task, the intercept of PEP was associated with negative linear trends in RSA across the challenge, but the reverse was not true. Although further replication is needed to generalize beyond the directional coupling effects observed here, this investigation illustrates how BLCS modeling can be used to test theories about the coordinated regulation of sympathetic and parasympathetic systems, as well as varying degrees of reciprocal and coupled actions (Berntson et al., 2007, 1994; Obrist, 2012; Porges, 2007).

In this study, 6-year-old children responded to a time-sensitive challenge of completing a difficult puzzle “before the examiner returned” with reciprocal sympathetic activation (i.e., PEP attenuation and RSA withdrawal). The difficulty of the task in conjunction with the time limit and its placement as the first task in this ANS protocol likely increased the degree and salience of children's arousal and anticipation, which would be mobilized by reciprocal sympathetic activation. The proportional change parameters for both PEP and RSA were negative such that the rate of activation slowed across the

four-minute challenge. Thus, although the task presented a sufficient challenge to children, children's rate of activation to the stressor did not continue to increase exponentially across the task, but instead lessened as children acclimated to the task at hand. Importantly, both PEP and RSA demonstrated a slowing of change across the task, which points to sustained coordinated action across these systems, even as the level of activation decreased. Further, although the magnitude of the unidirectional coupling effect appeared small by objective standards (Cohen, 1988), the scaling of RSA responses, wherein a full point change would be very drastic, renders an acceleration of .009 standard deviations, accumulating over time, of moderate strength in terms of practical effect size. Moreover, this effect was comparable to those obtained in prior studies (e.g., Obradović & Finch, 2016). Translating these normalized scores back to observed change in RSA for various PEP values is difficult due to important individual differences, however, a child with a relatively high PEP score (e.g., 107.341, which is 1 *SD* above the mean) would be expected to evidence a sizable decrease of .3 in RSA across the challenge task as calculated using the .180 RSA slope of change and the .015 rate of RSA change (i.e., .009 *SD*) across epochs.

Although this study suggests that sympathetic activation took temporal precedence of subsequent changes in parasympathetic regulation during this challenging task, ANS regulation and autonomic coordination are known to vary as a function of social, cognitive, and emotional task demands (Burt & Obradović, 2013; Gatzke-Kopp et al., 2020; Gatzke-Kopp & Ram, 2018). Given the unique context of the current puzzle challenge as a dyadic, time-limited task, the generalizability of the obtained regulation and coupling patterns awaits further evaluation, especially across varied task demands. For example, a task that requires sympathetic mobilization (e.g., a startle or a timed puzzle task) may elicit a leading pattern from PEP to lagging changes in RSA as higher order systems activate and direct the necessary responses. In contrast, a task that requires parasympathetic activation (e.g., reading a complex passage) may evidence a leading pattern from RSA to lagging changes in PEP. In this view, the activated branch of the ANS may take on the “leading” or primary regulatory role with “lagging” or secondary responses emerging from the inhibited branch of the ANS. Alternately, there may be a third, as yet unknown, variable that drives these temporal relations, and shifts therein, across contexts and time. Clarifying patterns of autonomic coordination within and across task contexts will be necessary to inform meaningful guidelines for efforts to interpret the development and adaptive significance of autonomic coordination patterns.

As noted earlier, sympathetic and parasympathetic response systems transact on far shorter timescales than the 30-s epochs used here. However, our reliance on indirect assessments of ANS regulation via cardiography introduced concerns about the reliability of PEP and RSA estimates using smaller timescales. Indeed, recent studies using shorter (e.g., Cui et al., 2015;

Miller et al., 2013) or variable length (e.g., Kahle et al., 2016) epoch durations still fail to capture the moment-to-moment transactions that typify ANS regulation, and introduce the added risk of unreliable measurement. That said, these methodological limitations do not negate the need to consider the implications of the 30-s epochs used in this investigation. The current findings suggest that, at the epoch level, PEP levels predict subsequent changes in RSA. However, these results must be interpreted on the scale at which they were measured. By averaging across second-by-second autonomic dynamics to produce our 30-s epochs, these analyses may have occluded true patterns of PEP and RSA coordination. For example, the 30-s epoch assessment may favor the appearance of PEP dominance and reflect a relatively slower response time of the sympathetic nervous system to mount and recover from a challenge response, as compared to the parasympathetic system, which may lead these dynamics on finer timescales. Investigations harnessing real-time dynamics may find a leading influence from RSA that could not be detected with the current data design. Further, similar to the association between PEP intercept and the slope of RSA, level of PEP at each epoch may predict RSA trends from epoch to epoch but movement within epoch may be independent.

Despite the need for ongoing research efforts to reliably capture anatomical timescales in the ANS, this study illustrates the utility of BLSC models as a valuable step toward elucidating the dynamics that underlie autonomic coordination processes. Ultimately, these steps will be realized with increasing accuracy as physiological methods of PEP and RSA data extraction advance toward finer resolution timescales. That said, the novelty of the current BLSC analytic approach heightened the need to maximize the validity and reliability of our ANS measures by using standard epoch durations of 30-s. Moreover, because most prior research has employed 30-s epochs (e.g., Alkon, Boyce, Neilands, & Eskenazi, 2017; Fisher et al., 2016; Gatzke-Kopp et al., 2020), this analytic choice also facilitated our capacity to interpret and compare the obtained findings with extant studies. Nevertheless, it is possible that meaningful transactions within the 30-s epochs were aggregated in ways that jeopardized the clarity and validity of the obtained findings. Likewise, beyond the temporal leading pattern of PEP to lagging changes in RSA suggested here, causal mechanisms underlying autonomic coordination remain to be elucidated and likely involve higher order central nervous system afferents to the brain stem nuclei involved in regulating autonomic action.

## 4.1 | Strengths and limitations

Notable strengths of this investigation include the use of a fairly large and diverse sample of children, cardiac measurements of both PEP and RSA, and the implementation of

dynamic statistical methods, namely BLCS models, to investigate temporal patterns of PEP and RSA coordination over time. Despite these strengths, however, a number of limitations should be considered when interpreting the implications of the current findings.

First, we evaluated linear models characterized by exponential changes with either positive or negative variations due to coupling effects. Nonlinear trajectories, such as quadratic effects, are difficult to model with BLCS models because they require many measurement occasions to obtain reliable parameter estimates (Grimm, An, McArdle, Zonderman, & Resnick, 2012). Although most studies support linear patterns of ANS regulation across various challenge tasks and linear change best characterized the current data, a handful of studies suggest that trajectories of PEP and RSA may be best characterized by nonlinear patterns (Kogan et al., 2014; Miller et al., 2013; Miller, Kahle, & Hastings, 2017). Thus, future research should consider nonlinear dynamics, as they may be relevant for understanding patterns of autonomic coordination in some challenge contexts.

Second, the respiratory frequency band used in this study was appropriate for most, but not all, epochs of ANS responses in the current sample. Extracting and cleaning RSA for between subject analyses requires that all cases use the same respiratory frequency range, but a number of factors can cause variation in respiratory frequency, even within children of the same age (Cacioppo, Tassinary, & Berntson, 2007). Although very few (i.e., 1.1%) of the epochs in our sample evidenced respiratory frequencies outside the specified frequency band, to the extent respiratory frequencies were mis-specified, children's true reactivity scores may have been underestimated (Shader et al., 2018). Importantly, post-hoc analyses probing the effect of this mis-specification revealed that all findings replicated in pattern and significance when these mis-specified epochs were removed from analyses.

Third, the BLCS models used in this study represent one of many statistical approaches for modeling dynamic systems. Each available analytic approach features unique strengths and vulnerabilities. For example, BLCS models yield indices of proportional change and coupling, yet, both estimates reflect a combination of within- and between-person effects. Failing to differentiate within- from between-person differences can lead to biased and difficult-to-interpret coefficients, as well as erroneous conclusions about causal patterns (Berry & Willoughby, 2017; Hamaker et al., 2015). Although a central advantage of longitudinal modeling is the ability to disaggregate within- and between-person effects (Curran & Bauer, 2011), the complex nature of the BLCS approach, as well as its implementation within a single challenge task in this study, precluded our ability to separate these effects. Autoregressive latent trajectory modeling with structured residuals (Curran, Howard, Bainter, Lane, & McGinley, 2014)

is an alternate analytic strategy that is well-suited to disaggregate within- and between-person effects. However, the goal of this study was to characterize the complex growth and temporal patterns of coordination across the challenge task, rather than elucidate within- and between-person effects. In fact, recent studies examining the characteristics of autonomic coordination suggest that trait-level factors account for very little variance in the coordination of PEP and RSA (Gatzke-Kopp & Ram, 2018), which further mitigated our concern about these combined effects.

Fourth, although the challenge task yielded sufficient epochs to evaluate a BLCS model, the current design may have limited the generalizability of our findings in a number of ways. For example, the puzzle task was the first challenge introduced to the children following the resting baseline period. As noted earlier, this temporal precedence, as well as the implicit time limit in the task administration, may have contributed to the appearance of reciprocal sympathetic activation in this task. Future work will need to examine ANS regulation patterns during similar tasks as administered at different points in an ANS protocol and in varied samples to ascertain whether or not there is a uniform activation of sympathetic responses across challenging puzzle tasks. Likewise, research using different kinds of challenge tasks is needed to determine whether a sympathetic lead model characterizes autonomic coordination dynamics generally, or only in response to specific kinds of challenge. Another unique feature of the current task was the presence of the caregiver during the ANS protocol. Recent evidence suggests that the presence of others may influence patterns of physiological regulation, as well as their adaptive implications (Skowron et al., 2014). Thus, the generalizability of the observed findings may be limited to dyadic contexts, and the quality of the parent-child relationship may have influenced the obtained regulation and coupling patterns. In future research, it will be important to differentiate social and cognitive task demands (e.g., a counterbalanced administration of the same task with and without a caregiver present) in ways that were not possible here.

Finally, the current design did not support the evaluation of autonomic coordination across a recovery episode. Likewise, our baseline resting task was too short in duration to support convergence of a BLCS model. Although rarely examined in the extant literature, recent findings suggest that the capacity to restore homeostasis, or recover from challenge, is an equally and uniquely informative dimension of self-regulation (Beckmann & Kellmann, 2004), particularly with regard to the ANS (Kahle et al., 2016; Obradović & Finch, 2016; Rudd, Alkon, & Yates, 2017; Rudd & Yates, 2018). Moreover, several studies point to the relevance of baseline regulation as an indicator of children's capacity to respond to challenge (Beauchaine et al., 2013; Miller et al., 2017). In future research, it will be important to ascertain whether autonomic coordination during rest, reactivity and recovery episodes

evidence a similar pattern to the ANS regulation findings obtained in this study.

## 4.2 | Implications and future directions

As one of the first studies to apply BLCS models to physiological data, these findings illuminate new directions for future research. Current efforts to understand ANS regulation have favored studies of RSA, likely due to its relative ease of collection and interpretation as compared with PEP. However, this investigation demonstrates the importance of examining sympathetic ANS regulatory processes as well. Moreover, the current analytic paradigm illustrates the need for ongoing efforts to elucidate the development and adaptive significance of ANS regulation using both single- and multi-system lenses of analysis.

Importantly, the exploratory nature of this study not only warrants caution when interpreting the current findings, but also introduces exciting opportunities for future research. Further studies examining similar and varied challenge paradigms (particularly ones that may elicit reciprocal parasympathetic responses) are needed to elucidate the exact nature of task influences on autonomic coordination, and to replicate the identified unidirectional coupling between sympathetic leading PEP activity and parasympathetic lagging RSA activity. Through ongoing research, we will be able to understand if and how autonomic leading and lagging influences may shift over individual tasks, samples, and/or developmental time.

Following further clarification of the nature of ANS regulatory coupling influences, researchers should work to identify factors that contribute to individual differences in the dynamic coordination of PEP and RSA, as well as to the adaptive implications of such differences for children's multi-domain adaptation. Single-system studies of physiological regulation have identified early adversity exposure as an important factor in the development and regulation of sympathetic and parasympathetic systems (McLaughlin, Alves, & Sheridan, 2014; Obradović, 2012). Expanding this knowledge to evaluate how early (and chronic) adversity exposure may influence ANS regulatory dynamics constitutes an important step toward understanding the meaning and implications of autonomic coordination. Similarly, prior research has documented the importance of single-system measures of ANS regulation (e.g., Gatzke-Kopp & Ram, 2018), and, to a lesser degree, of aggregated (e.g., Alkon et al., 2017) and interactive (e.g., Quas et al., 2014; Rudd & Yates, 2018) assessments of coordination for children's adaptation in both psychosocial and physical health domains. However, recent studies using dynamic modeling approaches demonstrate that, though broad patterns of association between ANS regulation and adaptation can be seen in mean-based studies,

dynamic modeling procedures provide more detailed information with which to evaluate these hypothesized relations (Blair, Raver, & Berry, 2014; Brooker & Buss, 2010).

This examination illustrates the application of BLCS models to support much needed dual and dynamic evaluations of autonomic coordination. Using the procedures described herein, researchers can begin to investigate the unique development and adaptive contributions of autonomic coordination patterns to child development. Further, as precision increases our ability to measure the responsiveness of the ANS on finer, more anatomically accurate, timescales, future research will be better-able to evaluate the moment-to-moment temporal dynamics of autonomic coordination with greater accuracy and reliability. In turn, these studies can evaluate central tenets of dynamic systems theory focused on whether the relation between systems (i.e., autonomic coordination) is more informative and influential in determining the adaptive implications of ANS regulation than more straightforward aggregated measures within or between sympathetic and parasympathetic branches of the ANS. Together, ongoing efforts to understand the process of autonomic coordination will highlight meaningful pathways to positive child adjustment via physiological self-regulation.

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### REFERENCES

- Alkon, A., Boyce, W. T., Davis, N. V., & Eskenazi, B. (2011). Developmental changes in autonomic nervous system resting and reactivity measures in latino children from 6 to 60 months of age. *Journal of Developmental & Behavioral Pediatrics, 32*(9), 668–677. <https://doi.org/10.1097/DBP.0b013e3182331fa6>
- Alkon, A., Boyce, W. T., Neilands, T. B., & Eskenazi, B. (2017). children's autonomic nervous system reactivity moderates the relations between family adversity and sleep problems in latino 5-year olds in the chaMacOs study. *Frontiers in Public Health, 5*, 155. <https://doi.org/10.3389/fpubh.2017.00155>
- Alkon, A., Boyce, W. T., Tran, L., Harley, K. G., Neuhaus, J., & Eskenazi, B. (2014). Prenatal adversities and latino children's autonomic nervous system reactivity trajectories from 6 months to 5 years of age. *PLoS One, 9*(1), e86283. <https://doi.org/10.1371/journal.pone.0086283>
- Bar-Haim, Y., Marshall, P. J., & Fox, N. A. (2000). Developmental changes in heart period and high-frequency heart period variability from 4 months to 4 years of age. *Developmental Psychobiology, 37*(1), 44–56. [https://doi.org/10.1002/1098-2302\(200007\)37:1<44::AID-DEV6>3.0.CO;2-7](https://doi.org/10.1002/1098-2302(200007)37:1<44::AID-DEV6>3.0.CO;2-7)
- Beauchaine, T. P., Gatzke-Kopp, L., Neuhaus, E., Chipman, J., Reid, M. J., & Webster-Stratton, C. (2013). Sympathetic- and parasympathetic-linked cardiac function and prediction of externalizing behavior, emotion regulation, and prosocial behavior among preschoolers treated for ADHD. *Journal of Consulting and Clinical Psychology, 81*(3), 481–493. <https://doi.org/10.1037/a0032302>



- Beckmann, J., & Kellmann, M. (2004). Self-regulation and recovery: Approaching an understanding of the process of recovery from stress. *Psychological Reports*, *95*(3\_suppl), 1135–1153. <https://doi.org/10.2466/pr0.95.3f.1135-1153>
- Bentler, P. M. (1990). Comparative fit indexes in structural models. *Psychological Bulletin*, *107*(2), 238–246. <http://doi.org/10.1037/0033-2909.107.2.238>
- Berntson, G. G., & Cacioppo, J. T. (2004). Heart rate variability: Stress and psychiatric conditions. *Dynamic Electrocardiography*, *41*(2), 57–64. <https://doi.org/10.1111/j.1469-8986.2004.00156.x>
- Berntson, G. G., Cacioppo, J. T., & Grossman, P. (2007). Whither vagal tone. *Biological Psychology*, *74*(2), 295–300. <https://doi.org/10.1016/j.biopsycho.2006.08.006>
- Berntson, G. G., Cacioppo, J. T., & Quigley, K. S. (1991). Autonomic determinism: The modes of autonomic control, the doctrine of autonomic space, and the laws of autonomic constraint. *Psychological Review*, *98*(4), 459–487. <https://doi.org/10.1037/0033-295X.98.4.459>
- Berntson, G. G., Cacioppo, J. T., Quigley, K. S., & Fabro, V. T. (1994). Autonomic space and psychophysiological response. *Psychophysiology*, *31*(1), 44–61. <https://doi.org/10.1111/j.1469-8986.1994.tb01024.x>
- Berntson, G. G., Lozano, D. L., Chen, Y. J., & Cacioppo, J. T. (2004). Where to Q in PEP. *Psychophysiology*, *41*(2), 333–337. <https://doi.org/10.1111/j.1469-8986.2004.00156.x>
- Berry, D., Blair, C., Ursache, A., Willoughby, M. T., & Granger, D. A. (2014). Early childcare, executive functioning, and the moderating role of early stress physiology. *Developmental Psychology*, *50*(4), 1250–1261. <https://doi.org/10.1037/a0034700>
- Berry, D., & Willoughby, M. T. (2017). On the practical interpretability of cross-lagged panel models: Rethinking a developmental workhorse. *Child Development*, *88*(4), 1186–1206. <https://doi.org/10.1111/cdev.12660>
- Blair, C. (2010). Stress and the development of self-regulation in context. *Child Development Perspectives*, *4*(3), 181–188. <https://doi.org/10.1111/j.1750-8606.2010.00145.x>
- Blair, C., Raver, C. C., & Berry, D. J. (2014). Two approaches to estimating the effect of parenting on the development of executive function in early childhood. *Developmental Psychology*, *50*(2), 554–565. <https://doi.org/10.1037/a0033647>
- Boyce, T. W., Quas, J., Alkon, A., Smider, N. A., Essex, M. J., & Kupfer, D. J. (2001). Autonomic reactivity and psychopathology in middle childhood. *The British Journal of Psychiatry*, *179*(2), 144–150. <https://doi.org/10.1192/bjp.179.2.144>
- Brooker, R. J., & Buss, K. A. (2010). Dynamic measures of RSA predict distress and regulation in toddlers. *Developmental Psychobiology*, *52*(4), 372–382. <https://doi.org/10.1002/dev.20432>
- Browne, M. W., & Cudeck, R. (1992). Alternative ways of assessing model fit. *Sociological Methods & Research*, *21*(2), 230–258. <http://doi.org/10.1177/0049124192021002005>
- Bureau, U. S. C. (2011). *State and county quickfacts*. Retrieved from <http://quickfacts.census.gov/qfd/states/06/06065.html>
- Burt, K. B., & Obradović, J. (2013). The construct of psychophysiological reactivity: Statistical and psychometric issues. *Developmental Review*, *33*(1), 29–57. <https://doi.org/10.1016/j.dr.2012.10.002>
- Cacioppo, J. T., Gardner, W. L., & Berntson, G. G. (1997). Beyond bipolar conceptualizations and measures: The case of attitudes and evaluative space. *Personality and Social Psychology Review*, *1*(1), 3–25. [https://doi.org/10.1207/s15327957pspr0101\\_2](https://doi.org/10.1207/s15327957pspr0101_2)
- Cacioppo, J. T., Tassinary, L. G., & Berntson, G. (2007). *Handbook of psychophysiology*. New York, NY: Cambridge University Press.
- Chen, F., Curran, P. J., Bollen, K. A., Kirby, J., & Paxton, P. (2008). An empirical evaluation of the use of fixed cutoff points in RMSEA test statistic in structural equation models. *Sociological Methods & Research*, *36*(4), 462–494. <https://doi.org/10.1177/0049124108314720>
- Clark, C. A., Skowron, E. A., Giuliano, R. J., & Fisher, P. A. (2016). Intersections between cardiac physiology, emotion regulation and interpersonal warmth in preschoolers: Implications for drug abuse prevention from translational neuroscience. *Drug and Alcohol Dependence*, *163*, S60–S69. <https://doi.org/10.1016/j.druga.2016.01.033>
- Cohen, J. (1988). *Statistical power: Analysis for the behavioural sciences*. New York, NY: Routledge.
- Cui, L., Morris, A. S., Harrist, A. W., Larzelere, R. E., & Criss, M. M. (2015). Dynamic changes in parent affect and adolescent cardiac vagal regulation: A real-time analysis. *Journal of Family Psychology*, *29*(2), 180–190. <https://doi.org/10.1037/fam0000067>
- Curran, P. J., & Bauer, D. J. (2011). The disaggregation of within-person and between-person effects in longitudinal models of change. *Annual Review of Psychology*, *62*, 583–619. <https://doi.org/10.1146/annurev.psych.093008.100356>
- Curran, P. J., Howard, A. L., Bainter, S. A., Lane, S. T., & McGinley, J. S. (2014). The separation of between-person and within-person components of individual change over time: A latent curve model with structured residuals. *Journal of Consulting and Clinical Psychology*, *82*(5), 879–894. <http://doi.org/10.1037/a0035297>
- Davis, E. L., Brooker, R. J., & Kahle, S. (2020). Considering context in the developmental psychobiology of self-regulation. *Developmental Psychobiology*, *62*, 423–435. <https://doi.org/10.1002/dev.21945>
- Davis, E. L., Quiñones-Camacho, L. E., & Buss, K. A. (2016). The effects of distraction and reappraisal on children's parasympathetic regulation of sadness and fear. *Journal of Experimental Child Psychology*, *142*, 344–358. <https://doi.org/10.1016/j.jecp.2015.09.020>
- El-Sheikh, M., Keiley, M., & Hinnant, J. B. (2010). Developmental trajectories of skin conductance level in middle childhood: Sex, race, and externalizing behavior problems as predictors of growth. *Biological Psychology*, *83*(2), 116–124. <https://doi.org/10.1016/j.biopsycho.2009.11.009>
- El-Sheikh, M., Kouros, C. D., Erath, S., Cummings, E. M., Keller, P., & Staton, L. (2009). Marital conflict and children's externalizing behavior: Pathways involving interactions between parasympathetic and sympathetic nervous system activity. *Monographs of the Society for Research in Child Development*, *74*(1), vii–79. <https://doi.org/10.1111/j.1540-5834.2009.00501.x>
- Erath, S., & El-Sheikh, M. (2015). Linking bioregulatory systems: Reciprocal autonomic activation predicts sleep over 1 year in middle childhood. *Developmental Psychobiology*, *57*(1), 17–24. <https://doi.org/10.1002/dev.21246>
- Esler, M., & Kaye, D. (2000). Sympathetic nervous system activation in essential hypertension, cardiac failure and psychosomatic heart disease. *Journal of Cardiovascular Pharmacology*, *35*, S1–S7. <https://doi.org/10.1097/00005344-200000004-00001>
- Ferrer, E., & McArdle, J. J. (2010). Longitudinal modeling of developmental changes in psychological research. *Current Directions in Psychological Science*, *19*(3), 149–154. <https://doi.org/10.1177/0963721410370300>
- Fisher, A. J., Reeves, J. W., & Chi, C. (2016). Dynamic RSA: Examining parasympathetic regulatory dynamics via vector-autoregressive modeling of time-varying RSA and heart period. *Psychophysiology*, *53*(7), 1093–1099. <https://doi.org/10.1111/psyp.12644>



- Flam, D., & Powell, W. (2009). Dynamic systems theory. In C. Bryant & D. Peck (Eds.), *The handbook of 21st century sociology* (pp. 569–582). Thousand Oaks, CA: Sage Publications.
- Gates, K. M., Gatzke-Kopp, L. M., Sandsten, M., & Blandon, A. Y. (2015). Estimating time-varying RSA to examine psychophysiological linkage of marital dyads. *Psychophysiology*, *52*(8), 1059–1065. <https://doi.org/10.1111/psyp.12428>
- Gatzke-Kopp, L. M., Benson, L., Ryan, P. J., & Ram, N. (2020). Cortical and affective regulation of autonomic coordination. *Psychophysiology*, *57*, e13544. <https://doi.org/10.1111/psyp.13544>
- Gatzke-Kopp, L., & Ram, N. (2018). Developmental dynamics of autonomic function in childhood. *Psychophysiology*, *55*(11), e13218. <https://doi.org/10.1111/psyp.13218>
- Gordis, E. B., Feres, N., Oleszki, C. L., Rabkin, A. N., & Trickett, P. K. (2010). Skin conductance reactivity and respiratory sinus arrhythmia among maltreated and comparison youth: Relations with aggressive behavior. *Journal of Pediatric Psychology*, *35*(5), 547–558. <https://doi.org/10.1093/jpepsy/jsp113>
- Gottlieb, G., & Halpern, C. T. (2002). A relational view of causality in normal and abnormal development. *Development and Psychopathology*, *14*(3), 421–435. <https://doi.org/10.1017/s0954579402003024>
- Griffiths, K. R., Quintana, D. S., Hermens, D. F., Spooner, C., Tsang, T. W., Clarke, S., & Kohn, M. R. (2017). Sustained attention and heart rate variability in children and adolescents with ADHD. *Biological Psychology*, *124*, 11–20. <https://doi.org/10.1016/j.biopsycho.2017.01.004>
- Grimm, K. J., An, Y., McArdle, J. J., Zonderman, A. B., & Resnick, S. M. (2012). Recent changes leading to subsequent changes: Extensions of multivariate latent difference score models. *Structural Equation Modeling: A Multidisciplinary Journal*, *19*(2), 268–292. <https://doi.org/10.1080/10705511.2012.659627>
- Grimm, K. J., Ram, N., & Estabrook, R. (2006). *Growth modeling: Structural equation and multilevel modeling approaches*. New York, NY: Guilford Publications.
- Grossman, P., & Taylor, E. W. (2007). Toward understanding respiratory sinus arrhythmia: Relations to cardiac vagal tone, evolution and biobehavioral functions. *Biological Psychology*, *74*(2), 263–285. <https://doi.org/10.1016/j.biopsycho.2005.11.014>
- Hagan, M. J., Roubinov, D. S., Adler, N. E., Boyce, W. T., & Bush, N. R. (2016). Socioeconomic adversity, negativity in the parent child-relationship, and physiological reactivity: An examination of pathways and interactive processes affecting young children's physical health. *Psychosomatic Medicine*, *78*(9), 998–1007. <https://doi.org/10.1097/PSY.0000000000000379>
- Hamaker, E. L., Kuiper, R. M., & Grasman, R. P. (2015). A critique of the cross-lagged panel model. *Psychological Methods*, *20*(1), 102–116. <https://doi.org/10.1037/a0038889>
- Hastings, P. D., Nuselovici, J. N., Utendale, W. T., Coutya, J., McShane, K. E., & Sullivan, C. (2008). Applying the polyvagal theory to children's emotion regulation: Social context, socialization, and adjustment. *Biological Psychology*, *79*(3), 299–306. <https://doi.org/10.1016/j.biopsycho.2008.07.005>
- Helm, J. L., Sbarra, D. A., & Ferrer, E. (2014). Coregulation of respiratory sinus arrhythmia in adult romantic partners. *Emotion*, *14*(3), 522–531. <https://doi.org/10.1037/a0035960>
- Hollingshead, A. B. (1975). Four factor index of social status. *Yale Journal of Sociology*, *8*, 21–52.
- Houtveen, J. H., Groot, P. F., & De Geus, E. J. (2005). Effects of variation in posture and respiration on RSA and pre-ejection period. *Psychophysiology*, *42*(6), 713–719. <https://doi.org/10.1111/j.1469-8986.2005.00363.x>
- Hu, L. T., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal*, *6*(1), 1–55. <http://doi.org/10.1080/10705519909540118>
- Jänig, W., & McLachlan, E. M. (1992). Characteristics of function-specific pathways in the sympathetic nervous system. *Trends in Neurosciences*, *15*(12), 475–481. [https://doi.org/10.1016/0166-2236\(92\)90092-M](https://doi.org/10.1016/0166-2236(92)90092-M)
- Kahle, S., Miller, J. G., Lopez, M., & Hastings, P. D. (2016). Sympathetic recovery from anger is associated with emotion regulation. *Journal of Experimental Child Psychology*, *142*, 359–371. <https://doi.org/10.1016/j.jecp.2015.10.004>
- Keller, P. S., & El-Sheikh, M. (2009). Salivary alpha-amylase as a longitudinal predictor of children's externalizing symptoms: Respiratory sinus arrhythmia as a moderator of effects. *Psychoneuroendocrinology*, *34*(5), 633–643. <https://doi.org/10.1016/j.psyneuen.2008.12.016>
- Kogan, A., Oveis, C., Carr, E. W., Gruber, J., Mauss, I. B., Shallcross, A., ... Keltner, D. (2014). Vagal activity is quadratically related to prosocial traits, prosocial emotions, and observer perceptions of prosociality. *Journal of Personality and Social Psychology*, *107*(6), 1051–1063. <https://doi.org/10.1037/a0037509>
- Lai, K., & Green, S. B. (2016). The problem with having two watches: Assessment of fit when RMSEA and CFI disagree. *Multivariate Behavioral Research*, *51*(2–3), 220–239. <https://doi.org/10.1080/00273171.2015.1134306>
- MacCallum, R. C., Browne, M. W., & Sugawara, H. M. (1996). Power analysis and determination of sample size for covariance structure modeling. *Psychological Methods*, *1*(2), 130.
- Malone, P. S., Lansford, J. E., Castellino, D. R., Berlin, L. J., Dodge, K. A., Bates, J. E., & Pettit, G. S. (2004). Divorce and child behavior problems: Applying latent change score models to life event data. *Structural Equation Modeling*, *11*(3), 401–423. [https://doi.org/10.1207/s15328007sem1103\\_6](https://doi.org/10.1207/s15328007sem1103_6)
- McArdle, J. J. (1994). Structural factor analysis experiments with incomplete data. *Multivariate Behavioral Research*, *29*(4), 409–454. [http://doi.org/10.1207/s15327906mbr2904\\_5](http://doi.org/10.1207/s15327906mbr2904_5)
- McArdle, J. J., & Grimm, K. J. (2010). Five steps in latent curve and latent change score modeling with longitudinal data. In K. van Montfort, J. Oud, & A. Satorra (Eds.), *Longitudinal research with latent variables* (pp. 245–273). Berlin, Heidelberg: Springer.
- McEwen, B. S. (2007). Physiology and neurobiology of stress and adaptation: Central role of the brain. *Physiological Reviews*, *87*(3), 873–904. <https://doi.org/10.1152/physrev.00041.2006>
- McLaughlin, K. A., Alves, S., & Sheridan, M. A. (2014). Vagal regulation and internalizing psychopathology among adolescents exposed to childhood adversity. *Developmental Psychobiology*, *56*(5), 1036–1051. <https://doi.org/10.1002/dev.21187>
- Miller, J. G., Choccol, C., Nuselovici, J. N., Utendale, W. T., Simard, M., & Hastings, P. D. (2013). Children's dynamic RSA change during anger and its relations with parenting, temperament, and control of aggression. *Biological Psychology*, *92*(2), 417–425. <https://doi.org/10.1016/j.biopsycho.2012.12.005>
- Miller, J. G., Kahle, S., & Hastings, P. D. (2017). Moderate baseline vagal tone predicts greater prosociality in children. *Developmental Psychology*, *53*(2), 274–289. <https://doi.org/10.1037/dev0000238>



- Muthén, L. K., & Muthén, B. O. (2013). Version 7.1 Mplus language addendum. Retrieved from <https://www.statmodel.com/download/Version7.1xLanguage.pdf>
- Obradović, J. (2012). How can the study of physiological reactivity contribute to our understanding of adversity and resilience processes in development? *Development and Psychopathology*, *24*(2), 371–387. <https://doi.org/10.1017/S0954579412000053>
- Obradović, J., & Finch, J. E. (2016). Linking executive function skills and physiological challenge response: Piecewise growth curve modeling. *Developmental Science*, *20*(3), e12476. <https://doi.org/10.1111/desc.12476>
- Obrist, P. A. (2012). *Cardiovascular psychophysiology: A perspective*. New York, NY: Springer Science & Business Media.
- Overbeek, T. J., van Boxtel, A., & Westerink, J. H. (2014). Respiratory sinus arrhythmia responses to cognitive tasks: Effects of task factors and RSA indices. *Biological Psychology*, *99*, 1–14. <https://doi.org/10.1016/j.biopsycho.2014.02.006>
- Patriquin, M. A., Lorenzi, J., Scarpa, A., & Bell, M. A. (2014). Developmental trajectories of respiratory sinus arrhythmia: Associations with social responsiveness. *Developmental Psychobiology*, *56*(3), 317–326. <https://doi.org/10.1002/dev.21100>
- Philbrook, L. E., Erath, S. A., Hinnant, J. B., & El-Sheikh, M. (2018). Marital conflict and trajectories of adolescent adjustment: The role of autonomic nervous system coordination. *Developmental Psychology*, *54*(9), 1687–1696. <https://doi.org/10.1037/dev0000501>
- Phillips, D. A., & Shonkoff, J. P. (2000). *From neurons to neighborhoods: The science of early childhood development*. Washington, DC: National Academies Press.
- Porges, S. W. (2001). The polyvagal theory: Phylogenetic substrates of a social nervous system. *International Journal of Psychophysiology*, *42*(2), 123–146. [https://doi.org/10.1016/S0167-8760\(01\)00162-3](https://doi.org/10.1016/S0167-8760(01)00162-3)
- Porges, S. W. (2007). The polyvagal perspective. *Biological Psychology*, *74*(2), 116–143. <https://doi.org/10.1016/j.biopsycho.2006.06.009>
- Porges, S. W. (2009). The polyvagal theory: new insights into adaptive reactions of the autonomic nervous system. *Cleveland Clinic Journal of Medicine*, *76*(Suppl. 2), S86–S90. <https://doi.org/10.3949/ccjm.76.s2.17>
- Porges, S. W., Doussard-Roosevelt, J. A., Portales, A. L., & Greenspan, S. I. (1996). Infant regulation of the vagal “brake” predicts child behavior problems: A psychobiological model of social behavior. *Developmental Psychobiology*, *29*(8), 697–712. [https://doi.org/10.1002/\(SICI\)1098-2302\(199612\)29:8<697:AID-DEV5>3.0.CO;2-O](https://doi.org/10.1002/(SICI)1098-2302(199612)29:8<697:AID-DEV5>3.0.CO;2-O)
- Porges, S. W., & Furman, S. A. (2011). The early development of the autonomic nervous system provides a neural platform for social behaviour: A polyvagal perspective. *Infant and Child Development*, *20*(1), 106–118. <https://doi.org/10.1002/icd.688>
- Quas, J. A., Yim, I. S., Oberlander, T. F., Nordstokke, D., Essex, M. J., Armstrong, J. M., ... Boyce, W. T. (2014). The symphonic structure of childhood stress reactivity: Patterns of sympathetic, parasympathetic, and adrenocortical responses to psychological challenge. *Development and Psychopathology*, *26*(4pt1), 963–982. <https://doi.org/10.1017/S0954579414000480>
- Quinn, J. M., Wagner, R. K., Petscher, Y., & Lopez, D. (2015). Developmental relations between vocabulary knowledge and reading comprehension: A latent change score modeling study. *Child Development*, *86*(1), 159–175. <https://doi.org/10.1111/cdev.12292>
- Roos, L. E., Giuliano, R. J., Beauchamp, K. G., Gunnar, M., Amidon, B., & Fisher, P. A. (2017). Validation of autonomic and endocrine reactivity to a laboratory stressor in young children. *Psychoneuroendocrinology*, *77*, 51–55. <https://doi.org/10.1016/j.psyneuen.2016.11.023>
- Rudd, K. L., Alkon, A., & Yates, T. M. (2017). Prospective relations between intrusive parenting and child behavior problems: Differential moderation by parasympathetic nervous system regulation and child sex. *Physiology & Behavior*, *180*, 120–130. <https://doi.org/10.1016/j.physbeh.2017.08.014>
- Rudd, K. L., & Yates, T. M. (2018). The implications of sympathetic and parasympathetic regulatory coordination for understanding child adjustment. *Developmental Psychobiology*, *60*(8), 1023–1036. <https://doi.org/10.1002/dev.21784>
- Salomon, K., Matthews, K. A., & Allen, M. T. (2000). Patterns of sympathetic and parasympathetic reactivity in a sample of children and adolescents. *Psychophysiology*, *37*(6), 842–849. <https://doi.org/10.1111/1469-8986.3760842>
- Satorra, A., & Bentler, P. M. (2001). A scaled difference chi-square test statistic for moment structure analysis. *Psychometrika*, *66*(4), 507–514.
- Schwarz, G. (1978). The Bayesian information criterion. *Annals of Statistics*, *6*, 461–464.
- Shader, T. M., Gatzke-Kopp, L. M., Crowell, S. E., Jamila Reid, M., Thayer, J. F., Vasey, M. W., ... Beauchaine, T. P. (2018). Quantifying respiratory sinus arrhythmia: Effects of misspecifying breathing frequencies across development. *Development and Psychopathology*, *30*(1), 351–366. <https://doi.org/10.1017/S0954579417000669>
- Shibata, R. (1976). Selection of the order of an autoregressive model by Akaike's information criterion. *Biometrika*, *63*(1), 117–126. <https://doi.org/10.1093/biomet/63.1.117>
- Skowron, E. A., Cipriano-Essel, E., Gatzke-Kopp, L. M., Teti, D. M., & Ammerman, R. T. (2014). Early adversity, RSA, and inhibitory control: Evidence of children's neurobiological sensitivity to social context. *Developmental Psychobiology*, *56*(5), 964–978. <https://doi.org/10.1002/dev.21175>
- Smith, R., Thayer, J. F., Khalsa, S. S., & Lane, R. D. (2017). The hierarchical basis of neurovisceral integration. *Neuroscience & Biobehavioral Reviews*, *75*, 274–296. <https://doi.org/10.1016/j.neubiorev.2017.02.003>
- Suurland, J., van der Heijden, K., Huijbregts, S., Van Goozen, S., & Swaab, H. (2017). Interaction between prenatal risk and infant parasympathetic and sympathetic stress reactivity predicts early aggression. *Biological Psychology*, *128*, 98–104. <https://doi.org/10.1016/j.biopsycho.2017.07.005>
- Thelen, E. (2005). Dynamic systems theory and the complexity of change. *Psychoanalytic Dialogues*, *15*(2), 255–283. <https://doi.org/10.1080/10481881509348831>
- Toth, S. L., Sturge-Apple, M. L., Rogosch, F. A., & Cicchetti, D. (2015). Mechanisms of change: Testing how preventative interventions impact psychological and physiological stress functioning in mothers in neglectful families. *Development and Psychopathology*, *27*(4pt2), 1661–1674. <https://doi.org/10.1017/S0954579415001017>
- Tucker, L. R., & Lewis, C. (1973). A reliability coefficient for maximum likelihood factor analysis. *Psychometrika*, *38*(1), 1–10. <http://doi.org/10.1007/bf02291170>
- Wechsler, D. (2002). WPPSI-III technical and interpretive manual. *The Psychological Corporation*.

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