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A Latent Change Score Approach to Understanding Autonomic Coordination

A Dissertation submitted in partial satisfaction
of the requirements for the degree of

Doctor of Philosophy

in

Psychology

by

Kristen L. Rudd

June 2019

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ABSTRACT OF THE DISSERTATION

A Latent Change Score Approach to Understanding Autonomic Coordination

by

Kristen L. Rudd

Doctor of Philosophy, Graduate Program in Psychology
University of California, Riverside, June 2019
Dr. Tuppett M. Yates, Chairperson

Children's self-regulation has long been considered a key component of child development. Over the past two decades, physiological indices of self-regulation, particularly the autonomic nervous system (ANS), have garnered increased attention as an informative level of analysis in regulation research. The ANS is comprised of excitatory sympathetic and inhibitory parasympathetic branches, which serve to control core adaptive systems. Cardiography supports the simultaneous examination of both ANS branches across periods of rest, reactivity, and recovery via measures of pre-ejection period (PEP) and respiratory sinus arrythmia (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 research has favored static, mean level reactivity analyses, despite the dynamic nature of ANS regulation and the availability of analytic tools that can model these processes in real-time.

This dissertation drew on a sample of 198 six-year-old children from a diverse community sample (49.5% female, 43.9% Latinx) to examine autonomic coordination by 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 driven by the leading influence of PEP on lagging changes in RSA. The current findings advance our understanding of children's sympathetic and parasympathetic autonomic coordination while illustrating a novel analytic technique to support ongoing efforts to understand the etiology and developmental significance of children's physiological self-regulation.

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Whether it be preparing to take an important exam, completing a challenging puzzle, or evading an abusive caregiver, physiological responses support (or thwart) our capacity to navigate an ever-changing world. Patterns of physiological reactivity and recovery in response to life's challenges comprise one pillar of broader self-regulatory capacities. Self-regulation entails the ability to modulate behavior, cognition, emotion, and biology in accordance with contextual demands (Montroy, Bowles, Skibbe, McClelland, & Morrison, 2016; Posner & Rothbart, 2000; Vohs & Baumeister, 2016). In turn, self-regulation is central to adaptive development and is heavily implicated in psychological adjustment (Beckmann & Kellmann, 2004; Gross & Jazaieri, 2014; Phillips & Shonkoff, 2000).

Research on physiological regulation has examined multiple biological indices (e.g., heart rate, cortisol, skin conductance) to assess patterns of reactivity (Berry, Blair, Ursache, Willoughby, & Granger, 2014; Cipriano, Skowron, & Gatzke-Kopp, 2011; Hagan, Roubinov, Adler, Boyce, & Bush, 2016) and, to a lesser degree, recovery (Cui, Morris, Harrist, Larzelere, & Criss, 2015; Obradović & Finch, 2016; Rudd, Alkon, & Yates, 2017) in response to a challenging task or situation. Likewise, a robust body of research has shown that these varied indices are related to a wide range of adaptive outcomes, including behavior, secure attachment, and physical health (Bauer, Quas, & Boyce, 2002; Boyce et al., 2001; Diamond, Fagundes, & Cribbet, 2012). Although there are numerous biological systems involved in self-regulation, the autonomic nervous system (ANS) has piqued the interest of researchers because it permits time-sensitive,

dynamic analyses of physiological regulation, and, using cardiography, it supports studies of both sympathetic (i.e., fight/flight) and parasympathetic (i.e, rest/digest) influences on ANS regulation. That said, prior studies have primarily focused on one branch of the ANS using static, mean-level indicators of self-regulation during a single task (e.g., aggregating sympathetic *or* parasympathetic activity values across a 4-minute challenge task), rather than dynamic, multi-level indicators of self-regulation (e.g., patterns of change across a 4-minute challenge task). This dissertation addressed the need for dual and dynamic investigations of both sympathetic and parasympathetic ANS regulation using multi-level modeling to evaluate the dynamics within sympathetic and parasympathetic regulatory systems as they work in tandem to influence adaptive responses to stress (i.e., autonomic coordination).

The Autonomic Nervous System

The ANS controls several biological systems that are fundamental to mobilizing adaptive responses to stress, including internal organs, smooth muscles, pupillary dilation, respiration, and heart rate (McEwen, 2007). Autonomic processes are co-regulated by two complementary inputs – the sympathetic excitatory system and the parasympathetic inhibitory system. In the ideal, these systems work in a coordinated manner to mobilize flexible ANS regulation and support the adaptive navigation of contextual demands. The sympathetic branch of the ANS subserves energy mobilization and action (i.e., 'fight or flight'), including increases in heart rate, dilation of pupils, and catabolic metabolism processes to fuel vital organs. In contrast, the parasympathetic branch of the ANS subserves energy preservation and maintenance (i.e., 'rest and digest';

Porges, 2007), including a low and steady heart rate, digestive secretions, and dilated intestinal blood flow.

In optimal regulation, activities of the sympathetic and parasympathetic branches of the ANS complement one another (Jänig & McLachlan, 1992). At rest, sympathetic activation should be low, which, in concert with the inhibitory influence of the parasympathetic nervous system, allows the body to retain a readiness for response mobilization (Esler & Kaye, 2000). In response to a challenge that warrants behavioral mobilization, such as a startling stimulus, the sympathetic system should increase in activation to support action, while the parasympathetic system should decrease in activation to release its inhibitory influence on the sympathetic system. Conversely, in response to a challenge that requires sustained attention, such as a challenging memorization task, the sympathetic system should decrease its activity as the parasympathetic system increases its inhibitory influence to further constrain the sympathetic nervous system and enhance the organism's capacity to sustain a calm focus (Cipriano et al., 2011; Hastings et al., 2008).

Although there are multiple measures that index sympathetic *or* parasympathetic activity (e.g., salivary alpha-amylase for sympathetic activity, pupil dilation for parasympathetic activity), the cardiac system affords the unique opportunity to examine both branches of ANS regulation as they operate in tandem to modulate heart rate. Impedance cardiography and electrocardiograms allow researchers to assess sympathetic and parasympathetic activity via pre-ejection period (PEP) and respiratory sinus arrhythmia (RSA), respectively. PEP 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). Thus, a shorter PEP

time interval represents sympathetic activation, which is accompanied by increases in

heart rate. RSA represents the naturally occurring variation in heart rate as a function of

respiration (Porges, 2007). When RSA scores are relatively high, the parasympathetic

system is activated and sympathetic activity is inhibited yielding longer PEP time

intervals. 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. Further, only a handful of studies have examined

autonomic coordination, and all have employed static (rather than dynamic) analytic

approaches.

Theories of Autonomic Coordination

Bernston 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). In this multi-

dimensional view of the autonomic space, sympathetic and parasympathetic systems are

conceptualized as equal partners in self-regulation. Although Bernston posited that

cardiac systems operate in either reciprocal/non-reciprocal (i.e., opposing activation

versus coactivation/coinhibition) and coupled/un-coupled fashion (i.e., correlated versus

uncorrelated activity, such as when activation in one system is accompanied by no change in the other system), early models of autonomic coordination neither considered, nor posited one branch of the ANS as more or less likely to take the lead in this regulatory dance. Instead, Bernston and colleagues argued that supraordinate neural mechanisms, such as rostral brain areas, combined with the timing of neural signals (e.g., direct versus indirect afferent pathways) determine patterns of ANS regulation.

Whereas Bernston's theory of the autonomic space emphasizes the degree, rather than direction, of coordination between systems, Porges' (2001, 2007, 2009) polyvagal theory places comparatively greater emphasis on the parasympathetic system as the driving force of ANS regulation and highlights the implications of parasympathetic determinants of cardiac regulation in the context of a dynamically changing social world (Porges & Furman, 2011). Indeed, polyvagal theory posits that there are two processes of regulation *within* the parasympathetic system, which are mediated by separate pathways of the vagus, or 10th cranial nerve. The first pathway is thought to mediate relatively primitive behavioral responses (e.g., immobilization, playing dead, behavioral shut down), whereas the second pathway is thought to mediate more recently evolved responses (e.g., social communication, self-soothing, self-regulation). Further, Porges (2007) positions RSA as a pure index of parasympathetically-mediated vagal tone and control, which supports sympathetic mobilization during challenge when withdrawn, and inhibits the excitatory activity of the sympathetic branch of the ANS and hold it in check when augmented (Porges, Doussard-Roosevelt, Portales, & Greenspan, 1996). Thus,

Porges suggests that the sympathetic nervous system functions akin to the gas in a motor vehicle, and the parasympathetic system operates as a so-called "vagal brake."

Although Porges' polyvagal theory, and its attendant presumption of parasympathetic dominance in ANS regulation, has gained the most traction in the field, several researchers remain critical of its postulates (Berntson, Cacioppo, & Grossman, 2007; Grossman & Taylor, 2007). First, ongoing debates about the differentiation of neural origins that represent functionally distinct parasympathetic responses (i.e., the primitive versus evolved responses described earlier) offered by polyvagal theory suggest that this premise may be unsupported (Grossman & Taylor, 2007). For example, the pathway that is proposed to mediate more evolved responses in this theory has since been shown in non-mammal invertebrates, which raises questions about Porges' (2001, 2007) evolutionary foundation for emphasizing RSA and vagal dominance. Second, researchers have highlighted the potential for shifts in sympathetic activity to influence measures of RSA, which counters Porges' (2007) assertion that RSA indexes direct or pure vagal control of the heart (Berntson et al., 2007). In this view, RSA is an important, but not necessarily dominant, piece of the autonomic puzzle; one that may be affected by multiple inputs, including the vagus, environmental/social context, and/or sympathetic activity. Together, these critiques highlight the need to assess the complex dynamics of autonomic coordination and evaluate both sympathetic and parasympathetic inputs to understand the multidetermined nature of ANS responses in challenging contexts.

In all likelihood, rather than unilateral dominance, the leading and lagging influences of either PEP or RSA vary by contextual factors, such as task demands or

participant histories. For example, a challenge that entails high levels of attentional focus, such as reading a complex book in preparation for a comprehension test, may be largely driven by parasympathetic influences. However, a challenge that requires behavior mobilization, such as a buzzer signaling the start of a race, may be primarily driven by sympathetic influences. Still other challenges, particularly those that demand a mix of engagement and mobilization, may not feature a distinguishable lead-lag relation between PEP and RSA. In such cases, a third variable may drive these associations and/or fluctuations in whether PEP or RSA drives or leads ANS regulation. Importantly, additional task features, such as the relative social, cognitive, and emotional demands, have the potential to influence both the direction of the coordinated response and the dynamics of autonomic coordination. For example, in line with Porges' polyvagal theory (2001, 2007, 2009), reactivity patterns during a dyadic task that is more socially engaging may be influenced most strongly by parasympathetic activity, whereas a task that is more cognitively engaging may be driven by sympathetic activity. Finally, a number of individual differences, such as early adversity exposure, biological vulnerability (e.g., cardiac illness), and/or gender, may contribute to the relative dominance or equality of ANS coordination processes.

Studies of Autonomic Coordination

Despite extant theory demonstrating the importance of the dynamics between and within regulatory systems (Cacioppo, Berntson, Sheridan, & McClintock, 2000; 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 (El-Sheikh, Erath, Buckhalt, Granger, & Mize, 2008; El-Sheikh, Hinnant, & Erath, 2011; Erath & El-Sheikh, 2015; Gatzke-Kopp & Ram, 2018; Gordis, Feres, Olezeski, Rabkin, & Trickett, 2010; Quas et al., 2014). For example, in a study examining skin conductance as an indicator of sympathetic activity and RSA as an indicator of parasympathetic activity, El Sheikh and colleagues (2009) found that a discoordinated *resting* pattern of coinhibition between sympathetic (i.e., low skin conductance) and parasympathetic (i.e., low RSA) systems was associated with higher levels of mother-reported delinquency among 8-year-olds. In contrast, a coordinated *reactivity* pattern of sympathetic inhibition (i.e., low skin conductance) and parasympathetic activation (i.e., high RSA) was associated with lower levels of delinquency. Interestingly, in a second study examining salivary alpha amylase (sAA) as an indicator of sympathetic activity and RSA as an indicator of parasympathetic activity, Keller and El Sheikh (2009) found that children who evidenced relatively low levels of ANS arousal (i.e., reciprocal parasympathetic activation characterized by low sAA and high RSA) in response to an audio-recorded verbal argument also evidenced higher mother-reports of externalizing problems concurrently, though this association did not hold over time. Together, these studies suggest that patterns of sympathetic and parasympathetic coordination, as well as their developmental significance, may vary across studies, perhaps as a function of the indices used to assess each facet of ANS regulation.

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Relatively fewer studies have examined autonomic coordination within a single

system, such as cardiac physiology (Bylsma et al., 2015; Clark, Skowron, Giuliano, &

Fisher, 2016). In a series of studies that examined profile-based conceptualizations of

autonomic coordination, Alkon and colleagues found that the proportion of children with

discoordinated profiles of PEP and RSA co-activation (i.e., short PEP, high RSA) or co-

inhibition (i.e., long PEP, low RSA) gradually declined, and the proportion of children

with coordinated patterns of reciprocal activation increased across the first five years of

life (Alkon, Boyce, Davis, & Eskenazi, 2011; Alkon et al., 2014). Moreover, preliminary

findings suggest that, in a sample of children who had experienced relatively high rates of

stressful life events, reciprocal parasympathetic activation was associated with increased

sleep problems one year later (Alkon, Boyce, Neilands, & Eskenazi, 2017; Salomon,

Matthews, & Allen, 2000). A recent study using a continuous interactive analytic

approach found that infants with discoordinated ANS profiles of cardiac regulation (i.e.,

sympathetic and parasympathetic co-activation or co-inhibition) in response to an audio-

recorded adult conflict challenge were more likely to display heightened physical

aggression two years later than were infants who exhibited coordinated ANS responses

characterized by reciprocal sympathetic activation (i.e., short PEP, low RSA) or

reciprocal parasympathetic activation (i.e., long PEP, high RSA; Suurland, Van der

Heijden, Huijbregts, Van Goozen, & Swaab, 2017). Further, in one of the first studies to

assess autonomic coordination across reactivity *and* recovery periods, coordinated

regulation of PEP activation and RSA withdrawal (i.e., reciprocal sympathetic reactivity),

followed by RSA augmentation and PEP withdrawal (i.e., reciprocal parasympathetic

recovery) in response to a startling challenge predicted children's increased adaptability and decreased behavior problems two years later (Rudd & Yates, 2018).

Consistent with broader tenets of dynamic systems theory (Thelen, 2005), extant studies of autonomic coordination suggest that reciprocal activation patterns across sympathetic and parasympathetic systems may be more informative for understanding child adaptation than examining either system alone. Although prior studies have advanced the desired effort to understand ANS regulation as a totality of both sympathetic and parasympathetic influences, the field remains limited by primarily cross-system investigations using static person- or variable-centered approaches to the study of autonomic coordination. This dissertation addressed these limitations by utilizing advanced statistical procedures to assess sympathetic and parasympathetic regulatory dynamics within the cardiac system.

Analytic Strategies to Study Autonomic Coordination

As with the broader literature on ANS regulation, static statistical approaches dominate extant efforts to examine autonomic coordination. These analytic options involve calculating the average value of sympathetic and parasympathetic activation during a single task (e.g., Rudd & Yates, 2018), or across multiple tasks (e.g., Alkon et al., 2017), and then comparing these average values in various ways.

First, adopting a person-centered analytic strategy, categorical profile analyses allocate participants to groups that are characterized by coactivation, coinhibition, reciprocal sympathetic activation, or reciprocal parasympathetic activation based on mean splits. As reviewed previously (Alkon et al., 2011; Alkon et al., 2017; Salomon et

al., 2000), this technique yields sample-specific distinctions based on relative levels of activation or inhibition across sympathetic and parasympathetic systems. In turn, these categorical designations provide easy-to-visualize depictions of adaptive outcomes among participants who evidence coordinated/reciprocal versus discoordinated/non-reciprocal autonomic coordination patterns.

Second, adopting a variable-centered analytic strategy, interactive analyses rely on linear regression techniques to examine sympathetic and parasympathetic regulatory dynamics across the continuum of activity. Although these analyses can be more difficult to interpret than profile-based approaches because they involve continuous variables, they provide more detail about potentially 'uncoupled' responses (e.g., activation in one system, but no change in the other system) that is otherwise lost when using categorical analyses. Despite recent data suggesting that profile approaches may yield superior estimates of autonomic coordination in social contexts (Rudd, Alkon, & Yates, 2019), neither profile, nor interactive analytic approaches can fully capture the dynamic nature of ANS regulation.

Over the past five years, a handful of researchers have begun to employ a variety of 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). In 2014, Helm and colleagues were among the first to adopt a dynamic analytic lens using a cross-lagged panel analysis to evaluate dyadic co-regulation of RSA between adult romantic partners across six 30-second epochs within a three-minute conversation task. Building on this

study, Gates and colleagues (2015) utilized similar autoregressive cross-lag analyses to explore dyadic co-regulation of RSA between adult romantic partners during 20 30-epochs within a 10-minute conversation task. To our knowledge, cross-lagged panel studies have not yet assessed PEP between partners, nor have they 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 two constructs while controlling for autoregressive effects, they necessarily ignore actual growth over time since only covariance, but not mean structures, are modeled.

Addressing the need for analytic models that can evaluate the direct impact of growth factors for child adjustment, researchers have used growth modeling techniques to examine single-system ANS regulation over multiple assessments across time (El-Sheikh, Keiley, & Hinnant, 2010; Patriquin, Lorenzi, Scarpa, & Bell, 2014; Porges & Furman, 2011), as well as single-system changes across one task within time (Cui et al., 2015; Miller et al., 2013; Obradović & Finch, 2016). In one of the few studies to examine dynamic patterns of sympathetic regulation, researchers utilized piecewise growth curves to assess PEP among 3.5-year-old children (Kahle, Miller, Lopez, & Hastings, 2016). The researchers utilized a variable epoch length over an anger-induction task (i.e., attempting to draw a 'perfect circle' while receiving negative feedback from examiners), which was defined based on the length of time the child participated in the task (e.g., two 30-second epochs if the child quit the task after 1-minute). This approach ensured that the challenge immediately preceded the two 30-second epochs used to represent the recovery period.

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On average, children evidenced significant sympathetic activation across the anger-induction task (i.e., negative PEP slope connoting attenuation of the PEP interval). Although children did not display a significant mean level recovery pattern following the task, there was significant inter-individual variability in recovery trajectories, which predicted concurrent emotion regulation. Specifically, children who evidenced greater sympathetic recovery (i.e., positive PEP slope connoting a lengthening of the PEP interval) were also rated as having better emotion regulation capacities by their mothers. In a second study, Miller and colleagues utilized growth models to map 4.5-year-olds' parasympathetic responses over four 15-second epochs of a 1-minute anger induction video. On average, children evidenced RSA suppression during the first epochs of exposure, followed by RSA rebound toward initial levels as the video played on, which the researchers identified as their RSA recovery period (Miller et al., 2013). Growth modeling procedures provide information about the dynamic nature of ANS regulation within a task that are washed out in traditional static approaches that use the arithmetic mean of an ANS response across an entire task (or set of tasks). Further, in contrast to cross-lagged panel models, these techniques explicitly model covariances *and* means to support the direct evaluation of growth factors. To our knowledge, researchers have not yet employed parallel growth curve modeling to assess autonomic coordination between PEP and RSA over time. Despite the strengths of growth modeling procedures (particularly if and when these approaches are used in parallel), these models cannot account for the influence of previous states in the growth parameters (i.e., autoregressive effects) on subsequent growth within or across systems.

This dissertation employed bivariate latent change score models as a novel dynamic approach to evaluate autonomic coordination between children's PEP and RSA across a single problem-solving task, while accounting for relations between moment-to-moment changes in one autonomic branch and changes in the opposing branch. These models combine the strengths of autoregressive cross-lagged panel analyses with growth models to support the investigation of directional dynamics between constructs over time (Ferrer & McArdle, 2010; McArdle & Grimm, 2010). By assessing within- and between-person differences in change, dynamic relations within a latent change model can be characterized as '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 these 'leading' or 'lagging' dynamics. These coupling indicators also provide an important window into possible underlying causal influences between indicators over time by controlling for autoregressive effects.

Although this dissertation provides the first application of a bivariate latent change score model to the study of autonomic coordination, studies of other psychological constructs using this approach supported the feasibility of this analytic approach 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 bivariate latent change score models to evaluate competing

models of unidirectional (i.e., vocabulary knowledge influencing reading comprehension versus reading comprehension influencing 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 from first to fourth grade. Extending to the ANS, prior studies of ANS 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 of utilizing latent change score models to elucidate patterns of autonomic coordination.

Current Study

This dissertation sought to advance and integrate two growing edges of contemporary research efforts in the field of ANS regulation. First, although the ANS has long been described as a system of complementary sympathetic and parasympathetic inputs that work together to modulate responses to stress, the vast majority of research in this area has examined each system in isolation. Second, prior studies that have looked at autonomic coordination have focused on mean-level changes across tasks, or across time within a task, which limits our capacity to understand the dynamic interplay between PEP and RSA during a stress response. To address these gaps, this dissertation implemented bivariate latent change score modeling as a novel and dynamic statistical approach to evaluate bidirectional influences of sympathetic and parasympathetic activity over the course of a challenging puzzle completion task in a large sample of six-year-old children.

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Early childhood has long been considered an important time period for physiological development. Research on the development of ANS regulation across infancy and early childhood has documented high levels of variability throughout the first year of life (Patriquin et al., 2014), with increasing stability through age 5 (Calkins & Keane, 2004). Given this variability in early development, the current effort to examine autonomic coordination among 6-year-old children was expected to yield more reliable and generalizable information than studies in earlier development.

I hypothesized that, on average, children would evidence coordinated ANS regulation in response to the challenging puzzle task. However, based on previous literature suggesting task-specific patterns of ANS regulation across arousing versus engaging challenges (Davis, Quiñones-Camacho, & Buss, 2016; Skowron, Cipriano-Essel, Gatzke-Kopp, Teti, & Ammerman, 2014), as well as across tasks entailing varying levels of social, cognitive, and emotional demands (Davis, Brooker, & Kahle, 2019; Roos et al., 2017), I remained agnostic as to whether the coordinated regulatory pattern would be characterized by reciprocal sympathetic or parasympathetic activation. Although solving a challenging puzzle does warrant attentional engagement, which would be supported by PEP elongation and RSA augmentation (i.e., reciprocal parasympathetic activation), the inclusion of a short and clear time limit for puzzle completion, as well as the placement of this challenge at the start of the current ANS protocol may increase children's anticipation and arousal to press for a mobilizing regulatory response, which would be supported by PEP attenuation and RSA withdrawal (i.e., reciprocal sympathetic activation). Beyond a pattern of coordinated ANS regulation, I 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 research on autonomic coordination, I evaluated three potential coupling patterns between PEP and RSA in this study. First, PEP may lead autonomic coordination such that preceding levels of PEP would influence change in RSA across time, supporting suppositions of the multidetermined nature of RSA (Berntson et al., 2007). Second, RSA may lead PEP change over time as suggested by Porges' (2001, 2007, 2009) Polyvagal theory, such that the direction of coupling responses may be influenced by the social or non-social nature of the task. For example, the presence of the caregiver in the current challenge paradigm increased the social component of the task, which may yield a parasympathetically mediated response. However, the challenging nature of the puzzle task also increased cognitive demands, which may elicit driving forces from the sympathetic system (i.e., PEP leading changes in RSA). Third, there may be full-coupling such that both PEP and RSA influence each other in unique ways.

Methods

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

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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 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).

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 1) 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), 2) proficient in English, and 3) not diagnosed with a developmental disability or delay. Dyads completed a 3-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.

Measures

Autonomic Nervous System Regulation was assessed using measures of the child's PEP and RSA during a resting baseline task and during 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. The ANS protocol included a 5-minute calibration period after initial placement of the electrodes to allow time for the child to adjust to the equipment. Following the calibration period, the child and caregiver were 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 measure to serve as a baseline for the challenge task, which involved dyadic 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 and when they thought their child needed assistance.

ANS data were collected using Mindware MW1000A ambulatory cardiography via Kendall Medi-Trace #133 spot electrodes. PEP data were extracted and scored using

the IMP 3.0.3 analysis program (www.mindware.com) where 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). Consistent with prior studies (Alkon et al., 2011; Boyce et al., 2001), data were extracted in 30-second epochs across the four-minute challenge yielding a total of eight PEP and eight RSA values for each child. Further data cleaning procedures for PEP and RSA included screening for outliers (i.e., > 3SD) epoch-by-epoch in relation to each child's data pattern and deleting a child's data if more than 25% of their epochs were missing due to computer malfunction, electrode conduction problems, or outliers.

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.

Model fit parameters were assessed sequentially as described by Grimm (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*, followed by a second *constant change model* that posited linear growth within the regulatory system being modeled (i.e., PEP *or* RSA). The third model was a *proportional change model* where growth was positioned as a function of previous levels of regulation. Finally, the fourth model was a *dual-change model* that incorporated both linear and proportional change components.

Following the evaluation of separate growth parameters 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 both regulatory parameters 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 influenced change in the other autonomic branch.

Chi-square difference tests evaluated comparative fit across each pair of nested models (Satorra, 2000). However, given that the likelihood ratio test is influenced by large sample size (Browne & Cudeck, 1993), 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, 1977) and the Bayesian Information Criterion (BIC;

Schwarz, 1978) were used to assess fit across non-nested models, such that lower values

indicated better fit (Grimm et al., 2006).

Results

Means and standard deviations for the eight 30-second epochs of PEP and RSA

across the challenge task and 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.

Univariate Models

Competing models were fit separately for PEP and RSA to assess individual

growth parameters. Model fit was evaluated across multiple indices in line with

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).

Haystack plots modeling trajectories of PEP are displayed in Figure 1 and fit

statistics for univariate PEP models are presented in Table 2. A review of 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 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 parameters 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 2. 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 duration of the puzzle task, but there was no significant variation in growth over the task ($\sigma_{PEP} = 1.689$, $p = .216$). In other words, children evidenced a progressive attenuation of PEP over the task (i.e., sympathetic activation) in similar ways. The proportional change component was significant and positive ($\beta_{PEP} = 0.512$, $p = .018$), reflecting an accelerating effect of PEP on growth across the duration of the puzzle challenge (i.e., high PEP values, which were modeled at one standard deviation above the group mean, contributed to increases in sympathetic activation, which was indicated by attenuation of

the PEP interval, .512 standard deviations faster across the duration of the puzzle challenge).

Haystack plots modeling trajectories of RSA are displayed in Figure 3 and fit statistics for univariate RSA models are presented in Table 3. A review of 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. Next, a comparison of nested models indicated that the dual change model of RSA fit significantly better than the constant change model, which removed the proportional change component from the dual change model; $\Delta\chi^2(1) = 9.693, p < .001$. Similarly, the proportional change model of RSA, which removed the constant change component from the dual change model, fit significantly worse than the dual change model; $\Delta\chi^2(3) = 39.394, p < .001$. Consistent with the PEP univariate models, these analyses indicated that both constant change and proportional change parameters were required for appropriate modeling of RSA change across the challenge task (i.e., a dual change model of RSA).

Parameter estimates from the univariate dual change score model of RSA are presented in Figure 4. The average initial RSA score during the first epoch was significantly different from zero ($M_{RSA} = 6.492 \; p < .001$), and there was significant variation in initial mean values indicating individual differences in starting values of RSA. There was significant decline in RSA ($G_{RSA} = -0.219, p < .001$) across the duration of the puzzle task, as well as significant variation in these patterns ($\sigma_{RSA} = 0.003, p = .005$). In other words, on average, children exhibited a pattern of declining RSA (i.e., parasympathetic withdrawal) across the task, but there were significant individual

differences in these patterns across individuals. The proportional change component was negative and significant ($\beta_{RSA} = -0.036$, $p < .001$), reflecting a decelerating effect of RSA on growth across the duration of the puzzle challenge (i.e., high RSA values, which were modeled at one standard deviation above the group mean, contributed to decreases in parasympathetic activation, which was indicated by a reduction of RSA, 0.036 standard deviations slower across the duration of the puzzle challenge).

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 accounted for individual differences in 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 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, the more parsimonious unidirectional coupled PEP model wherein PEP was positioned to lead changes in RSA was selected as the final best-fitting model.

Parameter estimates for the unidirectional coupling model of PEP to RSA are displayed in Figure 5. The negative correlation between the slope and intercept of PEP (r = -0.336, p = .003), and the positive correlation between the slope and intercept of RSA (r = 0.545, p = .043) was consistent with the reciprocal sympathetic activation that was evident in the univariate dual change models (i.e., progressive attenuation of PEP and reduction in RSA). A positive correlation between the intercept of PEP and the intercept of RSA (r = 0.227, p = .006) indicated that higher initial RSA values (i.e., greater parasympathetic activation) were associated with longer initial PEP intervals (i.e., lower sympathetic activation). The negative correlation between the intercept of PEP and the slope of RSA (r = -0.468, 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 standardized units indicated that negative growth in RSA was accounted for, in part, by the preceding level of PEP. 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 across the challenging puzzle task.

Discussion

This dissertation examined the dynamic autonomic coordination of PEP and RSA regulation across a challenging puzzle task using bivariate latent change score models. The results of univariate models examining separate, within-system influences demonstrated that both PEP and RSA were adequately described by dual-change models. For PEP, growth was reflected by a negative constant change and a positive proportional change, such that attenuation of the PEP interval (i.e., sympathetic activation) occurred over each epoch and this rate of attenuation accelerated across the task. For RSA, growth was reflected by a negative constant change and a negative proportional change, such that decreases in RSA (i.e., parasympathetic withdrawal) occurred over each epoch, but the rate of RSA withdrawal diminished across the task. Dynamic assessments of PEP and RSA coordination supported a unidirectional coupling model wherein PEP was the leading influence on lagging changes in RSA across the task. Thus, the current findings suggest that children evidenced reciprocal sympathetic activation across the challenging puzzle completion task in this study, and this activation reflected coordinated exchanges between the two branches of the ANS characterized by PEP leading patterns of regulation.

Dynamic modeling techniques elucidated directional influences of PEP and RSA across the challenging puzzle task. Although further replication is needed to generalize beyond the directional coupling effects observed here, the current investigation illustrates how bivariate latent change score modeling can be used to test theories about the coordinated regulation of sympathetic and parasympathetic systems (Berntson et al.,

2007; Obrist, 2012; Porges, 2007). The current results suggest that sympathetic activity

can drive ANS regulation in some contexts (Berntson et al., 2007; Obrist, 2012), and

RSA may not always index "pure" parasympathetic activity (Berntson et al., 2007;

Grossman & Taylor, 2007). Despite the preliminary nature of these findings, this

investigation clearly illustrates the importance of understanding the ANS as an

intertwined regulatory process, and of adequately modeling this process by attending to

varying degrees of reciprocal and coupled actions (Berntson et al., 1994).

The current findings demonstrate that 6-year-old children responded to the

challenge of completing a difficult puzzle 'before the examiner returned' with reciprocal

sympathetic activation (i.e., PEP attenuation and RSA withdrawal). Moreover, these

regulatory responses were driven by the leading influence of PEP on lagging changes in

RSA. As noted earlier, although a puzzle task does necessitate a degree of attentional

engagement, 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, over their need for calm and sustained attentional focus, which would be

supported by reciprocal parasympathetic activation. Indeed, the positive proportional

change parameter for PEP is consistent with an increase in children's arousal as they

began to sense that time was running out and the probability of task failure increased.

Although the current study suggests that sympathetic activation patterns may

drive or 'lead' parasympathetic regulation, ANS regulation (and likely autonomic

coordination) is known to vary by the social, cognitive, and emotion demands of the task

(Burt & Obradović, 2013). 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. For example, a task that requires sympathetic mobilization (e.g., a startle or a challenging puzzle task) may elicit a driving force from PEP as it activates and directs the necessary responses. However, a task that requires parasympathetic activation (e.g., a test of reading comprehension) may evidence a driving force from RSA to influence subsequent changes in PEP. In this view, the activated branch of the ANS takes on the 'leading' role to guide the responses of its 'lagging' counterpart. Similarly, a task that demands high levels of social engagement may require parasympathetic dominance, but if cognitive or motivational demands take precedence, the sympathetic system may drive regulation. Alternately, rather than being driven by which system needs to mobilize, shifts in 'lead' and 'lag' roles across autonomic coordination may reflect varying degrees to which RSA represents pure vagal control versus mixed sympathetic and parasympathetic influences. For example, when RSA represents a more direct measure of vagal control of the heart (e.g., when sympathetic influences are minimal and/or physical movement is limited), RSA may take on this leading role. However, in situations that preclude this parasympathetic clarity (e.g., when there are quick and dramatic shifts in sympathetic responses), the sympathetic system may take on relatively more influence in autonomic coordination. Of course, there may be a third, unknown variable that drives these 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.

In addition to task contexts, patterns of autonomic coordination may vary across

regulation phases (e.g., rest versus recovery). Of note, the current findings evaluated

ANS regulation during a challenge without consideration of baseline levels. Thus, these

findings captured regulation, rather than ANS reactivity per se. As can be seen in

Appendix A, follow-up analyses controlling for baseline levels of PEP and RSA

evidenced similar results as the regulation models presented earlier. However, although

comparisons of nested reactivity models demonstrated that the unidirectional PEP model

fit the data best (see Table 5), adding these resting covariates reduced some practical

indices of reactivity model fit below acceptable levels (e.g., CFI <.950; Hu & Bentler,

1999).

Although the current study evaluated autonomic coordination across a single task,

bivariate latent change score models can be employed to advance our understanding of

coordinated processes across development. For example, these models can be applied to

similar tasks across successive assessments to determine if and how coupling patterns

change over time. Further, by evaluating the effect size of each coupling parameter, we

can assess the strength of autonomic coupling within and across time.

Strengths and Limitations

The current dissertation provides new information about the dynamics underlying

6-year-olds' sympathetic and parasympathetic autonomic coordination across a

challenging puzzle task. Notable strengths of this investigation include the use of a large

and diverse sample of children, cardiac measurements of both PEP and RSA, and the implementation of dynamic statistical methods. Bivariate latent change score models afforded a unique opportunity to investigate directional dynamics between PEP and RSA over time. However, despite these strengths, a number of limitations should be considered when interpreting the implications of the current findings.

First, trajectories of change were limited to linear examinations in the current study, such that evaluated changes were exponential with either positive or negative variations due to coupling effects. A limitation of extant bivariate latent change models is that non-linear trajectories, such as quadratic effects, are difficult to model because they would require many measurement occasions to produce reliable parameter estimates (Grimm, An, McArdle, Zonderman, & Resnick, 2012). This limitation is especially concerning in the study of autonomic coordination because prior research suggests that trajectories of PEP and RSA across development may be best characterized with non-linear models (Kogan et al., 2014; Miller, Kahle, & Hastings, 2017). Just as longitudinal studies illustrate the likely complexity of regulatory development across time (e.g., Roubinov, Boyce, Lee, & Bush, 2019), a handful of studies suggest that non-linear models may characterize ANS regulation within shorter time spans. For example, a study using growth modeling across an anger-induction task with 3.5-year-olds found that, on average, children evidenced RSA suppression during the first moments of exposure, followed by RSA rebound toward initial levels as the video continued (Miller et al., 2013). It is possible that non-linear dynamics will be relevant for understanding patterns of autonomic coordination in future research.

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Second, although bivariate dual change models yield indices of proportional change and coupling, both estimates reflect a combination of within- and between-person effects. A central advantage of longitudinal modeling is the ability to disaggregate within- and between-person effects (Curran & Bauer, 2011), however, the complex nature of the bivariate dual change score model, as well as its implementation within a single challenge task, precluded the ability to separate these effects. Failing to examine within- and between-person differences can lead to the misspecification and/or misinterpretation of parameter estimates. For example, in cross-lagged panel analyses, conflating these distinct sources of influence can yield biased and difficult-to-interpret coefficients, as well as erroneous conclusions about causal patterns (Berry & Willoughby, 2017; Hamaker, Kuiper, & Grasman, 2015). Recent advances in cross-lagged panel analyses have sought to disaggregate within- and between-person differences by creating a global trait factor, and multiple state factors to differentiate time-varying differences (e.g., within-person effects) from trait-invariant differences (e.g., between-person effects; Kenny & Zautra, 2001; Tyrell, Yates, Reynolds, Fabricius, & Braver, 2018). Developing similar techniques to differentiate these influences within bivariate latent change score models would greatly benefit future studies of ANS regulatory dynamics.

Third, although the puzzle task yielded sufficient epochs to conduct a bivariate latent change score model, the current design may have limited the generalizability of our findings in a number of ways. First, the puzzle task was the first challenge introduced to the children following the resting baseline period. This temporal precedence may have

contributed to the reciprocal sympathetic activation that was evident in this task. Future work will need to examine ANS regulation patterns during this task at different points in an ANS protocol and in varied samples to ascertain whether or not there is a uniform activation of sympathetic responses to challenging puzzle completion tasks. Likewise, research using different kinds of challenge tasks is needed to ascertain whether or not a sympathetic lead model characterizes autonomic coordination dynamics generally, or only in response to specific kinds of challenge. Second, a unique feature of the current task was that the caregiver was present during the entire 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 presence of the caregiver in this study may have limited the generalizability of the observed findings. In particular, 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. 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 (Obradović & Finch, 2016; Rudd et al., 2017; Rudd & Yates, 2018). In future research, it will be important to ascertain whether autonomic coordination during reactivity and recovery episodes evidence a similar pattern to the

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ANS regulation findings presented in this dissertation. As discussed previously, when controlling for baseline levels of PEP and RSA in this study, autonomic coordination demonstrated similar patterns of leading and lagging influences, but model fit indices fit the data worse than models with no covariates (see Appendix A).

Finally, the current study revealed a snapshot of autonomic coordination among 6-year-old children during a challenging puzzle task. Patterns of autonomic coordination across developmental time have rarely been examined, and never with the dynamic modeling approaches used here. Although a few studies have documented stability in patterns of ANS regulation by age 5 (Alkon et al., 2014; Feldman, 2009; Patriquin et al., 2014), only one study has assessed autonomic coordination across early childhood to examine coordination profiles from infancy through age 5 (Alkon et al., 2011). In this study, children tended to move from discoordinated profiles of either coactivation or coinhibition to coordinated profiles of either reciprocal sympathetic or parasympathetic activation across time. Additional research is needed to ascertain whether or not the leading and lagging patterns of PEP and RSA regulation in this study will hold across developmental time, as well as if and when these patterns stabilize within or across childhood.

Implications and Future Directions

The current study illustrated that sympathetic and parasympathetic ANS regulatory processes evidence coordinated dynamics across a challenging puzzle task. Specifically, the findings documented leading influences of sympathetic input on ANS coordination during this sympathetically activating challenge. My analyses supported

contemporary theorists who conceptualize RSA as a multiply determined, rather than pure, measure of parasympathetic vagal activity and highlight the special significance of sympathetic processes (i.e., PEP) as a driving force underlying the coordinated actions of the ANS. As one of the first studies to apply bivariate latent change score models to physiological data, this dissertation illuminates 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 understanding sympathetic ANS regulatory processes as well. Moreover, the current analytic paradigm revealed significant and coordinated coupling between sympathetic and parasympathetic systems. Thus, this study 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 dissertation warrants relatively greater 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 further elucidate the exact nature of task influences on autonomic coordination, and to replicate the identified bivariate model of sympathetic leading PEP influences on parasympathetic lagging RSA effects. 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 exact 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 the adaptive implications of such differences for children's multi-domain adaptation. For example, 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 separately (McLaughlin, Alves, & Sheridan, 2014; Obradović, 2012). Expanding this knowledge to evaluate how early (and chronic) adversity exposure may influence ANS regulatory dynamics is an important step toward fully understanding the meaning and implications of autonomic coordination. With regard to the developmental significance of such dynamics, prior research has documented the importance of single-system measures of ANS regulation (e.g., PEP or RSA alone; Gatzke-Kopp & Ram, 2018), and, to a lesser degree, of aggregated assessments of coordination (Alkon et al., 2017; El-Sheikh & Erath, 2011; Rudd & Yates, 2018) 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 static, 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 dissertation illustrates the application of bivariate latent change 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 adaptation. Future

work utilizing these dynamic models to understand the process of coordination may

highlight meaningful pathways to positive child adjustment via physiological self-

regulation.

Table 1. Descriptive Statistics and Bivariate Correlations among Study Variables

	M	SD	1	2	3	4	5	6	7	8
1. RSA Rest	6.74	0.99	---							
2. RSA 1	6.72	1.13	.79***	---						
3. RSA 2	6.38	1.21	.79***	.78***	---					
4. RSA 3	6.38	1.22	.76***	.74***	.81***	---				
5. RSA 4	6.28	1.16	.78***	.72***	.73***	.77**	---			
6. RSA 5	6.38	1.21	.77***	.73***	.73***	.72**	.76***	---		
7. RSA 6	6.42	1.11	.73***	.67***	.71***	.68**	.71***	.73***	---	
8. RSA 7	6.47	1.12	.75***	.65***	.69***	.63**	.65***	.70***	.66***	---
9. RSA 8	6.50	1.07	.72***	.64***	.69***	.62**	.61***	.63***	.58***	.71***
10. PEP Rest	98.93	7.67	.21**	.18**	.15*	.22**	.16*	.06	.08	.10
11. PEP 1	99.76	7.57	.19**	.16*	.13	.18*	.14	.05	.04	.09
12. PEP 2	99.56	7.37	.16	.13	.09	.18*	.15*	.04	.03	.01
13. PEP 3	99.58	6.89	.19*	.18*	.14	.21**	.21**	.08	.07	.08
14. PEP 4	99.65	7.28	.16*	.13	.09	.18*	.17*	.06	.02	.07
15. PEP 5	98.92	7.09	.20*	.13	.12	.23**	.17*	.07	.04	.06
16. PEP 6	98.60	7.23	.15*	.11	.05	.16*	.17*	.04	.04	.03
17. PEP 7	98.68	7.34	.11	.13	.06	.15*	.14	.03	.02	-.03
18. PEP 8	98.32	7.26	.16*	.16*	.09	.18*	.18*	.10	.07	.04

Note. $*p < .05$, $**p < .01$, $***p < .001$.

Table 1. Descriptive Statistics and Bivariate Correlations among Study Variables

	9	10	11	12	13	14	15	16	17	18
1. RSA Rest										
2. RSA 1										
3. RSA 2										
4. RSA 3										
5. RSA 4										
6. RSA 5										
7. RSA 6										
8. RSA 7										
9. RSA 8	---									
10. PEP Rest	.10	---								
11. PEP 1	.16*	.74***	---							
12. PEP 2	.09	.77***	.64***	---						
13. PEP 3	.11	.74***	.80***	.71***	---					
14. PEP 4	.11	.82***	.69***	.75***	.76***	---				
15. PEP 5	.18*	.74***	.66***	.73***	.70***	.78***	---			
16. PEP 6	.13	.73***	.65***	.69***	.76***	.75***	.71***	---		
17. PEP 7	.07	.75***	.64***	.66***	.72***	.72***	.65***	.76***	---	
18. PEP 8	.05	.72***	.53**	.62***	.57***	.64***	.54**	.64***	.69***	---

Note: *p < .05, **p < .01, ***p < .001.

Table 2. Univariate PEP Model Fit Comparisons

|	χ^2	df	RMSEA	CFI	TLI	AIC	BIC
1. No Change	152.049	41	< 0.001	0.913	0.940	9074.667	9084.440
2. Constant Change	100.005	38	0.001	0.951	0.964	9028.623	9048.168
3. Proportional Change	129.701	40	< 0.001	0.929	0.951	9054.319	9067.349
4. Dual Change	90.307	37	0.005	0.958	0.968	9020.925	9043.728
Nested Comparisons			$\Delta\chi^2$		Δdf		p
Constant Change to Dual Change			9.698		1		< .001
Proportional Change to Dual Change			39.394		3		< .001

Note: RMSEA = Root Mean Square Error of Approximation, CFI = Comparative Fit Index, TLI = Tucker Lewis Index, AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion

Table 3. Univariate RSA Model Fit Comparisons

	χ^2	Df	RMSEA	CFI	TLI	AIC	BIC
No Change	144.844	41	< 0.001	0.922	0.946	3639.911	3649.745
Constant Change	122.778	38	< 0.001	0.936	0.953	3623.845	3643.514
Proportional Change	141.437	40	< 0.001	0.923	0.946	3638.504	3651.616
Dual Change	123.384	38	0.001	0.954	0.964	3624.450	3644.119

| Nested Comparisons	$\Delta\chi^2$			Δdf			p
Constant Change to Dual Change	0.606			1			.493
Proportional Change to Dual Change	18.053			2			< .001

Note: RMSEA = Root Mean Square Error of Approximation, CFI = Comparative Fit Index, TLI = Tucker Lewis Index, AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion

Table 4. Bivariate Model Fit Comparisons

	χ^2	df	RMSEA	CFI	TLI	AIC	BIC
1. Uncoupled	281.646	134	0.001	0.934	0.949	12660.014	12719.112
2. Unidirectional PEP Influence	271.475	132	0.001	0.946	0.951	12653.842	12719.507
3. Unidirectional RSA Influence	281.253	133	0.005	0.943	0.948	12656.816	12719.197
4. Bidirectional Coupling	270.467	131	0.001	0.946	0.951	12654.835	12723.783

Nested Comparisons	$\Delta\chi^2$	Δdf	p
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

Note: RMSEA = Root Mean Square Error of Approximation, CFI = Comparative Fit Index, TLI = Tucker Lewis Index, AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion

Figure 1. Haystack Plot of Univariate PEP trajectories
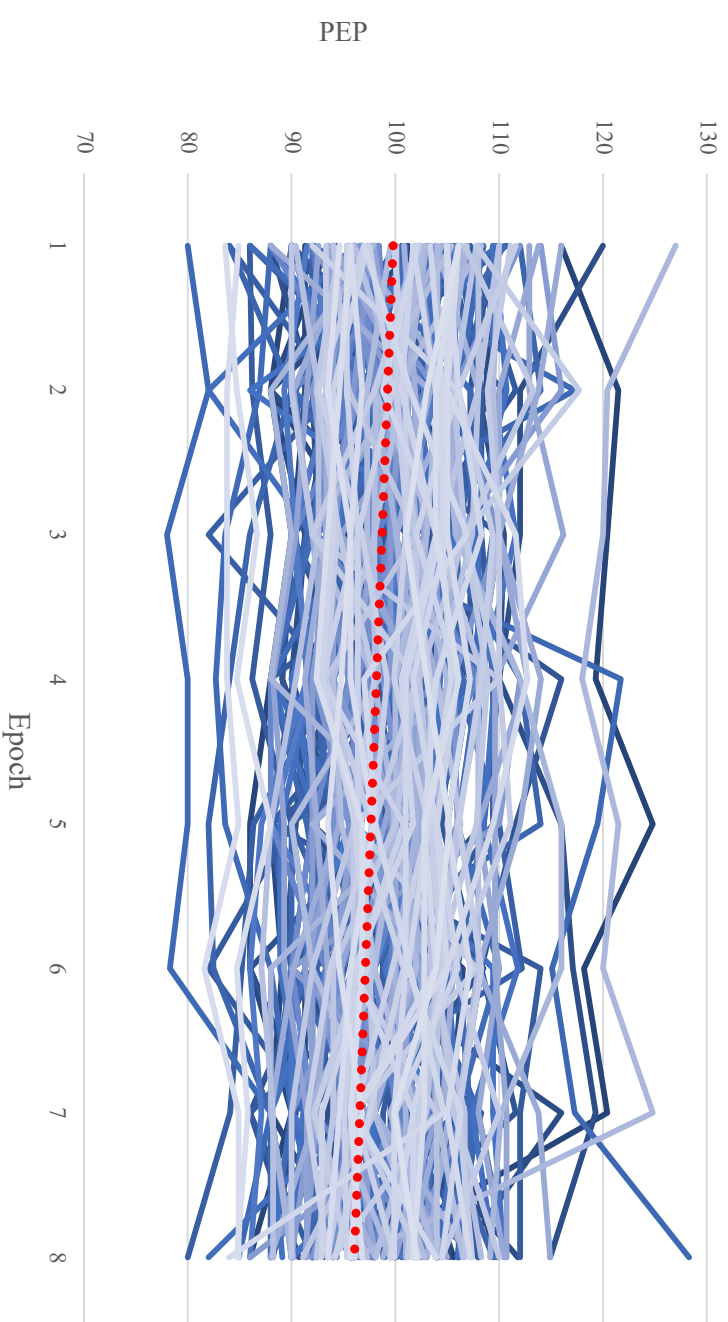
Note: Raw individual trajectories of PEP values over the either 30-second epoch challenging puzzle task.

Figure 2. Haystack Plot of Univariate RSA trajectories
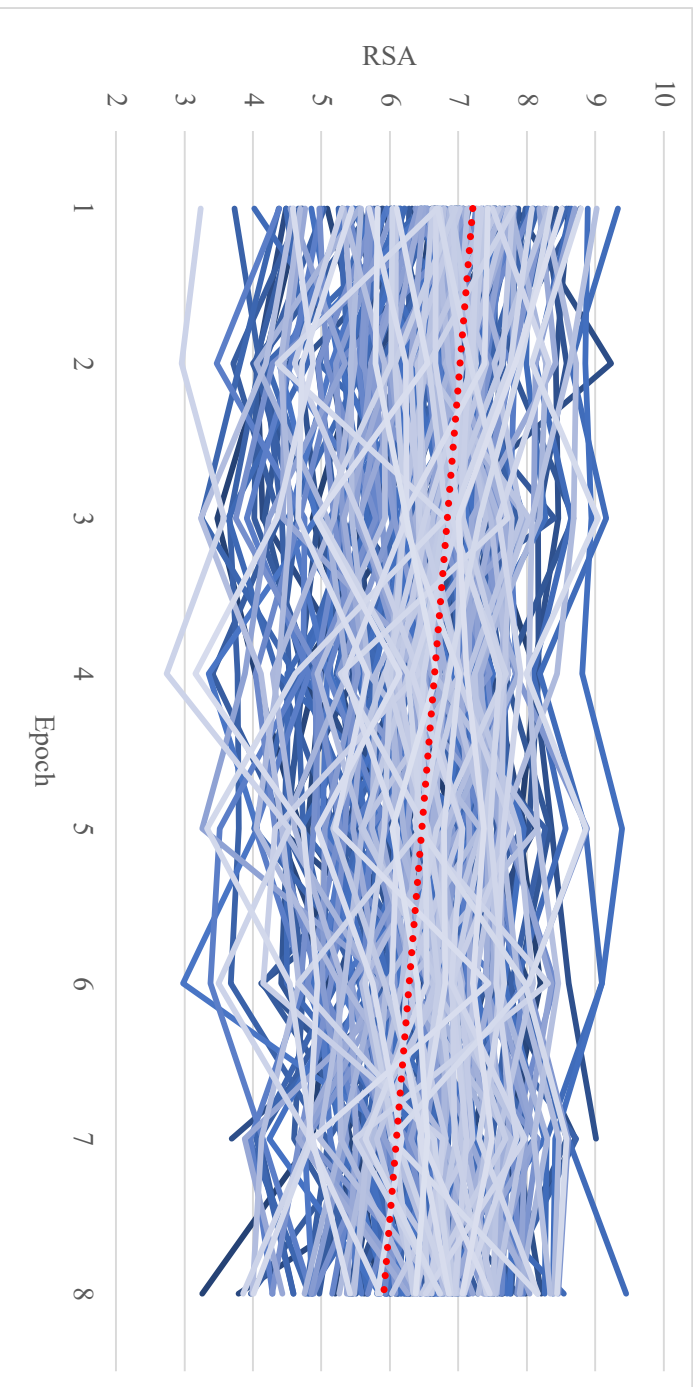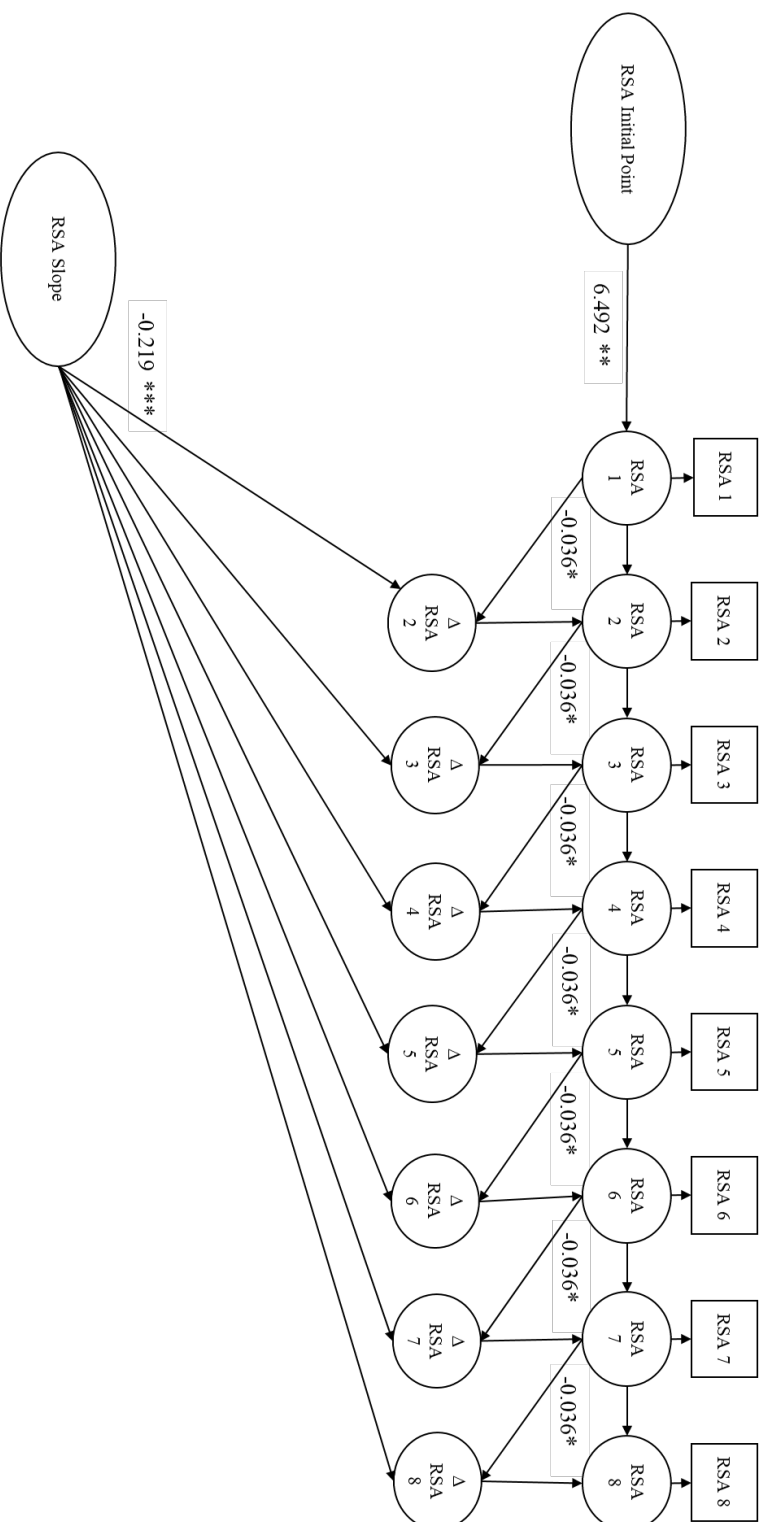

Note: Raw individual trajectories of RSA values over the either 30-second epoch challenging puzzle task.
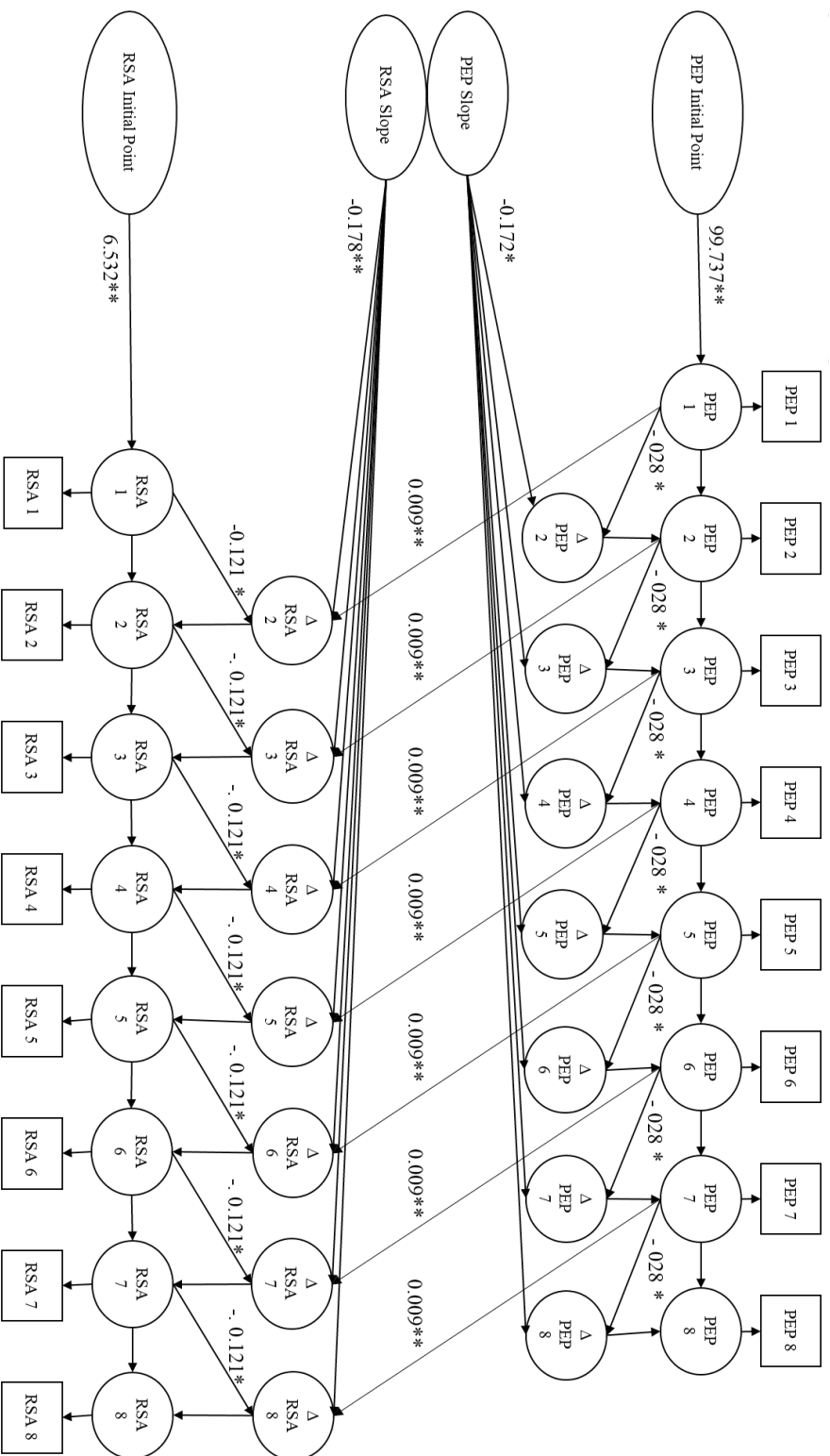
Figure 3. Univariate PEP Dual Change Model
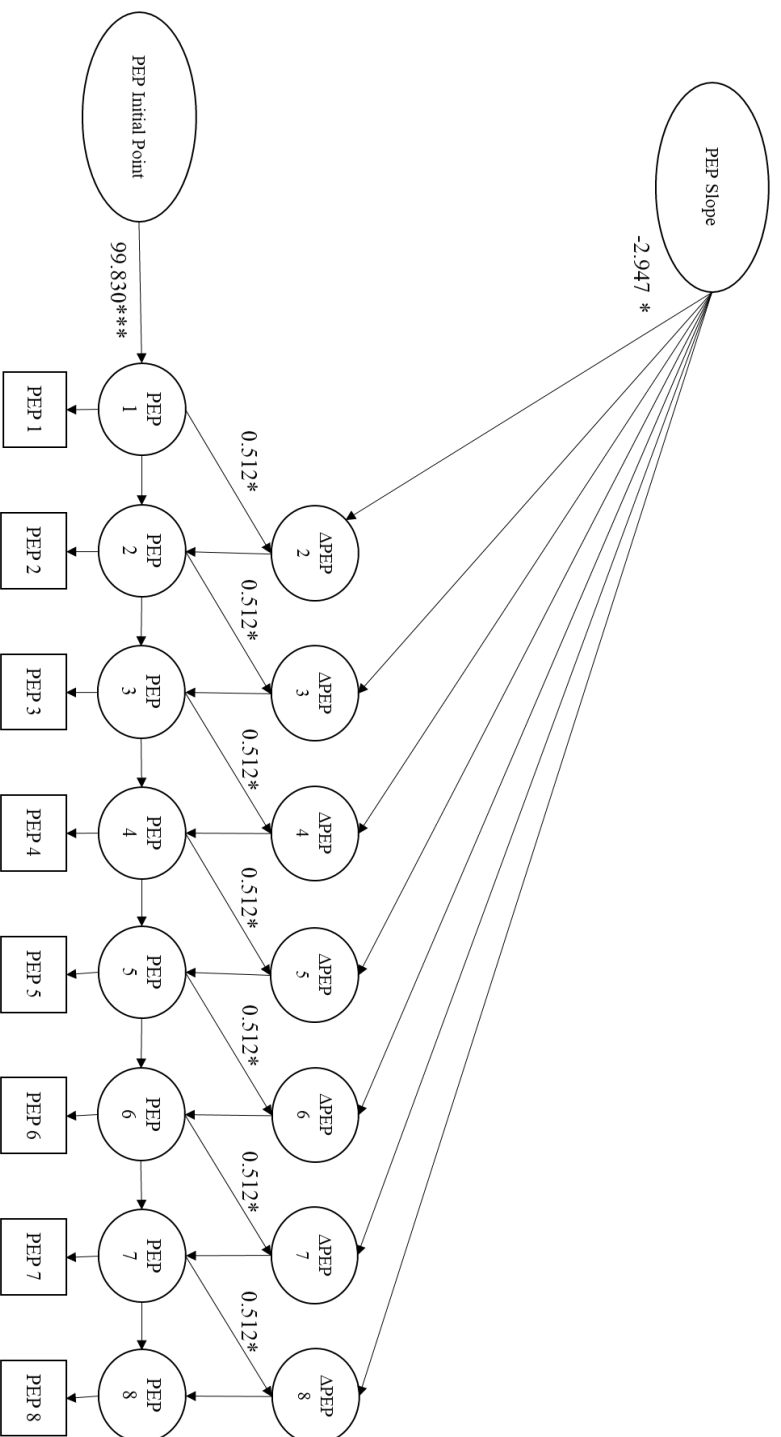
Note. Linear change coefficients, variances, and covariances are not presented for clarity. * $p < .05$, ** $p < .01$ *** $p < .001$.

Figure 4. Univariate PEP Dual Change Model

Note. Linear change coefficients, variances, and covariances are not presented for clarity. * $p < .05$, ** $p < .01$ *** $p < .001$.

Figure 5. Bivariate Dual Change Model

Note. Linear change coefficients, variances, and covariances are not presented for clarity. $* p < .05$, $** p < .01$ $*** p < .001$

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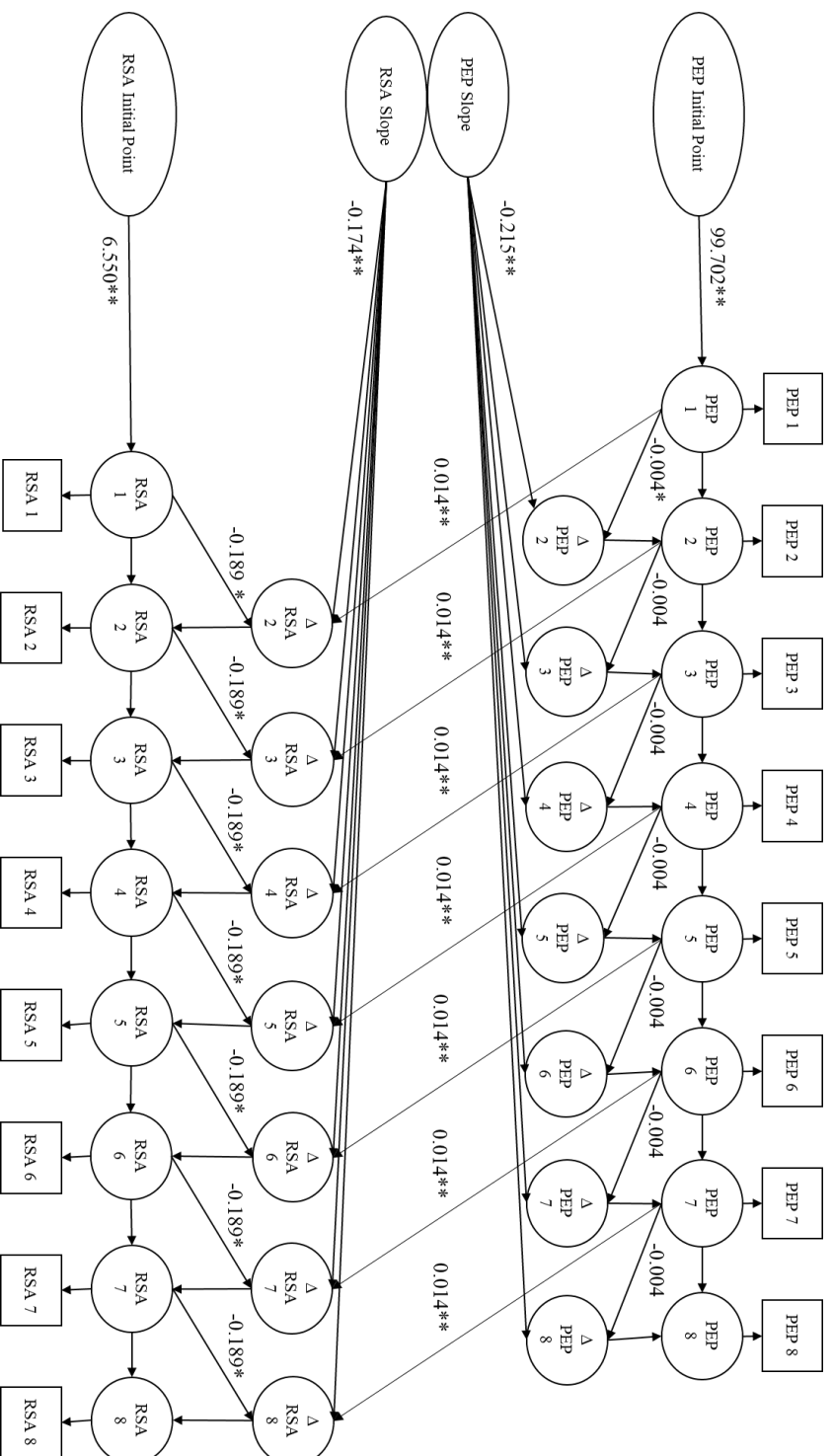Wechsler, D. (2002). WPPSI-III technical and interpretive manual. *The Psychological Corporation*.

Appendix A

Table 5. Alternate Bivariate Model Fit Comparisons with Covariates

	χ^2	df	RMSEA	CFI	TLI	AIC	BIC
1. No Coupling	629.265	165	.000	.844	.855	14634.255	14713.173
2. Unidirectional PEP Influence	615.265	163	.000	.848	.857	14624.255	14709.750
3. Unidirectional RSA Influence	628.091	164	.000	.844	.854	14635.081	14717.288
4. Bidirectional Coupling	614.797	162	.000	.847	.856	14625.787	14714.571

Nested Comparisons	$\Delta \chi^2$	df	p
No coupling to Unidirectional PEP	14.000	2	.0009
No coupling to Unidirectional RSA	1.174	1	.278
Unidirectional PEP to Bidirectional	0.468	1	.493
Unidirectional RSA to Bidirectional	13.294	2	.001

Note: RMSEA = Root Mean Square Error of Approximation, CFI = Comparative Fit Index, TLI = Tucker Lewis Index,
AIC = Akaike Information Criterion, BIC = Bayesian Information Criterion

Figure 5. Alternate Bivariate Dual Change Model

Note. Linear change coefficients, variances, and covariances are not presented for clarity. * $p < .05$, ** $p < .01$ *** $p < .001$.