THE ROLE OF PARENT-CHILD INTERACTION THERAPY IN MODIFYING CHILDREN'S NEURAL PROFILES: A RESTING EEG STUDY OF CHILDREN'S RESPONSE TO EXPERIENCE

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Title: The role of Parent-Child Interaction Therapy in Modifying Children's Neural Profiles: A Resting EEG Study of Children's Response to Experience

The neural networks responsible for coordinating top-down self-regulatory processes, or executive functions, undergo intense fine-tuning and reorganization in early childhood. For children faced with prolonged stress (e.g., chaotic household environment, uncertainty) or adversity (e.g., poverty, maltreatment), these executive function processes are sculpted to aid in retaining information about threats to well-being, which may be protective short-term, but can become particularly maladaptive over time. Interventions that modify the caregiving environment have been shown to buffer the effects of adversity on children's neural development. Parent-Child Interaction Therapy (PCIT) is one such intervention that has been shown to improve both parenting behavior and child outcomes in meta-analyses and is one of the only interventions evidenced to reduce child maltreatment recidivism. The present study sought to evaluate the effects of PCIT on 3-8-year-old children's theta/beta ratio, a neural marker of attention regulation as measured by electroencephalogram (EEG). Next, this study sought to examine whether individual differences in parenting changes across the PCIT intervention were related to children's theta/beta ratio, for the PCIT group only.

Data for this dissertation were drawn from a randomized control trial investigating the biobehavioral mechanisms of change in parent and child self-regulation skills as a result of PCIT for child-welfare involved families (NIDA R01 036533; PIs: Skowron & Fisher). 204 parent-child dyads with a history of child welfare involvement were referred into the study by the local Lane County Department of Human Services and randomized to PCIT or services-as-usual control conditions. The hypothesis that adversity-exposed children in PCIT would show lower theta/beta ratios, indicative of better attention regulation, after accounting for psychosocial risk, was supported for the eyes-closed but not the eyes-open condition. The hypothesis that individual differences in parenting skill change in PCIT group would be associated with children's post-treatment theta/beta ratio was not supported. Taken together, this study fills a valuable gap in understanding whether parenting intervention, namely PCIT, can modify children's neural markers of attention regulation after accounting for early adversity exposure.

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Nekkanti, A.K., Parsafar, P., & Davis, E. L. (2016). The effects of mindfulness meditation on adolescents' stress management. *UC Riverside Undergraduate Research Journal, X,* 49-54. https://se.ucr.edu/sites/g/files/rcwecm586/files/2019-04/VOL%20X_0.pdf

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I. BACKGROUND AND SIGNIFICANCE

Adversity in Early Childhood Dramatically Impacts Children's Development

Children's developmental trajectories are shaped by both experience-expectant and experience-dependent processes in infancy and early childhood (Gabard-Durnam & McLaughlin, 2019). Namely, the neural networks responsible for coordinating top-down self-regulatory processes (orbitofrontal cortex and its relations with the amygdala and anterior cingulate cortex) undergo intense fine-tuning and reorganization of network connections in response to contextual input (Abraham et al., 2010; Diamond, 2006; Gilmore et al., 2018; Lyall et al., 2015). These top-down cognitive processes, commonly termed executive functions (EF), are implicated in working memory, inhibitory control, stress responsivity, and attentional flexibility (Miller & Cohen, 2001; Ochsner & Gross, 2008; Stuss & Alexander, 2000). Adaptive development of such executive functions in early childhood is critical for children's growing capacity for self-regulation, socio-emotional competence, and academic success (Blair & Razza, 2007; Rhoades et al., 2009; Shonkoff & Phillips, 2000).

Executive functioning processes allow children to 1) flexibly choose their behavior based on internal representations of working memory and to 2) inhibit dominant maladaptive behaviors in exchange for adaptive self-regulatory behaviors (Bryck & Fisher, 2012). Examples of such processes that are critical for success in school and other settings include: holding instructions in mind while completing a task, waiting for one's turn, and problem-solving to achieve a goal. For children faced with prolonged stress (e.g., chaotic household environment, uncertainty) or adversity (e.g., poverty, maltreatment), these processes are sculpted to aid in retaining information about threats to well-being, often resulting in greater vigilance and reactivity (Loman & Gunnar, 2010; Roth et al., 2009; Szyf, 2009). Though such changes in stress-responsivity may be protective short-term, they can become particularly maladaptive over time for other social situations (e.g., school, peer relationships). Long-term, children with poor executive function abilities are at greater risk for oppositional disorders, learning problems, and development of psychopathology (Cicchetti & Toth, 2005; Diamond, 2012).

The ways in which experiences of early adversity impact children's development isn't always straightforward. Variations in the types of enrichment provided across childhood (e.g., affective, cognitive) interact uniquely with the child's genetic makeup and contextual experience to elicit markedly different neural profiles, executive function capacities, and stress response patterns (King et al., 2019; Shields et al., 2016). Enrichment, in the form of greater parental sensitivity has been shown to promote children's neural maturation and normalize diurnal cortisol rhythms (Bernard et al., 2015; Bick et al., 2019). Enrichment in the form of educational input and increased resources, on the other hand, has been associated with greater attention regulation and adaptive neural profiles (Raine et al., 2001). In contrast, sustained levels of high stress and adversity are associated with overactivity of the amygdala and orbitofrontal cortex, and greater loss of neural connections in the hippocampus and medial prefrontal cortex, which often manifest as anxiety, impaired memory, poor mood control, and challenges for learning new skills (Coley et al., 2015; Deater-Deckard et al., 2010; Johnson et al., 2016; McEwen & Gianaros, 2011; Shonkoff et al., 2012). A recent study shows that higher chronic maternal stress is associated with increased low-frequency brain activity (i.e., higher theta power) and decreased high-frequency brain activity (i.e., less alpha and beta power) in children, suggestive of maturational lags in development (Troller-Renfree et al., 2020) As such, children raised in high-stress or low-resource environments are at disproportionately higher risk for developing regulatory patterns that put them at a disadvantage for school and settings with expectations that may differ from home. Learned behavior patterns that may be effective or acceptable in a high-risk home context can disrupt the child's external relationships (e.g., peers, teachers; Dodge et al., 1990), and put them at further risk for deviant developmental trajectories well into adolescence and adulthood (Blair & Raver, 2012; Moylan et al., 2010).

Developmental psychobiology models (e.g., experiential canalization model; ecobiodevelopmental framework) argue that early intervention targeting reductions in environmental chaos, threat, and inconsistency, and improvements in caregiving capacities can have drastic impacts on children's physiological development and overall well-being by buffering the effects of early adversity (Blair & Raver, 2012; Shonkoff et al., 2012). Early adversity, such as poverty and environmental chaos, undoubtedly impacts quality of caregiving as parents are put under significantly greater parenting stress (Huth-Bocks & Hughes, 2008). While post-birth reductions in maternal sensitivity have been found to further exacerbate any adverse effects of early stress on children's brain development (Wang et al., 2019) and executive functioning abilities (Evans et al., 2005; Repetti et al., 2002), interventions that improve parent sensitivity have been shown to buffer the effects of early life stress on children's stress-response physiology (Dozier et al., 2008; Fisher et al., 2006). In this study, I aim to build on this existing research to test whether an intervention that supports contingent, sensitive caregiving amidst the presence of chronic stressors may promote more adaptive development of children's brain activity. Intrinsic neural activity, such as what is captured by resting-state electroencephalogram (EEG), reflects how various parts of the brain communicate with each other and ultimately drive behaviors. For example, resting neural activity in the frontal lobe can provide an understanding of what patterns of electrical impulses in the brain might be driving poor inhibitory control or attention regulation.

Children's Intrinsic Neural Activity May be Particularly Susceptible to Early Experience

Resting EEG, hereby referred to as rsEEG, captures synchronized neural activation patterns while an individual is at rest (i.e., not engaged in any particular task requiring a response). These activation patterns are highly complex and occur at multiple underlying base frequencies simultaneously. Each of these base frequencies, or bands, vary slightly based on individual and contextual factors but can be classified as follows from low to high: theta (4-8 Hz), alpha (8-13 Hz), beta (13-30 Hz), and gamma (30-50 Hz). The power within each of these bands reflects the amount of energy in that band; higher power is reflective of more neurons firing synchronously. RsEEG studies of band power in children thus capture rapidly changing alterations in children's neural activity, often grouped by region (e.g., frontal), with keen sensitivity to individual differences.

Theta

Through development in early childhood, children are expected to display decreases in low-frequency rhythms such as theta, and increases in higher frequency rhythms such as alpha and beta (Matousek et al., 1973). Of course, these expected trajectories have been observed primarily in children who are raised in contexts free from severe adversity. From infancy to age 2, high levels of theta at rest are argued to be a marker of greater plasticity, or in other words, greater susceptibility to neural changes as a function of environmental input (Stroganova & Orekhova, 2007). In the first couple years of life, this enhanced/greater plasticity enables rapid reorganization of neural patterns in response to the presence or absence of various contextual inputs. In this way, plasticity promotes development in ways that enable the child to adapt to their immediate environment (e.g., greater vigilance in high-threat environments), but may or may not be adaptive long term. Over time as the brain matures, theta power, and concurrently brain plasticity, is expected to decrease (Matousek et al., 1973). Children who display sustained high levels of theta however, tend to also present with difficulties learning and regulating attention (Barry et al., 2003; Clarke et al., 2002; Snyder & Hall, 2006). Research has linked sustained high levels of theta to maturational lags in cortical development (Corning et al., 1982; Matsuura et al., 1993), and more recently linked difficulties in attention regulation with a developmental lag in the maturation of ventral fronto-subcortical circuitry (Liechti et al., 2013; Shaw at al., 2007). Similar findings are present in adult samples, where theta oscillations are associated with working memory and decision making (Jacobs et al., 2006), such that high theta power indicates difficulties with executive functioning and regulation.

Alpha

Alpha frequency is expected to increase over the course of development (Marshall et al., 2002; Matousek et al., 1973; Miskovic et al., 2015; Perone et al., 2017) and is typically associated with active inhibition or "turning off" of brain networks that are not needed for task-based control or alertness in resting tasks (Coste et al., 2011). In infants, high frontal resting alpha has been associated with a greater ability to engage working memory and inhibitory control processes as measured by the Piagetian A-not-B task (Bell & Fox, 1992). High alpha in early childhood has been associated with better executive functioning abilities in later childhood (Cuevas et al., 2012). Recall that adaptive development that promotes better executive functioning is marked by decreasing theta (4-8 Hz) with increasing age and increasing alpha (8-13 Hz) with increasing age. Recent research has demonstrated that children with difficulties in regulating attention may also have slow alpha with increasing age (Arns et al., 2008; Chabot & Serfontein,1996) Importantly, research that uses fixed frequency ranges for alpha and theta bands may result in erroneous findings of high theta power related to executive functioning, when actually capturing power of slow alpha frequency (Arns et al., 2008; Lansbergen et al., 2011).

Beta

Higher gvbb beta power during rest is indicative of attentional arousal and concentration in children (Loo & Makeig, 2012), while excessive levels of beta power in the frontal region have been associated with temper tantrums and moodiness (Clarke et al., 2001). Similar to alpha power, beta power is expected to increase slightly as a function of age for adaptive development that promotes better executive functioning.

Theta/Beta Ratio

Overall neural profiles comprised of excess power in low-frequency bands (e.g., theta) and deficits in power for high-frequency bands (e.g., alpha, beta) have been associated with learning disorders and difficulties with attention regulation in children (Barry et al., 2003; Chabot et al., 2001). The theta/beta ratio is one such neural profile comprised of excessive theta activity and concomitant reductions in beta activity over the frontocentral scalp. A high theta/beta ratio has been conceptualized to mark poor regulation of bottom-up processes by top down processes (e.g., executive functions; Putman et al., 2014) in both children and adults. Recall however, that slow alpha can sometimes inflate theta, resulting in an artificially higher theta/beta ratio. This phenomenon has led to some mixed findings on the validity of theta/beta ratio in capturing attention processes (Loo et al., 2016). Recent research has found that after accounting for individual differences in alpha frequency, the theta/beta ratio is indeed a reliable marker of executive function in children (Perone et al., 2018). In adults, a lower theta/beta ratio has similarly been associated with better executive functioning, while a higher theta/beta ratio has been associated with risk taking (Massar et al., 2014; Schutter & Van Honk, 2005), less inhibited responses to fearful faces (Putman et al., 2010), and ADHD diagnoses (Loo et al., 2013). In children, this profile has been validated as a robust diagnostic marker of ADHD (effect size = 3.08; Snyder & Hall, 2006) and shown to be highly stable over time (Monastra et al., 2001). Studies examining neurofeedback training have often focused on training individuals to lower their theta/beta ratio (Egner & Gruzelier, 2004; Kouijzer et al., 2009; Wangler et al., 2011) via direct feedback on particular aspects of their EEG signal, in order to improve self-regulation in children and adults. Recent work by Clarke et al. (2019) found the theta/beta ratio to be associated with P300 latency but not P300 amplitude (components of event-related potentials), solidifying previous findings that the theta/beta ratio is truly capturing cognitive processing capacity (i.e., executive function) rather than context-dependent arousal (Barry et al., 2009).

Consistent with research relating early adverse experiences with difficulties with attention and executive function (Teicher et al., 2016), higher theta/beta profiles have been observed in children exposed to high levels of psychosocial risk (Marshall et al., 2004), and mediate the negative association of institutionalization on later ADHD diagnoses (McLaughlin et al., 2010). Though the theta/beta ratio was not measured outright in the Buchacrest Early Intervention Project, higher levels of theta and lower levels of beta have been observed in institutionalized children, relative to never institutionalized children (Marshall et al., 2004). On a less severe scale and similarly not measured outright, recent research demonstrates higher early home adversity (Bick et al., 2019), and higher maternal stress (Troller-Renfree et al., 2020) in early childhood is associated with greater power in theta, and lower power in higher frequency bands such as alpha and beta. These findings are consistent with the neural profile described above: high theta, slow alpha, and low beta are each associated with poor executive function capacity in early childhood.

Resting EEG methodologies are especially versatile in assessing neural activity in young children who may have difficulty laying still as in a functional magnetic resonance imaging scanner or staying focused for extended periods of time as in task-based methods. Despite this versatility and clear understanding of rsEEG methods' sensitivity to capture individual differences in early experience, there exists a limited understanding of how intervention can improve children's neural trajectories. Preventative interventions that alter the theta/beta ratio in children faced with early adversity may improve trajectories of well-being by directly altering neural markers related to executive function capacities during a critical developmental period.

Intervention in Early Childhood Can Change Frontal Neural Activity

Burgeoning evidence shows that parenting interventions that alter the immediate caregiving environment during early childhood can promote adaptive neural profiles. Few studies have been conducted with typically developing populations. Mothers who showed more positive affect during parent-child interactions had children with more rapidly increasing frontal alpha power up to 24-months in typically developing children (Bernier et al., 2016). Raine and colleagues (2001) tested the effects of early educational and health enrichment at 3-5 years-old, on children's attention regulation at 11 years-old. The intervention was delivered in a nursery school setting and included: preschool education, nutrition education, nutritional meals, physical exercise, health screening and referral, parental involvement, remediation of learning and behavior problems, and home visits. When children were 11 years old, those who participated in the nursery intervention displayed lower theta power during both rest and attention tasks, but showed no significant differences in alpha or beta bands (Raine et al., 2001). EEG was assessed at only a single time-point, so interpretation of longitudinal effects is not possible.

Further up the risk spectrum, Bick and colleagues (2019) studied a sample of children who were referred to Child Protective Services for concerns of child maltreatment. In this study, children who participated in the Attachment and Biobehavioral Catchup intervention at 3 years-old displayed greater high-frequency power (beta, 12–20 Hz) when assessed later at 8 years old, than children assigned to the control intervention (Bick et al., 2019). In this study, EEG was measured at a single time point at the age 8 follow-up, so like the study by Raine and colleagues (2001), interpretation of longitudinal effects is not possible. Further research that examines longitudinal neural responses to caregiving intervention is warranted.

At the extreme end of the risk spectrum are studies of resting EEG from the Bucharest Early Intervention Project (BEIP), in which children were faced with extreme neglect and abuse during institutionalization (Marshall et al., 2004). The first resting EEG study with this sample was conducted with infants and young children between 5 and 31 months, and examined power in the alpha, theta, and beta bands during an eyes-open resting condition (Marshall et al., 2004). Results indicated significant group effects for absolute power in all bands such that institutionalized children displayed greater theta power, lower overall alpha power, and lower beta power relative to the never-institutionalized group. Institutionalized children displayed significantly greater relative theta power and lower relative alpha power, but no differences in relative beta power. Importantly, relative power accounts for differences in head circumference and weight which may have impacted findings. A follow-up study conducted in 2008 examined whether age of placement in a foster care intervention relative to institutionalized care was associated with EEG power at 42 months of age in the eyes-open condition (Marshall et al., 2008). Findings showed that children who were placed in foster care intervention before 24 months of age had higher levels of alpha power compared to those who were placed in the intervention after 24 months of age. Next, a longitudinal study conducted with the same participants with data points at baseline, 30-33 months, 42 months, and 96 months (8 years) examined oscillation frequency, amplitude, and cross-frequency coupling during an eyes-closed resting condition (Stamoulis et al., 2015). Overall, findings reflected significant group differences in all three components of resting EEG such that children placed in the foster care intervention following institutionalization displayed neural profiles similar to those in the never-institutionalized group reflective of decreased risk for neuropsychiatric disorders and better cognitive ability. Findings specific to trajectories of power showed that children placed into the foster care intervention by 2 years old displayed greater alpha and beta power until 42 months, but not at 8-years. A separate study examined how foster-care placement impacted band power at 8-years of age in the eyes-open condition (Vanderwert et al., 2010). Unlike Stamoulis et al., that found no differences in alpha power in the eyes-open task at 8-years, Vanderwert and colleagues (2010) found that children who were placed in foster-care before 2 years of age showed improvements in alpha power comparable to children who had never been institutionalized. In the latest study of the Bucharest sample, Vanderwert and colleagues (2016) examined relative power between the 8-year and 12-year assessments in the eyes-open resting condition. Overall, findings showed that children placed in the foster care intervention (relative to those who remained in institutions) displayed decreases in theta power and increases in alpha power, but no changes in beta power. Recall that this profile of decreased theta power and increased alpha power is indicative of developmentally appropriate maturation and is associated with adaptive executive function capacities.

To date, our causal understanding of how caregiving environments can impact children's resting neural activity following adversity depends largely on studies of children who are faced with immense psychosocial deprivation and atypical institutional rearing. Though the BEIP study provides causal evidence for the impacts of caregiving enrichment on children's attachments, cognitive functioning and psychopathology

(Almas et al., 2016; Humphreys et al., 2015; Smyke et al., 2010), in addition to resting EEG profiles, there remains a large gap in understanding whether such findings generalize to samples with greater variation in types of adversity exposures (e.g., poverty; interpersonal violence; and child maltreatment). While the Bick and colleagues' (2019) study examined band power in children referred to Child Protective Services, rsEEG was only collected at one time point following completion of the caregiving intervention.

Further, each of the rsEEG intervention studies to date vary by resting condition. Recall that in previous work examining associations between the Attachment and Biobehavioral Catchup intervention and rsEEG in children at 8 years-old, band power was averaged across both eyes-open and eyes-closed tasks (Bick et al., 2019). Alternatively in studies of the Bucharest Early Intervention Project, rsEEG was collected across both eyes-closed and eyes-open tasks, but it was analyzed primarily in the eyes-open condition (Marshall et al., 2004; Marshall et al., 2008; Vanderwert et al., 2010; Vanderwart et al., 2016), with one study choosing to focus primarily on the eyes-closed condition (Stamoulis et al., 2015). Recent research highlights significant differences in observed band power from 3 to 9 years of age, across eyes-closed and eyes-open conditions (Perone et al., 2018). Alpha and theta were found to be generally higher when eyes were closed, while beta was found to be higher when eyes were open. Theta/beta ratio after accounting for individual alpha frequency was also found to be higher in eyes-closed conditions, relative to eyes-open conditions. Taken together, these findings suggest that eyes-closed and eyes-open conditions may be providing different information about attention regulation and top-down processes.

The first aim of this dissertation will address these gaps by testing the effects of an intensive parenting intervention (i.e., PCIT) on pre-post changes in children's resting theta/beta ratio following variable exposure to early adversity, relative to a services-as-usual control group in both eyes-closed and eyes-open resting conditions. Early adversity in this sample includes: child-welfare involvement, adverse early experiences, and socioeconomic disadvantage. My primary hypothesis is that children in the PCIT group will show more adaptive neural profiles (i.e., lower theta/beta ratio, anchored to individual alpha frequency) relative to the control group, after accounting for early adversity.

Parent-Child Interaction Therapy May Impact Children's Neural Activity

The caregiving environment interacts with the child's genetic make-up and sociocultural context to influence a transactional pattern of behavior and self-regulation (Skowron & Funderburk, 2021). Contingent intervention that disrupts this interaction, especially in the case of maladaptive caregiving processes, can directly influence the child's development. Founded from social learning and developmental-organizational theories, Parent-Child Interaction Therapy (PCIT) has been shown to improve both parenting behavior and child outcomes in meta-analyses (Thomas et al., 2017), and is one of the only interventions evidenced to reduce child maltreatment recidivism (Chaffin et al., 2004; Chaffin et al., 2011; Thomas & Zimmer-Gembeck, 2011). That is, PCIT is one of the few interventions to prevent parents who have a history of physically abusing their children from re-entering the child-welfare system. Since originally being developed for treating disruptive child behaviors such as tantrums and externalizing behavior (e.g., Eyberg, 1995) PCIT has been used as an effective treatment for ADHD (Wagner &

McNeil, 2008), behavioral adjustment (Chaffin et al., 2004), internalizing symptoms (Carpenter et al., 2014), and for parents with caregiving difficulties in the absence of child behavior problems (Herschell & McNeil, 2005).

A meta-analysis by Kaminski et al., (2008) identified four components of parenting programs that successfully reduce children's externalizing symptoms with large effect sizes: 1) positive interactions with child, 2) use of time out procedures, 3) consistent responding, and 4) skills practice with own child. PCIT utilizes each of these components throughout treatment and can help parents develop new caregiving skills, adopt effective discipline strategies that replace negative practices, and engage in more consistent, sensitive interactions with their child. The live coaching component of PCIT in which therapists provide parents with in-the-moment coaching to redirect attention, regulate emotion, and implement positive PCIT skills allows for immediate disruption of coercive cycles (Skowron & Funderburk,2021; Nekkanti et al., 2020).

The first phase of treatment, child-directed interaction, focuses on enhancing parental sensitivity and responsiveness to foster greater warmth, responsiveness and nurturing in the parent-child relationship (Herschell & McNeil, 2005; Urquiza & McNeil, 1996). Parents are guided to purposefully orient their attention to children's positive behavior (e.g., waiting for their turn) by narrating their actions (i.e., behavior descriptions), active listening (i.e., reflections), or providing enthusiastic praise (i.e., labelled praises). Describing children's behavior and reflecting their verbalizations during play each build parent responsiveness by encouraging consistent positive interaction with the child's behaviors. Use of specific, directed praise during play reinforces child behaviors that are positive or expected, thus encouraging behavior regulation (i.e., refraining from behavior that does not elicit praise). That is, parents learn how to notice children's behavior patterns and either describe or praise behaviors that are neutral or positive. This process of drawing the child's attention to the task at hand through parent verbalizations is thought to improve children's ability to slow distracting thoughts and focus on the task at hand. At the same time, parents are coached to avoid negative behaviors or those that interfere with children's lead during play. Specifically, parents are coached to refrain from using criticism, asking questions, or making commands during child directed play (e.g., move the block). Previous work by Hakman and colleagues (2009) demonstrates that the most rapid improvements in positive parenting skills and reduction in negative parenting skills for parents with a history of perpetrating physical abuse happens during the first three sessions of this child-directed interaction phase of PCIT.

The second phase of PCIT, Parent-Directed Interaction, focuses on training parents to use clear, consistent, and safe child management techniques. Parents are coached to utilize a contingent sequence of warnings, time-out, and praise for disruptive behavior. Such a scripted, consistent discipline protocol is thought to reduce parent stress and increase consistency and predictability in the child's environment. All behaviors taught and coached across both child-directed and parent-directed phases of treatment are further reinforced by brief homework to complete between weekly sessions.

Whether intervention such as PCIT that enhances positive parenting and reduces maladaptive parenting using live, remote coaching techniques can yield linked improvements in children's neural development is largely unknown. The second aim of this project will test whether trajectories of session-by-session improvements in positive skills and reductions in negative skills, assessed at study entry, during the child-directed phase of PCIT at mid-treatment and post-treatment, account for differences in children's neural development. Specifically, I will examine how over time change in parenting skills that draw children's attention to the present moment (behavior descriptions, reflections) and encourage sustained positive child behavior (direct labeled praise), and harsh control parenting contribute to the variation in children's theta/beta profile change from pre- to post-treatment. I predict that greater growth in PCIT-driven improvements in warm, responsive parenting and reductions in negative parenting will account for lower theta/beta ratio in children's resting brain activity, indicative better top-down attention regulation.

Study Aims

This study is designed to evaluate the effects of PCIT on adversity-exposed children's resting brain activity, relative to a services-as-usual control condition. The primary aims of this dissertation are as follows:

Aim 1: Test the effects of PCIT on children's resting theta/beta ratio, a neural marker of attention regulation, relative to family services-as-usual controls.

Hypothesis: Children randomized to the PCIT intervention will show lower theta/beta ratios, reflective of better attention regulation, compared to the control group.

Aim 2: Test whether differences in children's resting neural profiles are predicted by trajectories of inter-individual change in session-by-session parenting skills in the PCIT group.

> *Hypothesis 1:* Trajectories of growth in positive parenting skills and reduction in negative parenting skills predict children's theta/beta ratio at post-treatment, such that steeper growth in parenting skills is predictive of better attention regulation as marked by theta/beta.

A deeper understanding of how an intervention that targets parent-child interactions is related to changes in children's intrinsic neural activity can help researchers further evaluate the extent to which deviant developmental trajectories are preventable.

II. METHODS

Sample

Data were drawn from a randomized control trial investigating the biobehavioral mechanisms of change in parent and child self-regulation skills as a result of PCIT for child-welfare involved families (NIDA R01 036533; PIs: Skowron & Fisher). Parents and children with a history of child welfare involvement were referred into the study by the local Lane County Department of Human Services. 204 participating parents and their 3 to 8-year-old children completed baseline assessments. 120 dyads were randomized to the PCIT intervention (84 randomized to active control), and 167 total dyads successfully completed the post-intervention assessment. Information regarding child-maltreatment recidivism is collected for all families where possible, though that data collection is ongoing. Caregivers primarily include biological or adoptive mothers ($n_{mothers}$ = 180, $n_{fathers}$ = 24). Family inclusion criteria are: (a) the participating parent was at least 18+ years old at study entry, (b) children participate with their biological or custodial parent; (c) the participating child was between 3 and 8-years-old at study entry; (d) no parent or caregiver in the home was a documented child sexual abuse perpetrator per child welfare records (contraindicated with PCIT), (e) the child was living with their participating parent at least half the time, and (f) the parent provided written informed consent to participate. No group differences were found on children's demographic characteristics (see Table 1).

Table 1
Baseline Characteristics Across Conditions

	Services as Usual (n = 84)	PCIT (n = 120)	PCIT Engagers (n = 79)
Race/ Ethnicity			
European American/ White	93% (78)	93% (112)	94% (74)
Hispanic American / Latinx	13% (11)	17% (20)	18% (14)
African American/ Black	8% (7)	9% (11)	5% (4)
Asian/ Asian American	4% (3)	3% (3)	4% (3)
Pacific Islander	2% (2)	4% (5)	6% (5)
Native American/ Alaskan Aleut	21% (18)	18% (22)	19% (15)
Other	1% (1)	1% (1)	1% (1)
Mean Child age at baseline	4.75 (1.44)	4.70 (1.36)	5.24 (1.48)
Family income below poverty	88% (63)	72% (72)	61% (48)
Parent's marital status			
Married or living together	24% (20)	36% (43)	32% (25)
Single	76% (64)	64% (77)	68% (54)
Child gender			
Male	60% (50)	51.7% (62)	54% (43)
Female	41% (34)	48% (58)	46% (36)

Note. Descriptives come from original data prior to imputation. Frequencies are displayed in parentheses for all variables except child age, for which standard deviation is within parentheses. PCIT Engagers are a subgroup of those randomized to PCIT (n = 120), and include those families that engaged in at least one session of PCIT.

Procedure

Procedures relevant to the present study are described here. Pre-intervention and post-intervention assessments were conducted with all participants in the study (both PCIT and control groups), each wave completed in two successive laboratory visits scheduled one week apart. Mid-treatment assessments were conducted only with PCIT intervention group families, after completion of the first PCIT phase (i.e., child-directed interaction; CDI) and before beginning the second PCIT phase (i.e., parent-directed interaction; PDI). Dyadic interaction tasks are collected during pre-, mid-, and post-intervention assessments, while children's EEG was collected during pre- and post-intervention assessments only. Please see Nekkanti et al., (2020) for a description of the full clinical trial study protocol.

PCIT Intervention

Parent Child Interaction Therapy (PCIT) is an intensive, behavioral parent-training model that uses live coaching of parent–child interactions. It is designed to improve child functioning by interrupting patterns of harsh, coercive interaction and enhancing parents' warm, positive parenting, autonomy support, and competent child management skills. Parents receive live coaching from a therapist who provides immediate prompts via "bug-in-the-ear" technology while the parent interacts with their child, creating opportunities in the moment for parents to adjust their behavior and correct errors on the spot. With the PCIT therapist out of sight, children experience their parent as a critical agent of positive change (Skowron & Funderburk, 2021). Time-limited PCIT is delivered in two sequential treatment phases following a motivational enhancement training tailored to improve attrition with child welfare families. Phase 1, Child-Directed Interaction (CDI) aims to enhance positive parenting and interrupt coercive cycles by coaching parents to let the child lead and use more: labelled praises, behavior descriptions, and reflections, while avoiding use of: criticisms, questions, and commands. Phase 2, Parent-Directed Interaction (PDI) aims to coach effective parent commands within the context of a positive parent-child relationship and establish a consistent time-out protocol to replace parents' negative or ineffective disciplining strategies. The skills taught in CDI are coached as-needed and reinforced in PDI to ensure parents maintain a warm, positive interaction even amidst employing discipline strategies.

Services-as-Usual Control

The family services-as-usual (SAU) control condition is an ethical comparison group in which families receive typically delivered services provided by child welfare agencies. These services include but are not limited to in-home family visitation, parent education training, food benefits (e.g., supplemental nutrition assistance program). Service utilization by all families (including those randomized to PCIT) are collected at post-treatment.

Measures

Resting EEG

Children completed measures of resting EEG at a pre-treatment assessment prior to randomization, and at their post-treatment assessment. All children were fitted with a 64-channel EGI Hydrocel Geodesic Sensor Net (EGI Philips; Eugene, OR) except if the child's cap was too small, whereby a high-density 256-channel net was used (n = 9). EEG was recorded at a sampling rate of 500 Hz with 0.1 Hz high-pass filter and Net Amp

300 amplifier integrated with Net Station software version 5.2.0.2 (EGI Philips; Eugene, OR).

Rest Tasks. After the net was placed, impedance was measured and corrected where possible. Children were then asked to sit in the acquisition room with a trained research assistant (who had greeted them, given them stickers, and assisted in EEG cap placement), with the lights turned off. Research assistants used a standardized script to ensure all participants were provided with the same instructions. Children completed 1-minute alternating eyes-open (EO) and eyes-closed (EC) tasks for a total of 4 minutes. For the eyes-open task, children were instructed to fixate on a blank screen, while the research assistant sat nearby. Previous work has found significant variation in amplitude and frequency depending on the task (Stamoulis et al., 2015; Anderson & Perone, 2018).

Processing and Data Reduction. EEG data were processed using the EEGLAB toolbox (Delorme & Makeig, 2004) in Matlab 9.6.0 (The Mathworks, Inc. EEG data collected across both resting and cognitive tasks were processed together using the following pipeline. Data were filtered using low-pass (50 Hz) and high-pass filters (1 Hz) and resampled to a rate of 250 Hz. The EEGLAB plug-in, *clean_rawdata*, was used to remove major artifacts prior to spherical channel interpolation. Channels were then re-referenced to the average which allows for more consistent comparisons across studies and samples. EEGLAB plug-in, *pop_runica*, was used to conduct infomax independent component analysis across all 64 channels, across all tasks. Data were then epoched into resting eyes-open and eyes-closed tasks. To account for remaining artifacts, the *IClabel* function was used to identify and remove any artifacts sourced from eye or muscle movements. The *pwelch* function was used to calculate the power spectral density (PSD) via a discrete Fourier Transform using 50% overlapping, 2-second Hanning window with a frequency bin of 250 Hz for eyes-open and eyes-closed tasks separately.

Power in theta, alpha, and beta were computed and boundaries for frequency bands were defined based on individual alpha peak frequency (IAF). Anchoring frequency bands to IAFs more accurately captures age-related changes and minimizes the contribution of slow alpha activity to frequency estimates (Lansbergen et al., 2011). Previous research has demonstrated that IAFs are known to increase over the posterior region from infancy to late childhood (Marshall et al., 2002; Miskovic et al., 2015; Perone et al., 2017). IAFs were calculated by identifying the maximum attenuation of power in the 6-13 Hz range from the difference between eyes-open posterior power and eyes-closed posterior power (Arns et al., 2012). Posterior power was calculated from channels 33 to 39. Frequency bands were then anchored to IAFs (Lansbergen et al., 2011; Perone et al., 2017) as follows:

Theta: 0.4*IAF – 0.8*IAF

Beta: 1.2*IAF – 30 Hz

Alpha: 0.8*IAF – 1.2*IAF

Relative power was used instead of absolute power in order to account for developmental differences in skull thickness (Clarke et al., 2001) in our age-varying sample. Relative power was calculated by dividing the power in each frequency band by the total power for each individual. The analyses for this study focused on frontal regions of the brain, including channels: 11, 13, 12, 14, 9, 8, 6, 2, 3, 60, 59, 57 (see Figure 1).

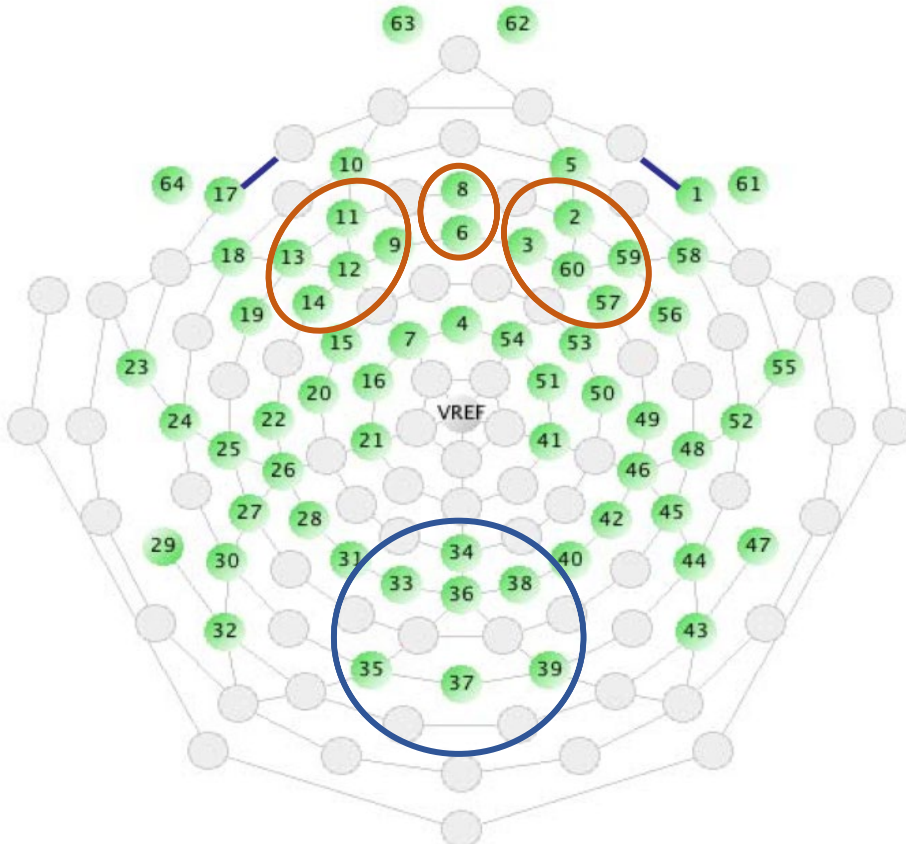

Figure 1. EGI 64-channel Sensor Layout. The EGI 64-channel HydroCel Geodesic Sensor Net is displayed above. Channels circled in orange indicate frontal recording sites for theta/beta ratios. Channels circled in blue indicate recording sites for posterior alpha. The electrode map displayed here is used with written permission from Electrical Geodesics, Inc. (EGI; Eugene, OR, USA).

Psychosocial Risk Factors

Adverse Childhood Experiences. Parents reported on their child's exposure to adverse childhood experiences (ACES; Adverse Childhood Experiences Scale; Felitti et al., 1998) at their pre-treatment assessment. Items reflect parental substance abuse, parental divorce, domestic violence exposure, parental incarceration, parental mental health, and abuse. Each item is coded 0 or 1 for the absence or presence of each risk factor, respectively. Items were summed to create a composite risk score ranging from 0 to 12, such that higher scores indicated a greater frequency of experienced risk factors.

Household Chaos. Parents also completed the Confusion, Hubbub, and Order Scale (CHAOS; Matheny et al., 1995) at pre-treatment, a measure of environmental processes that are distinct from sociodemographic measures. Examples of these processes include noise, crowding, and overall commotion in the home setting. Each item is coded 0 or 1 for the absence or presence of household characteristics, respectively. Scores ranged from 0 to 14, with higher scores indicating greater household chaos.

Session-by-Session Behavioral Coding of Parent-Child Interaction

In this study, trajectories of change in parenting skills were mapped only for families who engaged in PCIT. PCIT parents completed a 5-minute child-led play segment of the standard PCIT Dyadic Assessment Protocol at pre-treatment, each session of the first, child-directed interaction (CDI) phase of treatment, mid-treatment conducted immediately after the first phase, and post-treatment conducted immediately after the second phase. During each 5-minute data collection period, parents were instructed to let the child lead the play. All segments were video recorded, transcribed, and coded using the validated Dyadic Parent-Child Interaction Coding System (DPICS-IV; Eyberg et al., 2014). Of note, PCIT parents completed the 5-minute child-led play segment during select sessions of the second PDI phase, but these data are not included in this study. Coding was completed by PCIT therapists on the day of each CDI session to inform their coaching and treatment plan. 27% of all the CDI coding segments that occurred during PCIT were coded for reliability. The average inter-rater agreement was 78%.

Parent verbalizations from each segment were coded as: labelled praises (e.g., *Great job sitting quietly!*), unlabeled praises (e.g., *Great job!*), behavior descriptions (e.g., *You're putting the blue one on top*), reflections (e.g., repeating the child's statement), questions, commands (e.g., *Please tie your shoes*), and criticisms (e.g., *I don't like that tower).* As indicated in the PCIT protocol, behavior descriptions, labelled praises, and reflections were classified as positive skills, and criticisms, questions, and commands were classified as negative skills. Unlabeled praises and 'other talk' are coded neutrally, and not included in the present study. A positive skill score and negative skill score were computed for each time point by summing the positive and negative skills respectively.

For this study of standard length PCIT, parents can progress from the first phase of treatment by either reaching mastery of skills or completing the maximum number of sessions (9 on average). Parents are coached to increase their positive skills so that they achieve 10 of each behavior descriptions, labelled praises, and reflections during the 5-minute segment of child-led play. Simultaneously, parents are coached to use less than three total of criticisms, questions, or commands. In order to achieve mastery, parents must meet the 10-10-10 criteria for positive skills as well as the less-than-3 criteria for negative skills. Mastery of these skills that are taught during the child-directed interaction phase of treatment will hereby be referred to as CDI mastery.

Analysis Plan for Aim 1

Missing Data

Missing data in resting EEG scores were evaluated using missing values analyses. Results show that 34.3% and 45.6% of children's resting EEG data was missing at pre-treatment and post-treatment, respectively. Known reasons for missingness in EEG data are depicted in Figure 2. Missingness at pre-treatment was primarily due to difficulty placing the EEG cap on participants or participant refusal. Missingness at post-treatment was primarily due to children not completing the post-treatment assessment entirely (n = 51) or participant refusal (n = 17). Little's missing completely at random test was conducted for all EEG variables and psychosocial risk factors using the 'naniar' package (Version 0.6.0.9000; Tierney et al., 2021) in R (R Core Team, 2013). Results indicated that I reject the null hypothesis that data are missing completely at random, $\chi2$ (1990) = 2452, $p < .001$. The missingness at random assumption was tested by examining patterns of missingness in EEG using t-tests and $\chi2$ tests with demographic variables and psychosocial risk variables, as well as across randomization groups. Proportions of missingness at both pre- and post-treatment differed significantly by age, $\chi2$ (30) = 48.97, $p = .016$, $\chi2$ (5) = 19.01, $p = .002$, with younger children producing more missing data than older children. 67% of missing EEG data at pre-treatment and 69% of missing EEG data at post-treatment were in children ages 3-4 at baseline. Because the missing completely at random hypothesis was rejected and missingness was not significantly different across most other demographic variables, multiple imputation was employed with child age as a predictor in each imputation model (Rubin, 2004). For comparison, complete case analyses were also conducted.

Incomplete variables were imputed using the 'mice' package in R (Version 3.3.0; van Buuren & Groothuis-Oudshoorn, 2011). Initially selected auxiliary variables include those that were theoretically correlated to children's neural indices of executive function

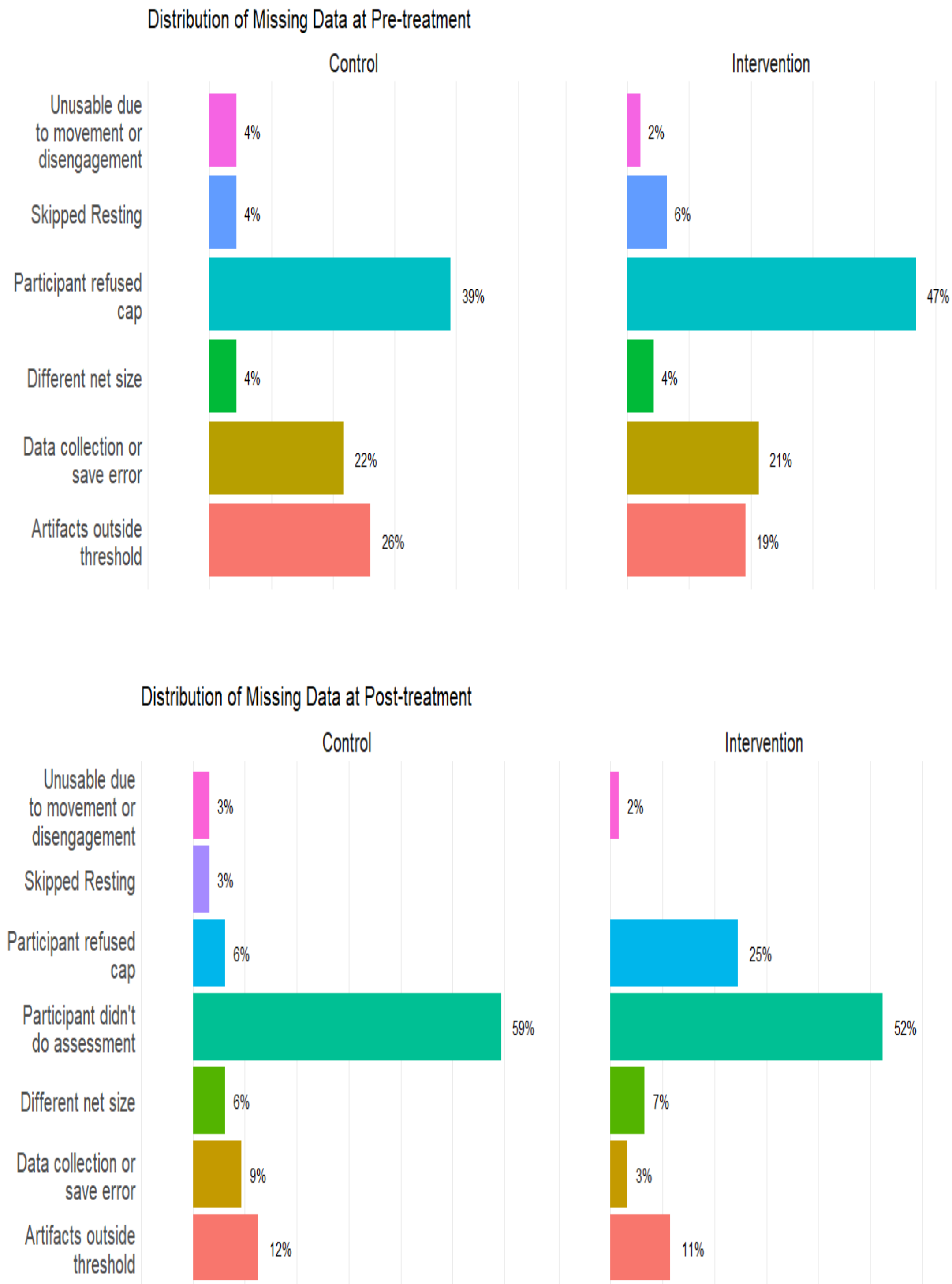

Figure 2. Missing EEG Data. Distributions of missing EEG data for children at pre-treatment and post-treatment are displayed.

and demographic variables such as: survey and behavioral measures of children's inhibitory control and executive function, child gender, child age, ACES scores, CHAOS scores, and measures of children's cognitive ability (Woodcock Johnson III Tests of Achievement; Woodcock et al., 2001). Next, the *quick_pred* function within the 'mice' package was used to implement a predictor selection strategy based on simple statistics. Child age and each of the primary aim variables were specified to serve as predictors for each imputation model. The mean number of predictors was equal to 22.63, which is within the recommended range suggested by Van Buuren (2018). Variables were imputed in the sequence of treatment, such that pre-treatment variables were imputed prior to post-treatment variables. The method of imputation was set to be predictive mean matching for all variables except composite theta/beta ratio scores. These scores were specified to be calculated and imputed following the individual imputations of theta and beta variables. Forty total imputations with 35 iterations each were conducted to maximize power and minimize bias, as suggested by Graham (2009).

Figure 3 shows an overlay of real values atop imputed values across all 40 imputations after removal of outliers, and provides some evidence that the imputation was successful. Scatter plots and density plots of imputed values across the 40 imputations were also evaluated to diagnose whether imputed values could be real if data was not missing.

Analysis parameters were estimated in each of the 40 imputed datasets and pooled using Rubin's rules. For comparison, analyses were conducted on complete cases as well. After accounting for age in the imputation models however, the missingness at random pattern can be reasonably assumed and findings from multiply imputed data should take precedence over complete case analyses (Van Buuren, 2018).

Model Specifications

All variables were examined for outliers and possible deviation from the assumption of normality using data visualization. Theta/beta ratio values were normally distributed for eyes-open but not eyes-closed tasks. Theta/beta ratio values in the eyes-closed task were significantly positively skewed and thus log transformed. Outliers

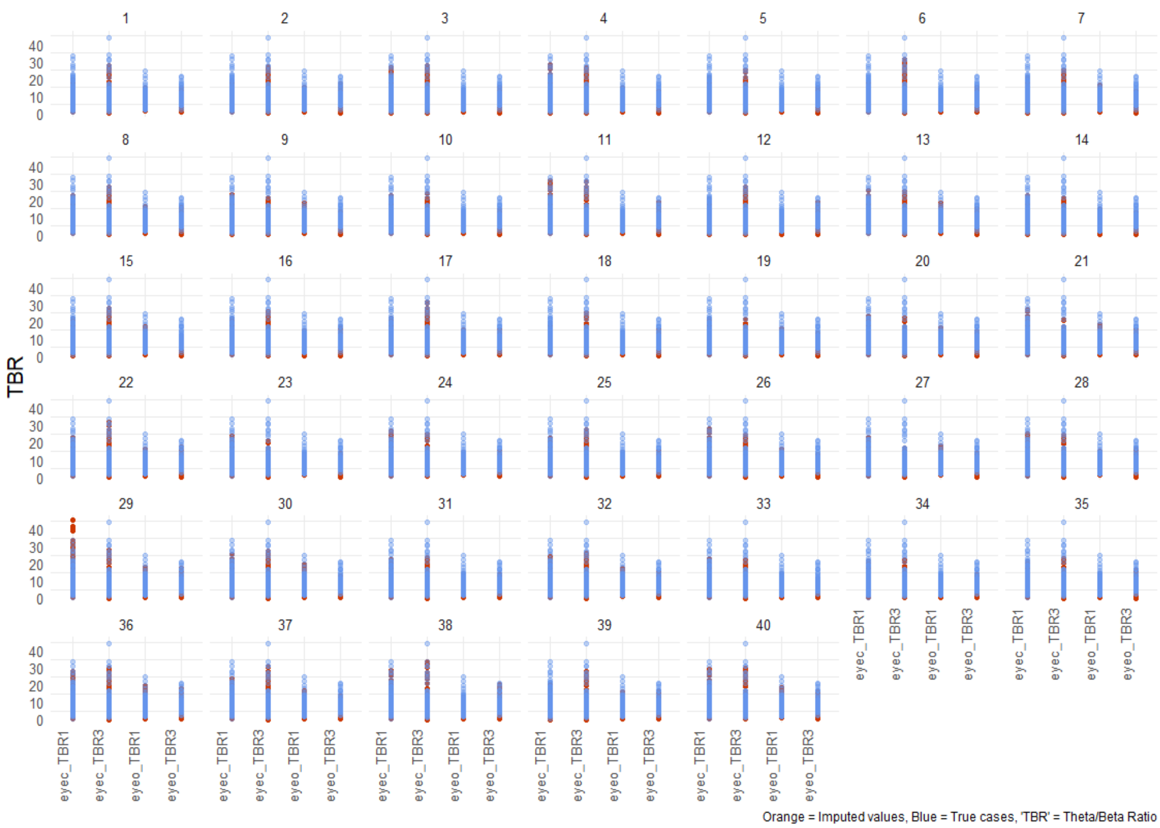

Figure 3. Imputation Estimates. Imputation estimates for each imputation model are presented. Blue dots represent real values with complete data and are overlayed on orange dots which represent imputed data. Eyec = Eyes-Closed condition. Eyeo = Eyes-Open Condition. TBR1 = Theta/beta ratio at pre-treatment. TBR3 = Theta/beta ratio at post-treatment.

greater than 3 standard deviations from the mean were removed prior to multiple imputation and following multiple imputation.

Primary Intention-to-Treat Analyses

Intention-to-treat (ITT) superiority analyses were conducted to test the effects of PCIT on children's theta/beta ratio. ITT analysis is a stringent, unbiased analytic design that includes all randomized participants, regardless of their level of engagement in the treatment (Schulz et al., 2010). An ordinary least squares regression analysis was conducted to test the main effects of PCIT and rsEEG task, and the interaction effect between the two on children's post-treatment theta/beta ratio, controlling for age and pre-treatment theta/beta ratio. Next, the moderating effects of psychosocial risk were tested by adding both ACES and CHAOS scores to the regression model. Since relative power scores accounted for variations in age and skull size, age was not added as a covariate in order to minimize the number of predictors in the model.

Secondary Per-Protocol Analyses

ITT analyses treat PCIT participants who are fully compliant to the treatment protocol equally with those who are not at all compliant to treatment, resulting in a conservative treatment effect estimate. Though this can provide a highly conservative superiority test of PCIT and reduce selection-bias associated with excluding participants who do not engage with the intervention, it neglects the fact that partial compliance to treatment may also significantly impact the dependent variable. Per-protocol analyses were thus conducted on control group participants (n = 84) and PCIT group participants who engaged in at least one session of PCIT (i.e., CDI Teach+), n = 79. Identical regression models to those run for ITT analysis were conducted.

Complete Case Analyses

Following analyses with multiply imputed data (*n* = 204), both ITT and per-protocol analyses were repeated with complete cases (*n* = 71), for an examination of how findings may vary among those who provided complete and usable EEG data. Complete cases included all children that had usable EEG data at pre-treatment and post-treatment, from both control and treatment groups. Of these data, 34 children were from the control group, and 37 were from the PCIT group. Descriptive statistics for children's age, theta/beta ratios, and psychosocial risk factors are presented in Table 2 alongside descriptive statistics on multiply imputed data. As noted above, 67-69% of missing data was from children 3-4 years old at baseline. The remaining 31 – 33% of missing EEG data was due to a variety of random factors including data collection error, or excessive artifacts, skipping resting tasks due to time constraints, or variation in net size due to lack of fit.

The distribution of cases by age was roughly even in the full multiply imputed sample, with 47.3% of children aged 3-4 years-old and 52.7% of children 5-8 years old. Alternatively in the complete-case sample, 34.8% of children were between 3-4 years old at baseline, and 65.5% of children were between 5-7 years old. A closer examination of the means for theta/beta ratios in Table 2 shows that theta/beta ratios decrease over time from pre-treatment to post-treatment (as expected) in multiply imputed data. However for complete case data, theta/beta ratios increase from pre-treatment to post-treatment for the control group in the eyes-open condition, and for the PCIT engager group in the eyes-closed condition. Recall that an increasing theta/beta ratio over time is associated with poorer executive functioning capacity. Notably, cases did not differ by psychosocial risk factors across both multiply imputed and complete case data, as indicated by t-tests. Taken together, results of complete case analyses should be interpreted with extreme caution for the following reasons: 1) complete cases represent only 35% of the full sample (n = 71, relative to n = 204), 2) distributions of cases vary by age, such that complete cases include a greater proportion of older children, and 3) directionality of change in theta/beta ratios for complete cases varies by condition and group, suggesting that these children are markedly different than the full sample. This reduced sample size and difference in distribution may contribute to reduced statistical efficiency and high potential for bias.

Post-hoc Exploratory Analyses

An exploratory examination of correlations with original, non-imputed data using pair-wise deletion, was conducted between theta/beta ratios and alpha power to further examine why PCIT effects varied by resting condition. Original data was used because alpha power was not included in the multiple imputation models conducted with this study. Correlation analyses showed significant negative associations between theta/beta ratios and alpha power in the eyes-closed task at both pre-treatment ($r = -.31$, $p < .001$) and post-treatment ($r = -.32$, $p = .002$), but not the eyes-open task. Note that these correlations, like other analyses with unimputed data, should be interpreted with caution.

Analysis Plan for Aim 2

Missing Data

Missing data for positive and negative parenting scores was analyzed within Hierarchical Linear Modelling (HLM) 7 software (Raudenbush et al., 2011) and the

Table 2
Descriptive Statistics for Aim 1 Variables (*n* = 204)

	Services as Usual	PCIT	PCIT Engagers
Multiply Imputed Data	(*n* = 84)	(*n* = 120)	(*n* = 79)
Theta/ Beta Ratios			
Eyes-Closed Pre	8.78 (5.26)	7.70 (4.42)	7.39 (5.30)
Eyes-Closed Post	8.46 (5.11)	6.93 (3.47)	6.67 (5.68)
Eyes-Open Pre	7.36 (3.20)	6.61 (3.47)	6.31 (3.43)
Eyes-Open Post	7.24 (3.10)	6.19 (3.45)	6.13 (3.42)
Psychosocial Risk			
ACES	3.65 (1.84)	3.29 (1.97)	3.61 (1.95)
CHAOS	4.77 (3.35)	4.99 (3.26)	4.92 (3.43)
Child Age	4.90 (1.44)	4.73 (1.40)	4.68 (1.38)
Complete Case Data	(*n* = 34)	(*n* = 37)	(*n* = 28)
Theta/ Beta Ratios			
Eyes-Closed Pre	11.10 (5.24)	10.60 (8.33)	9.56 (7.69)
Eyes-Closed Post	10.21 (5.36)	10.26 (7.70)	10.43 (7.92)
Eyes-Open Pre	9.30 (3.88)	8.14 (5.41)	10.43 (7.92)
Eyes-Open Post	10.09 (4.61)	7.77 (4.19)	7.67 (3.54)
Psychosocial Risk			
ACES	3.82 (1.59)	3.11 (1.93)	3.25 (2.08)
CHAOS	5.09 (3.55)	5.57 (3.16)	5.36 (3.38)
Child Age	5.30 (1.29)	4.78 (1.38)	4.67 (1.27)

Note. Means and standard deviations on multiply imputed data were conducted on each of the 40 imputed datasets and pooled using Rubin's rule.

'naniar' package in R (Version 0.6.0.9000; Tierney et al., 2021). Level-1 parenting behaviors data were missing primarily due to variations in treatment length associated with drop-out from treatment or CDI mastery (leading to transition into PDI phase sessions). Nesting measurement observations within person-level characteristics accounted for variations in the number of timepoints per individual as well as duration between timepoints. HLM 7 weights each case by the number of available data points (without using pairwise or listwise deletion), thus resulting in a consistent pattern of skill acquisition in relation to session. Other reasons for missing dyadic interaction data include video recording errors associated with equipment malfunction or therapist error, clinically indicated reasons to skip skill assessment. Patterns of missing data in the longitudinal session-by session data were examined using Little's Missing Completely at Random test with the 'naniar' package in R (Version 0.6.0.9000; Tierney et al., 2021). Analyses indicated that session-by-session data at level 1 were not missing completely at random, $\chi 2$ (9) = 125, $p < .001$. There was no missing data at level 2 (intervention mastery). Full Information Maximum Likelihood (FIML) approaches were used for all hierarchical models. Unlike other approaches such as restricted maximum likelihood, FIML is model-specific and provides estimates that are 1) very near the true parameter with high probability, and 2) approximately unbiased with minimum variance (Raudenbusch & Bryck, 2002). The large number of measurements and sample size both support the use of FIML.

Model Specifications

Three key assumptions of hierarchical models were tested: the homogeneity of residual variance at level-1 and level-2 by examining Q-Q/P-P plots and using HLM 7 hypothesis tests; multivariate normality using the Mahalanobis distance test; and linearity examining scatterplots of residuals against fitted values. The assumptions of normality and homogeneity of residual variance were not met. Both positive and negative parenting skills showed some positive skew, overall. While PCIT is a manualized intervention, the focus of in-session coaching is individually-tailored to client families based on the specific parent skill levels observed at each session. For this reason, heterogeneity in skill levels across individuals and sessions is expected. Previous work indicates that estimation of fixed effects and standard errors in HLM are robust to violations of these assumptions (Kasim & Raudenbusch, 1998). The assumption of linearity was met. No outliers were identified for the positive or negative parenting skill variables.

Hierarchical Growth Curves

A two-level, random effects analysis of growth curves for both positive and negative parenting scores was conducted using Hierarchical Linear Modelling (HLM) 7 software (Raudenbush et al., 2011). Parenting skills as a function of time were included at level-1. Standard length PCIT was employed in this study, with families offered a total of 9 child-directed interaction sessions and 11 parent-direction interaction sessions. As described in the Methods above, families progress through treatment either by meeting CDI mastery, or by reaching the maximum number of child-directed interaction sessions offered. In other words, a family may have progressed from phase 1 of PCIT (child-directed interaction) to phase 2 (parent-directed interaction) either because they (a) achieved mastery criteria or because (b) they completed the maximum number of allowable sessions. To account for variation in measurement occasions, mastery-achievement was included as a level-2 participant-level characteristic.

Three consecutive HLM models were conducted for each outcome variable (positive parenting skills and negative parenting skills) to identify the functional form of skill change across sessions. First, a fully unconditional two-level random effects model with no predictors was specified to estimate both intercepts and slopes of growth trajectories. Slope was modeled as random effects to allow change in skills to vary across individuals. Next, two polynomial terms (linear, quadratic) were sequentially included at level-1 to the unconditional model (Royston & Altman, 1994). Deviance testing was used to identify model fit and parsimony (Snijders & Bosker, 1999). After identifying the most parsimonious model for each outcome, a dichotomous mastery-achievement variable was added at level-2. Individual slopes and intercepts for both positive and negative parenting skills from the models of best fit were extracted and applied as predictors of children's post-treatment theta/beta ratio level, accounting for baseline levels in an ordinary least-squares regression analysis.

III. RESULTS

Aim 1

Intention-to-treat and per-protocol analyses were conducted with multiply imputed data to test the effects of PCIT on children's post-treatment theta/beta ratio. Means and standard deviations for all variables used in Aim 1 are presented in Table 2. The average number of ACEs experienced by children 3-7 at pre-treatment was 3.45 (SD = 1.93), while the average level of chaos in the home environment was 4.93 (SD = 3.32). Eyes-closed theta/beta ratio was significantly correlated with eyes-open theta/beta ratio at pre-treatment ($r = 0.64$, $p < .001$) and post-treatment ($r = 0.60$, $p < .001$). Findings with multiply imputed data and complete-case data are reported. As noted in the Analysis Plan for Aim 1 above, findings from complete case analyses should be interpreted with caution.

Primary Intention-to-Treat Analyses

Separate ordinary least squares, multiple regression analyses were employed in R to predict children's post-treatment eyes-closed and eyes-open theta/beta ratio, as shown in Table 3. Results from analyses conducted with all randomized participants on multiply imputed data are presented in this section.

Eyes-Closed. First, children's pre-treatment ACES scores, CHAOS scores, and eyes-closed theta/beta ratio were entered as predictors of post-treatment eyes-closed theta/beta ratio. This model accounted for 4.43% of the total variance in post-treatment theta/beta ratio. Next, randomization group (PCIT or services-as-usual control) was added to this model to test the effects of PCIT after accounting for psychosocial risk scores. The full model accounted for an additional 4.64% of the variance in post-treatment eyes-closed theta/beta ratio, $F(1, 120.90) = 3.87$, $p = .05$. Children in the PCIT group were predicted to have eyes-closed theta/beta ratio 0.28 units lower than the services-as-usual control group after accounting for psychosocial risk, $t(50.53) = -1.97$, $p = .05$. The difference in post-treatment eyes-closed theta/beta ratio between PCIT and control groups was significant, and the hypothesis that those in the PCIT group would show lower theta/beta ratios at post-treatment was supported.

Eyes-Open. Children's pre-treatment ACES scores, CHAOS scores, and eyes-open theta/beta ratio accounted for 2.41% of the total variance in post-treatment eyes-open theta/beta ratio. The full model including randomization group, accounted for an additional 3.03% of the total variance at post-treatment, though this difference in variance was not statistically different, $F(1, 94.10) = 1.80$, $p > .05$. The effect of PCIT on eyes-open theta/beta ratio after controlling for psychosocial risk was not statistically significant, $t(40.38) = -1.34$, $p = .19$.

Secondary Per-protocol Analyses

Per-protocol analyses were conducted in a similar manner to ITT analyses, after excluding participants in the PCIT group who did not engage with at least one session of PCIT. Findings from multiply imputed data are reported here and included in Table 4.

Eyes-Closed. Children's pre-treatment ACES scores, CHAOS scores, and eyes-closed theta/beta ratio accounted for 3.58% of the total variance in post-treatment eyes-closed theta/beta ratio. The full model including randomization group, accounted for an additional 5.70% of the total variance at post-treatment, resulting in a statistically significant difference in model fit, $F(1, 130.39) = 4.02$, $p < .05$. The effect of PCIT on eyes-closed theta/beta ratio after controlling for psychosocial risk was marginally significant, $t(46) = -2.00$, $p = .05$. Children in the PCIT group were predicted to have theta/beta ratios 0.32 units lower than the services-as-usual control group.

Eyes-Open. Children's pre-treatment ACES scores, CHAOS scores, and eyes-open theta/beta ratio accounted for 1.66% of the total variance in post-treatment eyes-open theta/beta ratio. The full model including randomization group, accounted for an additional 3.69% of the total variance at post-treatment, though this difference in addition variance was not statistically significant, $F(1, 105.22) = 1.96$, $p = .16$. The effect of PCIT on eyes-closed theta/beta ratio after controlling for psychosocial risk was not significant, $t(38.20) = -1.40$, $p = .17$.

Complete-Case Analyses

Complete-case analyses were conducted with a subsample of children who had complete rsEEG data at both pre-treatment and post-treatment ($n_{PCIT} = 37$, $n_{control} = 34$; $n_{total} = 71$). Similar to analyses reported above on multiply imputed data, both ITT and per-protocol analyses were conducted with complete cases. ITT analysis included all children in the control and PCIT groups, as randomized. Per-protocol analysis included all individuals in the control group, and only those who engaged in at least one session of PCIT in the treatment group.

Eyes-Closed, Complete Case ITT Analysis. Pre-treatment theta/beta ratio and psychosocial risk variables accounted for 13.1% of the total variance in post-treatment eyes-closed theta/beta ratios, $F(2, 67) = 4.52$, SE = 0.59, $p < 0.01$. The full model with the randomization group was not significantly different from the psychosocial risk model,

Table 3

Intention-to-treat Analyses of PCIT effects on Children's Theta/Beta Ratio

	Multiple Imputation				Complete Cases			
	b	*SE*	*t*-ratio	*d.f.*	*b*	*SE*	*t*-ratio	*95% CI*
Eyes Open								
Intercept	7.18^	1.26	5.70	53.88	7.21^	1.70	4.25	(3.82, 10.60)
Pre-treatment TBR	0.04	0.11	0.40	51.35	0.39^	0.10	3.74	(0.18, 10.60)
CHAOS	0.07	0.10	0.79	74.92	-0.27	0.15	-1.77	(-0.57, 0.03)
ACES	-0.17	0.19	-0.88	49.77	0.17	0.29	0.57	(-0.41, 0.75)
PCIT	-1.09	0.81	-1.34	40.38	-1.61	1.00	-1.61	(-3.61, 0.38)
Eyes Closed								
Intercept	1.91^	0.33	5.86	52.48	1.68^	0.35	4.84	(0.99, 2.38)
Pre-treatment TBR	0.13	0.14	0.94	38.73	0.37**	0.12	3.16	(0.14, 0.62)
CHAOS	0.01	0.02	0.63	51.26	-0.02	0.02	-1.28	(-0.07, 0.02)
ACES	-0.04	0.04	-1.07	51.38	-0.03	0.04	-0.76	(-0.12, 0.05)
PCIT	-0.29*	0.15	-1.96	50.52	-0.08	0.15	-0.56	(-038, 0.21)

Note. Separate regression analyses were conducted for 'Eyes Open' and 'Eyes Closed' tasks, with all children randomized to PCIT or services-as-usual control. The full models conducted on multiply imputed data are reported here. CHAOS = Chaos, Hubbub and Order Scale. ACES = Adverse Childhood Experiences. TBR = Theta/beta ratio.

**p* < .05 ***p* < .01 ^*p* < .001

Table 4.

Per-protocol Analyses of PCIT effects on Children's Theta/Beta Ratio

	Multiple Imputation				Complete Cases			
	b	*SE*	*t*-ratio	*d.f.*	*b*	*SE*	*t*-ratio	*95% CI*
Eyes Open								
Intercept	7.29**	1.30	5.61	50.78	7.19^	1.78	4.05	(3.63, 10.75)
Pre-treatment TBR	0.004	0.11	0.03	54.26	0.33**	0.12	2.75	(0.09, 0.57)
CHAOS	0.06	0.10	0.56	70.62	-0.33*	0.15	-2.15	(-0.64, -0.02)
ACES	-0.09	0.20	-0.47	53.39	0.39	0.29	1.34	(-0.19, 0.98)
PCIT	-1.19	0.85	-1.40	38.20	-1.36	1.05	-1.30	(-3.46, 0.74)
Eyes Closed								
Intercept	1.97^	0.33	5.98	55.10	1.65	0.36	4.56	(0.93, 2.38)
Pre-treatment TBR	0.08	0.14	0.61	41.85	0.37	0.13	2.85	(0.11, 0.62)
CHAOS	0.01	0.02	0.62	51.63	-0.03	0.02	-1.41	(-0.08, 0.01)
ACES	-0.03	0.04	-0.81	57.94	-0.01	0.04	-0.26	(-0.09, 0.08)
PCIT	-0.32*	0.16	-2.00	46.00	-0.03	0.15	-0.20	(-0.34, 0.28)

Note. Separate regression analyses were conducted for 'Eyes Open' and 'Eyes Closed' tasks, with all children randomized to services-as-usual control, and only those in the PCIT group who engaged in at least one session of PCIT. The full models conducted on multiply imputed data are reported here. CHAOS = Chaos, Hubbub and Order Scale. ACES = Adverse Childhood Experiences.

*$p < .05$ **$p < .01$ ^$p < .001$

$F(1, 67) = 0.34$, $p = 0.56$ The hypothesis that children in PCIT would show lower theta/beta ratios was not supported in these complete case analyses for the eyes-closed task, $t(66) = -0.59$, SE = 0.15, $p = 0.56$.

Eyes-Open, Complete Case ITT Analysis. Pre-treatment theta/beta ratio and psychosocial risk variables accounted for 18.44% of the total variance in post-treatment eyes-open theta/beta ratios, $F(3, 67) = 6.27$, $p < 0.001$. The full model including the randomization group was not significantly different from the psychosocial risk model, $F(1, 67) = 2.60$, $p = 0.11$. The hypothesis that children in PCIT would show lower theta/beta ratios was not supported win these complete case analyses for the eyes-open task, $t(66) = -1.61$, SE = 1.00, $p = 0.11$.

Eyes-Closed, Complete Case Per-protocol Analysis. Pre-treatment theta/beta ratio and psychosocial risk variables accounted for 12.23% of the total variance in post-treatment eyes-closed theta/beta ratio, $F(3,58) = 3.83$, SE = 0.57, $p = 0.01$. The full model including intervention group status accounted for 1.45% less variance, and was not significantly different overall, $F(1,57) = 0.04$, $p = 0.84$. The effect of PCIT after accounting for psychosocial risk was not significant, $t(57) = -0.20$, SE = 0.15, $p = 0.84$.

Eyes-Open, Complete Case Per-protocol Analysis. Pre-treatment theta/beta ratio and psychosocial risk variables accounted for 17.64% of the total variance in post-treatment eyes-open theta/beta ratios, $F(3,58) = 5.36$, SE = 3.91, $p < .001$. The full model with PCIT group accounted for an addition 1% of variance, but was not statistically different overall, $F(1, 57) = 1.68$, $p = .20$. In the full model, household chaos had a significant negative weight, suggesting that higher household chaos is associated with lower theta/beta ratios at post-treatment, independent of participation in PCIT, $t(57) = -2.15$, SE = 0.15, $p < 0.05$.

Aim 2

Hierarchical Growth Curves

In order to test whether trajectories of change in parenting behaviors predicted children's post-treatment theta/beta ratios, hierarchical growth modeling was utilized first to estimate the longitudinal curvilinear form of changes in both positive and negative parenting skills. As noted earlier, linear time was centered at CDI session 4 to estimate parents' average rate of growth across the CDI phase of treatment. Without centering, linear slope would provide an estimate of parents' rate of growth at pre-treatment, which is unreliable with the present data. Chi-squared deviance tests were used to determine the best-fitting model (Snijder & Bosker, 1999), and are detailed in Table 5. Results from deviance testing indicated that the quadratic model was best fitting for both the trajectory of positive parenting skills, $\chi 2$ (4) = 550.28, $p < .001$, and the negative parenting skills, $\chi 2$ (4) = 286.85, $p < .001$. Finally, a dummy coded variable indicating whether parents met CDI mastery was added at level-2 to the best fitting model for both positive and negative skills outcomes, to account for variation in parenting skills progression across sessions.

Positive Parenting Skills.

Level-1 Model

$$POS_{ti} = \pi_{0i} + \pi_{1i}*(LINEAR_{ti}) + \pi_{2i}*(QUAD_{ti}) + e_{ti}$$

Level-2 Model

$$\pi_{0i} = \beta_{00} + \beta_{01}*(METCDIMA_i) + r_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11}*(METCDIMA_i) + r_{1i}$$

$$\pi_{2i} = \beta_{20} + \beta_{21}*(METCDIMA_i) + r_{2i}$$

The positive parenting skills model examined trajectories of DPICS-coded positive parent verbalizations across pre-treatment, each session in the first CDI phase PCIT, mid-treatment, and post-treatment assessments (see Table 6). The average estimated positive parenting skills frequency at CDI session 4 for parents who did not achieve mastery in PCIT was 15.41, $t(77) = 18.17$, SE = 0.85, $p < 0.001$. Parents who achieved mastery in the CDI phase of treatment were predicted to have 24.20 positive skills at CDI 4, $t(77) = 5.23$, SE = 1.68, $p < 0.001$.

Table 5

Deviance Testing for Functional Form of Parenting Skill Trajectories

Model	Deviance	χ^2	Pseudo-R^2	p
Positive Parenting				
Linear	5252.03			
Quadratic	4701.76	550.28	0.31	<0.001
Negative Parenting				
Linear	4861.61			
Quadratic	4574.77	286.85	1.67	<0.001

Note. Linear and quadratic terms were tested at level 1 to determine the curvilinear change across pre-treatment, CDI sessions, mid-treatment, and post-treatment. For both the positive and negative skill models, the quadratic form was determined to be best-fitting, based on outlines for deviance testing provided by Snijder & Bosker (1999).

The average rate of linear change in positive skills at CDI 4 was 2.93 for those who did not achieve mastery, $t(77) = 14.80$, $SE = 0.20$, $p < 0.001$, and 5.04 for those who did achieve mastery, $t(77) = 6.23$, $SE = 0.33$, $p < 0.001$. In other words, parents who achieved CDI mastery in the CDI phase of treatment had a greater frequency of positive skills at CDI 4, but also improved their use positive parenting skills at a significantly faster rate. The quadratic growth rate across treatment was predicted to be -0.34 for the non-mastery group, and -0.55 for the mastery group $t(77) = -4.85$, SE = 0.04, $p < .001$, suggesting a more rapid negative curvilinear change in positive skills for those who achieved mastery during CDI. That is, all PCIT parents tend to increase in positive skills and gradually decrease in positive skills over time, but parents who achieve CDI mastery tend to display narrower trajectories that indicate a faster increase and decrease in skill change. Figure 4 shows change in positive skills across sessions for parents who achieved CDI skills mastery and those who did not. Average linear change and growth rate estimates for each person were then used as predictors in testing the effect of positive parenting skill change on children's theta/beta ratios, as described below. Greater rates of gains in positive skills were expected to predict lower theta/beta ratios at post-treatment.

Negative Parenting Skills.

Level-1 Model

$$NEG_{ti} = \pi_{0i} + \pi_{1i}*(LINEAR_{ti}) + \pi_{2i}*(QUAD_{ti}) + e_{ti}$$

Level-2 Model

$$\pi_{0i} = \beta_{00} + \beta_{01}*(METCDIMA_{i}) + r_{0i}$$

$$\pi_{1i} = \beta_{10} + \beta_{11}*(METCDIMA_{i}) + r_{1i}$$

$$\pi_{2i} = \beta_{20} + \beta_{21}*(METCDIMA_{i}) + r_{2i}$$

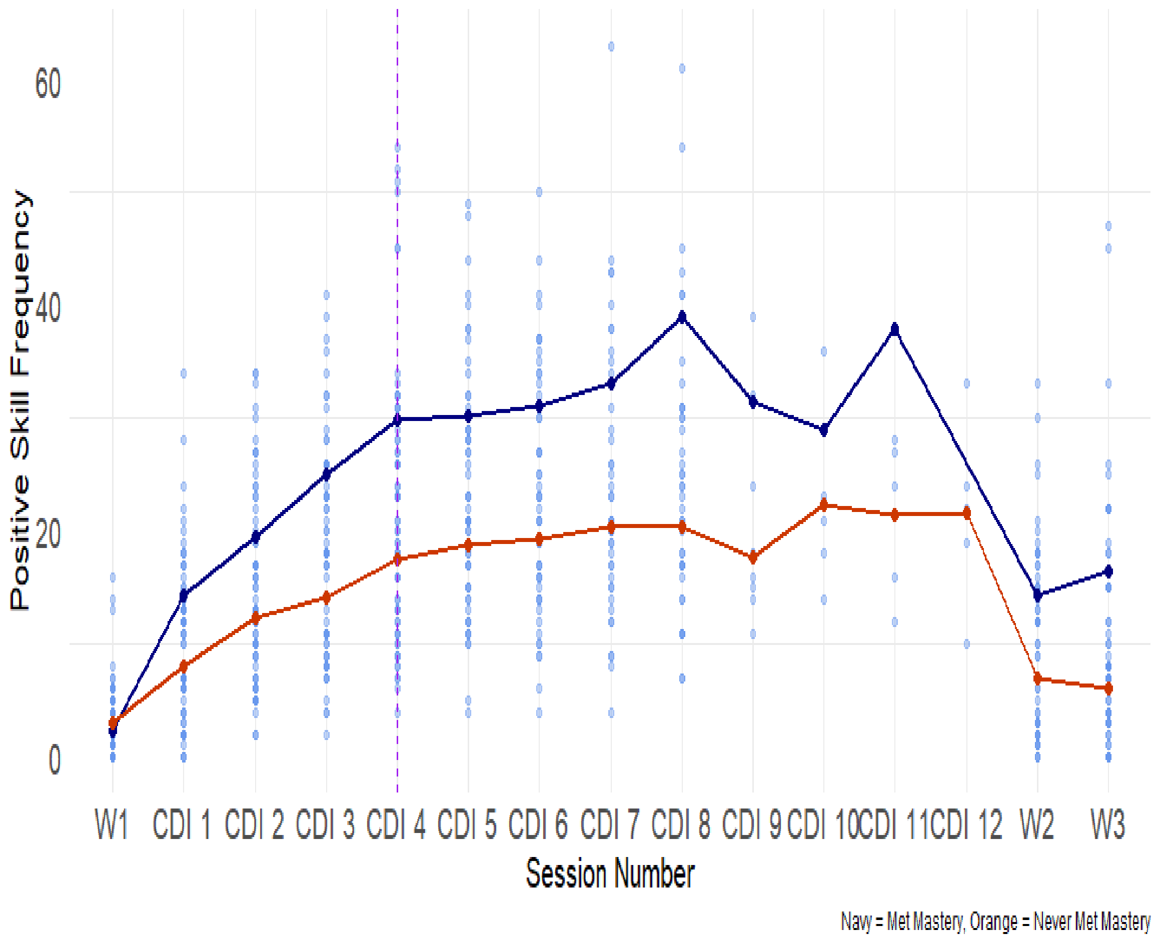

Figure 4. Trajectories of Positive Parenting Skill Change. Hierarchical models were centered at CDI session 4.

The negative parenting skills model examined trajectories of DPICS-coded negative parent verbalizations observed across pre-treatment, each session of the CDI phase of PCIT, mid-treatment, and post-treatment assessments (see Table 6). The average estimated frequency of negative parenting skills at CDI 4 for parents who did not achieve mastery in PCIT was 12.12, $t(77) = 16.12$, SE = 0.75, $p < 0.001$. Parents who achieved CDI mastery were predicted to have 3.71 fewer negative skills at CDI 4, $t(77) = -4.02$, SE = 0.92, $p < 0.001$. The average rate of linear change in negative skills at CDI 4 was -2.31 for those who did not achieve mastery, $t(77) = -11.43$, $SE = 0.20$, $p < 0.001$, and -2.86 for those who did achieve mastery, $t(77) = -1.27$, $SE = 0.43$, $p < 0.208$. In other words, while parents who achieved CDI mastery showed fewer negative parenting behaviors at CDI 4, the average rate of decline in their negative behaviors was no different from those who didn't achieve mastery.

The quadratic growth rate across treatment was predicted to be 0.23 for the non-mastery group, and 0.29 for the mastery group, indicating that parents who achieved CDI mastery displayed slightly narrower trajectories with a faster decrease and subsequent increase in negative skills over time. However, this difference in quadratic growth rates between CDI-mastery and no-mastery groups was not statistically significant. Figure 5 shows the average change in negative skills across sessions for both groups. Average linear change and growth rate estimates for each person were later used as predictors in testing the effect of change in negative parenting skills on children's theta/beta ratios, as described below. Greater reductions in negative parenting skills were expected to predict lower theta/beta ratios at post-treatment.

Main Effects of Parenting

Linear and quadratic slope estimates for parents who engaged in the PCIT group (n = 79) were extracted from the positive and negative parenting hierarchical models and used as predictors of children's post-treatment theta/beta ratio in linear regression analyses. Linear and quadratic slope estimates for both positive and negative parenting skills were normally distributed. Results from multiple regression analyses are presented in Table 7. Individual gains in parents' positive parenting and reductions in negative parenting skills assessed from pre-treatment, across the first CDI phase of PCIT, mid-treatment, and post-treatment were not significantly associated with children's theta/beta ratio at post-treatment, assessed during both eyes-open and eyes-closed tasks. Taken together, findings did not support the hypothesis that greater rates of parenting skill change would be associated with reductions in children's theta/beta ratio at post-treatment.

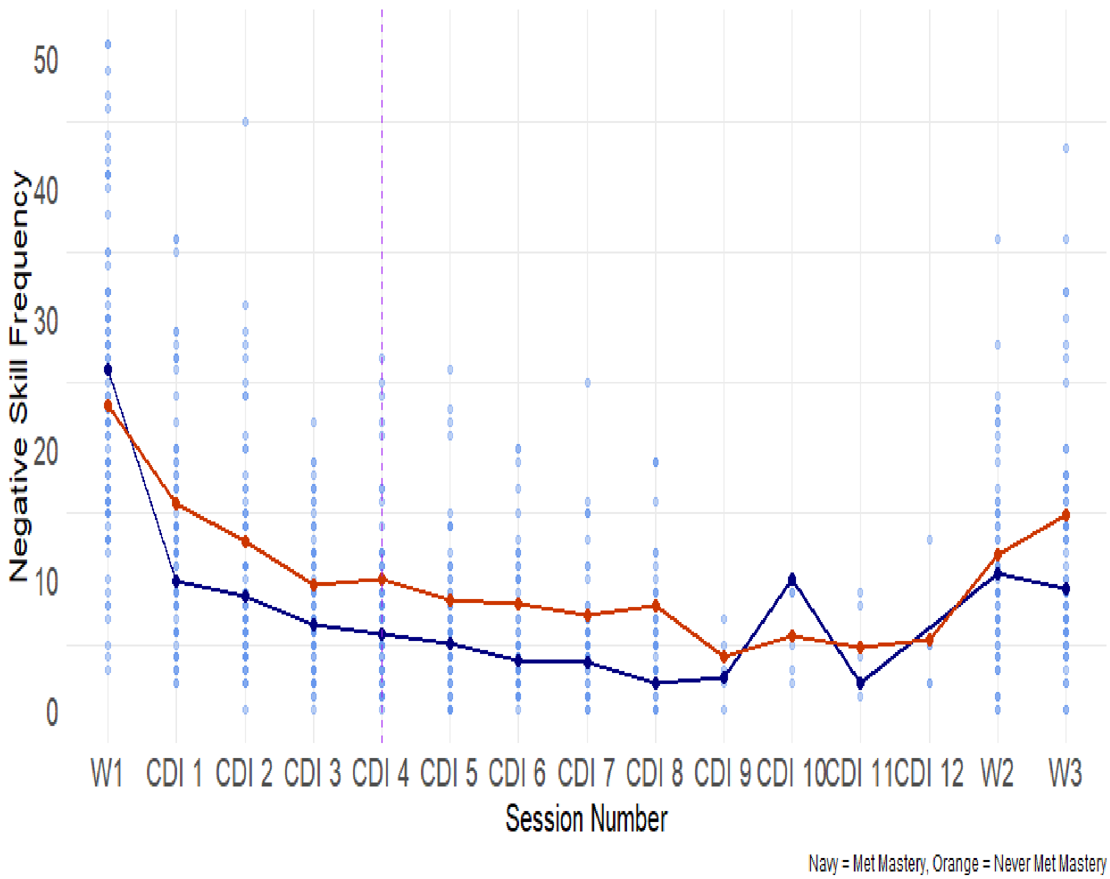

Figure 5. Trajectories of Negative Parenting Skill Change. Hierarchical models were centered at CDI session 4.

Table 6

Changes in Parenting Skills Across Treatment

Fixed Effect	Coefficient	Standard error	*t*-ratio
Positive Skills			
Intercept, π_0			
No Mastery, β_{00}	*15.41	0.85	18.18
Met Mastery, β_{01}	*8.78	1.68	5.23
For LINEAR slope, π_1			
No Mastery, β_{10}	*2.93	0.20	14.80
Met Mastery, β_{11}	*2.11	0.34	6.23
For QUAD slope, π_2			
No Mastery, β_{20}	*-0.35	0.02	-14.72
Met Mastery, β_{21}	*-0.21	0.04	-4.85
Negative Skills			
Intercept, π_0			
No Mastery, β_{00}	*12.12	0.75	16.12
Met Mastery, β_{01}	-3.71	0.92	-4.02
For LINEAR slope, π_1			
No Mastery, β_{10}	*-2.31	0.20	-11.43
Met Mastery, β_{11}	-0.55	0.43	-1.27
For QUAD slope, π_2			
No Mastery, β_{20}	*0.24	0.02	10.95
Met Mastery, β_{21}	0.05	0.04	1.19

Note. CDI mastery level was dummy coded, with ‘No Mastery’ serving as the reference group. Coefficients for the ‘Met Mastery’ group should be interpreted in relation to the ‘No Mastery’ group. Intercepts represent skill level estimates at CDI session 4. Linear slope estimates represent the average rates of growth across phase 1 of PCIT. Quadratic slope estimates represent the rate of acceleration across PCIT.

*$p < .001$

Table 7

Regression Analyses of the Effects of Session-by-Session Change in PCIT on Children's Theta/Beta Ratio

	Positive Parenting Skills					Negative Parenting Skills				
	b	*SE*	*t*-ratio	*d.f.*	*p*	*b*	*SE*	*t*-ratio	*d.f.*	*p*
Eyes Open										
Intercept	6.90^	2.00	3.45	28.40	0.002	7.01^	1.59	4.42	35.66	< .001
Pre-treatment TBR	-0.03	0.17	-0.19	26.22	0.85	-0.01	0.17	-0.11	26.50	0.91
Linear change	0.68	1.63	0.42	35.99	0.68	-0.81	2.15	-0.28	39.07	0.71
Quadratic change	6.24	15.10	0.41	36.38	0.68	-9.22	22.67	-0.41	40.55	0.69
Eyes Closed										
Intercept	1.81	0.52	3.50	32.54	0.001	1.79	0.44	4.08	37.96	<.001
Pre-treatment TBR	0.05	0.18	0.25	35.46	0.80	0.02	0.19	0.13	34.47	0.89
Linear change	0.18	0.37	0.49	38.44	0.63	-0.50	0.52	-0.96	32.96	0.34
Quadratic change	1.57	3.34	0.47	40.00	0.64	-4.69	5.42	-0.86	34.70	0.39

Note. Separate regression analyses were conducted for 'Eyes Open' and 'Eyes Closed' tasks, with families who engaged in treatment for at least one session. The full models conducted on multiply imputed data are reported here.

*$p < .05$ **$p < .01$ ^$p < .001$

IV. DISCUSSION

PCIT Impacts Children's Theta/Beta Ratio the Eyes-Closed Condition

First, this study examined changes in patterns of resting-state neural activity in children who were involved with child-welfare, and randomized to PCIT relative to a services-as-usual control condition. The hypothesis that adversity-exposed children in PCIT would show lower theta/beta ratios, indicative of better attention regulation, after accounting for psychosocial risk, was supported for the eyes-closed but not the eyes-open condition in ITT and per-protocol analyses alike. Interpretations of why the effects of PCIT vary by resting state EEG condition should be made with the understanding that differences may be due to a lack of sufficient power to detect small effect sizes.

Consistent with prior intervention work with institutionally neglected children (Stamoulis et al., 2015; Vanderwert et al., 2010) and children involved with child protective services (Bick et al., 2019), this study demonstrates that an early caregiving intervention is associated with more adaptive cognitive processing capacities, as evidenced by resting EEG in children from families involved with child-welfare. This study extends our understanding of this association by demonstrating that a well-validated neural marker of attention regulation, the theta/beta ratio, decreases over time for those who participate in PCIT relative to those who do not. Further, while Bick and colleagues demonstrate associations between caregiving intervention and neural activity 5-7 years following participation, this study shows that improvements in neural activity can be observed immediately after completion of PCIT. Researchers have long posited that PCIT may be an effective treatment for children with attention deficit hyperactivity disorder (Wagner & McNeil, 2008). A culturally adapted version of PCIT has been associated with improvements in children's parent-reported ADHD for a small sample of children (Matos et al., 2009), while older research has demonstrated that PCIT improves children's attentional skills as measured by self-report measures (Eyberg et al., 2001; Funderburk et al., 1998). No studies to date to my knowledge have examined pre- to post-treatment changes in physiological markers of children's attention regulation capacity.

There are several potential explanations for why improvements in theta/beta ratios were observed in the eyes-closed condition, but not the eyes-open condition. First, recall that previous work examining the effects of a caregiving intervention on children's rsEEG focused on power averaged across eyes-closed and eyes-open tasks (Bick et al., 2019), or only on eyes-open tasks (Marshall et al., 2004; Marshall et al., 2008; Vanderwert et al., 2010; Vanderwert et al., 2016), or only on eyes-closed tasks (Stamoulis et al., 2015). However, several studies have established that rsEEG activity varies across eyes-closed and eyes-open conditions (Barry et al., 2007; Barry et al., 2009; Johnstone et al., 2020), thus impacting how findings are interpreted. Specifically, previous work with children 8 to 12 years-old demonstrates that alpha is higher during eyes-closed tasks and has been theorized to mark active suppression of distracting stimuli (Barry et al., 2009). The lower alpha in eyes-open tasks on the other hand, has been theorized to reflect focused attention (Barry et al., 2009; Klimesch, 2012). More recent work with younger children shows that children 3-9 years-old, whose alpha may not be fully developed, also tend to display greater alpha during eyes-closed conditions relative to the eyes-open condition (Perone et al., 2018). This same study also found that theta/beta ratios were higher during the eyes-closed condition, compared to the eyes-open condition.

Children in the present study demonstrate similarly higher theta/beta ratios when eyes were closed relative to when eyes were open, at both pre- and post-treatment assessments. While differences in alpha power that reflect levels of suppression or focused attention were not examined in the present study, digging a bit deeper into this work may provide some insights for our condition-varied findings. Suppression is observed by greater alpha in eyes-closed conditions, and reflects the ability to suppress distracting task-irrelevant stimuli. Enhancement is reflected by lower alpha in eyes-open conditions, and reflects the ability to focus attention on a particular target. Suppression and enhancement are known to independently contribute to attention regulation processes (Chan & Egeth, 2019). In high-risk environments, the ability to pay attention to many stimuli at once (that is, to *not* suppress) allows children to quickly notice and react to threat signals (e.g., angry faces or angry voices) that may predict danger. A strong body of evidence shows that children who have experienced physical abuse tend to develop broader perceptual boundaries for categorizing visual and audible anger cues (Pollak & Kistler, 2002; Shackman et al., 2007). Further, prolonged early life adversity has been shown to modify neurophysiological systems in ways that aid in retaining information about threats to well-being, often resulting in greater vigilance and reactivity (Roth et al., 2009; Szyf, 2009; Loman & Gunnar, 2010). The characteristics of our sample fall well within this adverse context: most children live below the poverty line and have experienced an average of 3 adverse childhood experiences. Taken together, this finding that children in the PCIT group have better attention regulation (i.e., lower theta/beta ratios) as measured in the eyes-closed task, might indicate that PCIT improves attention regulation processes by way of improving children's ability to suppress distractors. Given that PCIT is effective in reducing rates of maltreatment recidivism in families with a history of physical abuse Chaffin et al., 2004; Kennedy et al., 2016), future work can build on the present study to examine mechanisms of action. Specifically, an examination of whether reductions in harsh, aversive parenting are uniquely associated with children's theta/beta ratios in the eyes-closed task, relative to the eyes-open task, can explicitly test whether improvements in attention regulation are associated with children's ability to suppress distractors.

Indeed, an exploratory examination of correlations with our original, non-imputed data showed significant negative associations between theta/beta ratios and alpha power in the eyes-closed task, but not the eyes-open task. That is, children with lower theta/beta ratios (better top-down attention regulation) in this study were likely to be better at suppressing distractors (high alpha in eyes-closed), but not better at focusing specific attention (low alpha in eyes-open). This provides some preliminary support that future work should examine how theta/beta ratios vary by differences in alpha power across resting conditions.

Trajectories of Parenting Skills Unrelated to Theta/Beta Ratios

The second aim of this study was to examine the association between children's post-treatment theta/beta ratios and trajectories of individual changes in parenting behaviors from pre-treatment, across the first phase of PCIT, mid-treatment, and posttreatment. The hypothesis that steeper gains in positive parenting skills and declines in negative parenting skills would be associated with lower post-treatment theta/beta ratios was not supported. Trajectories of positive skill change took a negative quadratic form and differed by parents' mastery achievement such that parents who achieved CDI mastery displayed more rapid improvements in positive skills and faster relative decline in negative parenting across treatment. Trajectories of change in negative parenting took a positive quadratic form, such that negative gradually decreased across the first phase of treatment before increasing towards the end of treatment, and did not differ by parents' mastery achievement.

One possible interpretation for this null finding, given that PCIT group effects were observed in ITT and per-protocol analyses in Aim 1, is that PCIT may be working to improve children's theta/beta ratios through alternate processes. Previous work on PCIT has shown dramatic decreases in parent-reported stress (Timmer et al., 2005) and use of physical discipline (Chaffin et al., 2011). In contexts where parenting stress is especially high, or the risk for child maltreatment is higher than average as in our sample, reductions in these areas may lead to marked changes in the child's caregiving environment. Similarly, it may not be the rates of change but rather the level of change in skills that account for variation in children's theta/beta ratio. Other work by our team demonstrates significant improvements in positive skills and reductions in negative skills from pre-treatment to post-treatment. A second possible interpretation for this null finding may be that the processes accounting for change in children's theta/beta ratios actually take place in the second phase of treatment, parent-directed interaction. During this phase, parents are coached to develop safe, effective child management skills, including use of consistent, contingent discipline techniques. While the first phase of treatment accounts for rapid growth in parent verbalizations that are hypothesized to improve children's attention regulation, it may be the maintenance of these skills through the second phase of treatment that actually contributes to theta/beta ratios. Future work should extend the current findings across the second phase of treatment via piecewise growth models to clearly identify whether changes in the first or second phases are related to changes in child characteristics.

The Impact of Missingness in Interpretation of Findings

Large amounts of EEG data were missing at both pre- and post-treatment (34 - 46%) in this study. As noted previously, 67 - 69% of this missing data was in children aged 3 to 4 at pre-treatment. Further, 57% of missingness in 3 to 4 year-olds at pre-treatment was due to participant refusal to wear the EEG cap. 3 to 4 year-olds who refused the EEG cap were not significantly different from 3 to 4 year-olds who were successfully capped in key behavioral measures of inhibitory control, cognitive ability, psychosocial risk, or demographic characteristics. To account for age-related missing data in our sample, child age and age-dependent indices of executive function were included in the multiple imputation model to improve estimation. Guidance provided by Van Buuren (2018) suggests that if the missing at random assumption is plausible after accounting for potential reasons for missingness (e.g., age), then findings from multiple imputation analyses should take precedence.

Complete case analyses for this study were conducted with children who had usable rsEEG data at both pre- and post-treatment. Findings from multiply imputed data were different from complete-case data, across both ITT and per-protocol analyses. Given that the mechanism for missingness is related to age and data are not missing completely at random, findings from complete case analyses are expected to be underestimated and contain high bias. As such, complete case analyses are not interpreted here.

Limitations and Future Directions

Findings from the present study should be interpreted in the context of several limitations. As noted above, the adversity experienced by this sample is multi-fold. Though our measures of adverse childhood experiences and chaotic home environment have been associated with poor executive function, they do not capture the wide array of risk factors experienced by the families in this study. Comprehensive measures of maltreatment experience, parental mental health, and resource availability could provide a deeper understanding of how PCIT impacts neurodevelopmental profiles in children who experience varying levels of cumulative risk.

A second limitation is related to the sample characteristics of the study. Although the racial and ethnic categories of this sample are representative of the pacific northwest region from which they are drawn, White participants are significantly overrepresented, with only 35% of participating children identified as holding a non-White identity (see Table 1). Across the U.S. however, Black and Indigenous children are significantly overrepresented in the child welfare system (Skowron & Woehrle, 2012), and experience additional risk factors associated with structural racism and discrimination. A lack of sufficient representation of these groups in empirical studies of intervention effectiveness is a significant barrier to developing a true understanding of how and for whom interventions work.

A third limitation is limited statistical power. While multiple imputation methods improved our ability to capture changes in band power across all children who were randomized, the pre-post design of Aim 1 and addition of psychosocial risk covariates limited statistical power to detect small effect sizes. It is possible that with greater power, that effects may either become stronger for the eyes-open condition or remain the same.

Future work can build on this study in a few ways. First, an examination of the link between theta/beta ratios across resting conditions and behavioral measures of selective attention processes can further tease apart how PCIT might be working to improve children's self-regulation. Further, an examination of how PCIT is associated with individual frequency bands can provide a broader understanding of changes in children's neural capacity. For example, beta frequency has been independently associated with specific aspects of cognitive control such as working memory and language processing (Engel et al., 2010), while theta frequency has been associated with stimulus-driven changes in attention (Orekhova et al., 2006).

Conclusions

The findings from this study contribute to the extant literature in several meaningful ways. First, this is the first study to my knowledge that mapped changes in children's theta/beta ratios across a critical developmental period for children that participated in an intensive early parenting intervention, relative to controls. I extended the existing literature in this area by uniquely testing the effects of PCIT on a known marker of top-down attention regulation (i.e., theta/beta ratio), as opposed to several rhythms individually. I calculated theta/beta ratios accounting for individual variations in alpha frequencies to minimize bias and allow for more accurate comparison across children of varying ages (e.g., 3-8 years; Lansbergen et al., 2011; Perone et al., 2017). Further, while resting EEG studies in adults tend to be collected with similar methods, resting EEG in children is far more variable (e.g., eyes-open fixation on a cross, eyes-open passive task, eyes-closed). To account for variations in these methods in the existing literature and improve generalizability of the current findings, I measured changes in theta/beta ratios across both eyes-closed and eyes-open fixation tasks.

REFERENCES CITED

Ábrahám, H., Vincze, A., Veszprémi, B., Kravják, A., Gömöri, É., Kovács, G. G., & Seress, L. (2012). Impaired myelination of the human hippocampal formation in Down syndrome. *International Journal of Developmental Neuroscience*, *30*(2), 147-158. https://doi.org/10.1016/j.ijdevneu.2011.11.005

Almas, A. N., Degnan, K. A., Nelson, C. A., Zeanah, C. H., & Fox, N. A. (2016). IQ at age 12 following a history of institutional care: Findings from the Bucharest Early Intervention Project. *Developmental Psychology*, *52*(11), 1858. https://doi.org/10.1037/dev0000167

Anderson, A. J., & Perone, S. (2018). Developmental change in the resting state electroencephalogram: insights into cognition and the brain. *Brain and Cognition*, *126*, 40-52. https://doi.org/10.1016/j.bandc.2018.08.001

Arns, M., Drinkenburg, W. H., Fitzgerald, P. B., & Kenemans, J. L. (2012). Neurophysiological predictors of non-response to rTMS in depression. *Brain stimulation*, *5*(4), 569-576. https://doi.org/10.1016/j.brs.2011.12.003

Arns, M., Gunkelman, J., Breteler, M., & Spronk, D. (2008). EEG phenotypes predict treatment outcome to stimulants in children with ADHD. *Journal of Integrative Neuroscience*, *7*(03), 421-438. https://doi.org/10.1142/S0219635208001897

Barry, R. J., Clarke, A. R., & Johnstone, S. J. (2003). A review of electrophysiology in attention-deficit/hyperactivity disorder: I. Qualitative and quantitative electroencephalography. *Clinical Neurophysiology*, *114*(2), 171-183. https://doi.org/ 10.1016/s1388-2457(02)00362-0

Barry, R. J., Clarke, A. R., Johnstone, S. J., & Brown, C. R. (2009). EEG differences in children between eyes-closed and eyes-open resting conditions. *Clinical Neurophysiology*, *120*(10), 1806-1811. https://doi.org/10.1016/j.clinph.2009.08.006

Barry, R. J., Clarke, A. R., Johnstone, S. J., Magee, C. A., & Rushby, J. A. (2007). EEG differences between eyes-closed and eyes-open resting conditions. *Clinical Neurophysiology*, *118*(12), 2765-2773. https://doi.org/ 10.1016/j.clinph.2007.07.028

Bell, M. A., & Fox, N. A. (1992). The relations between frontal brain electrical activity and cognitive development during infancy. *Child Development*, *63*(5), 1142-1163. https://doi.org/10.1111/j.1467-8624.1992.tb01685.x

Bernard, K., Dozier, M., Bick, J., & Gordon, M. K. (2015). Intervening to enhance cortisol regulation among children at risk for neglect: Results of a randomized clinical trial. *Development and Psychopathology*, *27*(3), 829-841. https://doi.org/10.1017/S095457941400073X

Bernier, A., Calkins, S. D., & Bell, M. A. (2016). Longitudinal associations between the quality of mother–infant interactions and brain development across infancy. *Child Development*, *87*(4), 1159-1174. https://doi.org/ 10.1111/cdev.12518

Bick, J., Palmwood, E. N., Zajac, L., Simons, R., & Dozier, M. (2019). Early parenting intervention and adverse family environments affect neural function in middle childhood. *Biological Psychiatry*, *85*(4), 326-335. https://doi.org/10.1016/j.biopsych.2018.09.020

Blair, C., & Raver, C. C. (2012). Child development in the context of adversity: Experiential canalization of brain and behavior. *American Psychologist*, *67*(4), 309. https://doi.org/10.1037/a0027493

Blair, C., & Razza, R. P. (2007). Relating effortful control, executive function, and false belief understanding to emerging math and literacy ability in kindergarten. *Child Development*, *78*(2), 647-663. https://doi.org/ 10.1111/j.1467-8624.2007.01019.x

Bryck, R. L., & Fisher, P. A. (2012). Training the brain: Practical applications of neural plasticity from the intersection of cognitive neuroscience, developmental psychology, and prevention science. *American Psychologist*, *67*(2), 87. https://doi.org/10.1037/a0024657

Carpenter, A. L., Puliafico, A. C., Kurtz, S. M., Pincus, D. B., & Comer, J. S. (2014). Extending parent–child interaction therapy for early childhood internalizing problems: New advances for an overlooked population. *Clinical Child and Family Psychology Review*, *17*(4), 340-356. https://doi.org/10.1007/s10567-014-0172-4

Chabot, R. J., di Michele, F., Prichep, L., & John, E. R. (2001). The clinical role of computerized EEG in the evaluation and treatment of learning and attention disorders in children and adolescents. *The Journal of Neuropsychiatry and Clinical Neurosciences*, *13*(2), 171-186. https://doi.org/10.1176/jnp.13.2.171

Chabot, R. A., & Serfontein, G. (1996). Quantitative electroencephalographic profiles of children with attention deficit disorder. *Biological Psychiatry*, *40*(10), 951–963. https://doi.org/10.1016/0006-3223(95)00576-5

Chaffin, M., Funderburk, B., Bard, D., Valle, L. A., & Gurwitch, R. (2011). A combined motivation and parent–child interaction therapy package reduces child welfare recidivism in a randomized dismantling field trial. *Journal of Consulting and Clinical Psychology*, *79*(1), 84. https://doi.org/10.1037/a0021227

Chaffin, M., Silovsky, J. F., Funderburk, B., Valle, L. A., Brestan, E. V., Balachova, T., Jackson, S., Lensgraf, J., & Bonner, B. L. (2004). Parent-child interaction therapy with physically abusive parents: efficacy for reducing future abuse reports. *Journal of Consulting and Clinical Psychology*, *72*(3), 500. https://doi.org/10.1037/0022-006x.72.3.500

Chang, S., & Egeth, H. E. (2019). Enhancement and suppression flexibly guide attention. *Psychological science*, *30*(12), 1724-1732. https://doi.org/10.1177/0956797619878813

Cheung, M. C., Chan, A. S., Han, Y. M., & Sze, S. L. (2014). Brain activity during resting state in relation to academic performance: Evidence of neural efficiency. *Journal of Psychophysiology*, *28*(2), 47. https://doi.org/10.1027/0269-8803/a000107

Cicchetti, D., & Toth, S. L. (2005). Child maltreatment. *Annual Review of Clinical Psychology*, *1*(1), 409-438. https://doi.org/10.1146/annurev.clinpsy.1.102803.144029

Clarke, A. R., Barry, R. J., Karamacoska, D., & Johnstone, S. J. (2019). The EEG theta/beta ratio: a marker of arousal or cognitive processing capacity?. *Applied Psychophysiology and Biofeedback*, *44*(2), 123-129. https://doi.org/10.1007/s10484-018-09428-6

Clarke, A. R., Barry, R. J., McCarthy, R., & Selikowitz, M. (2001). Excess beta activity in children with attention-deficit/hyperactivity disorder: an atypical electrophysiological group. *Psychiatry Research*, *103*(2-3), 205-218. https://doi.org/10.1016/S0165-1781(01)00277-3

Clarke, A. R., Barry, R. J., McCarthy, R., & Selikowitz, M. (2002). EEG analysis of children with attention-deficit/hyperactivity disorder and comorbid reading disabilities. *Journal of Learning Disabilities*, *35*(3), 276-285. https://doi.org/10.1177/002221940203500309

Coley, R. L., Lynch, A. D., & Kull, M. (2015). Early exposure to environmental chaos and children's physical and mental health. *Early Childhood Research Quarterly*, *32*, 94-104. https://dx.doi.org/10.1016%2Fj.ecresq.2015.03.001

Corning, W. C., Steffy, R. A., & Chaprin, I. C. (1982). EEG slow frequency and WISC-R correlates. *Journal of Abnormal Child Psychology*, *10*(4), 511-530. https://doi.org/10.1007/bf00920751

Coste, C. P., Sadaghiani, S., Friston, K. J., & Kleinschmidt, A. (2011). Ongoing brain activity fluctuations directly account for intertrial and indirectly for intersubject variability in Stroop task performance. *Cerebral Cortex*, *21*(11), 2612-2619. https://doi.org/10.1093/cercor/bhr050

Cuevas, K., Hubble, M., & Bell, M. A. (2012). Early childhood predictors of post-kindergarten executive function: Behavior, parent report, and psychophysiology. *Early Education & Development*, *23*(1), 59-73. https://doi.org/10.1111/bjdp.12021

Cuevas, K., Hubble, M., & Bell, M. A. (2012). Early childhood predictors of post-kindergarten executive function: Behavior, parent report, and psychophysiology. *Early Education & Development*, *23*(1), 59-73. https://doi.org/10.1111/bjdp.12021

Damoiseaux, J. S., Rombouts, S. A. R. B., Barkhof, F., Scheltens, P., Stam, C. J., Smith, S. M., & Beckmann, C. F. (2006). Consistent resting-state networks across healthy subjects. *Proceedings of the National Academy of Sciences*, *103*(37), 13848-13853. https://doi.org/10.1073/pnas.0601417103

Deater-Deckard, K., Sewell, M. D., Petrill, S. A., & Thompson, L. A. (2010). Maternal working memory and reactive negativity in parenting. *Psychological Science*, *21*(1), 75-79. https://doi.org/10.1177/0956797609354073

Delorme, A., & Makeig, S. (2004). EEGLAB: an open source toolbox for analysis of single-trial EEG dynamics including independent component analysis. *Journal of Neuroscience Methods*, *134*(1), 9-21. https://doi.org/10.1016/j.jneumeth.2003.10.009

Diamond, A. (2006). The early development of executive functions. *Lifespan Cognition: Mechanisms of Change*, *210*, 70-95. https://doi.org/10.1093/acprof:oso/9780195169539.003.0006

Diamond, A. (2012). Executive functions. *Annual Review of Psychology*, *64*, 135-168. https://doi.org/10.1146/annurev-psych-113011-143750

Dodge, K. A., Bates, J. E., & Pettit, G. S. (1990). Mechanisms in the cycle of violence. *Science*, *250*(4988), 1678-1683. https://doi.org/10.1126/science.2270481

Dozier, M., Peloso, E., Lewis, E., Laurenceau, J. P., & Levine, S. (2008). Effects of an attachment-based intervention on the cortisol production of infants and toddlers in foster care. *Development and Psychopathology*, *20*(3), 845-859. https://doi.org/10.1017/s0954579408000400

Egner, T., & Gruzelier, J. H. (2004). EEG biofeedback of low beta band components: frequency-specific effects on variables of attention and event-related brain potentials. *Clinical Neurophysiology*, *115*(1), 131-139. https://doi.org/10.1016/s1388-2457(03)00353-5

Evans, G. W., Gonnella, C., Marcynyszyn, L. A., Gentile, L., & Salpekar, N. (2005). The role of chaos in poverty and children's socioemotional adjustment. *Psychological Science*, *16*(7), 560-565. https://doi.org/10.1111/j.0956-7976.2005.01575.x

Eyberg, S. M., Boggs, S. R., & Algina, J. (1995). Parent-child interaction therapy: A psychosocial model for the treatment of young children with conduct problem behavior and their families. *Psychopharmacology Bulletin*.

Eyberg, S. M., Chase, R. M., Fernandez, M. A., & Nelson, M. M. (2014). *Dyadic Parent-Child Interaction Coding System (DPICS) Clinical Manual (4th Ed.).* PCIT International Inc.

Eyberg, S. M., Funderburk, B. W., Hembree-Kigin, T. L., McNeil, C. B., Querido, J. G., & Hood, K. K. (2001). Parent-child interaction therapy with behavior problem children: One and two year maintenance of treatment effects in the family. *Child & Family Behavior Therapy*, *23*(4), 1-20. https://doi.org/10.1300/J019v23n04_01

Felitti, V. J., Anda, R. F., Nordenberg, D., Williamson, D. F., Spitz, A. M., Edwards, V., & Marks, J. S. (1998). Relationship of childhood abuse and household dysfunction to many of the leading causes of death in adults: The Adverse Childhood Experiences (ACE) Study. *American Journal of Preventive Medicine*, *14*(4), 245-258. https://doi.org/10.1016/s0749-3797(98)00017-8

Fisher, P. A., Gunnar, M. R., Dozier, M., Bruce, J., & Pears, K. C. (2006). Effects of therapeutic interventions for foster children on behavioral problems, caregiver attachment, and stress regulatory neural systems. *Annals of the New York Academy of Sciences*, *1094*(1), 215-225. https://doi.org/10.1196/annals.1376.023. PMID: 17347353.

Funderburk, B. W., Eyberg, S. M., Newcomb, K., McNeil, C. B., Hembree-Kigin, T., & Capage, L. (1998). Parent-child interaction therapy with behavior problem children: Maintenance of treatment effects in the school setting. *Child and Family Behaviour Therapy*, *20*(2), 17-38. https://doi.org/10.1300/J019v20n02_02

Gabard-Durnam, Laurel J., and Katie A. McLaughlin. "Do Sensitive Periods Exist for Exposure to Adversity?" Biological Psychiatry, vol. 85, no. 10, 2019, pp. 789–791. https://doi.org/10.1016/j.biopsych.2019.03.975

Gilmore, J. H., Knickmeyer, R. C., & Gao, W. (2018). Imaging structural and functional brain development in early childhood. *Nature Reviews Neuroscience*, *19*(3), 123. https://doi.org/10.1038/nrn.2018.1

Graham, J. W. (2009). Missing data analysis: Making it work in the real world. *Annual Review of Psychology*, *60*, 549-576. https://doi.org/10.1146/annurev.psych.58.110405.085530

Hakman, M., Chaffin, M., Funderburk, B., & Silovsky, J. F. (2009). Change trajectories for parent-child interaction sequences during parent-child interaction therapy for child physical abuse. *Child Abuse & Neglect*, *33*(7), 461-470. https://doi.org/10.1016/j.chiabu.2008.08.003

Herschell, A. D., & McNeil, C. B. (2005). Theoretical and empirical underpinnings of parent-child interaction therapy with child physical abuse populations. *Education and Treatment of Children*, 142-162. https://www.jstor.org/stable/42899838

Humphreys, K. L., Gleason, M. M., Drury, S. S., Miron, D., Nelson 3rd, C. A., Fox, N. A., & Zeanah, C. H. (2015). Effects of institutional rearing and foster care on psychopathology at age 12 years in Romania: follow-up of an open, randomised controlled trial. *The Lancet Psychiatry*, *2*(7), 625-634. https://doi.org/10.1016/s2215-0366(15)00095-4

Huth-Bocks, A. C., & Hughes, H. M. (2008). Parenting stress, parenting behavior, and children's adjustment in families experiencing intimate partner violence. *Journal of Family Violence*, *23*(4), 243-251. https://doi.org/10.1007/s10896-007-9148-1

Jacobs, J., Hwang, G., Curran, T., & Kahana, M. J. (2006). EEG oscillations and recognition memory: theta correlates of memory retrieval and decision making. *Neuroimage*, *32*(2), 978-987. https://doi.org/10.1016/j.neuroimage.2006.02.018

Johnson, S. B., Riis, J. L., & Noble, K. G. (2016). State of the art review: Poverty and the developing brain. *Pediatrics*, *137*(4), e20153075. https://doi.org/10.1542/peds.2015-3075

Johnstone, S. J., Jiang, H., Sun, L., Rogers, J. M., Valderrama, J., & Zhang, D. (2020). Development of frontal EEG differences between eyes-closed and eyes-open resting conditions in children: Data from a single-channel dry-sensor portable device. *Clinical EEG and Neuroscience*, *52*(4). https://doi.org/10.1177/1550059420946648

Kaminski, J. W., Valle, L. A., Filene, J. H., & Boyle, C. L. (2008). A meta-analytic review of components associated with parent training program effectiveness. *Journal of Abnormal Child Psychology*, *36*(4), 567-589. https://doi.org/10.1007/s10802-007-9201-9

Kasim, R. M., & Raudenbush, S. W. (1998). Application of Gibbs sampling to nested variance components models with heterogeneous within-group variance. *Journal of Educational and Behavioral Statistics*, *23*(2), 93-116. https://doi.org/10.3102/10769986023002093

Kennedy, S. C., Kim, J. S., Tripodi, S. J., Brown, S. M., & Gowdy, G. (2016). Does parent–child interaction therapy reduce future physical abuse? A meta-analysis. *Research on social work practice*, *26*(2), 147-156. https://doi.org/10.1177/1049731514543024

King, L. S., Humphreys, K. L., Camacho, M. C., & Gotlib, I. H. (2019). A person-centered approach to the assessment of early life stress: Associations with the volume of stress-sensitive brain regions in early adolescence. *Development and psychopathology*, *31*(2), 643-655. https://doi.org/10.1017/s0954579418000184

Klimesch, W. (2012). Alpha-band oscillations, attention, and controlled access to stored information. *Trends in cognitive sciences*, *16*(12), 606-617. https://doi.org/10.1016/j.tics.2012.10.007

Kouijzer, M. E., de Moor, J. M., Gerrits, B. J., Congedo, M., & van Schie, H. T. (2009). Neurofeedback improves executive functioning in children with autism spectrum disorders. *Research in Autism Spectrum Disorders*, *3*(1), 145-162. https://doi.org/10.1007/s10484-012-9204-3

Lansbergen, M. M., Arns, M., van Dongen-Boomsma, M., Spronk, D., & Buitelaar, J. K. (2011). The increase in theta/beta ratio on resting-state EEG in boys with attention-deficit/hyperactivity disorder is mediated by slow alpha peak frequency. *Progress in Neuro-Psychopharmacology and Biological Psychiatry*, *35*(1), 47-52. https://doi.org/10.1016/j.pnpbp.2010.08.004

Liechti, M. D., Valko, L., Müller, U. C., Döhnert, M., Drechsler, R., Steinhausen, H. C., & Brandeis, D. (2013). Diagnostic value of resting electroencephalogram in attention-deficit/hyperactivity disorder across the lifespan. *Brain Topography*, *26*(1), 135-151. https://doi.org/10.1007/s10548-012-0258-6

Little, T. D., Jorgensen, T. D., Lang, K. M., & Moore, E. W. G. (2014). On the joys of missing data. *Journal of Pediatric Psychology*, *39*(2), 151-162. https://doi.org/10.1093/jpepsy/jst048

Loman, M. M., & Gunnar, M. R. (2010). Early experience and the development of stress reactivity and regulation in children. *Neuroscience & Biobehavioral Reviews*, *34*(6), 867-876. https://doi.org/10.1016/j.neubiorev.2009.05.007

Loo, S. K., & Makeig, S. (2012). Clinical utility of EEG in attention-deficit/hyperactivity disorder: a research update. *Neurotherapeutics*, *9*(3), 569-587. https://doi.org/10.1007/s13311-012-0131-z

Loo, S. K., Cho, A., Hale, T. S., McGough, J., McCracken, J., & Smalley, S. L. (2013). Characterization of the theta to beta ratio in ADHD: identifying potential sources of heterogeneity. *Journal of Attention Disorders*, *17*(5), 384-392. https://doi.org/10.1177/1087054712468050

Loo, S. K., Lenartowicz, A., & Makeig, S. (2016). Research review: Use of EEG biomarkers in child psychiatry research–current state and future directions. *Journal of Child Psychology and Psychiatry*, *57*(1), 4-17. https://doi.org/10.1111/jcpp.12435

Lyall, A. E., Shi, F., Geng, X., Woolson, S., Li, G., Wang, L., Hamer, R.M., Shen, D., & Gilmore, J. H. (2015). Dynamic development of regional cortical thickness and surface area in early childhood. *Cerebral Cortex*, *25*(8), 2204-2212. https://doi.org/10.1093/cercor/bhu027

Marshall, P. J., Bar-Haim, Y., & Fox, N. A. (2002). Development of the EEG from 5 months to 4 years of age. *Clinical Neurophysiology*, *113*(8), 1199-1208. https://doi.org/10.1016/S1388-2457(02)00163-3

Marshall, P. J., Fox, N. A., & Buchacrest Early Intervention Project Core Group. (2004). A comparison of the electroencephalogram between institutionalized and community children in Romania. *Journal of Cognitive Neuroscience*, *16*(8), 1327-1338. https://doi.org/10.1162/0898929042304723

Marshall, P. J., Reeb, B. C., Fox, N. A., Nelson III, C. A., & Zeanah, C. H. (2008). Effects of early intervention on EEG power and coherence in previously institutionalized children in Romania. *Development and psychopathology*, *20*(3), 861. https://doi.org/10.1017/S0954579408000412

Massar, S. A., Kenemans, J. L., & Schutter, D. J. (2014). Resting-state EEG theta activity and risk learning: sensitivity to reward or punishment?. *International Journal of Psychophysiology*, *91*(3), 172-177. https://doi.org/10.1016/j.ijpsycho.2013.10.013

Matheny Jr, A. P., Wachs, T. D., Ludwig, J. L., & Phillips, K. (1995). Bringing order out of chaos: Psychometric characteristics of the confusion, hubbub, and order scale. *Journal of Applied Developmental Psychology*, *16*(3), 429-444. https://doi.org/10.1016/0193-3973(95)90028-4

Matousek, M., Peterson, I., & Kelloway, P. (1973). Automation of clinical electroencephalography.

Matsuura, M., Okubo, Y., Toru, M., Kojima, T., He, Y., Shen, Y., & Lee, C. K. (1993). A cross-national EEG study of children with emotional and behavioral problems: A WHO collaborative study in the Western Pacific Region. Biological psychiatry, *34*(1-2), 59-65. https://doi.org/10.1016/0006-3223(93)90257-E

McEwen, B. S., & Gianaros, P. J. (2011). Stress-and allostasis-induced brain plasticity. *Annual Review of Medicine*, *62*, 431-445. https://doi.org/10.1146/annurev-med-052209-100430

McLaughlin, K. A., Fox, N. A., Zeanah, C. H., Sheridan, M. A., Marshall, P., & Nelson, C. A. (2010). Delayed maturation in brain electrical activity partially explains the association between early environmental deprivation and symptoms of attention-deficit/hyperactivity disorder. *Biological Psychiatry*, *68*(4), 329-336. https://doi.org/10.1016/j.biopsych.2010.04.005

Miller, E. K., & Cohen, J. D. (2001). An integrative theory of prefrontal cortex function. *Annual Review of Neuroscience*, *24*(1), 167-202. https://doi.org/10.1146/annurev.neuro.24.1.167

Miskovic, V., Ma, X., Chou, C. A., Fan, M., Owens, M., Sayama, H., & Gibb, B. E. (2015). Developmental changes in spontaneous electrocortical activity and network organization from early to late childhood. *Neuroimage*, *118*, 237-247. https://doi.org/10.1016/j.neuroimage.2015.06.013

Monastra, V. J., Lubar, J. F., & Linden, M. (2001). The development of a quantitative electroencephalographic scanning process for attention deficit–hyperactivity disorder: Reliability and validity studies. *Neuropsychology*, *15*(1), 136. https://doi.org/10.1037//0894-4105.15.1.136

Moylan, C. A., Herrenkohl, T. I., Sousa, C., Tajima, E. A., Herrenkohl, R. C., & Russo, M. J. (2010). The effects of child abuse and exposure to domestic violence on adolescent internalizing and externalizing behavior problems. *Journal of Family Violence*, *25*(1), 53-63. https://doi.org/10.1007/s10896-009-9269-9

Nekkanti, A. K., Jeffries, R., Scholtes, C. M., Shimomaeda, L., DeBow, K., Wells, J. N., ... & Skowron, E. A. (2020). Study Protocol: The Coaching Alternative Parenting Strategies (CAPS) Study of Parent-Child Interaction Therapy in Child Welfare Families. *Frontiers in Psychiatry*, *11*(839). https://10.3389/fpsyt.2020.00839

Nicholas Tierney, Di Cook, Miles McBain and Colin Fay (2021). naniar: Data Structures, Summaries, and Visualisations for Missing Data. R package version 0.6.0.9000. https://github.com/njtierney/naniar

Ochsner, K. N., & Gross, J. J. (2008). Cognitive emotion regulation: Insights from social cognitive and affective neuroscience. *Current Directions in Psychological Science*, *17*(2), 153-158. https://doi.org/10.1111/j.1467-8721.2008.00566.x

Perone, S., Palanisamy, J., & Carlson, S. M. (2018). Age-related change in brain rhythms from early to middle childhood: Links to executive function. *Developmental Science*, *21*(6), e12691. https://doi.org/10.1111/desc.12691

Pollak, S. D., & Kistler, D. J. (2002). Early experience is associated with the development of categorical representations for facial expressions of emotion. *Proceedings of the National Academy of Sciences*, *99*(13), 9072-9076. https://doi.org/10.1073/pnas.142165999

Putman, P., van Peer, J., Maimari, I., & van der Werff, S. (2010). EEG theta/beta ratio in relation to fear-modulated response-inhibition, attentional control, and affective traits. *Biological Psychology*, *83*(2), 73-78. https://doi.org/10.1016/j.biopsycho.2009.10.008

Putman, P., Verkuil, B., Arias-Garcia, E., Pantazi, I., & van Schie, C. (2014). EEG theta/beta ratio as a potential biomarker for attentional control and resilience against deleterious effects of stress on attention. *Cognitive, Affective, & Behavioral Neuroscience*, *14*(2), 782-791. https://doi.org/10.3758/s13415-013-0238-7

R Core Team (2013). R: A language and environment for statistical computing. R Foundation for Statistical Computing, Vienna, Austria. http://www.R-project.org/.

Raine, A., Venables, P. H., Dalais, C., Mellingen, K., Reynolds, C., & Mednick, S. A. (2001). Early educational and health enrichment at age 3–5 years is associated with increased autonomic and central nervous system arousal and orienting at age 11 years: Evidence from the Mauritius Child Health Project. *Psychophysiology*, *38*(2), 254-266. https://doi.org/10.1017/S0048577201990067

Raudenbush, S. W., & Bryk, A. S. (2002). *Hierarchical linear models: applications and data analysis methods*. Sage Publications.

Raudenbush, S. W., Bryk, A. S., Cheong, Y. F., Congdon, R., & Du Toit, M. (2011). Hierarchical linear and nonlinear modeling (HLM7). *Lincolnwood, IL: Scientific Software International*, *1112*.

Repetti, R. L., Taylor, S. E., & Seeman, T. E. (2002). Risky families: Family social environments and the mental and physical health of offspring. *Psychological bulletin*, *128*(2), 330. https://doi.org/10.1037/0033-2909.128.2.330

Rhoades, B. L., Greenberg, M. T., & Domitrovich, C. E. (2009). The contribution of inhibitory control to preschoolers' social–emotional competence. *Journal of Applied Developmental Psychology*, *30*(3), 310-320. https://doi.org/10.1016/j.appdev.2008.12.012

Roth, T. L., Lubin, F. D., Funk, A. J., & Sweatt, J. D. (2009). Lasting epigenetic influence of early-life adversity on the BDNF gene. *Biological Psychiatry*, *65*(9), 760-769. https://doi.org/10.1016/j.biopsych.2008.11.028

Rubin, D. B. (2004). Direct and indirect causal effects via potential outcomes. *Scandinavian Journal of Statistics*, *31*(2), 161-170. https://doi.org/10.1111/j.1467-9469.2004.02-123.x

Schulz, K. F., Altman, D. G., Moher, D., & Consort Group. (2010). CONSORT 2010 statement: updated guidelines for reporting parallel group randomised trials. *Trials*, *11*(1), 32. https://doi.org/10.1136/bmj.c332

Schutter, D. J., & Van Honk, J. (2005). Electrophysiological ratio markers for the balance between reward and punishment. *Cognitive Brain Research*, *24*(3), 685-690.

Shackman, J. E., Shackman, A. J., & Pollak, S. D. (2007). Physical abuse amplifies attention to threat and increases anxiety in children. *Emotion*, *7*(4), 838. https://doi.org/10.1037/1528-3542.7.4.838

Shaw, P., Eckstrand, K., Sharp, W., Blumenthal, J., Lerch, J. P., Greenstein, D., Clasen, L., Evans, A., Geidd, J., & Rapoport, J. L. (2007). Attention-deficit/hyperactivity disorder is characterized by a delay in cortical maturation. *Proceedings of the National Academy of Sciences*, *104*(49), 19649-19654. https://doi.org/10.1073/pnas.0707741104

Shields, G. S., Sazma, M. A., & Yonelinas, A. P. (2016). The effects of acute stress on core executive functions: A meta-analysis and comparison with cortisol. *Neuroscience & Biobehavioral Reviews*, *68*, 651-668. https://doi.org/10.1016/j.neubiorev.2016.06.038

Shonkoff, J. P., & Phillips, D. A. (Eds.). (2000). *From neurons to neighborhoods: The science of early childhood development.* National Academy Press. https://doi.org/10.17226/9824

Shonkoff, J. P., & Garner, A. S. (2012). Committee on psychosocial aspects of child and family health committee on early childhood, adoption, and dependent care section on developmental and behavioral pediatrics the lifelong effects of early childhood adversity and toxic stress. Pediatrics, 129(1), e232-e246.

Skowron, E. A., & Funderburk, B. W. (2021). In vivo social regulation of high-risk parenting: A conceptual model of Parent-Child Interaction Therapy for child maltreatment prevention. https://doi.org/10.31234/osf.io/agxd3

Skowron, E. A., & Woehrle, P. (2012). *Child maltreatment.* In N. A. Fouad, J. A. Carter, & L. M. Subich (Eds.), *APA handbooks in psychology. APA handbook of counseling psychology, Vol. 2. Practice, interventions, and applications* (p. 153–180). American Psychological Association. https://doi.org/10.1037/13755-007

Smyke, A. T., Zeanah, C. H., Fox, N. A., Nelson, C. A., & Guthrie, D. (2010). Placement in foster care enhances quality of attachment among young institutionalized children. *Child development*, *81*(1), 212-223. https://doi.org/10.1111/j.1467-8624.2009.01390.x

Snijders, T. A., & Bosker, R. J. (1999). An introduction to basic and advanced multilevel modeling. *Sage Publications Limited.*

Snyder, S. M., & Hall, J. R. (2006). A meta-analysis of quantitative EEG power associated with attention-deficit hyperactivity disorder. *Journal of Clinical Neurophysiology*, *23*(5), 441-456. https://doi.org/10.1097/01.wnp.0000221363.12503.78

Stamoulis, C., Vanderwert, R. E., Zeanah, C. H., Fox, N. A., & Nelson, C. A. (2015). Early psychosocial neglect adversely impacts developmental trajectories of brain oscillations and their interactions. *Journal of Cognitive Neuroscience*, *27*(12), 2512-2528. https://doi.org/10.1162/jocn_a_00877

Stroganova, T. A., & Orekhova, E. V. (2007). EEG and infant states. *Infant EEG and event-related potentials*. Psychology Press. https://doi.org/10.4324/9780203759660

Stuss, D. T., & Alexander, M. P. (2000). Executive functions and the frontal lobes: a conceptual view. *Psychological Research*, *63*(3-4), 289-298. https://doi.org/10.1007/s004269900007

Szyf, M. (2009). The early life environment and the epigenome. *Biochimica et Biophysica Acta (BBA)-General Subjects*, *1790*(9), 878-885. https://doi.org/10.1016/j.bbagen.2009.01.009

Teicher, M. H., & Samson, J. A. (2016). Annual research review: enduring neurobiological effects of childhood abuse and neglect. *Journal of child psychology and psychiatry*, *57*(3), 241-266. https://dx.doi.org/10.1111%2Fjcpp.12507

Thomas, R., & Zimmer-Gembeck, M. J. (2011). Accumulating evidence for parent–child interaction therapy in the prevention of child maltreatment. *Child Development*, *82*(1), 177-192. https://doi.org/10.1111/j.1467-8624.2010.01548.x

Thomas, R., Abell, B., Webb, H. J., Avdagic, E., & Zimmer-Gembeck, M. J. (2017). Parent-child interaction therapy: A meta-analysis. *Pediatrics*, *140*(3), e20170352. https://doi.org/10.1542/peds.2017-0352

Timmer, S. G., Urquiza, A. J., Zebell, N. M., & McGrath, J. M. (2005). Parent-child interaction therapy: Application to maltreating parent-child dyads. *Child abuse & neglect*, *29*(7), 825-842. https://doi.org/10.1016/j.chiabu.2005.01.003

Troller-Renfree, S. V., Brito, N. H., Desai, P. M., Leon-Santos, A. G., Wiltshire, C. A., Motton, S. N., ... & Noble, K. G. (2020). Infants of mothers with higher physiological stress show alterations in brain function. *Developmental Science*, *23*(6), e12976. https://doi.org/10.1111/desc.12976

Urquiza, A. J., & McNeil, C. B. (1996). Parent-child interaction therapy: An intensive dyadic intervention for physically abusive families. *Child Maltreatment*, *1*(2), 134-144. https://doi.org/10.1177/1077559596001002005

Van Buuren, S. (2018). *Flexible imputation of missing data*. CRC Press, Chapman & Hall/CRC.

Van Buuren, S., & Groothuis-Oudshoorn, S. (2011). mice: Multivariate imputation by chained equations in R. *Journal of Statistical Software*, *45*(3), 1-67. https://www.jstatsoft.org/v45/i03/

Vanderwert, R. E., Marshall, P. J., Nelson III, C. A., Zeanah, C. H., & Fox, N. A. (2010). Timing of intervention affects brain electrical activity in children exposed to severe psychosocial neglect. *PLoS One*, *5*(7), e11415. https://doi.org/10.1371/journal.pone.0011415

Vanderwert, R. E., Zeanah, C. H., Fox, N. A., & Nelson III, C. A. (2016). Normalization of EEG activity among previously institutionalized children placed into foster care: A 12-year follow-up of the Bucharest Early Intervention Project. *Developmental Cognitive Neuroscience*, *17*, 68-75. https://dx.doi.org/10.1016%2Fj.dcn.2015.12.004

Wagner, S. M., & McNeil, C. B. (2008). Parent-child interaction therapy for ADHD: A conceptual overview and critical literature review. *Child & Family Behavior Therapy*, *30*(3), 231-256. https://doi.org/10.1080/07317100802275546

Wang, Q., Zhang, H., Wee, C. Y., Lee, A., Poh, J. S., Chong, Y. S., Tan, K.H., Gluckman, P.D., Yap, F., Fortier, M.V., Rifkin-Graboi, A., Qiu, A. (2019). Maternal sensitivity predicts anterior hippocampal functional networks in early childhood. *Brain Structure and Function*, *224*(5), 1885-1895. https://doi.org/10.1007/s00429-019-01882-0

Wangler, S., Gevensleben, H., Albrecht, B., Studer, P., Rothenberger, A., Moll, G. H., & Heinrich, H. (2011). Neurofeedback in children with ADHD: specific event-related potential findings of a randomized controlled trial. *Clinical Neurophysiology*, *122*(5), 942-950. https://doi.org/10.1016/j.clinph.2010.06.036

Woodcock RW, McGrew KS, Mather N. Woodcock-Johnson III Tests of Achievement. Riverside Publishing: Itasca, IL: (2001).

Yau, L. H., & Little, R. J. (2001). Inference for the complier-average causal effect from longitudinal data subject to noncompliance and missing data, with application to a job training assessment for the unemployed. *Journal of the American Statistical Association*, *96*(456), 1232-1244. https://doi.org/10.1198/016214501753381887