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Modeling the interrelationships between brain activity and trait attention measures to predict individual differences in reaction times in children during a Go/No-Go task

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Abstract

Many researchers are utilizing event-related potentials (ERPs) to better understand brain-behavior relationships across development. The present study demonstrates how structural equation modeling (SEM) techniques can be used to refine descriptions of brain-behavior relationships in a sample of neurotypical children. We developed an exploratory latent variable model in which trait measures of maturation and attention are related to neural processing and task behaviors obtained during a cued Go/No-Go task. Model findings are compared to results of traditional analysis techniques such as bivariate correlations. The data suggest that more sophisticated statistical approaches are beneficial to accurately interpreting the nature of brain-behavior relationships.

Keywords

Event-related potentials; ERPs; structural equation modeling; SEM; development; brain-behavior relationships

1. Introduction

For over two decades now, brain imaging technologies have been applied to the study of cognitive development and neurological disorders in children. Although great progress has been made, past research has relied heavily on univariate statistical methods for exploring

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the relationships between brain activity and human behaviors. Some researchers focus more on simple task behaviors, such as reactions times within the task used to elicit the neural activity (e.g., Brunner et al., 2015; Jongen, Smulders, & Van Breukelen, 2006). Other researchers have tried to establish more complex relationships between brain and behavior, attempting to relate neural processing to clinical behavioral assessments which are believed to test trait measures of cognitive functioning (e.g., Brydges et al., 2014; Foti et al., 2016).

The E-wave component of the contingent negative variation (CNV) is a slow negative drift in ERPs resulting from attentional anticipation between two stimuli (see Figure 1 for examples; Walter et al., 1964). Specifically, the E-wave is believed to represent aspects of sustained attention processing (Bender et al., 2004; Segalowitz & Davies, 2004). Researchers have shown alterations to CNV E-wave amplitudes in different attentional states, such as wakeful, conscious activity versus sleep (Yasuda, Ray, & Cote, 2011). Additionally, research has shown that in adults, larger (more negative) E-wave amplitudes are related to faster reactions times during Go/No-Go ERP tasks (Brunner et al., 2015; Connor & Lang, 1969; Jongen et al., 2006). However, some investigators argue that the E-wave may relate more to motor preparation preceding a behavioral response than to attentional anticipation (i.e., the *Bereitschaftspotential*; Gomez, Marco, & Grau, 2003; Rockstroh et al., 1993). Given this paucity of research, investigators may argue that the field has yet to firmly establish the construct validity of the E-wave and continue to adopt the idea that the component represents sustained attention.

Interestingly, a previous study involving children found that across two assessment sessions conducted one-to-two weeks apart, CNV E-wave amplitudes became more negative in the second session. Furthermore, this increased negativity occurs despite consistent behavioral performance suggesting that the children were equally attentive and successful in completing the task during each session (Taylor et al., 2016). Although the E-wave is known to become more negative across development (e.g., Hämmerer et al., 2010; Jonkman, 2006; Jonkman, Lansbergen & Stauder, 2003; Segalowitz & Davies, 2004; Taylor et al., 2016), it is unlikely that developmental changes occurred over such a short period of time (i.e., one or two weeks in school-aged children). Prior research suggests that changes in ERP amplitudes after practicing a task, even without notable improvement in task performance, may indicate shifts in cognitive strategies as a result of practice (Pauli et al., 1994; Romero et al., 2008). Thus, Taylor et al. (2016) suggested that the shift in amplitude across sessions may have been the result of a shift in attentional strategies as the children practiced the task used to elicit the E-wave. Although interesting, such a shift in the *state* of participants across sessions (i.e., learning strategies) could affect the visibility and interpretation of brain-to-behavior relationships in the data in future investigations.

Gavin and Davies (2008) suggested that any given psychophysiological measure (PM), such as the amplitude of an ERP component, can be conceptualized as the combined effect of (1) the *stimulus processing* involved in eliciting the component; (2) the *state* of the individual participant during measurement such as current mood or sleepiness; (3) the *trait* characteristics of the individual such as general attention abilities or maturation level; (4) the *signal processing techniques* employed to calculate the ERP component including filtering and averaging of EEG signals; and (5) *measurement error* (ME), which is any other

unaccounted-for variance (see equation 1 below, reprinted from Gavin & Davies, 2008, p. 428).

Such a model can be simply written as

$$PM = \text{Effect}_{\text{STIMULUS}} + \text{Effect}_{\text{STATE}} + \text{Effect}_{\text{TRAIT}} + \text{Effect}_{\text{PM_PROCESSING}} + ME \quad (1)$$

and this type of model allows for the use of multiple regression techniques to understand the variation of brain activity across individuals performing a given task, particularly when examining performance repeated on two or more occasions. This is in contrast to what have historically been common statistical practices among neuropsychological researchers. For example, many studies have used *t*-test or ANOVA designs to compare group means across stimulus processing effects (Sartory, Becken, & Pothmann, 1997; Segalowitz, Unsal, Dywan, 1992) or between age groups (Barriga-Paulino, Rodríguez-Martínez, Rojas-Benjumea, & Gómez, 2014; Jonkman, 2006; Jonkman, et al., 2003), potentially ignoring sources of individual variability that may contribute to the ERP component measure of interest. As the equation in this model suggests, when researchers fail to account for one or more of these other potential sources of individual differences that are contributing to an ERP component measure, the researchers are compounding the unaccounted-for individual effects into the ME term (see equation 2 below reprinted from Gavin and Davies, 2008, p. 428 for an example).

$$PM = \text{Effect}_{\text{STIMULUS}} + ME_{\text{TOTAL}} \quad (2)$$

Larger measurement error may result in increased type I or type II error. For instance, if a significant statistical relationship is found between a physiological measure and a functional behavior, this relationship could be explained by either the stimulus effect *or* the undefined measurement error. Thus, it is important to reduce the amount of measurement error in analyses by accounting for variance of factors that are often folded into the measurement error. Such reductions are especially important in populations that are inherently more variable, such as children, if the study's conclusions are to be as unambiguous as possible. By reducing measurement error, researchers may increase their ability to detect effects of interest in the data, such as the effect of the stimulus or other experimental manipulations. The current investigation demonstrates how the use of more sophisticated statistical techniques, namely structural equation modeling (SEM), may better account for individual differences and allow for modelling the relationship between multiple variables. The study specifically examined the interrelationships among neural processing (E-wave), task behaviors (reaction times), and trait measures of maturation and attention.

In order to both examine our findings in relation to previous literature and to better account for individual variability in E-wave amplitude measures and task behavior measures, we used a combination of analysis techniques. Specifically, we began our analyses using more

traditional methods (t -tests and correlations), and then we employed SEM techniques, which can better manage individual variability and minimize measurement error. *Research Question 1* investigated whether the E-wave is related to task-specific reaction times using a variety of statistical techniques that differentially manage sources of variability stemming from individual differences within and between individuals during each session. *Research Question 2* explored whether E-wave or reaction time measures can be related to trait measures of attention defined by a valid, clinical behavioral assessment once we have effectively removed measurement error from the variables of interest.

1.1. Research Question 1

To answer the first research question, we first assessed the robustness of the findings from Taylor et al. (2016) by examining the test-retest reliability of E-wave and task performance measures, as well as group-level differences across sessions. Then, we employed a path analysis to examine whether E-wave measures could predict reaction time measures during each session after controlling for age, a trait measure for level of maturation. We expected to find a significant predictive relationship between brain and behavioral measures based on previous findings. We specifically included both mean and standard deviation measures of the E-wave and of reaction times on the basis that *typical* performance (i.e., means) and *intra-individual variability* in performance (i.e., standard deviations) are known to measure independent aspects of an individual's abilities (Kievit et al., 2016). Literature suggests that intra-individual variability in behavioral performance and in neural processing are important, unique measures of an individual's abilities (for a complete review, see MacDonald et al., 2006).

Finally, we examined whether using latent variable models could strengthen brain to behavior relationships due to the reduction in measurement error that occurs when the latent variables are created. We hypothesized that removing measurement error would result in a stronger relationship between E-wave measures and reaction times.

1.2. Research Question 2

The E-wave component has been described as a representation of sustained attention processing in the brain for a number of reasons, one of which is the finding that E-wave amplitudes are related to within-task reaction times (Brunner et al., 2015; Connor & Lang, 1969). However, to the best of our knowledge neither E-wave amplitudes nor within-task reaction time have been definitively related to validated behavioral assessment measures of attentional abilities. Behavioral assessment measures are often conceptualized as indicators of an individual's trait-based cognitive abilities, which should be relatively stable.

Thus, to answer the second research question we examined whether the E-wave or reaction times could be related to a behavioral assessment of attention designed for clinical use. We specifically focused on the Test of Everyday Attention for Children (TEA-Ch; Manly et al., 2001; Manly et al., 1999), which purports to measure three different types of attention: selective, switching, and sustained attention. Because the tripartite factor structure of the TEA-Ch has only been validated in a sample of 6- to 16-year-old Australian children, we began our investigation by first exploring the factor structure of the TEA-Ch in a younger

sample of neurotypical children in the United States. We then examined (1) whether the different types of attention measured by the TEA-Ch were related to the E-wave, and (2) whether the E-wave or the TEA-Ch factors were better predictors of reaction times during the ERP task. Based on prior literature, we hypothesized that both the E-wave and reaction time would have the strongest relationships with *sustained* attention, compared to selective or switching attention, as measured by the TEA-Ch.

2. Methods

2.1. Participants

Data were collected from a total of 91 neurotypical children between the ages of 7 and 13 years during two sessions scheduled one-to-two weeks apart. Eighteen children were excluded due to poor performance, as described in detail in the results. The final sample included 73 children (34 males; $M = 10.40$ years, $SD = 1.54$). The sample is comprised of data collected during two separate time periods. Fifty-one of the included children were assessed during the initial data collection period (previously published sample; see Taylor et al., 2016), and an additional 22 children were assessed in later period. Procedural differences in data collection between the two periods are described in detail below. Participants had no reported neurological or developmental diagnoses, nor were they currently taking any psychopharmaceutical medications, as reported by parents. Parents of children signed informed consent forms, and child participants signed assent forms. Children received their choice of a t-shirt or cocoa mug after completing their first visit, and their choice of a t-shirt, cocoa mug, or \$10 after their second visit. All procedures were approved by the local university institutional review board.

2.2. Procedure

Participants completed two EEG recording sessions scheduled one or two weeks apart with the second session being at the same time and day of the week as the first session. Participants were seated in a comfortable chair at a table in front of a computer screen. Two research assistants placed the EEG cap and sensors on the participant. For each participant, the same EEG cap was used for each session, and measurements were performed to assure proper placement each time. Next a research assistant gave participants a brief training on how to reduce production of artifacts from eye blinks and muscle movements. Then, three minutes of eyes-opened resting EEG were recorded while participants stared at a fixation point on the screen. Participants then performed a total of four EEG paradigms lasting approximately one hour. Only the cued Go/No-Go paradigm, which was the third paradigm, will be discussed in this study. Participants were given a short break of 2 to 4 minutes between each paradigm. Following EEG data collection, children completed a battery of behavioral assessments of attention and executive function. The TEA-Ch was completed following the second session of EEG data collection. In total, each session lasted approximately two hours.

2.3. Cued Go/No-Go Paradigm

The cued Go/No-Go paradigm (e.g., Segalowitz & Davies, 2004; Taylor et al., 2016) is specifically designed to assess sustained attention abilities rather than inhibition as is

traditionally measured with speeded Go/No-Go tasks. During each trial of the task, children saw a sequence of two stimuli: a conditional stimulus followed by an imperative stimulus. First, a circle, either red or green, was displayed in the center of the screen for 250ms (i.e., the conditional stimulus or cue). Then the screen went blank for 1750ms before a picture of a car appeared in the center of the screen with a duration of 250ms (i.e., the imperative stimulus). If the circle at the beginning of the trial was green, children were instructed to press a button in front of them as quickly as possible after the car appeared on the screen (i.e., a Go trial). However, if the circle was red, the children were instructed not to press the button (i.e., a No-Go trial). The task consisted of 40 Go and 40 No-Go trials presented in a pseudorandom order. The same task was performed during both EEG recording sessions.

Only correct Go trials were examined in this study. Correct Go trials were defined as any trial in which a green circle appeared before the car, and the button was pressed after the car appeared. The decision to model only correct Go trials were based on two considerations. First, only correct Go trials have a measurable behavior following the imperative stimulus (i.e., reaction times), thus No-Go trials were excluded from analyses. Secondly the incorrect Go-trials were excluded from analyses because the cued Go/No-Go task is a relatively simple paradigm that yields too few incorrect trials to obtain a reasonable signal-to-noise ratio for ERP analysis.

2.4. Electrophysiological Recording

EEG recordings were obtained using the same BioSemi ActiveTwo system with an Active Two Lycra head cap (BioSemi, Inc., Amsterdam, The Netherlands) for all children. For children who participated in the first period of data collection, active EEG was recorded from 32 Ag-AgCl sintered electrodes based on the American Electroencephalographic Society nomenclature guidelines (1994) with an additional pin-type Ag/AgCl electrode placed at FCz for a total of 33 scalp sites. EEG data from the additional 22 children who participated in the second period of data collection were recorded using a 64-channel BioSemi ActiveTwo system with Ag/AgCl sintered electrodes. Scalp electrodes were positioned according to a modified 10–20 system (American Electroencephalographic Society nomenclature guidelines, 1994). For both periods of data collection, there were additional common mode sense (CMS) and driven right leg (DRL) sensors, which served as reference and ground, respectively. An additional six sensors were placed on the face (on the left supra- and infra-orbital regions, and on the left and right outer canthi) and both the left and right earlobes to record eye movements and provide sites for offline re-referencing, respectively. Data were sampled at a rate of 1024Hz. Electrode offsets were maintained at ± 20 mV throughout each session.

2.5. Electrophysiological Data Reduction

Using BrainVision Analyzer 2.0 software (www.brainproducts.com), data from the continuous EEG recording were re-referenced to the averaged voltage of the two earlobe electrodes, filtered with a .03 to 30Hz bandpass filter (12dB/octave), and then the correct Go trials were segmented from 200ms prior to the conditional stimulus onset to 2250ms after the conditional stimulus onset. Baseline correction was performed on each segment using the EEG data from –200 to 0ms relative to the conditional stimulus onset. A regression

procedure used to remove eye blinks was applied to retained segments (Segalowitz, 1996). Following the regression procedure, segments were baseline corrected again using the –200 to 0ms window and then underwent an artifact rejection procedure to remove segments with voltages exceeding $\pm 100\mu\text{V}$. An averaged ERP was calculated for each participant and for each session using the Go segments retained after data reduction.

The E-wave was measured as the averaged amplitude in the 200ms window directly preceding the onset of the imperative stimulus for each session based on prior research (see Figure 1; e.g., Kropp et al., 2000; Taylor et al., 2016). All measurements were performed at scalp site Cz. The averaged amplitude and the standard deviation of the amplitude were calculated for each individual to understand typical neural processing and variability in neural processing during each session. Reaction times for each correct Go trial were calculated as the time in milliseconds from the onset of the imperative stimulus (i.e., the car) to the time of the button press. The mean and standard deviation of reaction times were calculated for each individual to better understand typical performance as well as variability in performance during each session.

2.6. TEA-Ch

The TEA-Ch consists of a battery of nine game-like subtests that purport to measure three types of attention: selective, switching, and sustained attention (Manly et al., 2001; Manly et al., 1999). Children are asked to perform auditory and visual tasks, such as counting the number of sounds on an audio clip or finding matching pairs of space ships among distractor stimuli on a large sheet. The assessment is normed for children ages 6 to 16 years, providing standardized scores for each subtest ranging from 1 to 20. With respect to standard scores, a score of 10 is an average score for a child of a particular sex and age, and larger scores are indicative of better attention abilities relative to other children of the same sex and age. Manly et al. (2001) demonstrated that, using standard scores, the TEA-Ch subtests comprise a three-factor structure representing the three different types of attention in 6 to 16 year-old Australian children.

In order to first validate the factor structure of the TEA-Ch in young, neurotypical children in the United States, we employed data from a larger sample of children who had completed the TEA-Ch in our lab. In addition to the 73 children previously described, 57 children between the ages of 6 and 13 years completed the TEA-Ch as part of other ongoing research studies. Although ERP paradigms of these studies were different from the present study, the general procedures for these studies were similar in that each of these 57 participants visited the lab twice within one-to-two weeks, with each visit consisting of an hour of EEG recordings followed by an hour of behavior assessments. Thus, for the TEA-Ch validation, we examined data from a total of 130 neurotypical children (63 males; $M = 9.34$ years, $SD = 1.86$).

2.7. Data Analysis

2.7.1. Research question 1—In order to determine whether the E-wave is related to task-specific reaction times, analyses began with basic descriptive statistics for each dependent measure obtained from the cued Go/No-Go task. We also completed a series of

paired-samples *t*-tests and Pearson product-moment correlations to confirm that the effects described in Taylor et al (2016) were still present in the larger sample of the present study. Namely, we assessed any changes across sessions in the dependent measures, and we examined each variable's test-retest reliability. All initial descriptive and confirmatory analyses were completed using SPSS version 23.

Following confirmation, we developed an exploratory path model to examine the interrelationships between all dependent measures simultaneously. The model included means and standard deviations of E-wave amplitudes and reaction times for each session. Session 1 variables were modeled as predictors of session 2 variables, and E-wave measures were modeled as predictors of behavior measures within each session. Additionally, the mean and standard deviation of a single measure (e.g., mean and standard deviation of session 1 reaction time) were correlated. Because "age" was found to have small-to-moderate correlations with each variable included in the model, age was used as a control variable on all measures using traditional SEM techniques. Namely, each variable was regressed on age within the model. All parameters were freely estimated.

After the path model, we tested an exploratory latent variable path. Latent variables are derived from the common variance of multiple manifest variables, essentially removing any measurement error from the resulting latent variable (i.e., any variance that is not common among the manifest variables is removed). We defined a latent variable by the combination of the two sessions of each dependent measure (e.g., session 1 and session 2 mean E-wave amplitudes combined into a latent variable). In order to allow all manifest variables loadings to be freely estimated, we identified each latent variable by its mean (set to 0) and variance (set to 1). The latent variable model was designed with E-wave latent variables as predictors of reaction time latent variables. Again, age served as a control on all latent variables. All structural equation modeling was performed using Mplus version 7.3.

2.7.2. Research question 2—To explore whether E-wave or reaction time measures can be related to trait measures of attention, we began by validating the TEA-Ch in our larger sample of children. Using the same techniques previously reported in Manly et al. (2001), we defined a three-factor model of attention using the nine TEA-Ch subtests. Each latent variable was identified by the first-listed manifest variable in accordance with Manly et al (2001). Once a viable model was established in the larger sample of children, factor loadings for the manifest variables were retained and fixed for the following analysis.

To examine the interrelationships between E-wave, reaction time, and TEA-Ch factors, we established a final latent variable model to investigate the relationship between a behaviorally-measured trait (TEA-Ch measures of attention), measures of brain activity (E-wave) and task performance (reaction time), and a trait measure of maturation (age). The TEA-Ch was defined using the fixed factor loadings obtained from the larger sample (as described above). All other TEA-Ch model parameters, including means, variances, and the correlation between factors, were allowed to freely vary. We then added in the E-wave and reaction time latent variables, which were freely estimated in this model (i.e., not fixed based on prior findings). This was specifically to allow parameters of interest to vary as we added in trait measures of attention. As in previous models, age was included as a control

variable on the E-wave and RT latent variables. The E-wave was correlated with TEA-Ch attention factors. Then, the E-wave and all TEA-Ch attention factors were used as predictors of reaction time.

2.7.3. Criteria for model fit—All models were examined for model fit. To evaluate overall model fit, we used the model fit criteria suggested by Hu and Bentler (1999), including comparative fit index (CFI) $> .95$, root mean square error of approximation (RMSEA) $< .06$, and standardized root mean square residual (SRMR) $< .08$. We also examined the chi-square test of model fit, where a non-statistically significant test indicates a lack of misfit of the model to the data.

3. Results and Discussion

3.1. Research Question 1

3.1.1. Descriptive and confirmatory statistics—A total of eighteen children were excluded from analyses due to having too few segments remaining for either session after data reduction procedures (i.e., < 12 correct Go segments). Using data from the remaining 73 participants, a series of paired samples *t*-tests and Pearson product-moment correlations were used to examine mean differences and test-retest reliability of five different variables across sessions: mean and standard deviation of the E-wave amplitude, mean and standard deviation of reaction times, and the total number of correctly performed Go trials. Descriptive statistics and results are reported in Table 1.

The data indicate that mean E-wave amplitudes were moderately reliable across sessions despite becoming more negative in session 2, suggesting a systematic group shift from session 1 to session 2. This conclusion matches the findings obtained from the smaller sample of data reported in Taylor et al. (2016). Interestingly, standard deviations of E-wave amplitudes were not reliable, nor did they differ significantly across visits. Thus, the data suggest that means and standard deviations of the E-wave component amplitude may be affected differently as children performed the Go/No-Go task across the two sessions. Example ERPs demonstrating the effects of means and standard deviations of the E-wave amplitude, given trial-to-trial variability, across sessions are shown in Figure 1.

Children's task behaviors, including means and standard deviations of reaction times, and accuracy on the Go/No-Go task, did not significantly differ across sessions. Average reaction time was reliable, whereas standard deviation of reaction time was not. Again, the data indicate differential effects on average performance versus variability of performance during each session.

3.1.2. Modeling brain and behavior—In order to better understand the relationships between E-wave and reaction time measures in children, we examined the correlations between measures. The intercorrelations between brain and behavioral measures are reported in Table 2.

Although the effects were small, correlations indicated significant positive associations between average E-wave amplitudes and average reaction times (see Table 2). Thus, the data

of the children in the present investigation were in accordance with prior literature with adult samples showing that individuals with larger (more negative) average E-wave amplitudes tended to have faster average reaction times (Brunner et al., 2015; Connor & Lang, 1969). The correlations indicated that mean E-wave amplitudes and mean reaction times shared 7.84% of their variance in session 1 and in session 2 (both r^2 's = .28, p 's < .05). Standard deviations of E-waves and reaction times were not significantly correlated with any measures other than Age.

3.1.3. Model results for the E-wave—Next, we used SEM techniques to evaluate a path model in order to further understand the interrelationships of brain processing and task behavior measures during each session. The model yielded fit indices that meet most of the criteria, $\chi^2(12) = 19.01$, $p = .09$, RMSEA = .09, 90% CI (.00, .16), CFI = .96, SRMR = .05, indicating that the proposed conceptual model may be viable (see Figure 2).

The averaged amplitudes of the E-wave in session 1 were related to age, such that children who were older also had significantly larger (more negative) E-wave amplitudes. Additionally, session 1 averaged amplitudes significantly predicted session 2 amplitudes, as was expected based on the test-retest reliability of the ERP component. The model corroborates evidence that the shift in ERP amplitudes over time was systematic within and between participants.

Importantly, there was no additional significant effect of age on session 2 averaged amplitudes *above and beyond* what was already accounted for in session 1. These data support the notion that the shift in E-wave averaged amplitudes over time cannot be explained by significant maturation between sessions.

The standard deviation of the E-wave amplitudes indicated a different pattern compared to the averaged amplitudes. Session 1 standard deviations indicated no significant relationship with age, nor was there a significant prediction to session 2 standard deviations. However, there was a significant age effect on session 2 standard deviations, such that older children had less variability in their E-wave amplitudes than younger children. The model suggests that children's overall variability in neural processing patterns was changing over time as they learned the task, but the effect was stronger for older children.

The associations between averaged amplitudes and standard deviations of amplitudes was not significant for either session. In combination with the differential effects of age and session, these data suggest that E-wave amplitudes and standard deviations may represent largely independent aspects of neural processing.

3.1.4. Model results for reaction times—Considering average reaction times, session 1 significantly predicted session 2, which was in accordance with the test-retest reliability reported in Table 1. There was a significant effect of age on session 1, such that older children tended to be faster than younger children. Interestingly, session 2 average reaction time had an additional age effect *above and beyond* what was already accounted for in session 1. The results indicated that although older children tended to be faster than younger children in the first session, the effect was further exaggerated in session 2. The effect was

present in spite of any significant group differences in average reaction times across sessions (see Table 1).

Standard deviations of reaction times were not significantly related across sessions, which was again in accordance with the previously established test-retest reliability. However, both sessions had a significant effect of age, such that older children were less variable in their response speed compared to younger children. Correlations between averages and standard deviations of reaction times indicated significant, positive relationships for each session. Specifically, the data indicated that children who were typically faster also tended to be less variable in their response times.

3.1.5. Can brain measures predict behavior?—The model indicated that, after accounting for age effects in E-wave and reaction time, none of the E-wave measures significantly predicted any of the reaction time measures (see Figure 2). This result is in contrast to the correlations between average E-wave amplitudes and average reaction times reported in Table 2. The results also contradicted prior literature in adults, reporting significant correlations between average E-wave amplitudes and reactions times such that individuals with more negative E-wave amplitudes tend to have faster responses (Brunner et al., 2015; Connor & Lang, 1969). However, the path model indicated large unique variances for most of the measures, suggesting that much of the variance was not explained by the correlations and predictive relationships estimated in the present exploratory model. To further reduce the influence of measurement error in E-wave amplitude and reaction time measures, we employed a more sophisticated form of SEM: a latent variable path analysis.

3.1.6. Latent variable modeling—We first attempted to develop a four-latent variable model in which the two sessions of each measure (e.g., mean of E-wave amplitude) were combined into a latent variable. Age was used as a control variable, and E-wave latent variables were predictors of reaction time latent variables. However, the model did not converge. The non-convergence was not surprising given that the standard deviations of E-wave amplitudes and of reaction times were not related across sessions, thus their latent variables were poorly-defined. We then simplified the model to include only the latent variables defined by average E-wave amplitudes and reaction times. The resulting model yielded the following fit indices, $\chi^2(3) = 5.12$, $p = .16$, RMSEA = .10, 90% CI (.00, .24), CFI = .98, SRMR = .03, indicating that the exploratory model may be viable (see Figure 3).

The latent variables were both well-defined by their contributing manifest variables, with all measures significantly contributing to the definition of their respective latent constructs. Additionally, the effect of age remained significant in the latent variable model, indicating that older children tended to have larger (more negative) average E-wave amplitudes, and faster reaction times. Because the effect of age was statistically significant for both latent variables, the model suggests that the effect of age on reaction times was unique, and could not be entirely accounted for by the effect of age on E-wave amplitude.

Interestingly, even after enforcing better control of measurement error by creating latent variables, brain measures still did not significantly predict behavior measures. The predictive relationship from the E-wave latent variable to the reaction time latent variable was small,

though still in the expected direction given prior research and the previously-established correlations ($\beta = .23$, $p = .10$; see Table 1). It was surprising to find that the association was not statistically significant given the previously established bivariate correlations, which *were* significant when the individual variables were contaminated with multiple sources of variance (e.g., age effects, individual differences across sessions). However, the model accounted for a significant proportion of the variance in the reaction time latent variable, $R^2 = .44$, $p < .001$.

3.2. Research Question 2

3.2.1. Validation of the TEA-Ch—To explore whether E-wave or reaction time measures can be related to trait measures of attention, we first determined the validity of the clinical behavioral assessment for children tested in our EEG lab. Using the sample of 130 children, we first tried to directly replicate the factor structure described by Manly and colleagues (2001). Specifically, we attempted to model a three-factor structure of Selective, Sustained, and Switching attention using the nine subtests of the TEA-Ch. Although the model yielded good fit across most fit indices, $\chi^2(24) = 33.66$, $p = .09$, RMSEA = .06, 90% CI (.00, .10), CFI = .94, SRMR = .06, there were two key problems with the resulting structure: (1) none of the manifest variables defining Sustained attention significantly loaded onto the latent variable; and (2) there was a high correlation between Selective and Switching attention ($\phi = .93$, $p < .001$), which could cause problems with further analysis due to multicollinearity between these two latent variables. Further examination using exploratory factor analysis indicated that a two-factor structure in which the subtests defining the Selective and Switching attention variables were collapsed into a single factor would be the most parsimonious structure given the data. Additionally, the manifest variable for the subtest *Score!*, which is the simplest of the nine subtests, did not significantly load onto either factor.

We attempted to fit two variations of the two-factor model: the first included the *Score!* manifest variable in the Sustained attention latent variable in accordance with Manly et al. (2001), and the second excluded *Score!* from the analysis entirely. When *Score!* was included, once again, none of the manifest variables were significantly loading onto the Sustained attention latent variable. However, removing *Score!* from the analysis produced a good-fitting model, $\chi^2(19) = 19.32$, $p = .44$, RMSEA = .01, 90% CI (.00, .08), CFI = .99, SRMR = .04, in which all manifest variables significantly contributed to their respective latent variable definitions at the $p < .01$ level. Additionally, the correlation between the resulting latent variables, which we termed Control Attention and Sustained Attention, was reasonable for further analysis, $\phi = .69$, $p < .001$. The factor loadings from this model, which was established with the larger sample of children, were retained and fixed in the following analysis, which only included the 73 children who had the E-wave and reaction time data from the Go/No-Go task (Note: the fixed TEA-Ch parameters can be viewed in Figure 4).

3.2.2. Connecting traits, brain measures, and simple task behaviors—Next, we attempted to model the interrelationships among the two obtained TEA-Ch latent variables of attention, the E-wave, and reaction times. Specifically, we defined a model in which Control and Sustained attention and the E-wave latent variable were correlated and served as

predictors of the reaction time latent variable. Age was a control variable on the E-wave and reaction time latent variables; the control variable was not necessary for the attention latent variables because they were defined using standard scores, which are already free of maturation effects. Although the Control and Sustained attention factor loadings were fixed, all other TEA-Ch parameters, the E-wave, reaction time, and age parameters (e.g., factor loadings, correlations, means, and variances) were all free to vary. The intent was to allow the brain and task behavior parameters to adequately shift once trait measures of attention were included, thereby better representing the full effects of the trait measures above and beyond what was established in our previous model (see Figure 3). The model yielded fit statistics of $\chi^2(64) = 66.13$, $p = .40$, RMSEA = .02, 90% CI (.00, .07), CFI = .99, SRMR = .08, indicating that the exploratory model was viable (see Figure 4). In a secondary model in which all parameters including TEA-Ch factor loadings are freely estimated, the conclusions remain the same and the model still has good overall fit, $\chi^2(58) = 62.23$, $p = .33$, RMSEA = .03, 90% CI (.00, .08), CFI = .98, SRMR = .07.

3.2.3. Model results for the E-wave—Despite the literature purporting that the E-wave is at least in part a representation of attentional abilities, the model indicated no significant relationships between the E-wave latent variable and either attention variable. That is to say, the variance in the averaged E-wave amplitudes that was common across sessions, after controlling for trait maturation effects (i.e., age), was not significantly related to the trait abilities of either Control or Sustained attention as measured by the TEA-Ch.

Although we failed to show a significant relationship to trait measures of attention, the model did indicate a significant age effect on the E-wave latent variable. The finding was in accordance with previous literature indicating that older children tend to have a larger (more negative) average E-wave amplitude compared to younger children (e.g., Hämmerer et al., 2010; Jonkman et al., 2003; Taylor et al., 2016). Although the predictive coefficient (β) was statistically significant, age did not account for a significant proportion of the variance in the E-wave latent variable, $R^2 = .13$, $p = .17$. The finding suggests that trait variables other than age may better explain the variance in the E-wave latent variable.

3.2.4. Model results for reaction time—The model explored whether Control attention, Sustained attention, or E-wave amplitude latent variables could predict the reaction time latent variable. Interestingly, none of the three predictors had statistically significant effects after accounting for trait maturation effects (i.e., age) in reaction times. Considering the trait attention measures, both Sustained and Control attention indicated a negative relationship with reaction time, suggesting that individuals with better trait attention tended to have faster reaction times. Sustained attention had a stronger predictive relationship to reaction time than Control attention, but again, neither prediction was statistically significant. Regardless, the model may suggest that Sustained attention is contributing to reaction times to a greater extent than Control attention, at least with respect to reaction times in the Go/No-Go task.

Considering the E-wave as a predictor, the results indicated a positive, though non-statistically significant prediction, such that children with larger (more negative) E-wave amplitudes tended to have faster reaction times. The only significant predictor of reaction time was age, indicating that older children tended to have faster reaction times than younger

children. The effect of age remained significant even after accounting for the effects of the E-wave (along with its own age effects) as well as trait measures of Control and Sustained attention. Based on these findings, one might conclude that reaction time is not entirely explained by either the E-wave or trait measures of attention, and that its variance contains unique developmental effects that may be better explained by other abilities and cognitive constructs, such as motor control or executive function. In total, the model explained a significant proportion of the variance in reaction time, $R^2 = .48$, $p < .001$, though there was still a large amount of variance that was not explained by E-wave amplitudes, trait attention, or age.

4. Conclusions

In the present investigation, we demonstrated how advanced statistical modeling techniques, namely SEM, can 1) effectively manage sources of variance resulting from individual differences, thereby allowing researchers to better examine potential brain-behavior relationships, and 2) allow for the simultaneous examination of a constellation of complex interrelationships. The study yielded a number of interesting findings, each of which contributes to our understanding of brain-behavior relationships.

From these data, it became clear that the variance defining a given measure, E-wave or reaction time, may be comprised of more unique, distinct constructs than research had previously suggested. For instance, we demonstrated that E-wave and reaction times measures each had unique trait maturation effects, even after removing measurement error by employing latent variable analysis. Where many researchers are quick to think of “age” as a single, non-changing construct (for a review, see Johnson & de Haan, 2011), these findings suggested that “age” may be indicative of unique maturation within different constructs (e.g., motor control, executive function, attention), each of which may have a differential effect on brain and behavioral measures.

Such effects would not have been easy to detect via more traditionally-used analyses such as bivariate correlations. Importantly, our bivariate correlations were in accordance with prior literature which has suggested significant relationships between E-wave amplitudes and reaction times (e.g., Brunner et al., 2015; Connor & Lang, 1969; Jongen, 2006; see Table 2). Moving to a multivariate approach allowed us to model multiple effects simultaneously and better understand how each of our variables of interest related to one another as well as other important trait variables like maturation (i.e., age). Thus, the multivariate approach afforded us a more complete, cohesive depiction of brain-behavior relationships in children than we detected with less sophisticated analyses.

Validation of the TEA-Ch factor structure indicated that, at least in the present sample of young, neurotypically-developing children in the United States, a two-factor solution was the most parsimonious in contrast to Manly et al.’s (2001) three-factor model, established in a sample of Australian children ages 6 to 16 years-old. Specifically, Selective and Switching attention measures were collapsed into a single factor which we termed Control attention. The finding was interesting given recent work by Petersen and Posner (2012), who also suggest that attention can be defined as a tripartite model. In their work, Petersen and Posner

(2012) define an orienting, an alerting, and an executive control attention network based on a compilation of neuropsychological research in human and animal samples. When compared to Manly et al.'s (1999) definitions, the orienting network is akin to Switching attention, the alerting system is similar to the Sustained Attention, and the executive control network is analogous to Selective attention. Interestingly, Petersen and Posner (2012) suggested that the orienting (i.e., Switching attention) and executive control (i.e., Selective attention) neural networks may not be differentiated in childhood. That is to say, children may not necessarily engage unique neural networks to perform Switching versus Selective attention tasks the way that adolescents and adults do, which may explain why our younger sample yielded only a two-factor model of attention, with Switching and Selective combined into one factor. Further work is needed to confirm the neural mechanisms underlying the obtained attention factors in this study.

When we expanded our model to include trait attention measures, we were unable to validate either the E-wave or reaction time measures as indicators of attentional processing after accounting for trait maturation effects. The result was surprising given previous studies suggesting that CNV E-waves in particular are representative of attention processing in the brain (e.g., O'Connell, Dockree, Robertson, Bellgrove, Foxe, Kelly, 2009; Tecce, 1972; Travis & Tecce, 1998). The findings underscore the importance of examining the interrelationships among multiple variables simultaneously in order to draw the most accurate conclusions possible from the data. By examining all potential relationships among our measures of interest simultaneously, we gained a clearer perspective on how the assorted variables may be interacting. For instance, although not all statistically significant, trait maturation (age), the E-wave, and the trait factor of Sustained attention were the strongest predictors of reaction time (RT), which collectively accounted for a significant portion of the variance in task behavior (48% of the variance in the latent variable RT). However, "age" being the only significant predictor suggests that there is some unique developmental effect underlying children's task performance that is not explained by the E-wave or trait attention abilities. The findings have important implications for future work looking to understand brain-behavior relationships.

A possible limitation of the present study is that the simplistic relationship we tried to establish between a select few trait constructs (maturation, Control and Sustained attention), a single ERP component, and a single task behavior measure was insufficient for explaining what is clearly a complex phenomenon. In future efforts, researchers may need to consider more sophisticated models to effectively map brain-behavior relationships. In other words, to better understand the complexities of neural processing and trait abilities that lead to functional output behaviors, we must introduce additional variables into our models that help us to understand the complete neural process. For instance, given the findings from the present study, it seems likely that the E-wave and reaction time may be better explained by other cognitive constructs and abilities besides Control and Sustained attention. Perchet and Garcia-Larrea (2005) suggested that the E-wave may be a representation of executive control processes and motor preparation in the brain, rather than sustained attention. Other researchers have suggested a greater influence of motor control processes on the E-wave, like energization (Brunner et al., 2015).

Additionally, in the case of CNV E-waves, the E-wave is only one phase of the complete CNV component. Researchers have described the CNV as a biphasic component comprised of an early orienting phase, the O-wave (Giard et al., 1990; Rohrbaugh et al., 1984; Zimmer & Demmel, 2000), and a late expectancy phase, the E-wave (Basile et al., 2002; Bender et al., 2004; Knott et al., 1991). It is possible that including both phases of the CNV as predictors of functional behaviors in the model may provide a more comprehensive picture of brain-behavior relationships. Additionally, including a more complete picture of the neural processing leading to task behaviors may better address Gavin and Davies' (2008) equation of individual differences (see equation 1 above). We were unable to measure the O-wave in the present study due to the children's overwhelming P3 response, which obscured the O-wave component (for similar discussion, see Jonkman et al., 2003; Taylor et al., 2016). However, future investigations may examine both the O-wave and E-wave in samples of older children in which both ERP components are more likely to be measurable.

Each phase of neural processing, like the phases of the complete CNV component, may have unique measurement variance that contributes to the prediction of behavioral outcomes. In our models including trait maturation and attention measures, a single ERP component, a single task behavior, we were able to account for 48% of the variance in functional behavior after removing measurement error. This far exceeds the small amount of variance explained by simple bivariate correlations between an ERP component and a reaction time (e.g., in our study mean E-wave and RT measures shared 7.8% of their variance in either session; see Table 2). By including additional neural processing measures, researchers may effectively reduce the ME term further, yielding stronger, more definitive predictions of brain-behavior relationships. If the field ever hopes to reliably use ERP components as biomarkers or measures of intervention efficacy, we must first be able to effectively manage ME in the data and indicate strong, stable brain-behavior relationships.

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Highlights

- Advanced multivariate statistics, such as structural equation modeling, have promise in showing relationships between neural processing and behavioral responses by allowing for the simultaneous examination of a constellation of complex interrelationships
- Validation of the factor structure for the Test of Everyday Attention for Children (TEACH) indicated that in a sample of 8 to 12 year old, neurotypically-developing children in the United States, a two-factor solution was more parsimonious in contrast to a three-factor model, established in a sample of Australian children ages 6 to 16 years-old.
- The outcome of the latent variable model which included trait attention factors failed to validate either the CNV E-wave or reaction time measures as indicators of attentional processing after accounting for maturation effects.
- The findings of this study suggest that “age” may be indicative of unique maturation within different constructs (e.g., motor control, executive function, attention) and using advanced statistics such as structural equation modeling may help define areas of measurement to be included in these different constructs.

Figure 1.

Trial-by-trial ERPs (thin black lines) and averaged ERPs (thick black lines) obtained during correct Go trials of the cued Go/No-Go task in two separate sessions from a single 8-year-old participant, and a single 12-year-old participant. The E-wave component window (1800–2000ms) is highlighted with a red box. Additionally, a section of the averaged ERP (1600–2000ms) has been extracted and enlarged to better show the E-wave component. All ERPs are shown at site Cz. Go trial stimuli from the cued Go/No-Go task are shown next to the vertical hash lines denoting the presentation of stimuli.

Figure 2.

The structural model exploring interrelationships among age, means and standard deviations of E-wave amplitudes, and means and standard deviations of reaction times (RT) during Go trials for both sessions. Note: All reported coefficients are standardized. Unique variances are reported next to each manifest variable in small font. Non-statistically significant relationships are shown as gray, dotted lines. Statistical significance is indicated as follows: * $p < .05$, ** $p < .01$, *** $p < .001$. Note: RT = reaction time; M₁ = mean session 1; M₂ = mean session 2; SD₁ = standard deviation session 1; SD₂ = standard deviation session 2.

Figure 3.

The latent variable model exploring interrelationships between means of E-wave amplitudes and reaction times (RT) during Go trials for both sessions. Note: All reported coefficients are standardized. Unique variances are reported next to each manifest variable, and disturbances are reported below latent variables in small font. Non-statistically significant relationships are shown as gray, dotted lines. Statistical significance is indicated as follows: * $p < .05$, ** $p < .01$, *** $p < .001$. Note: RT = reaction time; M₁ = mean session 1; M₂ = mean session 2; SD₁ = standard deviation session 1; SD₂ = standard deviation session 2; the triangle with the “1” indicates that the latent variables were identified by fixing their means to “0” and their variances to “1”, a statistical approach which allows all contributing manifest variables to be freely estimated.

Figure 4.

The latent variable model exploring interrelationships between TEA-Ch attention factors, the E-wave, and reaction time (RT). Note: All reported coefficients are standardized. Unique variances are reported next to each manifest variable, and disturbances are reported above the latent variables in small font. Non-statistically significant relationships are shown as gray, dotted lines. Statistical significance is indicated as follows: * $p < .05$, ** $p < .01$, *** $p < .001$. Note: RT = reaction time; M_1 = mean session 1; M_2 = mean session 2; SD_1 = standard deviation session 1; SD_2 = standard deviation session 2; the triangle with the “1” indicates that the latent variables were identified by fixing their means to “0” and their variances to “1”, a statistical approach which allows all contributing manifest variables to be freely estimated.

Table 1

Descriptive statistics, differences, and test-retest reliability for E-wave amplitudes and Go/No-Go task behaviors during each session.

	Session 1	Session 2	Difference	Reliability
Measure	<i>M</i> (<i>SD</i>)	<i>M</i> (<i>SD</i>)	<i>t</i>	<i>r</i>
E-wave _{<i>M</i>} (μ V)	−1.76 (4.65)	−3.32 (5.15)	2.71 **	.50 ***
E-wave _{<i>SD</i>}	22.62 (19.17)	23.31 (13.48)	−.26	.10
RT _{<i>M</i>} (ms)	289.51 (92.48)	293.02 (121.60)	−.34	.69 ***
RT _{<i>SD</i>}	115.39 (89.84)	149.20 (152.97)	−1.73	.13
Number Correct	33.68 (3.80)	32.73 (5.37)	1.65	.46 ***

*
 $p < .05$,

**
 $p < .01$,

 $p < .001$ – p -values were not corrected for multiple tests

Note: RT = reaction time; *M* = mean; *SD* = standard deviation

Table 2

The intercorrelations between means and standard deviations of E-wave (μV) and reaction time (ms) measures during both sessions, and mean age (years).

	RT_{M1}	RT_{M2}	RT_{SD1}	RT_{SD2}	Age
E-wave _{M1}	.28 [*]	.11	.16	.042	-.24 [*]
E-wave _{M2}	.31 ^{**}	.28 [*]	.18	.15	-.27 [*]
E-wave _{SD1}	.17	.18	.082	.067	-.12
E-wave _{SD2}	.11	.038	.16	.036	-.23 [*]
Age	-.51 ^{***}	-.53 ^{***}	-.40 ^{***}	-.39 ^{**}	—

^{*} $p < .05$,
^{**} $p < .01$,
^{***} $p < .001$ – p -values were not corrected for multiple tests

Note: RT = reaction time; $M1$ = mean session 1; $M2$ = mean session 2; $SD1$ = standard deviation session 1; $SD2$ = standard deviation session 2