Explanation of data and hypotheses

The dataset used in this project comes from DePaul Family and Community Services, where I am currently working as an extern and conducting Parent-Child Interaction Therapy (PCIT). This form of therapy is unique in the amount of data that is collected during each session. Parents complete a weekly measure of child behavior, and numerous sessions include five minutes of coding parent verbalizations during interactions with their children. Three skills in particular (labeled praises, behavior descriptions, and reflections of child statements) are emphasized during the first phase of treatment, child-direction interaction (CDI). The second phase of treatment, parent-directed interaction (PDI), focuses on parents' effective commands and increasing child compliance.

A subset of questions on the weekly behavior measure, the Eyberg Child Behavior Inventory (ECBI), are associated with inattentive child behavior problems (see Table 1). The full, 36-item measure asks parents to rate various child behavior problems on a scale from one to seven, resulting in a possible range from 36 to 252. The four items associated with child inattentive problems have a range from 4 to 28. Child inattention is thought to be a function of gender and diagnoses such as attention deficit hyperactivity disorder (ADHD). During PCIT, parent behavior descriptions are thought to help children organize their thoughts and increase focus on their activities. After weeks of play that includes behavior descriptions during therapy and five minutes of practice throughout the week, theory suggests children's overall inattentive symptoms may decrease. This study aims to evaluate the impact of parent behavior descriptions on child inattentive symptoms, and it is hypothesized that child inattentive symptoms will decrease over time, an effect that will be bolstered with increased behavior descriptions.

Methods

Child Behavior

Child behavior was measured using the ECBI, described above. Linear growth trajectories for the ECBI total and ECBI inattentive across participants are included in Figures 1 and 2 respectively. Overall, bivariate correlations between time (days since treatment start) and overall ECBI scores ranged from -0.97 to 0.32 (M = -0.63, SD = 0.30), with 95% of participants having a negative correlation. For ECBI inattentive scores, correlations ranged from -0.95 to 0.75 (M = -0.55, SD = 0.36), with 94% of participants having a negative correlation (see Figure 3). The participants that showed increases on the ECBI total (4) and ECBI inattentive (5) over time were examined further. The "spline" function was used to fit the four participants who had positive correlations on the ECBI total and the five participants who did on the ECBI inattentive (see Figures 4 and 5 respectively). In these figures, non-linearity is clearly observed in the data, and some of the figures show downward trends towards the end of treatment.

Because of the nature of treatment, it is possible that child behavior does not change in a linear manner. In addition, the two-stage course of treatment may also cause discontinuous change in this outcome variable (trajectories within each stage were evaluated but not included in this report to save space). Prior to understanding the effects of the predictor and covariates, the shapes of changes on the ECBI, both total and inattentive, were characterized. The equations used in this stage are included in Table 2.

Description of sample and covariates

79 families were included in the study, and 1515 sessions were included across these families. The majority of the children in the sample (74.7%) were males, and ages ranged from 2.67 to 9.29 (M = 5.24, SD =1.27) at baseline. ADHD problem behaviors were captured using the Achenbach Child Behavior Checklist (CBCL). These scores ranged from 50-80 (M = 63.53, SD = 9.38). Behavior descriptions were coded by therapists during select sessions. Behavior descriptions during these sessions ranged from 0 to 37 (M = 9.12, SD = 6.06). Behavior descriptions tended to increase over time, and within-person correlations between time and behavior descriptions are included in Figure 3.

Findings and Conclusions

Participant Session Data

Participants had data for between 10 and 37 sessions (M = 19.18, SD = 5.82), and session dates (i.e., Days since CDI) ranged from 0 days since baseline to 384 (M = 103.76, SD = 78.73). All sessions occurred between April 26, 2006 and August 20, 2019, meaning all sessions occurred prior to COVID-19 and were conducted inperson. Families spent up to 20 sessions in the CDI phase of treatment and up to 25 sessions in PDI. 717 sessions (47.3%) occurred before the PDI shift, and 798 (52.7%) occurred after.

Characterizing the Shape of Inattentive Behaviors

Models were evaluated in a stepwise fashion, with the most parsimonious model (i.e., an intercept-only "no growth" model) being evaluated as model a, and the most complex models (i.e., a cubic model) being evaluated as model g. These models were then compared to the logistic model (model h) using AIC, and nested logistic models were created by setting γ_1 to -1 (hneg), 0 (h0), and 1 (hlarge), which led to rapid jumps to the upper asymptote, no growth, and rapid jumps to the lower asymptote respectively. All model parameter estimates are summarized in Table 3. Unless otherwise specified, models were tested against comparable nested models, and the anova() function in R was used to compare model fits. As seen in Table 5, model h (the logistic model) was the best fit when compared to nested logistic models as well as to linear models. This was determined because this model had fewer degrees of freedom and a marginally different AIC value from these linear models. Further, as seen in Figure 6, this is the only model whose predicted values did not extend beyond the range of the measure. All non-logistic models eventually went below 4 or above 28 or, in the case of the quadratic model, predicted changes that were counter to theory.

After determining the logistic model was the best fit, discontinuous logistic models were evaluated, taking account of the shift to PDI. Discontinuous models were determined to have only marginally better fits than the continuous models, and only one model converged, as seen in Table 6.

Residual plots were evaluated for the logistic model. Figures 7 shows that residuals are normally distributed around zero, while Figure 8 shows constant variance in these residuals across fitted values.

Addition of Predictors

Once the logistic model was selected, covariates could be added to the model. Because missing values existed on the behavior descriptions variable, a new logistic model (model z) had to be created for comparison with the 913 cases with complete data. Table 7 includes a summary of parameter estimates and model fit for each model. Table 8 compares these models to one another. In the covariate-only model, the model that included ADHD had a better fit. In particular, the intercept shifted depending on an individual's baseline ADHD score. Figure 9 shows that those with high ADHD scores started with higher baseline levels of inattention on the ECBI but approached the asymptote at a similar rate to those with average and low ADHD scores. Adding the time-varying behavior description variable also improved the model above and beyond the logistic model. Figure 10 shows curves for those with consistently low, average, and high behavior descriptions. Children whose parents had low behavior descriptions at the start of treatment have the highest inattentive scores, and all three groups were around the same at week 15. At this point, the low BD group moved towards the asymptote more quickly, but all scores were below 6 by week 40. Attempting to combine ADHD and behavior descriptions resulted in a model that did not converge.

Future Directions

This project uncovered the optimal shape for understanding changes in inattentive behaviors on the ECBI and identified important covariates for continued study. Future projects that explore this relationship should pay closer attention to missing values. While this project was time-limited and had to be completed in only a matter of weeks, it could have benefitted from additional time devoted to imputing missing values. An additional way to help models converge could have been simplifying the structure of the data. Instead of including every session, certain landmarks in treatment could have been used. This would have opened the door to structural equation modeling techniques. Finally, the selection of variables could be re-evaluated. Behavior descriptions are only one of three positive skills focused on during PCIT. In addition, there are three negative skills that may have an impact on child inattention. Labeled praises such as, "I love how focused you are" and questions that re-direct a child's attention from their task may also have impacts on inattention. Broadly, this paper opens the door for exploring outcomes like these, and the incorporation of a logistic longitudinal model is a tool that can aid researchers in this area.

Appendix

Table 1

ECBI items and content with inattentive items denoted

Item Number	Item Content
1	Dawdles getting dressed
2	Dawdles at meal time
3	Poor table manners
4	Refuses food
5	Refuses chores
6	Slow in getting ready for bed
7	Refuses bed
8	Disobeys house rules
9	Refuses to obey
10	Acts defiant
11	Argues about rules
12	Gets angry when they don't get their way
13	Temper tantrums
14	Sasses adults
15	Whines
16	Cries easily
17	Yells or screams
18	Hits parents
19	Destroys toys
20	Is careless with toys
21	Steals
22	Lies
23	Teases or provokes other children
24	Verbally fights with friends
25	Verbally fights with siblings
26	Physically fights with friends
27	Physically fights with siblings
28	Constantly seeks attention
29	Interrupts
30*	**Easily distracted**
31*	**Short attention span**
32*	**Fails to finish tasks**
33	Difficulty entertaining self
34*	**Difficulty concentrating**
35	Overactive or restless
36	Wets the bed

***Inattentive Item**

Figure 1

Growth trajectories for each participant on the ECBI (total)

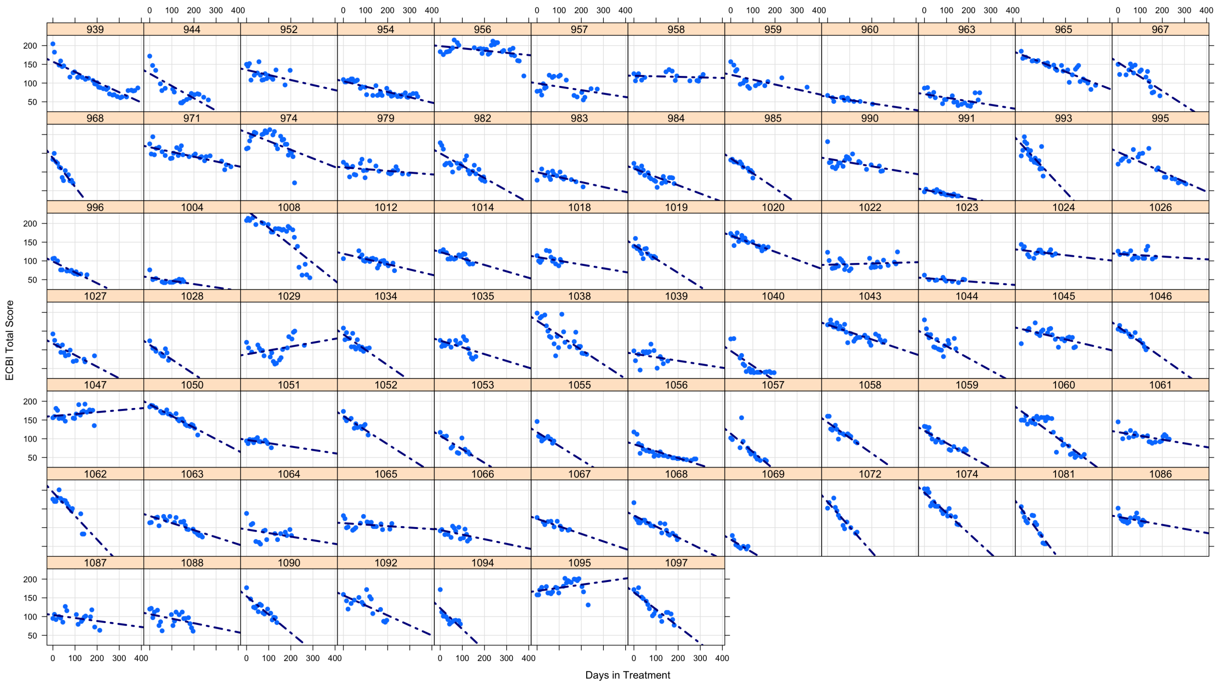


Figure 2

Growth trajectories for each participant on the ECBI (inattentive)

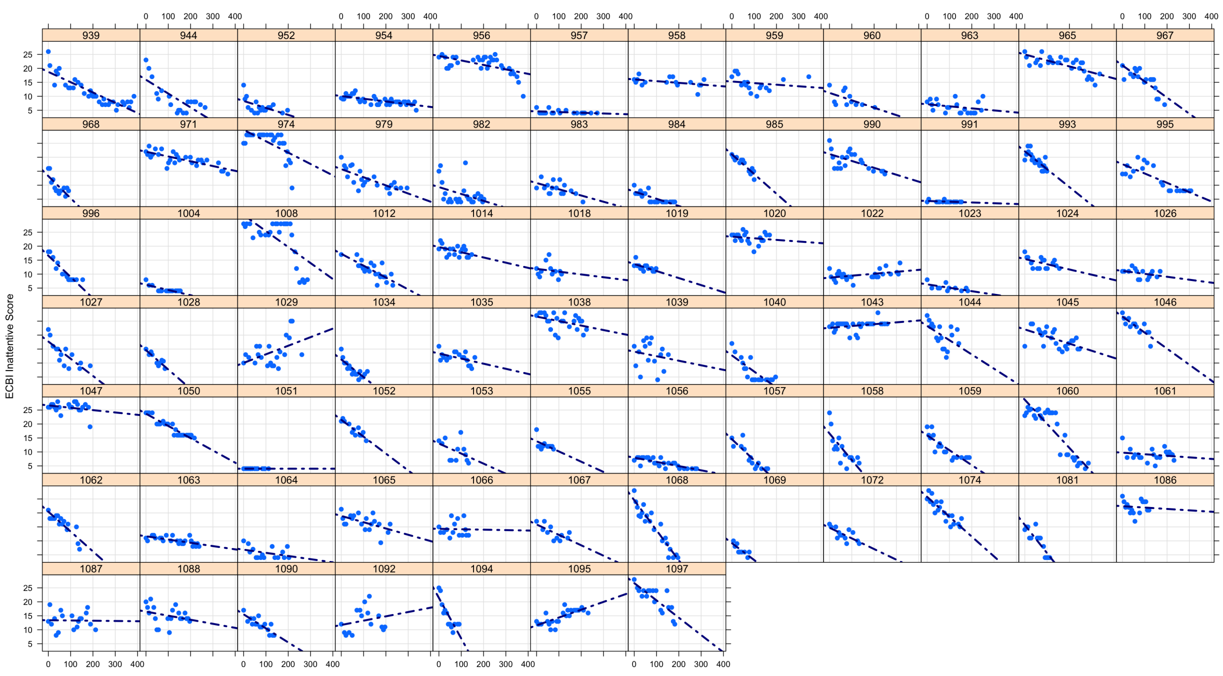


Figure 3

Distributions of within-person correlations between time and scores for ECBI total, ECBI inattentive, and behavior descriptions

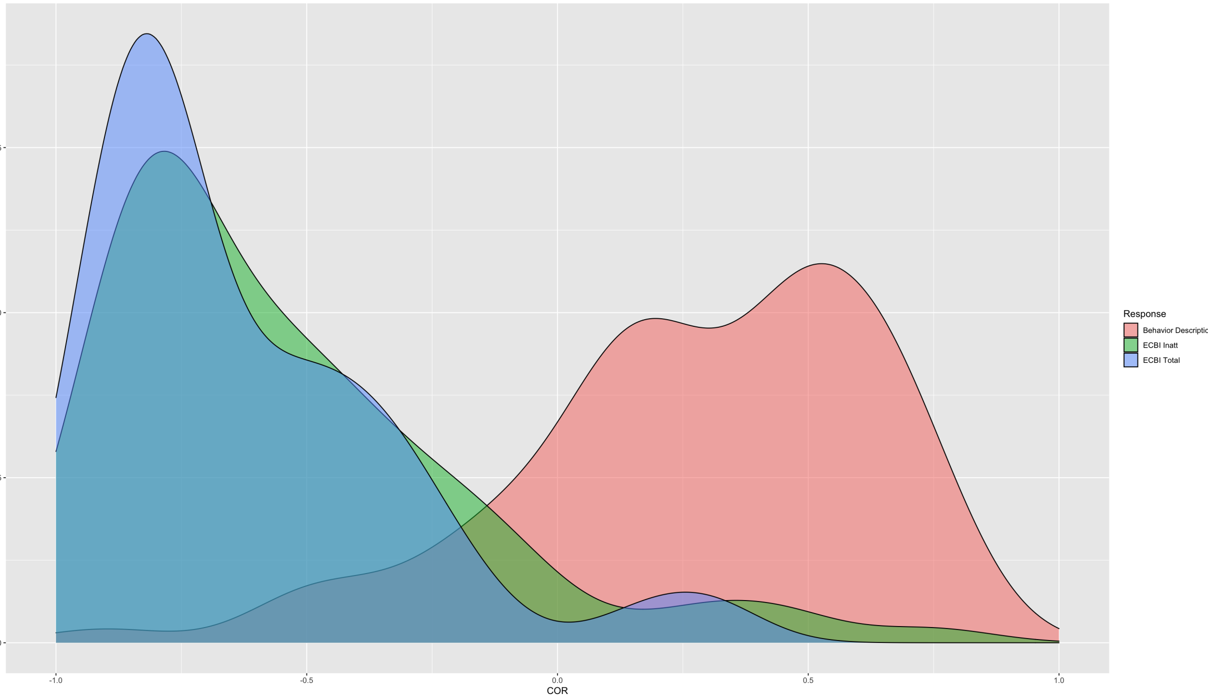


Figure 4

Trajectories for individuals with positive correlations between time and ECBI total scores

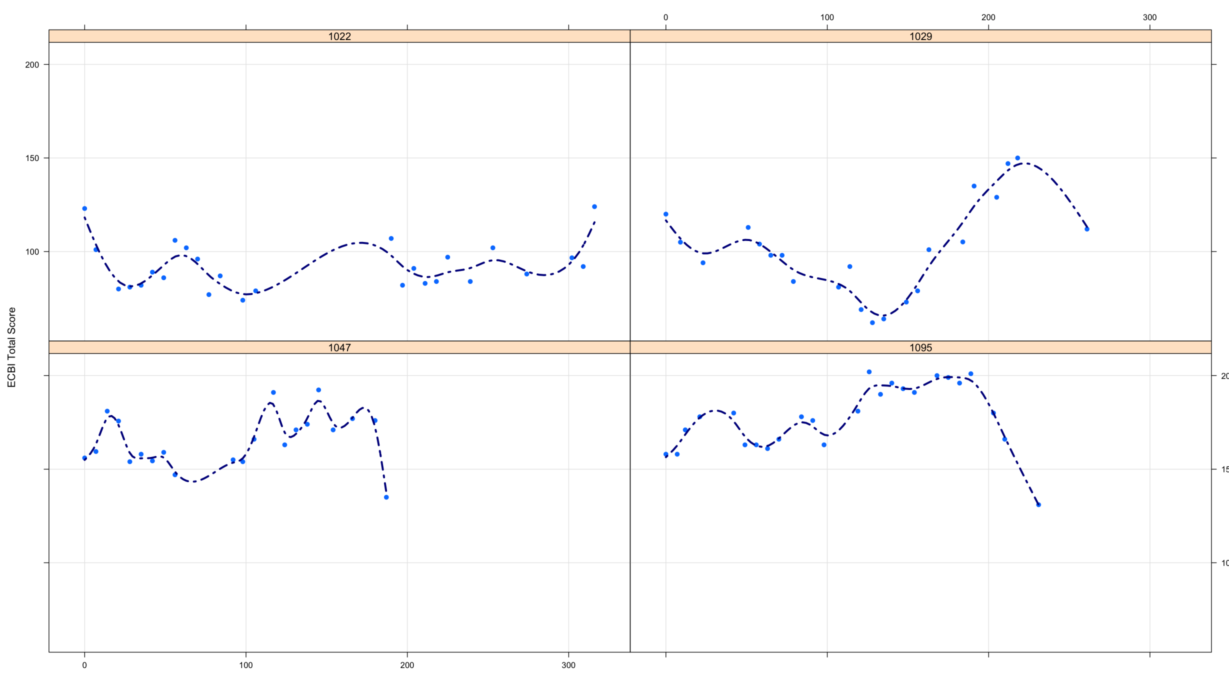


Figure 5

Trajectories for individuals with positive correlations between time and ECBI inattentive scores

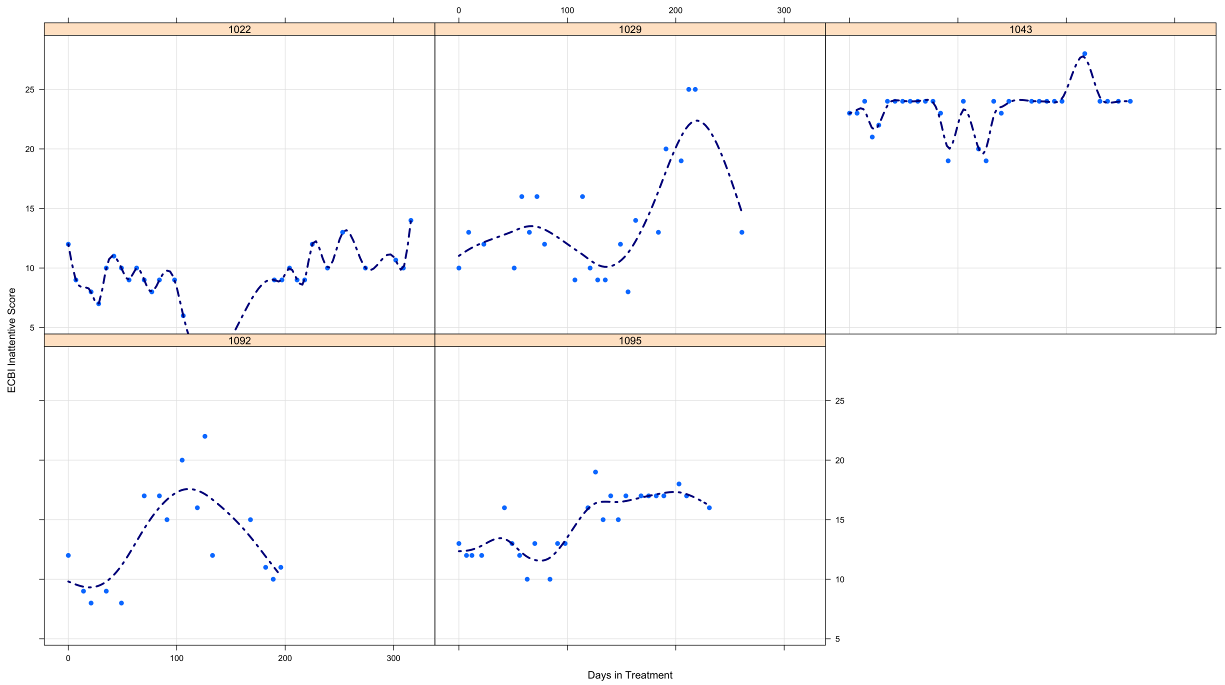


Table 2
Equations for characterizing the shape of the ECBI (inattentive shown here)

Model	Description	Composite Model Equation
a	No Growth	$Y_{ij} = \gamma_{00} + \varepsilon_{ij} + \zeta_{0i}$
b	Linear Growth	$Y_{ij} = \gamma_{00} + \gamma_{10}TIME_{ij} + \varepsilon_{ij} + \zeta_{0i} + \zeta_{1i}TIME_{ij}$
c	PDI Shift (slope only)	$Y_{ij} = \gamma_{00} + \gamma_{10}TIME_{ij} + \gamma_{20}PDITIME_{ij} + \varepsilon_{ij} + \zeta_{0i} + \zeta_{1i}TIME_{ij} + \zeta_{2i}PDITIME_{ij}$
d	PDI Shift (intercept only)	$Y_{ij} = \gamma_{00} + \gamma_{10}TIME_{ij} + \gamma_{30}PostPDI_{ij} + \varepsilon_{ij} + \zeta_{0i} + \zeta_{1i}TIME_{ij} + \zeta_{3i}PostPDI_{ij}$
e	PDI Shift (both sl/int)	$Y_{ij} = \gamma_{00} + \gamma_{10}TIME_{ij} + \gamma_{20}PDITIME_{ij} + \gamma_{30}PostPDI_{ij} + \varepsilon_{ij} + \zeta_{0i} + \zeta_{1i}TIME_{ij} + \zeta_{2i}PDITIME_{ij} + \zeta_{3i}PostPDI_{ij}$
f	Quadratic Growth	$Y_{ij} = \gamma_{00} + \gamma_{10}TIME_{ij} + \gamma_{20}{TIME_{ij}}^2 + \varepsilon_{ij} + \zeta_{0i} + \zeta_{1i}TIME_{ij} + \zeta_{2i}{TIME_{ij}}^2$
g	Cubic Growth	$Y_{ij} = \gamma_{00} + \gamma_{10}TIME_{ij} + \gamma_{20}{TIME_{ij}}^2 + \gamma_{30}{TIME_{ij}}^3 + \varepsilon_{ij} + \zeta_{0i} + \zeta_{1i}TIME_{ij} + \zeta_{2i}{TIME_{ij}}^2 + \zeta_{3i}{TIME_{ij}}^3$
h	Logistic Growth	$\frac{24}{1 + (\gamma_{00} + \zeta_{00}) * e^{(\gamma_{10} + \zeta_{10}) * TIME_{ij}}} + 4$
h0	Logistic "No-Growth"	$\frac{24}{1 + (\gamma_{00} + \zeta_{00})} + 4$
hlarge	Logistic "Large"	$\frac{24}{1 + (\gamma_{00} + \zeta_{00}) * e^{TIME_{ij}}} + 4$
hneg	Logistic "Negative"	$\frac{24}{1 + (\gamma_{00} + \zeta_{00}) * e^{-TIME_{ij}}} + 4$
i	Logistic spline (intercept)	$\frac{24}{1 + (\gamma_{00} + \zeta_{00}) * e^{(\gamma_{10} + \zeta_{10}) * TIME_{ij}}} + 4 + (\gamma_{40} + \zeta_{40}) * PostPDI_{ij}$
j	Logistic spline (slope)	$\frac{24}{1 + (\gamma_{00} + \zeta_{00}) * e^{(\gamma_{10} + \zeta_{10}) * TIME_{ij}}} + 4 + \frac{24}{1 + (\gamma_{20} + \zeta_{20}) * e^{(\gamma_{30} + \zeta_{30}) * PDITIME_{ij}}} + 4$
k	Logistic spline (both)	$\frac{24}{1 + (\gamma_{00} + \zeta_{00}) * e^{(\gamma_{10} + \zeta_{10}) * TIME_{ij}}} + 4 + \frac{24}{1 + (\gamma_{20} + \zeta_{20}) * e^{(\gamma_{30} + \zeta_{30}) * PDITIME_{ij}}} + 4 + (\gamma_{40} + \zeta_{40}) * PostPDI_{ij}$
zGen	Logistic with gender	$\frac{24}{1 + (\gamma_{00} + \gamma_{01} * Gender + \zeta_{00}) * e^{(\gamma_{10} + \gamma_{11} * Gender + \zeta_{10}) * TIME_{ij}}} + 4$
zADHD	Logistic with ADHD	$\frac{24}{1 + (\gamma_{00} + \gamma_{02} * ADHD + \zeta_{00}) * e^{(\gamma_{10} + \gamma_{12} * ADHD + \zeta_{10}) * TIME_{ij}}} + 4$
zCOV	Logistic with gen/ADHD	$\frac{24}{1 + (\gamma_{00} + \gamma_{01} * Gender + \gamma_{02} * ADHD + \zeta_{00}) * e^{(\gamma_{10} + \gamma_{11} * Gender + \gamma_{12} * ADHD + \zeta_{10}) * TIME_{ij}}} + 4$
zBDs	Logistic with Behavior Des.	$\frac{24}{1 + (\gamma_{00} + \zeta_{00}) * e^{((\gamma_{10} + \zeta_{10}) * TIME_{ij} + (\gamma_{20} + \zeta_{20}) * BDs_{ij} + (\gamma_{30} + \zeta_{30}) * BDsXTIME_{ij})}} + 4$
z	Full model*	$\frac{24}{1 + (\gamma_{00} + \gamma_{01} * Gender + \gamma_{02} * ADHD + \zeta_{00}) * e^{((\gamma_{10} + \gamma_{11} * Gender + \gamma_{12} * ADHD + \zeta_{10}) * TIME_{ij} + (\gamma_{20} + \gamma_{21} * Gender + \gamma_{22} * ADHD + \zeta_{20}) * BDs_{ij} + (\gamma_{30} + \gamma_{31} * Gender + \gamma_{32} * ADHD + \zeta_{30}) * BDsXTIME_{ij})}} + 4$

*Get your zoom button ready

Table 3
Parameter estimates and fit statistics for linear and linear nested models

Model	Desc.	γ_0	γ_1	γ_2	γ_3	AIC	df	LogLik	Wk.<4	Wk.>28
a	No growth	13.46***	-	-	-	8263.52	3	-4128.76	-	-
b	Linear	16.14***	-0.22***	-	-	7464.22	6	-3726.11	55	-
c	Linear+slope change	16.38***	-0.28***	-	0.01	7217.76	10	-3598.88	-	-
d	Linear+int. change	16.17***	-0.21***	0.02	-	7426.54	10	-3703.27	-	-
e	Linear Discontinuous	16.48***	-0.30***	0.34	0.01	7195.86	15	-3582.93	-	-
f	Quadratic	16.51***	-0.32***	0.005**	-	7247.96	10	-3613.98	-	93
g	Cubic	16.90***	-0.50***	0.020***	-0.001**	7179.28	15	-3574.64	45	-

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

Table 4

Parameter estimates and fit statistics for logistic and logistic nested models

Model	Desc.	γ_0	γ_1	AIC	df	LogLik	Wk.<4	Wk.>28
h	Logistic	1.35***	0.07***	7317.83	6	-3652.92	-	-
hneg	Log neg	7.51***	-	12287.39	3	-6140.70	-	-
hzero	Log zero	2.58***	-	8338.39	3	-4166.19	-	-
hlarge	Log pos	0.01***	-	11439.22	3	-5716.61	-	-

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

Table 5

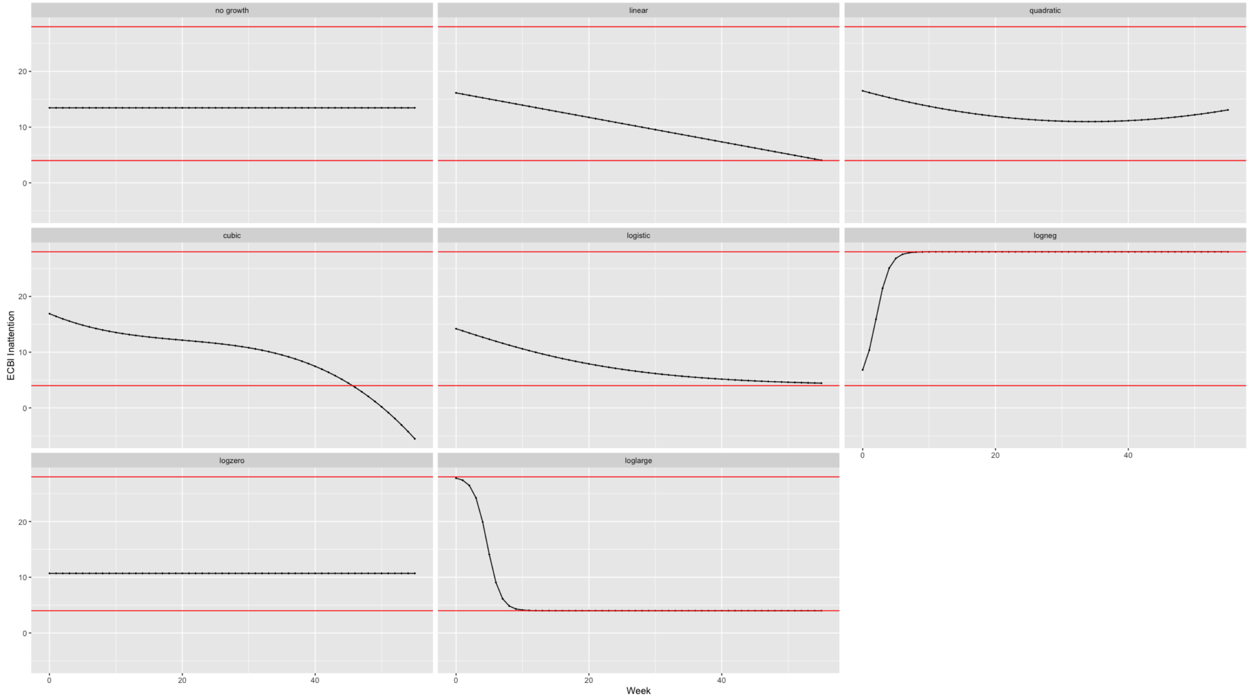
Comparisons of nested models and model AIC for linear and basic logistic models

Tested model	df	LogLik	AIC	Nested model	df	LogLik	AIC	ΔD	*p*
Linear	**6**	**-3726**	**7464**	No growth	3	-4129	8264	805.3	<.001
Linear+slope change	**10**	**-3599**	**7218**	Linear	6	-3726	7464	254.6	<.001
Linear+int. change	**10**	**-3703**	**7427**	Linear	6	-3726	7464	45.7	<.001
Linear Disc.	**15**	**-3726**	**7196**	Linear	6	-3726	7464	286.4	<.001
Linear Disc.	**15**	**-3726**	**7196**	Linear+slope	10	-3599	7218	31.9	<.001
Linear Disc.	**15**	**-3726**	**7196**	Linear+int.	10	-3703	7427	240.7	<.001
Quadratic	**10**	**-3614**	**7248**	Linear	6	-3726	7464	224.3	<.001
Cubic	**15**	**-3575**	**7179**	Quadratic	10	-3614	7248	78.7	<.001
Linear Disc.	15	-3726	7196	**Cubic**	**15**	**-3575**	**7179**	-	-
Logistic	**6**	**-3653**	**7318**	Cubic	15	-3575	7179	-	-
Logistic	**6**	**-3653**	**7318**	Log neg	3	-6141	12287	4976	<.001
Logistic	**6**	**-3653**	**7318**	Log zero	3	-4166	8338	1027	<.001
Logistic	**6**	**-3653**	**7318**	Log pos	3	-5717	11439	4127	<.001

Note. The preferred model is in bold text. All comparisons were made using log-likelihood unless models compared were not nested. In that case, AIC was used, and preference was given to more parsimonious models if AIC values were similar. Consideration was also given to whether the model predicted scores outside of the possible range of the scale.

Figure 6

Estimated growth trajectories using fitted ECBI inattention values from parameter estimates



Note. Red lines represent limits of ECBI inattention scale (4 and 28).

Table 6

Comparisons of nested models and model AIC for basic and discontinuous logistic models

Tested model	df	LogLik	AIC	Nested model	df	LogLik	AIC	L.Ratio	*p*
Logistic+slope change*	-	-	-	Logistic	6	-3653	7318	-	-
Logistic+int. change	10	-3643	7306	Logistic	6	-3653	7318	19.99	<.001
Logistic Disc.*	-	-	-	Logistic	6	-3653	7318	-	-

*Model did not converge

Figure 7
Histogram of residuals for logistic model

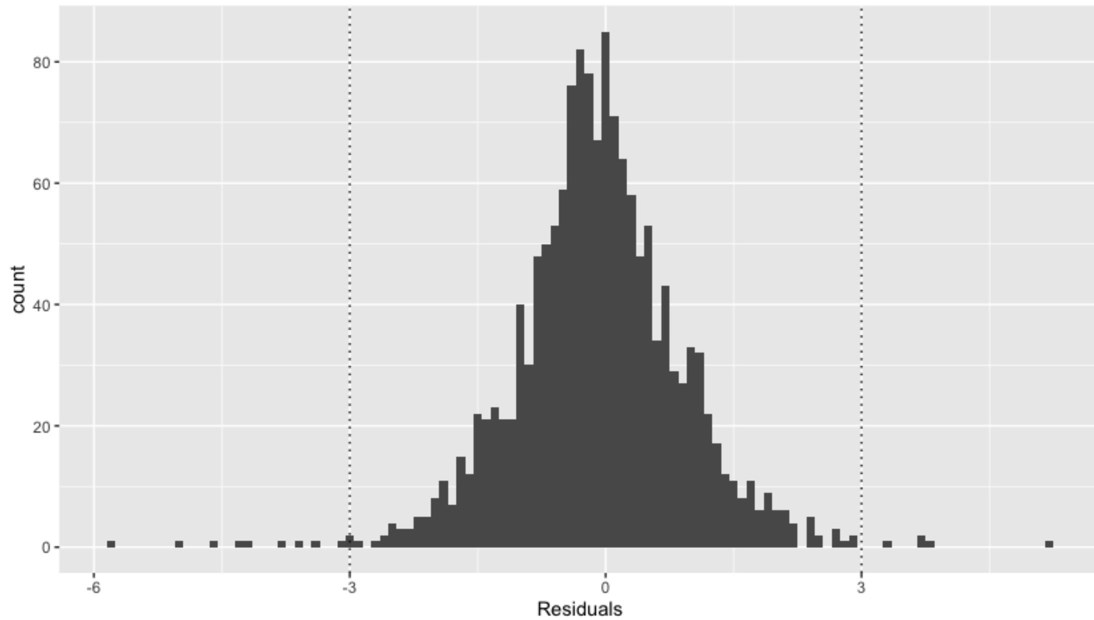


Figure 8
Residuals plotted against fitted values for logistic model

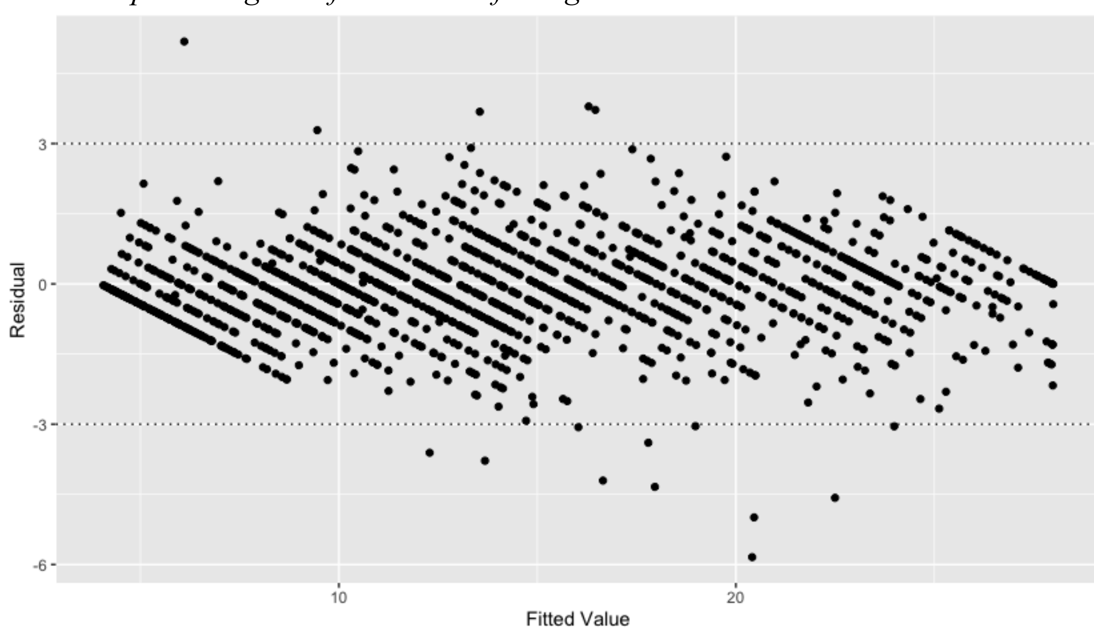


Table 7

Parameter estimates and fit statistics for logistic models with predictors

Model	Desc.	γ_{00}	γ_{01}	γ_{02}	γ_{10}	γ_{11}	γ_{12}	γ_{20}	γ_{30}	AIC	df	LogLik
zlog	Logistic	1.21***	-	-	0.08***	-	-	-	-	4619.93	6	-2303.97
zGEN	Log gender	1.29***	-	-0.25	0.07***	-	0.02	-	-	4623.10	8	-2303.55
zADHD	Log ADHD	5.17***	-0.06***	-	0.13*	0.00	-	-	-	4616.29	8	-2300.14
zCOV	Log Both	4.04***	-0.05***	-0.20***	0.19*	0.00	0.02	-	-	5133.30	10	-2556.65
zBDs	Log BD	0.90***	-	-	0.09***	-	-	0.04***	0.00***	4611.34	15	-2290.67
z	Full Log	-	-	-	-	-	-	-	-	-	-	-

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

Table 8

Comparisons of nested models and model AIC for logistic models with predictors

Tested model	df	LogLik	AIC	Nested model	df	LogLik	AIC	L.Ratio	*p*
Gender	8	-2303	4623	**Logistic**	**6**	**-2304**	**4620**	0.83	.661
ADHD	**8**	**-2300**	**4655**	Logistic	6	-2304	4620	7.64	.022
Both Covariates	10	-2557	5133	**Gender**	**8**	**-2303**	**4623**	506.20	<.001
Both Covariates	10	-2557	5133	**ADHD**	**8**	**-2300**	**4655**	513.02	<.001
Behavior Desc.	**15**	**-2290**	**4611**	Logistic	6	-2304	4620	26.59	.002
Full Model*	-	-	-	**ADHD**	**8**	**-2300**	**4655**	-	-
Full Model*	-	-	-	**BDs**	**15**	**-2290**	**4611**	-	-

*Model did not converge

Figure 9

Predicted trajectories for low, average, and high baseline ADHD symptoms

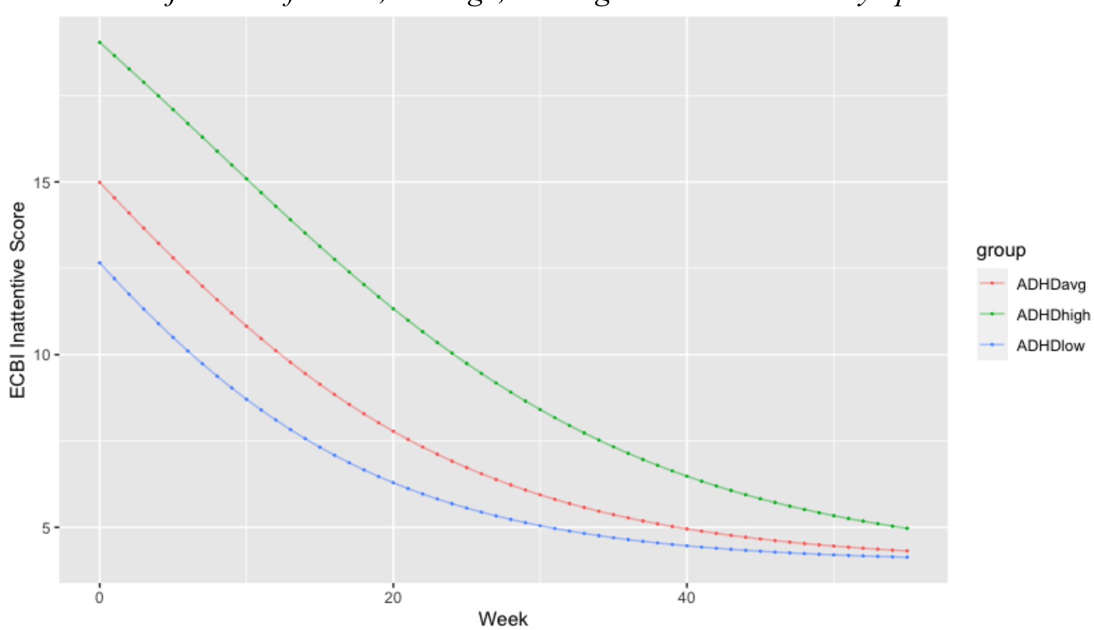


Figure 10

Predicted trajectories for low, average, and high behavior descriptions