Exploring seasonal trajectories in intensity of intervention use for children on the autism spectrum

ABC·CT Autism Biomarkers Consortium for Clinical Trials

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YALE CHILD STUDY CENTER
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Background

- Autistic individuals have a lifelong need for services across the lifespan[1], but studies over the last two decades have revealed gaps in service coverage[2] exacerbated by inequitable access based on race, ethnicity, and socioeconomic status[3,4].
- Despite this emerging literature, our understanding of longitudinal intervention use is limited. Studies examining this question[5,6] have studied demographically restricted samples or examined long-term (lifespan) changes, leaving trajectories of intervention use at the sub-yearly scale still unexplored.

Objectives:

1. To identify and describe trends in trajectories in intensity of intervention use for autistic children
2. To examine the association between different trajectories and child demographic factors

Methods

Participants

- As part of their participation in a multisite longitudinal biomarker study, parents of school-age (N=280) children on the autism spectrum reported the number of hours of each of 18 types of intervention their children received during a series of five consecutive six-week intervals. Parents also reported a range of demographic information, including race/ethnicity of child, parental education, and household income **(Table 1)**.
- The Differential Ability Scale, 2nd Edition (DAS-II)[7] was used to measure cognitive ability. Children were required to have a General Conceptual Ability (GCA) score (full-scale IQ) score between 60 and 150.

Table 1	N=188 (141 Male)
Age at Time 1 (years)	
Mean (SD) [Range]	8.57 (1.66) [6.01,11.5]
IQ	
Mean (SD) [Range]	98.6 (18.0) [60.0, 150]
ADOS-2 comparison score	
Mean (SD) [Range]	7.70 (1.84) [4.00, 10.0]
Race	
American Indian / Alaskan Native	1 (0.5%)
Asian	10 (5.3%)
Black or African American	16 (8.5%)
White	129 (68.6%)
Mixed race	27 (14.4%)
Other	5 (2.7%)
Ethnicity	
Hispanic or Latino	30 (16.0%)
Highest level of parental education	
Less than high school	1 (0.5%)
High school degree	5 (2.7%)
GED	3 (1.6%)
Some college	28 (14.9%)
Associate's degree	13 (6.9%)
Bachelor's degree	40 (21.3%)
Some graduate work	14 (7.4%)
Graduate degree	82 (43.6%)
Unsure	2 (1.1%)
Family annual income	
$0-5,000	1 (0.5%)
$5,001-10,000	3 (1.6%)
$10,001-15,000	1 (0.5%)
$15,001-25,000	7 (3.7%)
$25,001-35,000	13 (6.9%)
$35,001-50,000	15 (8.0%)
$50,001-75,000	25 (13.3%)
$75,001-100,000	29 (15.4%)
$100,001-150,000	44 (23.4%)
> $150,000	48 (25.5%)
Not Reported	2 (1.0%)

- Diagnosis was based on the on the Autism Diagnostic Observation Schedule-2 (ADOS-2)[8], the Autism Diagnostic Interview-Revised (ADI-R)[9] and expert clinical judgment of DSM-5 criteria[10].
- Only participants with all 5 data points and whose dates on the intervention forms matched their site assessment dates were included in the analysis (N=188).

Intervention Intensity Measures

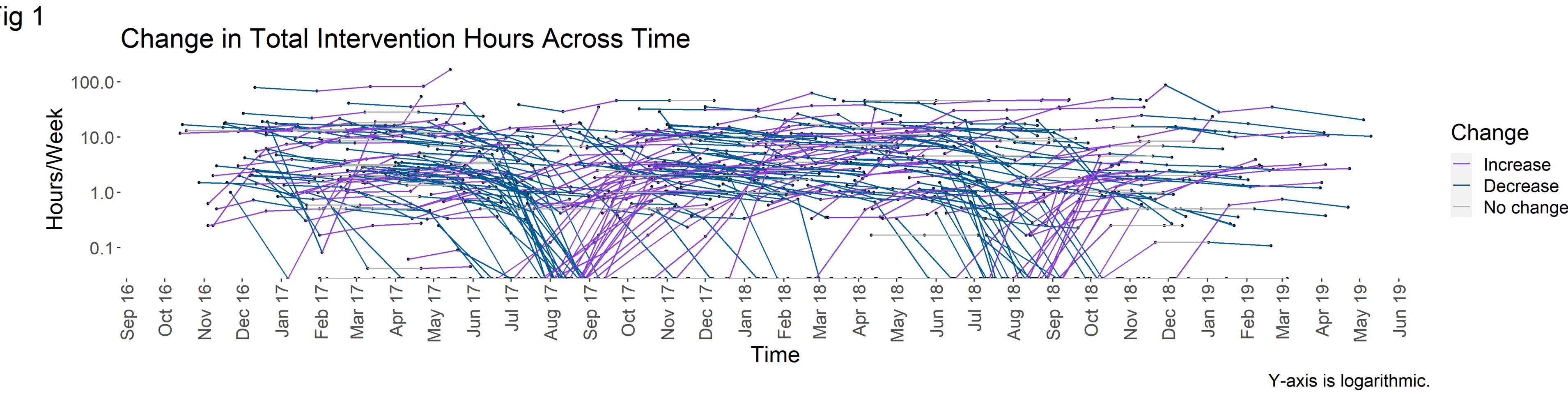
- **Total Intervention (Ix) Hours per Week:** Intervention hours for all 18 types of intervention were summed for each time point and divided by the number of weeks in each interval. Data were natural log-transformed for clustering and regression analyses.

Analysis

- **Monthly Changes in Weekly Intervention Hours:** Difference scores between consecutive measures of Ix hours/week were calculated for individual trajectories and aggregated by month. One-tailed Student's t-tests were performed to test difference from zero **(Figure 2)**.
- **Clustering Trajectories in Weekly Intervention Hours:** Individual trajectories were first clustered using a traditional *k*-means clustering algorithm via Euclidean distance partitioning to determine an appropriate number of clusters. The partition with the ideal number of clusters was identified by the lowest Bayesian Information Criterion (BIC). The trajectories were then re-partitioned using a shape-respecting *k*-means algorithm using Fréchet distance partitioning[11] **(Figure 3)**.
- **Modelling Cluster Membership with Demographic Independent Variables:** A multinomial logistic regression model was run with cluster membership as the dependent variable, and age, IQ, ADOS score, race, ethnicity, education, and income as predictors. Race, income, and education were coalesced into less sparse categories **(Figure 4)**.

Results

Fig 1



- Monthly changes in intervention hours display significant decreases for both August (t =-2.59, p=0.012) and January (t =-2.45, p=0.017) **(Figure 2)**.
- Traditional *k*-means clustering yielded an ideal partition of 6 clusters (BIC = 153.5). Re-partitioning into 6 clusters with a shape-respecting *k*-means algorithm yielded the 6 clusters and mean trajectories described in **Figures 3 and 4**.

Fig 2

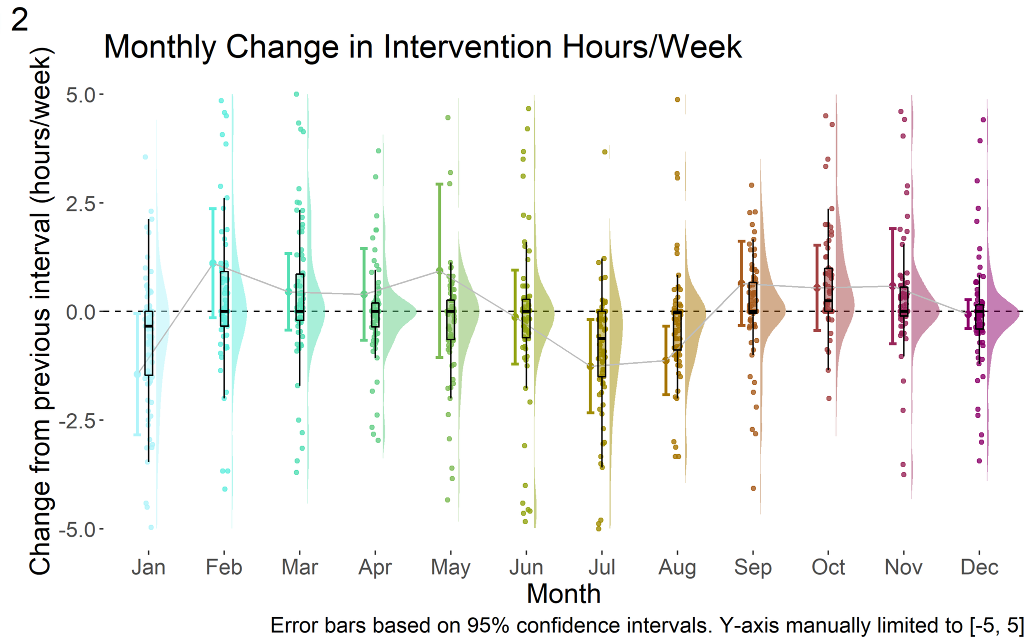
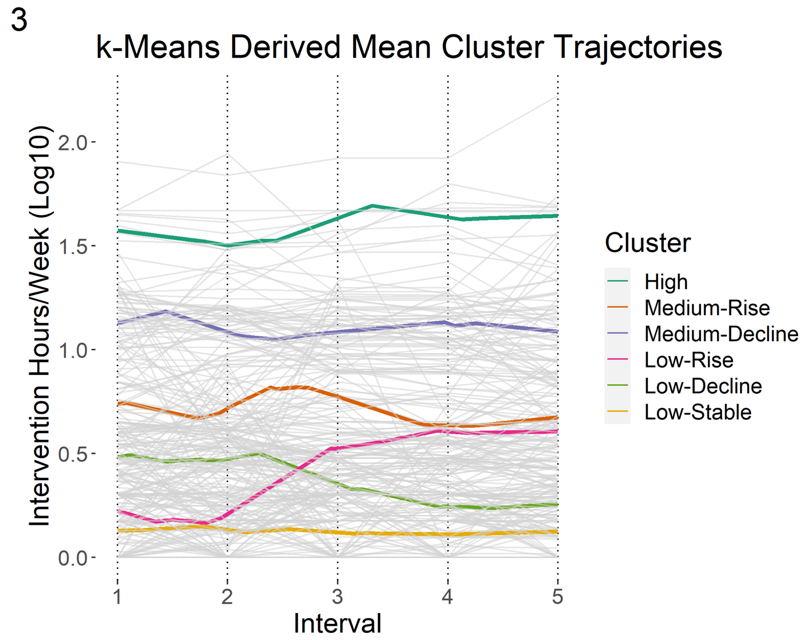


Fig 3



- Qualitatively, transitions into and out of the summer months seem to partly account for rising and declining trends in cluster means. For example, the Low-Rise cluster includes many participants that began their visits in the summer and ended in the fall, while Low-Decline displays the opposite pattern (**Figure 4**, red highlights).

Fig 4

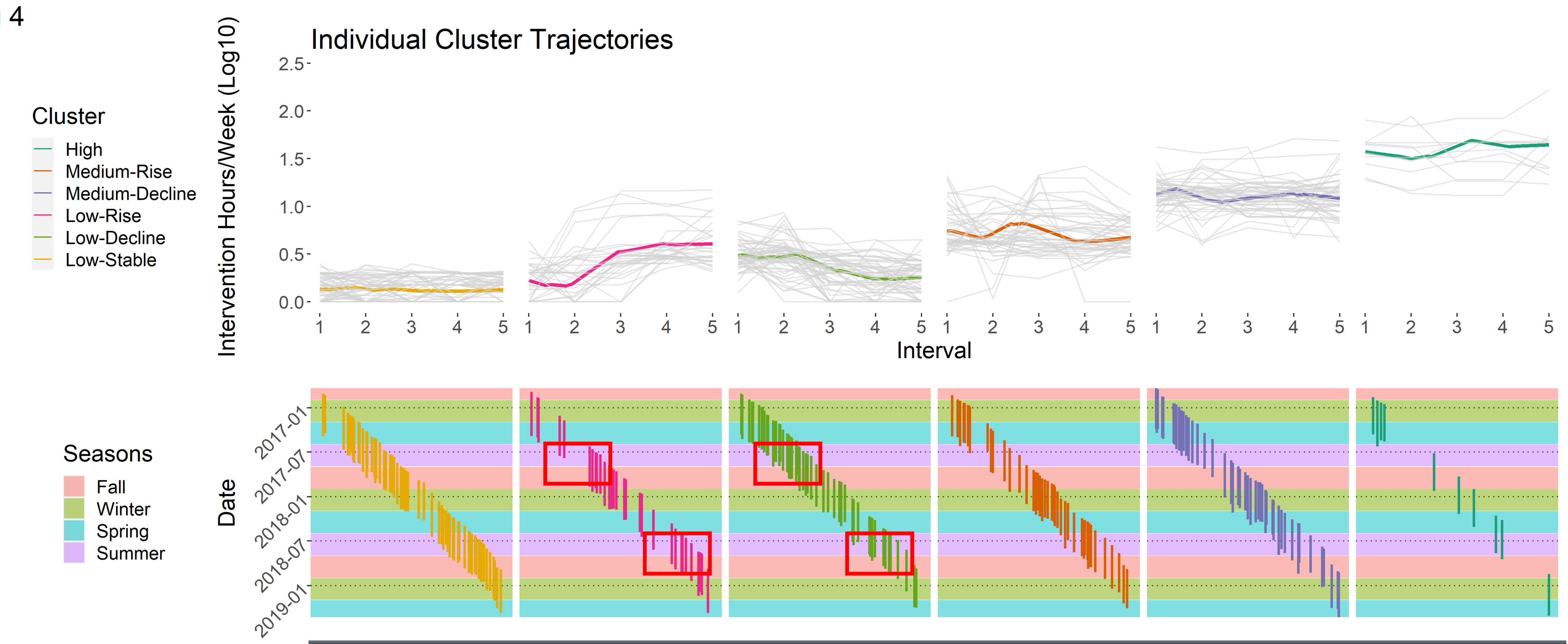


Table 2	Low-Stable (N=35)	Low-Rise (N=29)	Low-Decline (N=42)	Medium-Rise (N=36)	Medium-Decline (N=37)	High (N=9)
Age at T1 (years)						
Mean (SD)	9.09 (1.57)	8.79 (1.66)	8.56 (1.51)	8.26 (1.66)	8.40 (1.92)	7.88 (1.27)
IQ						
Mean (SD)	109 (15.7)	98.3 (21.9)	98.5 (16.9)	100 (17.3)	88.0 (15.0)	95.8 (8.80)
ADOS score						
Mean (SD)	6.94 (1.73)	7.34 (2.02)	7.45 (2.00)	8.14 (1.66)	8.32 (1.51)	8.56 (1.59)
Race						
White	30 (85.7%)	16 (55.2%)	33 (78.6%)	24 (66.7%)	18 (48.6%)	8 (88.9%)
Non-White	5 (14.3%)	13 (44.8%)	9 (21.4%)	12 (33.3%)	19 (51.4%)	1 (11.1%)
Ethnicity						
Hispanic or Latino	5 (14.3%)	6 (20.7%)	7 (16.7%)	4 (11.1%)	8 (21.6%)	0 (0%)
Not Hispanic or Latino	30 (85.7%)	23 (79.3%)	35 (83.3%)	32 (88.9%)	29 (78.4%)	9 (100%)
Highest level of parent education						
High school or less	0 (0%)	2 (6.9%)	0 (0%)	4 (11.1%)	3 (8.1%)	0 (0%)
College (<4y)	10 (28.6%)	6 (20.7%)	10 (23.8%)	4 (11.1%)	11 (29.7%)	0 (0%)
College (4y)	12 (34.3%)	6 (20.7%)	6 (14.3%)	9 (25.0%)	7 (18.9%)	0 (0%)
Graduate school	13 (37.1%)	15 (51.7%)	25 (59.5%)	18 (50.0%)	16 (43.2%)	9 (100%)
Family annual income						
Low	9 (25.7%)	2 (6.9%)	8 (19.0%)	12 (33.3%)	9 (24.3%)	0 (0%)
Middle	6 (17.1%)	12 (41.4%)	17 (40.5%)	8 (22.2%)	9 (24.3%)	2 (22.2%)
High	19 (54.3%)	15 (51.7%)	17 (40.5%)	16 (44.4%)	18 (48.6%)	7 (77.8%)

Results

- Given the homogeneity of our sample in race, income, and education, some of the clusters have no low-income, Hispanic, or individuals with parents at lower educational levels. As such, only age, IQ, and ADOS score were included as predictors for the multinomial logistic regression. Relative risk ratios (RRR) were derived by exponentiating the regression coefficients of the model, and *p*-values were computed via a two-tailed z-test based on the standard error of the coefficients. Risk ratios are relative to the Low-Stable cluster.
- An increase in age makes it less likely that a given participant will be in the High cluster compared to the Low-Stable cluster.
- An increase in ADOS score makes it more likely that a participant will be in either Medium cluster compared to the Low-Stable cluster.
- An increase in IQ score makes it (slightly) less likely that a participant will be in either Low cluster or the Medium-Decline cluster.

Table 3	Age (Years)		ADOS CSS		IQ	
	RRR	***P***	**RRR**	***p***	**RRR**	***p***
Low-Decline	0.810	0.155	1.063	0.642	**0.968**	**0.028**
Low-Rise	0.909	0.556	1.030	0.834	**0.966**	**0.034**
Medium-Decline	0.749	0.082	**1.380**	**0.045**	**0.938**	**< 0.001**
Medium-Rise	0.761	0.096	**1.413**	**0.025**	0.982	0.246
High	**0.555**	**0.035**	1.523	0.115	0.966	0.159

Conclusions

- Clustering the longitudinal trajectories in intensity of intervention use for autistic children yields clusters that not only reflect differences in absolute intensity of services received (High, Medium, Low), but also temporal instability associated with monthly change.
- Cross-sectional work on intervention or service use for autistic children should consider the effect of seasonality when analyzing intensity at a single time point in order to avoid possible confounds.
- The decrease in intervention hours during August and January is most likely attributable to interruptions in the school year, and a consequent lapse in school-based service delivery. Future work with access to data on intervention setting (school, home, clinic) and funding (public, private) is needed to confirm this hypothesis and better assess the extent and impact of service coverage in this population.
- Previous work has found racial and socioeconomic group differences in intervention use[12] that could not be evaluated in the present sample and should be studied in larger and more heterogeneous samples.
- General trends in relative risk ratios suggest that younger children with higher ASD symptomatology are more likely to have high intensity intervention utilization over time.
- Further research is also needed to properly ascertain the impact of short-term interruptions on quality of life and educational progress measures.

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