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Brief report

The developmental course of childhood inattention symptoms uniquely predicts educational attainment: A 16-year longitudinal study

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ABSTRACT

In this 16-year longitudinal study, a new trajectory estimation approach was used to verify whether the developmental course of childhood inattention significantly predicted functional impairment. A rising childhood inattention trajectory significantly predicted graduation failure (OR: 1.76 [1.32–2.34]) independently of averaged inattention levels. Rising inattention is, in itself, important for prognosis.

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1. Introduction

Childhood attention deficit hyperactivity disorder (ADHD) predicts a number of functional impairments, including long-term low educational attainment through its inattentive dimension (Pingault et al., 2011). Moreover, ADHD symptoms follow different developmental patterns: inattention symptoms remain stable or increase with age, while hyperactivity symptoms tend to decrease (Larsson et al., 2011; Willcutt et al., 2012).

One limitation in the literature is the lack of studies combining these two lines of research to test if developmental patterns of symptoms are accompanied by changes in functional impairment (Willoughby, 2003). In particular, design issues, such as the lack of regularly repeated assessments in follow-up studies (Willoughby, 2003; Langberg et al., 2008), have led to a lack of knowledge concerning the association between developmental patterns of inattention and low educational attainment. In one exception, Breslau et al. (2010) demonstrated that changes in inattention levels between two assessments at ages 6 and 11 were followed by changes in educational achievement between ages 11 and 17.

Developmental trajectories have been used to examine the heterogeneous developmental patterns of inattention symptoms (Willoughby, 2003; Larsson et al., 2011). However, developmental trajectory estimation combines information concerning the level (e.g. high) and the functional form (e.g. rising). As such, we do not know whether children in a high rising inattention trajectory had lower educational attainment because they were in a rising trajectory or simply because they had high mean levels of inattention across childhood. We aimed to test whether averaged levels of inattention across childhood and/or the functional form of childhood trajectories of inattention made a significant contribution to early adulthood low educational attainment. We used a new trajectory estimation approach to reanalyze previously published data (Pingault et al., 2011). Understanding the developmental course of inattention and the associated impairments is a neglected area of study despite potential benefits in terms of basic research – e.g. understanding underlying mechanisms – as well as clinical research – e.g. informing the prognosis (Willoughby, 2003).

2. Methods

2.1. Participants

The study sample included 2000 participants belonging to the Quebec Longitudinal Study of Kindergarten Children and selected to be representative of the children attending kindergarten in

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French-speaking state schools in the province of Quebec in the 1986–87 and 1987–88 school years (Pingault et al., 2011).

2.2. Measures

2.2.1. Outcome variable

Information about high school graduation was obtained through the Quebec Ministry of Education at age 22 and 23. The measure differentiated between participants who had a high school diploma (coded zero) and participants who did not (coded one).

2.2.2. Childhood inattention

Teachers assessed children's behaviors yearly between 6 and 12 years with the Social Behavior Questionnaire. Each item was rated on a 3-point scale (0 to 2) that ranged from "never applies" to "frequently applies" (total range: 0–8). The following four items were used to assess inattention: (1) weak capacity for concentration, cannot maintain his/her attention for a long time on the same task, (2) easily distracted, (3) absentmindedness, and (4) gives up easily (Cronbach's alpha coefficients between 0.85 and 0.90). The Family Socioeconomic Adversity Index included information on family structure (intact or not), parents' education, parents' occupational status and parents' age at birth of the first child (see online supplement).

2.3. Data analysis

We adapted a clustering algorithm designed to estimate non-parametric trajectories: k-means for longitudinal data (Genolini and Falissard, 2010). Briefly, we pre-processed the data for each participant by subtracting his/her average level of inattention across the seven years to each yearly score. As a result, a participant with *high* and *rising* levels of inattention is classified in the same rising trajectory than a participant with *low* and *rising* levels of inattention. Therefore, this new approach clusters participants according to the form of their trajectory excluding information about their mean levels (details in online supplement). Finally, a logistic regression was used to examine the link between trajectory membership and graduation failure, while controlling for inattention levels averaged over the 7 years, sex and family adversity.

3. Results

3.1. Inattention trajectories

Three adjusted trajectories resulted from the analysis: a stable trajectory, a fluctuating trajectory and a rising trajectory (see Fig. 1 and online supplement for details and a rationale regarding the number of trajectories).

3.2. Results

The final model included averaged levels of inattention (mean=2.26, S.D.=1.88), trajectory membership, adversity and sex. The averaged levels of inattention across years significantly predicted graduation failure (odds ratio [OR]: 1.78; 95% Confidence Interval [CI]: 1.66–1.91; $p < 0.001$, corresponding to a 1-point increase in average inattention). Children belonging to the rising trajectory were at higher risk of graduation failure (OR: 1.76; 95% CI: 1.32–2.34; $p < 0.001$). Conversely, the fluctuating trajectory was not significant (OR: 1.02; 95% CI: 0.77–1.37; $p = 0.87$). For a more intuitive understanding, we estimated expected percentages of graduation failure in the stable and in the rising trajectory, while holding constant the inattention average and the adversity index

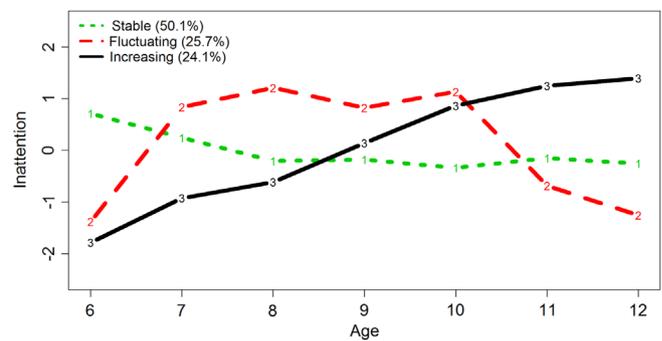


Fig. 1. Adjusted trajectories of inattention from 6 to 12 years old. *Note:* The trajectories will necessarily cross given the prior subtraction of the mean, which also explains the negative scores.

at their mean (using bootstrap resampling with 1000 simulations). Graduation failure was higher for boys in the rising trajectory (40.0%) than in the stable one (27.7%); the risk ratio was 1.46 (95% CI: 1.20–1.76). Corresponding results for girls were 27.9%, 18.2% and 1.56 (95% CI: 1.23–1.97).

4. Discussion

We aimed to verify whether mean levels of inattention across childhood and/or the form of inattention trajectories made significant contributions to high school graduation failure. Average levels of inattention strongly predicted graduation failure and, independent of these average levels, boys in the rising trajectory were still 46% more likely to fail than boys in the stable trajectory (56% for girls).

The fact that we detected a subgroup of children with rising inattention is coherent with the studies reporting stable or rising inattention levels with age (Larsson et al., 2011; Willcutt et al., 2012) and with the literature reporting a shift towards a greater proportion of the inattentive subtype with age (Willcutt et al., 2012).

Children with rising levels of inattention may have specific genetic and/or environmental liabilities. ADHD symptoms, including inattention, are highly heritable (Larsson et al., 2011). Yet, this does not preclude age-dependent genetic effects i.e. changes in heritability estimates and/or newly developing genetic influences emerging with advancing age (Franke et al., 2012). Environmental changes like transition to middle school may also play a part in these developmental changes (Langberg et al., 2008). Our study demonstrated that these putative liabilities manifested by rising levels of inattention were indeed associated with greater long-term impairment.

Due to the nature of the outcome (official graduation records), only one assessment was available, thus preventing us to model changes in the outcome. However, assessments by a different teacher each year over 7 years were available to monitor the development of inattention.

This study showed that increasing inattention during elementary school matter, even when mean levels of inattention are controlled for, providing evidence for the significance of developmental changes in inattention during elementary school. These results emphasize the need to further characterize the specific predictive value of developmental trends in inattention regarding diverse ADHD-related outcomes. In addition, the role of fixed or time-varying factors (e.g., family events) in explaining these developmental trends, and how such trends can be considered in the assessment of inattention, should be further investigated.

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Appendix A. Supplementary material

Supplementary data associated with this article can be found in the online version at <http://dx.doi.org/10.1016/j.psychres.2014.06.022>.

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Online supplement

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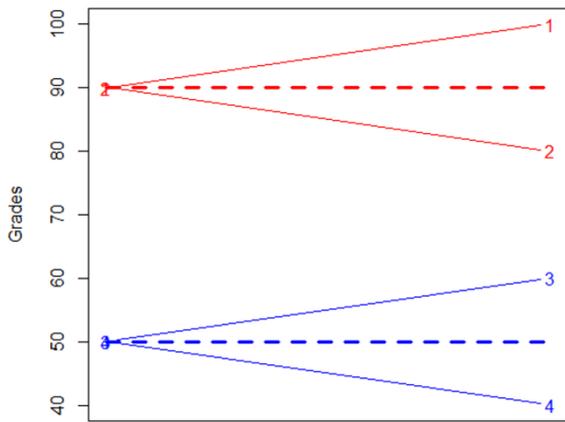
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Further explanations on the new trajectory estimation approach

When clustering longitudinal data, two types of information are relevant: on one side, the evolution of trajectories; on the other side, the mean level of trajectories. To our knowledge, the existing partitioning methods do not distinguish between these two types of information. Therefore, the means of the individual trajectories strongly influence clustering and, thus, the resulting trajectories. As a consequence, the average levels of trajectories are strongly associated to the trajectories.

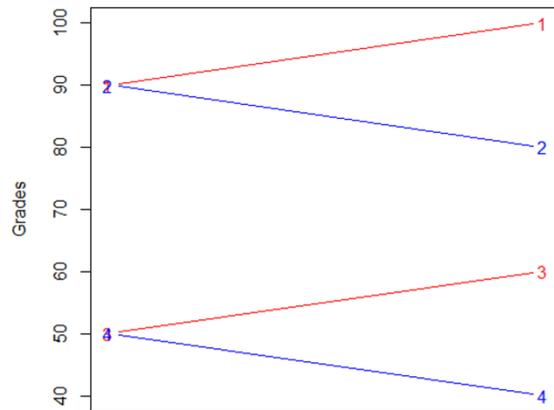
For a better understanding of these issues, we give the example of the clustering of student grades. Students whose mean is elevated often have repeated elevated grades across all assessment times and those with low means have repeated low grades. In this situation, classification algorithms group participants whose means are close without really taking into account the evolution of grades. The “good progressing” and “good regressing” will be classified in the same cluster, while the “weak progressing” and the “weak regressing” will be classified in another cluster (see Figure 1.a).

In a developmental perspective, the form of the trajectory (i.e. the evolution) conveys important information, independent of mean levels. In our example, it may be important to identify the clusters “Progressing vs. Regressing” than “Good vs. Weak” (see figure 1.b).



Repeated academic assessments

Fig1.a: Classical partition



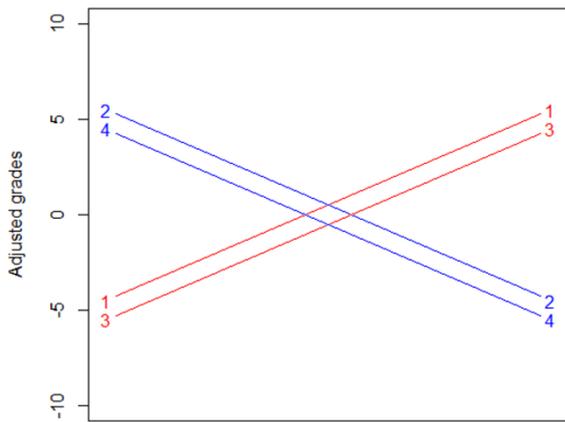
Repeated academic assessments

Fig 1.b: Alternative partition

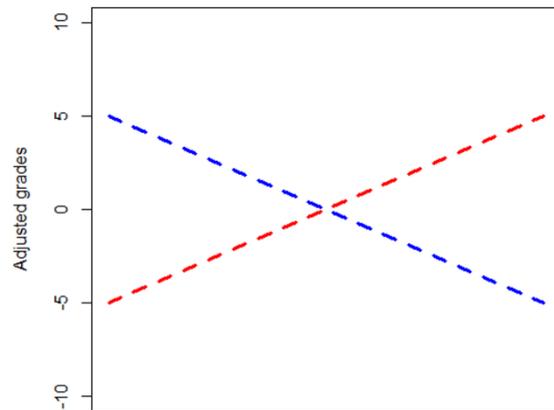
Figure 1.a: classical algorithms will cluster students 1 and 2 in one group and students 3 and 4 in a second group. The resulting clusters will be “good students” (in red) and “weak students” (in blue). The resulting trajectories (dots) will be parallel and will not grasp the distinction between progressing and regressing students. Figure 1.b: it may be more relevant to cluster students 1 and 3 (red) in a “progressing” trajectory and students 2 and 4 in a “regressing” trajectory (blue).

One way to achieve this result is to work on trajectories *adjusted on their means*: for individual i , let y_{ij} be the value of its trajectory at time j with $1 \leq j \leq t$ (t being the number of repeated assessments). The sequence of measures $(y_{i1}, y_{i2}, \dots, y_{it})$ is the trajectory of individual i and is noted y_i . To adjust a trajectory y_i on its mean is to transform it into a trajectory y'_i by subtracting its $mean(y_i)$ to each of its values : $y'_{ij} = y_{ij} - mean(y_i)$. Adjusted trajectories of our previous example (student grades) are shown in Figure 2.

The adjusted trajectories all have a mean of zero and, thus, are bound to cross. Partitioning such an adjusted population will focus on the group of participants with similar trends regardless of their level (those who progress together, those who regress together) which is our purpose.



Repeated academic assessments



Repeated academic assessments

Figure 2.a : Adjusted trajectories

Figure 2.b : Adjusted resulting trajectories

Figure 2.a presents students' trajectories after adjustment. Students 1 and 3 will be clustered in one group; students 2 and 4 will be clustered in another group. Therefore, two different typical trajectories (progressing in red and regressing in blue) are detected. They are presented in figure 2.b.

Adjusting on the mean before partitioning enables a focus on the form of the trajectories. A consequence of this approach is that the resulting groups are less associated to the mean levels than in the case of a classical clustering. However, the two variables – resulting trajectories and mean levels – will not necessarily be completely independent. For example, let us consider the case where 40 good students progress and 20 good students regress while 10 weak students progress and 30 weak students regress. Classical partitioning techniques will identify two groups, "good" and "weak". The link between the groups and the average will be very high (Table 1.a). Partitioning after adjustment on the mean would identify two groups, "progressing" and "regressing." A total of 40 good students and 20 weak students will be in the group "progressing", while 10 good students and 30 weak students will be in the group "Regressing". There is still an association between the groups and the means, but this association is weaker than in the classical case (Table 1.b).

		Clusters	
		Good	Weak
Mean	Good	60	0
	Weak	0	40

Table 1.a

		Clusters	
		Progressing	Regressing
Mean	Good	40	20
	Weak	10	30

Table 1.b

Table 1: association between the mean trajectory and the groups obtained after partitioning. In the classical case (1.a, left), the association between variables is very strong. After adjusting on the mean (1.b, right), it is less strong, but may still exist.

From a statistical point of view, the adjustment on the mean before clustering allow to include simultaneously the mean of the trajectories and the clusters in the same model, which is not possible in the classical case.

The same phenomenon, described in Table 1, is observed for our data on inattention. Table 2 presents the mean levels of inattention across the 7 years for the adjusted trajectories. As can be seen, the mean is significantly higher for the increasing as well as the fluctuating trajectories. In particular, the difference in averaged inattention levels between the increasing and stable trajectories is equal to 0.79 standard deviation (the standard deviation for inattention across the seven years being equal to 1.88, the mean being 2.26). However, the association between trajectories and mean levels is much stronger in the case of classical trajectories. For ease of comparison, we selected a three trajectory solution on the same sample, estimated with the normal Kml algorithm, resulting in three parallel trajectories: low, intermediate, high. The difference between the low and the high trajectories in the classical case is this time equal to 2.4 standard deviations of inattention. This important reduction in the association between trajectories and mean level can be seen in the F value of the one-way anova in each case.

In addition, it should be noted that the mean levels of inattention are higher for the increasing but also the fluctuating trajectories, compared to the stable trajectory. However, only the increasing trajectory makes a significant multivariate contribution to failure to graduate from high school (OR: 1.76, see manuscript) whereas the fluctuating trajectory makes no contribution (OR: 1.02). This is coherent with the interpretation that the effect of the increasing trajectory is due to developmental considerations rather than higher mean levels of inattention (in addition to the fact that we controlled in the model for mean levels).

Table 2: Association between Trajectories and Mean Levels of Inattention

Adjusted trajectories		Classical trajectories	
Group	Mean	Group	Mean
Increasing	3.08	High	5.19
Fluctuating	2.77	Intermediate	2.82
Stable	1.60	Low	0.69
Anova: F value = 147 (p <.001)		Anova: F value = 5034 (p <.001)	

Information on the *Family Socioeconomic Adversity Index*

The index was based on information collected at the start of the study and was created by averaging the following indices: 1) family structure (intact or not intact), 2) parents' levels of education, 3) parents' occupational status (Blishen et al., 1987) and 4) parents' age at birth of the first child. Families at or below the 30th percentile for each of these indices (or a non intact family) were coded as having 1 adversity point. The final score ranges from 0 to 1.

Information on missing data

The information regarding high-school graduation was extracted from official records and present for all participants. All participants had at least one measurement of inattention and were kept in the trajectory estimation (of note is that 98.1% of participants had 3 or more assessments available). A total of 104 participants (5.2%) had missing data on the adversity index so that the final model was estimated on the remaining participants, i.e. 1896.

Choice of the number of trajectories and sensitivity analyses

The choice of the number of trajectories is one of the more controversial aspects in trajectory estimation (Bauer, 2007). Among criteria used in the literature are: (1) convergence issues as the number of trajectories rises; (2) taxometric theory (e.g. ADHD subtypes); (3) previous research; (4) the relative fit of the model; (5) usefulness of classes.

(1) Contrary to parametric approaches, non-parametric approaches as the one used in the present study do not encounter convergence issues.

(2) In our case, the absence of developmental taxometric theories regarding the development of inattention prevented precise hypotheses concerning the number of trajectories.

(3) We know from previous research that inattention tends to be stable or rise (Larsson et al., 2011; Willcutt et al., 2012), which leads to a greater likelihood of rising inattention for at least a subgroup of children (contrary to what is reported in the literature for other behaviours like physical aggression (Nagin and Tremblay, 1999; Broidy et al., 2003).

(4) The fit of the model is a relevant criterion in our case. However, most of the literature on developmental trajectories has relied solely on the Bayesian Information Criterion (BIC), which tends to overestimate the number of trajectories (Nagin, 2005). When several fit indices are used, contradictions usually arise (Larsson et al., 2011). We used two indices, Calinski-Harabatz (Genolini and Falissard, 2010, 2011) and the BIC. We also examined the global average of post-probabilities (the post-probability being the probability for each participant to effectively belong to the trajectory he/her was classified in). As in other studies (Larsson et al., 2011), the fit indices were contradictory, with Calinski-Harabatz indicating 2 trajectories as the best solution, while the BIC continued to improve up to 5 trajectories (See Table 3 below). Of note is that the improvement in the BIC between the 4 and 5 trajectory solutions was minimal. Therefore, based on the two statistical criteria, a solution between 2 and 4 seemed indicated. The average post-probability was .85 for the 2 trajectory solution and .79 for the 3 trajectory solution. It continued to decrease thereafter with .76 for 4 trajectories.

Table 3: Fit indices & global post-probability for each model

Trajectories	2	3	4	5	6
Calinski-Harabatz	417.3	358.0	308.3	282.1	253.4
BIC	-41233.1	-41165.4	-41111.3	-41009.9	-41024.9
Post-probability	0.848	0.789	0.760	0.737	0.733

Note. A higher value for the Calinski-Harabatz criterion indicates a better fit. A value closer to zero for the BIC indicates a better fit.

(5) The usefulness of classes was defined in van Lier et al. (2007) (p.603) as “the subjective interpretation of the developmental course of the trajectories and the number of children in each class”. The two and three trajectory solutions gave interpretable results with a stable trajectory and a rising one in both cases, and, in the case of the three trajectories solution, a fluctuating one. Solutions with further trajectories added to the noise with crossing trajectories without a definite developmental course.

Finally, as mentioned above, the statistical criteria indicated a range from 2 to 4 trajectories as adequate solutions. However, the global post-probability was already well below

.80 for the 4 trajectory solution. Furthermore, the 3 trajectory solution appeared as the most useful solution as it yielded an interpretable result, in coherence with previous research, i.e. a steady increasing trajectory accompanied by a stable and a fluctuating trajectory. We therefore decided to select this solution. In addition, in order to test whether the results were sensitive to the chosen number of trajectories, we repeated the analyses with a two trajectory solutions: the rising trajectory also predicted graduation failure independently of mean levels of inattention, adversity and sex.

Some authors have also considered the construct validation i.e. the associations between the trajectories and other variables such as predictors or outcomes (Bauer, 2007; van Lier et al., 2007). In the present study, the predictive value of the trajectories regarding high-school graduation can be interpreted as an evidence of construct validity.

Additional information on the trajectories

Table 4. Additional information on the trajectories.

	Stable	Fluctuating	Rising
N (%)	1003 (50.1)	514 (25.7)	483 (24.1)
Males (%)	47.0	46.7	60.0
Graduation failure (%)	23.2	34.6	48.9
Graduation failure in males (%)	32.3	42.9	53.8
Graduation failure in females (%)	15.2	27.4	41.5
Adversity index score (M & SD)	0.25 (0.24)	0.30 (0.25)	0.31 (0.26)

Note. Graduation failure percentages are not adjusted for confounding variables in Table 4. Adjusted failure rates and risk ratios are provided in the manuscript.

Table 5. Absolute levels of inattention at each age in each trajectories

		6 years	7 years	8 years	9 years	10 years	11 years	12 years
Stable	Mean	2.34	1.86	1.45	1.09	1.26	1.47	1.32
	SD	2.48	2.34	2.02	1.73	1.88	2.08	2.02
Fluctuating	Mean	1.38	3.61	4.02	3.39	3.86	2.10	1.50
	SD	1.78	2.52	2.42	2.41	2.39	2.09	1.79
Rising	Mean	1.28	2.06	2.38	3.09	3.87	4.33	4.51
	SD	1.63	2.21	2.22	2.55	2.49	2.30	2.34

Note. The three trajectories (stable, fluctuating, rising) were computed based on adjusted means as detailed in the first section of this document. The figure presented in the manuscript shows the adjusted trajectories with the adjusted inattention scores. For each of these trajectories, the observed levels of inattention (prior to adjustment) are provided in Table 5. It shows, for example, that the level of inattention at 6 years is lower for the rising trajectory than for the two others but higher at 12 years than at any other time point for any trajectory.

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