

# Inattention in primary school is not good for your future school achievement - a pattern classification study

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## Abstract

*Objective.* Inattention in childhood is associated with academic problems later in life. The contribution of specific aspects of inattentive behaviour is, however, less known. We investigated feature importance of primary school teachers' reports on nine aspects of inattentive behaviour, gender and age in predicting future academic achievement.

*Methods.* Primary school teachers of  $n = 2491$  children (7 - 9 years) rated nine items reflecting different aspects of inattentive behaviour in 2002. A mean academic achievement score at high-school (2012) was available for each youth from an official school register. All scores were at a categorical level. Feature importance was assessed by including a classification and regression trees, a multinomial logistic regression, and a random forest algorithm. A comprehensive pattern classification procedure using  $k$ -fold cross-validation was implemented to vote for accuracy, precision and recall.

*Results.* Overall, inattention was rated as more severe in boys, who also obtained lower achievement scores at high school than girls. Problems related to sustained attention and distractibility were together with age and gender defined as the most important features to predict future achievement scores. A cross-validation model including these four features gave accuracy, precision and recall that were better than chance levels.

*Conclusion* Primary school teachers' reports of problems related to sustained attention and distractibility were the most important features of inattentive behaviour predicting academic achievement in high school. Identification and follow-up procedures of primary school children showing these features should be prioritised to prevent future academic failure.

## Introduction

Inattention in early childhood has been linked to a wide range of behavioural and social problems [3,12], including poor academic achievement. This has been shown in several studies of individuals with Attention Deficit Hyperactivity disorder (ADHD, see e.g. [21,26]), but is also widely documented in studies including community samples [16,17,20,24,29,30,35]. In most of these studies, inattention is defined as a sum score across a set of items.

Inattention is, however, a multidimensional concept, where the items reflect impairment of sustained and focused attention, impaired working memory, distractibility, forgetfulness, as well as impaired ability to organise and plan activities and tasks. These aspects of inattention have been described as independent at a biological level [6], but may be extremely difficult to disentangle behaviourally. They rather tend to occur as patterns of behaviour. For example, most children may be distracted by external stimuli in a classroom situation [32], and these distractions will probably be especially hard to handle by a child having problems in maintaining attention and engagement in a task. Thus, it may not be the total inattention score, but rather specific patterns of inattentive behaviour that have the most detrimental effect on the child's present and future function at school. Identification of important features of inattentive behaviour will therefore be of great importance when developing remediation procedures.

Primary school teachers' skills are crucial in the work to detect and help a child struggling with inattention. They observe their pupils on a regular basis and in a wide range of situations where inattention tends to have negative effects on performance. At the same time, one should be aware of the risk of biases. Primary school teachers may for example be more tolerant to the behaviour of a child in the lowest class levels, and previous studies have shown that teachers tend to rate girls as less impaired than boys, even when the girls exhibit problematic behaviour in the classroom [2,9,25]. The child's gender and age should therefore be taken into account when evaluating teacher ratings of inattentive behaviour.

The aim of the present study was to further investigate the importance of primary school teachers' reports of inattentive behaviour. To that end, we included data from the Bergen Child Study, where primary school teachers completed a questionnaire including nine items reflecting different aspects of inattentive behaviour when the children were between 7 and 9 years old. About ten years later, when the children had become high school students, academic achievement scores from the official school registry of Norway were available for a subset of the children from the original sample. **Described as a key determinant of later vocational career success and adult financial stability [15], there are strong arguments for using academic achievement as an outcome variable.** Each of the nine inattention items were rated on a Likert scale with three response alternatives, and the outcome variable, academic achievement, was discretised into three intervals, including an almost equal number of participants in each category. Teacher scores on each of the nine items were used as predictors together with gender and primary school class level (a proxy for age) to answer the following questions: **(1) which features of inattentive behaviour in primary school represent the strongest predictors of academic achievement in high school? (2) how well can the result be generalised to an independent data set?, and (3) are gender and the age of the child when evaluated by their primary school teachers of importance to the prediction?**

In this context, statistical approaches were selected according to the following criteria: **(i) the methods must handle multiple predictors with a small set of response alternatives, and with a small set of outcome categories; (ii) the methods should be generic and of interest to other similar data analysis situations and prediction challenges occurring in the behavioural sciences, and (iii) the methods should produce results that are easy to interpret at a clinical level.** Based on these criteria we selected a *multinomial logistic regression* (MLR), a *classification and regression trees* (CART), **and a random forest algorithm (RF) to assess feature importance, and a k-fold cross-validation procedure to estimate the accuracy of a model including the features identified as most important.**

## Materials and methods

The data included in the present study are from the Bergen Child Study (BCS), a longitudinal, population-based study on mental health and development. The first wave of the BCS was launched in October 2002, and included the total population of 9,430 children attending second to fourth grade (7–9 years old, born in 1993, 1994 and 1995) in all public, private, and special schools in Bergen. During the initial screening phase, parents and teachers were asked to complete a four-page questionnaire, including, among other scales, a somewhat modified Swanson, Nolan, and Pelham Questionnaire - Fourth Edition (SNAP-IV) [38]. Sample protocols of the first wave have been described in several previous publications from the Bergen Child Study group (e.g., [19, 22, 36]).

A fourth and final study-wave was conducted when the youth were between 16 and 19 years old. The sample for this wave included all adolescents born between 1993 and 1995 living in the county of Hordaland ( $n = 10,222$ ). This county includes the city of Bergen, and the BCS sample was thus nested within this Hordaland sample. Academic achievement scores during the previous semester were made available from the official school registry. The BCS was approved by the Regional Committee for Medical and Health Research Ethics (REC), Western Norway (2015/800 Barn i Bergen/ung@hordaland). Parents gave written consent for participation in the first wave of the study. In accordance with the regulations from the REC and Norwegian health authorities, adolescents aged 16 years and older can make decisions regarding their own health (including participation in health studies), and thus gave consent themselves to participate in the fourth wave of the study. Parents/guardians have the right to be informed, and in the current study, all parents/guardians received written information about the study in advance.

More information about the project is given at the BCS homepage: <http://uni.no/en/bergen-child-study/>.

### The sample

The sample selected for the present study included the participants with teacher reports on all selected SNAP-IV items when they were 7 to 9 years old (primary school class levels 2, 3, or 4), information about gender, and academic achievement when they attended high school (16 to 19 years old), i.e.,  $n = 2491$  participants (1192 boys). Within this sample, the percentages of children attending 2<sup>nd</sup>, 3<sup>rd</sup> and 4<sup>th</sup> primary school class levels when evaluated by their teachers were 42.3%, 34.4% and 23.4%, respectively.

### Teacher reports

*Inattention* items were selected from the SNAP-IV [38], describing problems used to define the inattentive symptoms of the Attention Deficit Hyperactivity Disorder (ADHD) according to the Diagnostic and Statistical Manual of Mental Disorders (DSM-5) [1]. The original SNAP-IV uses four levels to evaluate each item, whereas in our study, the teachers evaluated each item on a 3-level Likert-type scale (*not true*, *somewhat true*, or *certainly true*) in order to follow the response pattern of the remaining scales included in the first wave of the BCS questionnaire. Each answer was assigned a value 0, 1, or 2. The nine inattention items from SNAP-IV are listed in Table 1.

The percentages of children scored within the three response categories are given in Table 2, confirming that the frequency of girls reported with a (*not true*) response was significantly higher than in boys.

**Table 1. SNAP items, scored as *not true* (0), *somewhat true* (1), and *certainly true* (2)).**

SNAP 1:	Often fails to give close attention to details or makes careless mistakes in schoolwork, work, or other activities
SNAP 2:	Often has difficulty sustaining attention in tasks or play activities
SNAP 3:	Often does not seem to listen when spoken to directly
SNAP 4:	Often does not follow through on instructions and fails to finish schoolwork, chores, or duties
SNAP 5:	Often has difficulty organizing tasks and activities
SNAP 6:	Often avoids, dislikes, or is reluctant to engage in tasks that require sustained mental effort
SNAP 7:	Often loses things necessary for tasks or activities (e.g., toys, school assignments, pencils, books, or tools)
SNAP 8:	Often is distracted by extraneous stimuli
SNAP 9:	Often is forgetful in daily activities

**Table 2. Percentage of children obtaining a given response from their teachers on each inattention item (SNAP-IV).**

	<i>Not true</i>			<i>Somewhat true</i>			<i>Certainly true</i>		
	All (%) N=	Girls 1144	Boys 935	All (%)	Girls 96	Boys 176	All (%)	Girls 16	Boys 30
SNAP 1	87.0	91.3	82.3**	11.2	7.5	15.2	1.8	1.2	2.5
SNAP 2	88.5	94.1	82.5**	9.5	5.5	13.8	2.0	0.5	3.7
SNAP 3	92.0	96.7	86.9**	7.4	3.1	12.1	0.6	0.2	1.0
SNAP 4	92.5	96.2	88.4**	6.8	3.6	10.4	0.7	0.2	1.1
SNAP 5	91.5	96.1	86.5**	7.3	3.5	11.4	1.2	0.5	2.1
SNAP 6	91.7	96.3	86.7**	7.0	3.3	11.1	1.3	0.4	2.3
SNAP 7	96.5	98.5	94.4**	3.0	1.2	4.9	0.5	0.3	0.7
SNAP 8	75.2	84.4	65.1**	21.0	14.1	28.4	3.9	1.5	6.5
SNAP 9	89.5	93.4	85.2**	9.3	6.2	12.7	1.2	0.4	2.1

*Note:* Total number of children = 2491, girls = 1299, boys = 1192. \*\*:  $p$  value < .001 according to a chi-square test comparing a “not true” report in boys and girls.

## Academic achievement

Academic achievement scores were provided by the official registers from the Hordaland County. In Norway, secondary schools use a scale spanning from 1 to 6, with 6 being the highest grade (outstanding competence), 2 the lowest passing grade (low level of competence), and 1 being a *fail*. The scores included in the present study were the mean value of the grades during the previous semester, comprising all school subjects except for physical education. The mean score for girls was statistically significant higher ( $\mu = 4.11$  ( $SD = .72$ )) than for boys ( $\mu = 3.90$  ( $SD = .72$ ),  $p < .001$ ). For the present study, the academic achievement scores were categorised into three levels, calculated to generate groups with similar number of participants (see details below).

## Statistical analysis

The data analysis was divided into three parts: (a) data preparation, including discretising the average academic achievement into three levels (b) casting the data analysis problem into a machine learning classification task assessing feature importance using both a classification and regression tree (CART), multinomial logistic regression (MLR), and a random forest (RF) algorithm, and (c) a pattern classification procedure using  $k$ -fold cross-validation with five different linear and nonlinear classifiers (MLR, MLP, XGB, SVM, KNN, each described below) and incorporation of a voting classifier across these five. All these steps were implemented in a Jupyter notebook using Python (3.5.4), Numpy (1.12), Pandas (0.20), Statsmodels (0.8), XGboost (0.6), Scikit-learn (0.19), rpy2 (2.8.5) and Matplotlib (2.0) with an exception for Fig. 3, where MATLAB (R2015b) was used. Our Jupyter notebook, will be available on GitHub [address TBA].

### (a) Data preparation and explorative data analysis

The original data, provided to us as a SPSS-file, were imported into the Jupyter notebook environment via rpy2 and the r-foreign packages. For the analysis we used the sample of  $n = 2491$  children having complete data on the 11 predictor variables and academic achievement as outcome variable.

For classification purposes, the mean average academic achievement scores were discretised into three intervals (level of academic achievement) constructed using Pandas qcut(), to include about the same number of participants in each of the categories: *low* ( $[1.000 - 3.714]$ ,  $n = 834$ ), *medium* ( $(3.714 - 4.375]$ ,  $n = 831$ ), and *high* ( $(4.375 - 5.900]$ ,  $n = 826$ ). The distribution across the three levels - from *low* to *high* - was 40.3%, 33.3% and 26.4% for boys, and 27.3%, 33.4% and 39.3% for girls, confirming the overall higher academic scores achieved by the girls.

Depiction of the complete dataset, using gray scale heatmap columns for the  $n = 2491$  girls and boys, comprising predictor variables *gender*, *grade*, *SNAP 1*, ..., *SNAP 9*, the outcome variable *academic achievement*, and the six classifiers being used for prediction in a  $k$ -fold cross validation scheme, is given in Fig. 1.

### (b) Assessment of feature importance

To assess feature importance of the 11 candidate variables for predicting *low*, *medium*, and *high* academic achievement in the whole cohort, we performed three types of analyses: (i) Multinomial logistic regression with consideration of each parameter, i.e. the magnitude of its coefficient, the standard error of the corresponding parameter, and the odds ratio, cf. Tab. 3. (ii) A CART analysis with assessment of the top important decision nodes (cf. Fig. 2), and (iii) a random forest classification using a forest of 10000 trees (weak learners) and ordering of features importance according to the 'gini' information criterion (cf. Fig. 3).

**Multinomial logistic regression model (MLR)** The multinomial logistic regression analysis included the following set of variables on a nominal level: the three levels of academic achievement scores as outcome variable, and *gender*, primary school class level (*grade*), and teacher reports on the nine inattention items *SNAP 1*, ..., *SNAP 9* as predictors. Generally, the multinomial logistic regression model relates a set of explanatory variables  $x_1, \dots, x_p$  to a set of log-odds,  $\log(\pi_2/\pi_1), \dots, \log(\pi_J/\pi_1)$  according to

$$\log(\pi_j/\pi_1) = \beta_{j0} + \beta_{j1}x_1 + \dots + \beta_{jp}x_p \quad (1)$$

for  $j = 2, \dots, J$ . Here,  $j = 1$  represents the base level category,  
 $\pi_j = P(\text{academic achievement level} = j)$ ,  $\pi_j/\pi_{j'}$  denotes the odds of category  $j$  relative  
to  $j'$  (i.e. odds ratio, OR), and  $\sum_{j=1}^J \pi_j = 1$  (see e.g. [7] for details). In our case, we let  
the base level category  $j = 1$  be the *low* mean academic achievement, meaning that the  
*low* was compared separately to the *medium* and *high* categories. For computations we  
used `mnlogit()` from the `statsmodels.formula.api`.

**Classification trees (CART)** The *SNAP 1*, ..., *SNAP 9* items were included  
together with demographics (*gender* and primary school glass level (*grade*)) as predictor  
variables in a CART analysis [8] used to predict level of academic achievement score  
{*low*, *medium*, *high*}. In brief, the *root* of the classification tree is the top node and  
input patterns are passed down the tree such that decisions are made at each node until  
a terminal node (a *leaf*) is reached. At each non-terminal node a question is posed on  
which a binary split is made such that the “child” nodes are on average “purer” than  
their “parent”. A measure of “impurity” is low (i.e. close to 0) if the probability of the  
occurrence of a class at a given node for all subsets of patterns reaching that node is  
concentrated on that class. The “impurity” is maximal (i.e. close to 1) if the class  
probabilities at that node is uniform. In our analysis we used the  
`DecisionTreeClassifier()` from `sklearn.tree` with impurity *criterion*=‘*gini*’ and  
*max\_depth*=2. for growing the classification tree (cf. Fig. 2).

**Random forest ensemble learning (RF)** Random forest (RF) is an ensemble  
learning method for classification that constructs a multitude of decision trees at  
training time, and outputting the mode class among the generated classes. By using  
random decisions, RF is less prone to overfitting compared to CART, and will therefore  
produce more generalisable results [8]. The variables *gender*, *grade*, and the *SNAP*  
*1*, ..., *SNAP 9* items were included as predictors of the outcome level of academic  
achievement: *low* (*L*), *medium* (*M*), or *high* (*H*). In our analysis we used the  
`RandomForestClassifier()` from `sklearn.ensemble` with impurity *criterion*=‘*gini*’,  
*n\_estimators*=10000, *bootstrap*=True, *max\_features*=None, and *max\_depth*=None. After  
fitting the forest with the  $2397 \times 11$  predictor matrix *X* and academic achievement  
outcome  $y \in \{L, M, H\}$ , i.e. `forest.fit(X,y)`, the Scikit-learn RF algorithm enables the  
calculation of `forest.feature_importances_` which ranking is depicted graphically in  
Fig. 3.

### (c) Prediction using *k*-fold cross-validation

The most important predictors of academic achievement scores in high school according  
to the classification analyses will be selected for a *k*-folds cross-validation procedure.  
This procedure randomly splits the dataset into *k* consecutive fold, of which a single  
subsample is retained as a validation set, while the remaining *k* - 1 folds form the  
training set. The procedure is repeated unit each *k* subsamples are used once as the  
validation data. To obtain the best vote for accuracy, we used the following five  
classifiers: Two linear classifiers: the multinomial logistic regression (MLR) and the  
multinomial logistic P....(MLP), and three nonlinear classifiers: XGB, Support vector  
machine (SVM), CV and KNN to vote for overall accuracy, precision and recall.  
Precision is the number of items correctly labeled as belonging to the positive class  
divided by the sum of true positives and false positives, also called positive predictive  
value. Recall is the number of true positives divided by the sum of true positives and  
false negatives, also known as sensitivity. In the present study we used number of splits  
= 3, random size = 42, score average = weighted.

## Results

We first report the results from the analysis of feature importance, then the prediction results from  $k$ -fold cross validation using the six different classifiers.

### Assessment of feature importance

**Multinomial logistic regression model (MLR)** Performing MLR on the complete dataset, *gender* significantly predicted whether a child obtained a *low* rather than a *high* academic achievement score in high school ( $OR = .61, p < .001$ ) as well as a *low* rather than a *medium* score ( $OR = .80, p = .003$ ). This shows that boys were overall somewhat more likely to obtain a *low* academic achievement level in high school than the girls [Table 3](#).

Two of the teacher reported inattention items significantly predicted a *low* rather than a *medium* academic achievement score. The strongest effect was found for an item reflecting problems related to sustained attention, *SNAP2* ( $p < .001$ ). An odds ratio of .52 tells us that for each unit change in the score given by the teacher, the child was almost two times less likely to obtain a *medium* compared to a *low* academic achievement score ( $1/.52 = 1.9$ ). The second item reflects distractibility, *SNAP8* ( $p = .002$ ), with an odds ratio of .75 leaving the child with a somewhat increased odds (1.3) of obtaining a *low* score.

The predictions from these two items were even stronger when comparing *low* to *high* academic achievement scores, with the highest estimate on *SNAP2* ( $p < .001$ ) followed by *SNAP8* ( $p < .001$ ). The odds ratios show that the child was 2.6 times more likely to obtain a *low* score in high school for each more severe step in problems reported on *SNAP2* ( $OR = .38$ ) and 2.4 times more likely for each step on *SNAP8* ( $OR = .41$ ).

The prediction of *low* rather than *high* academic achievement score was also significant for two other items reflecting problems related to sustained attention, *SNAP1* ( $p < .001$ ) and *SNAP6* ( $p = .002$ ). With ORs of .56 and .52, the increase was almost twofold (1.9 and 1.8, respectively).

To sum up the results from the MLR, inattentive behaviour associated with problems related to sustained attention and distractibility predicted *low* rather than *medium* or *high* academic achievement levels in high school, with an overall higher odds-ratio in boys than in girls [Table 3](#).



**Table 3. Multinomial logistic regression model.**

Reference category: Low score						OR [0.025, 0.975]	
Variable	Estimate	SE	z	P> z			
Medium score	intercept	0.86	0.20	4.20	0.00	2.32	[0.46, 1.25]
	gender	-0.23	0.11	-2.14	0.03	0.80	[-0.43, -0.02]
	grade	-0.16	0.07	-2.51	0.01	0.85	[-0.29, -0.04]
	SNAP 1	-0.05	0.14	-0.40	0.69	0.95	[-0.32, 0.22]
	SNAP 2	-0.65	0.19	-3.34	0.01	0.52	[-1.03, -0.27]
	SNAP 3	0.02	0.20	0.12	0.90	1.02	[-0.36, 0.41]
	SNAP 4	0.17	0.24	0.70	0.49	1.18	[-0.30, 0.64]
	SNAP 5	0.04	0.22	0.19	0.85	1.04	[-0.39, 0.47]
	SNAP 6	-0.17	0.20	-0.85	0.40	0.84	[-0.57, 0.23]
	SNAP 7	0.16	0.26	0.62	0.53	1.18	[-0.35, 0.68]
	SNAP 8	-0.29	0.13	-2.25	0.02	0.75	[-0.55, -0.04]
	SNAP 9	-0.06	0.16	-0.39	0.69	0.94	[-0.38, 0.25]
High score	intercept	0.93	0.21	4.45	0.00	2.53	[0.52, 1.34]
	gender	-0.49	0.11	-4.48	0.00	0.61	[-0.70, -0.27]
	grade	-0.10	0.07	-1.52	0.13	0.90	[-0.23, 0.03]
	SNAP 1	-0.58	0.18	-3.20	0.01	0.56	[-0.94, -0.23]
	SNAP 2	-0.96	0.27	-3.59	0.00	0.38	[-1.48, -0.43]
	SNAP 3	-0.08	0.25	-0.32	0.75	0.92	[-0.56, 0.41]
	SNAP 4	0.11	0.32	0.33	0.74	1.11	[-0.53, 0.74]
	SNAP 5	0.47	0.27	1.70	0.09	1.59	[-0.07, 1.01]
	SNAP 6	-0.66	0.29	-2.29	0.02	0.52	[-1.22, -0.10]
	SNAP 7	-0.19	0.43	-0.45	0.65	0.82	[-1.04, 0.65]
	SNAP 8	-0.60	0.15	-4.05	0.00	0.55	[-0.89, -0.31]
	SNAP 9	-0.24	0.20	-1.21	0.23	0.79	[-0.63, 0.15]

Reference group = low academic achievement. OR = Odds ratio.

**Classification trees (CART)** The CART analysis, using maximum depth=2, generated four terminal nodes (Fig. 2). The first and most important split (the top node #0) was on *SNAP2*, assessing problems related to sustained attention. The “False” branch at this node, i.e. teachers reporting “somewhat true” or “certainly true” on this item, arriving at node #4 (11.7% of the sample), were mainly associated with a low academic achievement score in high school. In this subsample, primary school class level (*grade*) did matter. A higher portion of those those with “somewhat true” or “certainly true” reports on *SNAP2* in the 3<sup>rd</sup> and 4<sup>th</sup> grades (node #6) obtained lower academic scores than those in the 2<sup>nd</sup> grade (node #5), 71% versus 56%, respectively.

If primary school teachers reported “not true” on *SNAP2*, then the reports on problems related to distractibility (*SNAP8*) was important for prediction, i.e. node #1 comprising 88.3% of the sample. Reporting “somewhat true” or “certainly true” on *SNAP8*, i.e. the “false” branch from node #1 to node #3, led to the highest percentages towards a low academic achievement score (41%), while a “not true” report (node #2, 74.1% of the sample) was associated with the highest percentages towards the high score (39%).

To sum up the results from the CART analysis, problems related to sustained attention (*SNAP2*) or distractibility (*SNAP8*) were important predictors of low school academic achievement scores in 25.9% (nodes #3 and #4) of the children. Primary



school class *grade* did also matter, with a higher percentage of children obtaining a *low* score when assessments were done at 3<sup>nd</sup> or 4<sup>th</sup> grade.

**Random forest ensemble learning (RF)** The random forest algorithm with 10000 trees further explored feature importances in the cohort. Figure 3 shows the ranked importance of the 11 predictor variables, confirming the main findings from the MLR and CART analyses, where the top three most important features were *SNAP2* > *grade* > *SNAP8*.

## Prediction using *k*-fold cross-validation

The cross-validation procedure was performed separately for the three top features selected by the RF analysis. Gender was included due to its effect upon both the SNAP variables and the academic achievement score, and the statistically significant effect revealed by the MLR. Table 4 shows the results from the selected classifiers and the overall voting on the accuracy, precision and recall measures. All values were above chance level for the three categories of academic achievement scores (33%).

**Table 4. Cross-validation.**

	MLR	MLP	XGB	SVM	KNN	Voting
Accuracy	0.42 (-0.01)	0.41 (-0.02)	0.42 (-0.02)	0.4 (-0.02)	0.36 (-0.04)	0.41 (-0.03)
Precision	0.42 (-0.04)	0.38 (-0.05)	0.44 (-0.02)	0.42 (-0.02)	0.35 (-0.06)	0.41 (-0.04)
Recall	0.42 (-0.01)	0.41 (-0.02)	0.42 (-0.02)	0.42 (-0.02)	0.36 (-0.04)	0.41 (-0.03)

Note: MLR = ; MLP = ; XGB = ; SVM = ; KNN = ; Voting =

## Discussion

### Summary of results

The present study asked if specific features of inattentive behaviour in primary school - as reported by teachers - act as predictors of academic achievement in high school. Different types of multivariate analyses were used to handle the set of categorical variables included in the study. Overall, items reflecting problems related to sustained attention and distractibility were selected as the two most important features of inattention in predicting the achievement score. Gender and a proxy for age (primary school class level) were added as important features by the MLR analysis. The CART analysis showed that as many as 25.9% of the children were reported with either of the two inattention problems, and that these children had a high risk of obtaining a low academic achievement score. Age when assessed by their primary school teachers was of some importance, in that the chance of obtaining a low achievement score was somewhat lower when reported with problems in the 2<sup>nd</sup> than in higher grades (3<sup>rd</sup> and 4<sup>th</sup> grades). Age and the items reflecting sustained attention and distractibility were also identified with the highest importance by the RF analysis, suggesting that these results can be generalised to other samples. This was also confirmed by the cross-validation analyses, where a model including these three features and gender showed a fairly good accuracy, precision and recall.

## Early predictors of academic achievement in high school

The present results suggested that problems related to sustained attention and distractibility in primary school are important drivers of poor academic performance in high school. By this, the results partly overlapped with findings previously reported in a study by Holmberg et al. [20], where teacher reports of failure to finish a task were found to be one of the main factors explaining academic outcome. Our study add to this by revealing the importance of problems related to distractibility. The MLR analysis showed that this problem was associated with an almost two-fold increased odds-ratio of an achievement score in the lower than higher end of the scale. Its importance as a predictor of poor achievement scores was also supported by the CART analysis, with the strongest effect when reported as a problem in the 3<sup>rd</sup> and 4<sup>th</sup> grades. In a class situation, the relation between the two is obvious. A child with the ability to stay focused on a task over a longer period of time is expected to be less disturbed by habits and cues in the environment than a child with poor vigilance. This enables the child to obtain the basic skills and knowledge that are of importance to the academic achievement scores as the curriculum become more complex at high school level.

Inclusion of information about nine aspects of inattentive behaviour separately in the statistical analyses revealed their relative importance to high school academic performance. Most previous studies have rather defined inattention as a sum-score from reports of problems reflecting a range of different behaviours. A significant relation between such a sum score and academic achievement was shown in one of our previous studies. Inattention was found to be significant across two culturally and diagnostically diverse groups, subsamples from BCS and the Berkeley Girls with ADHD Longitudinal Study (BGALS), and the effect was over and above the effect of demographics and intellectual function [23]. The present results indicate that the effect on academic achievement is driven by a few features defined within the concept of inattention. Secondly, the results may have been different if the results were analysed by the set of statistical procedures included in the present study. We should for example expect an impact of socioeconomic factors on academic achievement. This is shown in previous studies (e.g., [34]), but are expected to be dependent on the welfare system of different countries. This was shown by a previous BCS study, showing a much weaker effect of socioeconomic status on intellectual function in Norway than expected from US samples [14].

The cross-diagnostically effect of inattention was, however, confirmed by the present study. Although inattention is one of the core symptoms of ADHD, the importance of inattentive behaviour in explaining future academic success is definitely not restricted to a diagnostic category; the present study documented this effect in a population-based sample. However, although a high proportion of children obtaining a low academic achievement score were reported as inattentive by their primary school teachers, the cross-validation model shows that there is a need of more information about the child to obtain a more perfect measures of accuracy, precision and recall. This probably reflects both the instability of inattentive behaviour and the large number of co-existing and new challenges influencing a child through childhood and adolescence.

Taken together, the present results should inspire assessment and treatment efforts in primary school children vulnerable to distractibility and with problems to sustain their attention in school-related work. The close relationship between inattentive behaviour and cognitive function [4,5] has lead to increased popularity of presenting cognitive training programs to school children with ADHD (see e.g., [31,39]). A sole focus on cognitive training of the child is, however, not expected to lead to successful alleviation of the inattentive behaviour described in the present paper. This was supported by the results from the meta-analysis presented by Cortese and collaborators [13], showing that cognitive training procedures had limited effects on

ADHD symptoms. Positive contributions from parents and teachers seems to be essential (see e.g., [28]). Whereas parent-focused training produces improvements in negative parenting and impairment at home, incorporation of child skill training and teacher consultation may be necessary to produce improvements at school [18].

Gender turned out to be another important predictor. Girls were reported by their primary school teachers to have less inattention symptoms and to obtain higher academic achievement in high school than boys. Although gender was identified as one of the main predictors of academic achievement scores in the feature extraction by the MLR analysis, but was not selected among the top features of importance by the the CART and RF analyses. The importance of gender when comparing boys and girls on the predictor and outcome variables led to inclusion of gender in the cross-validation model. This may be related to the higher number of girls than boys included in the present study. Further gender balanced longitudinal studies of functional outcomes of early inattentive behaviour are therefore warranted.

## Strengths and Limitations

The large population-based sample of high school students followed from childhood, inclusion of a standardised questionnaire assessing inattention, and inclusion of academic achievement scores from official National registers are main strengths of the present study. Another strength is the inclusion of statistical methods - the MLR , CART, RF for feature selection, and the cross-validation analyses to test the model including the top three most important features and gender. By these statistical models we could handle predictor variables with few categories and possible hidden multidimensional relationships, and still generate feature importance that was easy to interpret and validate. Inclusion of RF and the cross-validation procedure should correct for the danger of overfitting when including a high number of variables in a relatively small sample. We believe that the relevance of the present analytic approach is clearly not restricted to the topic of the present study, in that questionnaire data with only a few response categories are commonly used in psychological research.

In spite of the strengths and the importance of the present study, several limitations must be mentioned. Inclusion of very few features when predicting an outcome about 10 years ahead, is an obvious limitation of the present study. A stronger model could have been obtained by including results from psychometric test assessing vigilance and distractibility, similar to the one developed by Cassuto et al. [11], or more ecological valid virtual reality test as the one described by Pelham et al. [27]. Inclusion of teacher reports only may also be considered as a limitation. Furthermore, stronger conclusions could have been obtained by including information from repeated inattention reports to understand the trajectory from early symptoms of inattention to function in adolescence and adulthood. The importance of the latter was demonstrated in a study by Pingault and collaborators [29], showing that increase in symptoms of inattention during childhood really matters when it comes to school graduation failure. Such studies are important and should include analysis of behavioural patterns, because a specific pattern of vigilance and distraction was suggested by the present study. Finally, academic achievement level did not reflect overall high school achievement, in that it was operationalised as the mean of grades for one semester only.

## Figure legends

**Figure 1** The predictor data (explanatory variables), the academic achievement outcome, and the types of classification analyses being performed. Data values are

represented as grey level heat maps. See Fig. 1 for explanation of variables. MLR = Multinomial logistic regression, CART = Classification and regression trees.

**Figure 2** Fitted classification tree (CART analysis), including the predictor variables SNAP-IV items 1 to 9 (0 = *not true*; 1 = *somewhat true*; 2 = *certainly true*); gender (0 = *girl*; 1 = *boy*); grade (primary school class level 2, 3, 4) and the academic achievement outcome (H = *high*, L = *low*, M = *medium*, where the three occurrence frequencies in the node boxes are given in alphabetical order). The percentage in each node box denote the percentage of samples routed to that particular node - where the root node will contain 100% of the samples, and a leaf node will contain the least number of samples along a rooted path in the decision tree. The node numbers are given on top of each node box. For each split decision, ‘*yes*’ denotes that the corresponding statement is *false* and then pointing to the left child node (that is either a new internal decision node or a final leaf node), and ‘*no*’ denotes that the corresponding statement is *true* and then pointing to the right child node (that is either a new internal decision node or a final leaf node). The tree is plotted using the `fancyRpartPlot()` function from Graham Williams **rattle** package (<http://rattle.togaware.com>)

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