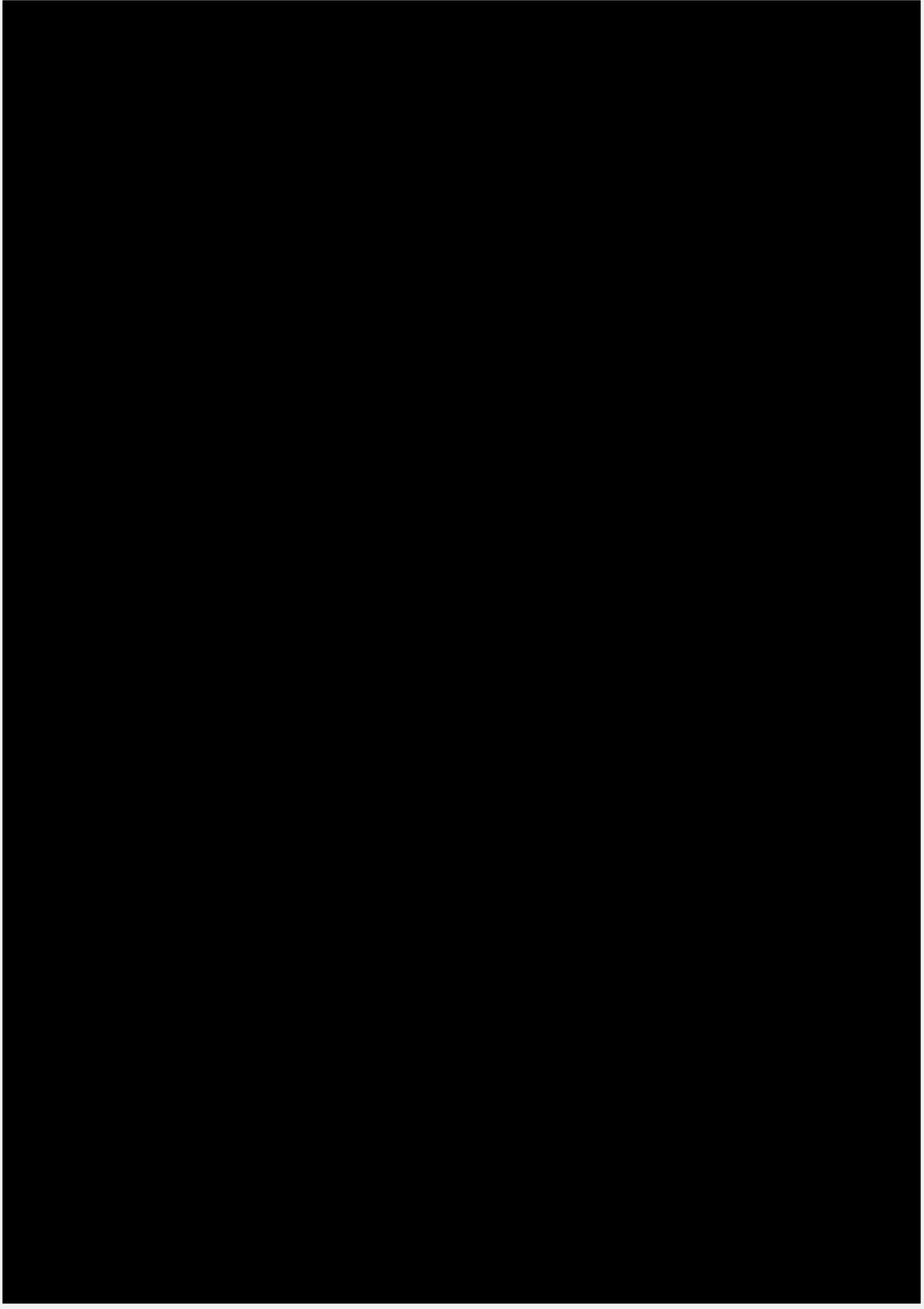




# **PART 1**

**Overweight related energy  
balance-related behaviors**



# 2

## **Mediators of Longitudinal Changes in Measures of Adiposity in Teenagers using Parallel Process Latent Growth Modeling**

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*Obesity, In press*

## **Abstract**

**Objective:** The aim of the study was to evaluate mediating effects of energy balance-related behaviors on measures of adiposity in the Dutch Obesity Intervention in Teenagers-study (DOiT).

**Design and Methods:** DOiT was an 8-month behavioral intervention program consisting of educational and environmental components and evaluated in 18 pre-vocational secondary schools in the Netherlands (n=1108, baseline age 12.7yr, 50% girls). Outcome measures were changes in body mass index (BMI), waist circumference and sum of skinfold thickness. Self-reported consumption of sugar-containing beverages and high caloric snacks, active transport to/from school, and screen-viewing behaviors were the hypothesized mediators. Data were collected at 0, 8, 12 and 20 months. We used parallel process latent growth modeling for the data analysis.

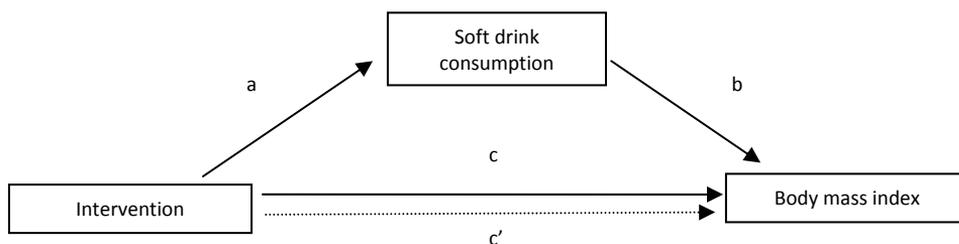
**Results:** Total sugar-containing beverages consumption mediated the intervention effects on BMI ( $ab=-0.01$ , 95%CI=-0.20, -0.001). The intervention group lowered their sugar-containing beverages consumption more than controls ( $B=-0.14$ , 95%CI=-0.22, -0.11) and this, in turn, led to smaller increases in BMI. No significant mediated effect by the targeted behaviors was found for waist circumference or sum of skinfolds.

**Conclusions:** Future school-based overweight prevention interventions may target decreasing sugar-containing beverages consumption.

## Introduction

Overweight, including obesity, is a complex global health problem and its prevalence among youth in some European countries has risen up to 44% in boys and 37% in girls (1). Schools are one of the most convenient and practical settings for obesity prevention in youth (2). A systematic review investigating the effectiveness of school-based overweight prevention studies concluded that interventions focusing on both sides of the energy balance and combining educational and environmental components were most effective (2). An example of such a school-based multi-component intervention is the Dutch Obesity Intervention in Teenagers (DOiT). In 2003, the DOiT-intervention was developed as a school-based weight gain prevention program targeting 12-13 year old children, aimed to prevent excessive weight gain by improving children's energy balance-related behaviors (EBRBs) (3).

Most obesity prevention studies only test the effect of the intervention on the primary outcome (e.g., weight status, BMI) (4). However, to further improve existing interventions and to inform future interventions, it is crucial to explore the underlying mechanisms of how an intervention achieved its effects, via which EBRBs intervention effects occur. This can be explored by mediation analysis, which provides exploration of a causal mediation mechanism (5,6). Mediation analysis is a stepwise procedure that first estimates the effect of the intervention on the presumed mediator, then the effect of the presumed mediator on the main outcome and finally the mediated effect that explains the effect of the intervention on the outcome through the presumed mediator. Figure 1 shows an example of a mediating effect of soft drink consumption in the intervention effect on body mass index (BMI). It indicates that the intervention exerts its effect on BMI indirectly through influencing soft drink consumption.



**Figure 1.** Mediating effect of soft drink consumption. a: intervention effect on the mediator; b: effect of the mediator on outcome variable while controlling for the intervention effect ; c: overall intervention effect on the outcome variable; c': direct effect of intervention on the outcome variable while controlling for the mediator variable.

Advanced statistical techniques have been called for evaluating mediating effects of overweight prevention interventions, with an emphasis on longitudinal mediation models (5). Evaluation of change can be done by several statistical methods depending on the number of measurement occasions. For intervention studies that have three or more measurements, as the DOiT-intervention, latent growth modeling (LGM) is an

advantageous method, which is referred to as 'state-of-the art' for modeling longitudinal meditation analysis (7). It models change over time and investigates the precursors and consequences of change (7). Singh et al. (8,9) reported on the short and long term effectiveness of the DOIT-intervention and showed some beneficial effects on sum skinfold thickness measurements, but the underlying mechanisms of the effects on changes in measures of adiposity have not been investigated yet. Chin A Paw et al. (10) investigated the mediating effect of cognitive variables on the DOIT-intervention effect on EBRBs, which can guide future development of more successful intervention strategies to change EBRBs. On the other hand, it is needed to explore which behavioral determinants mediated the intervention effect on indicators of weight status, which will help selecting the most important EBRBs to be targeted in future interventions (11). Exploring the mediating effects of EBRBs on adiposity measures using longitudinal data will also enrich the current literature that lacks studies reporting on this topic. Therefore, the primary aim of the present study was to understand the behavioral mediators of the intervention effect on the growth trajectories of measures of adiposity in the DOIT-intervention. We specifically looked at the mediating effects of sugar-containing beverages consumption, high-caloric snack consumption, active transport to/from school and screen viewing behaviors. Based on the existing evidence we hypothesized that improvements in EBRBs would be associated with a smaller increase in adiposity measures.

## **Methods**

### **Study Population and Intervention**

Secondary data analyses were performed on existing data of the DOIT-intervention (3). A total of 18 pre-vocational secondary schools (i.e. 10 intervention schools, 8 control schools) participated in the study including 1108 children aged 12-13 years old. The 8-month intervention conducted in 2003/2004 aimed at improving EBRBs, namely sugar-containing beverages consumption, high-caloric snack consumption, PA and sedentary behavior. The DOIT-intervention targeted especially adolescents with lower educational levels. DOIT was developed applying the Intervention Mapping protocol and consisted of an educational and an environmental component. The educational part covered 11 lessons for the subjects biology and physical education implemented by classroom teachers. The first part (six lessons) aimed at increasing awareness and information processing with regard to EBRBs, with supportive materials such as a pocket-sized diary to monitor own behavior, pedometer, video and a computer-tailored advice. The second part (5 lessons) aimed at facilitation of choice to improve one of the EBRBs, setting personal goals and implementation intentions, identifying barriers, improving self-efficacy, evaluating change process. The environmental part of the intervention consisted of school-specific advice on the assortment of the school canteen and possible change options, posters for the school canteens and financial support to schools for implementing additional PA options. Control schools followed their regular curriculum. The follow-up rate was 88% for the first follow-up (8 months), 85% for the second (12 months), and 82% for the last (20 months). Detailed information on the study is described elsewhere (3).

### **Outcome Measures**

Outcome measures were obtained at all four time points. Body weight and height were measured at the school by trained research assistants with a calibrated electronic flat scale (SECA 888) and a portable stadiometer (SECA 225). Body mass index (BMI) was calculated ( $\text{kg}/\text{m}^2$ ) and IOTF cut-off values were used to categorize weight status (normal weight and overweight/obese) (12). While it is common to use BMI z-scores to express change in BMI in children, Cole et al (13) recently showed that change in BMI is a better outcome measure of adiposity change compared to BMI z-scores. As the more obese the child is, the same change in BMI units will produce a smaller change in BMI z-scores due to the skewness in the BMI distribution. Waist circumference (centimeter) was measured by a flexible band (SECA 200). Triceps, biceps, subscapular, supriliac skinfold thickness (millimeter) were measured using a Harpenden skin fold caliper and summed. Inter- and intra-rater reliability values varied between 0.82-0.99 for the waist circumference and skinfold thickness measurements (8).

### **Putative mediators-EBRBs**

Data on EBRBs were collected by self-report, based on validated questionnaires used in earlier research including; 1) sugar-containing beverages consumption; daily intake of soft drinks (fizzy drinks ('diet' drinks not included), lemonade, ice tea, energy drinks, etc.) and fruit juices (liter/day), 2) High-caloric snacks intake; daily consumption of savory and sweet snacks (number of snacks/day), 3) Active transport (walking and/or cycling) to/from school (minutes/day), 4) Screen viewing behaviors; duration of TV-viewing and computer use per day (hours/day) (14-17). Test-retest reliability was assessed and the results were satisfactory (ICCs>0.70) (18). Reported EBRBs values above 95th percentile were considered as implausible probably due to over-reporting and recoded as the value of the 95th percentile in the dataset (9).

### **Covariates**

Gender and ethnicity were self-reported. Ethnicity was categorized into Dutch children or Non-Western immigrants. A child whose parents (both or one) were born in Turkey, Africa, Latin America or Asia was considered as a Non-Western immigrant (19). Non-Western immigrants born outside the Netherlands, but in Europe, or in North America, Oceania, Indonesia or Japan were excluded from the current analysis (n=40).

### **Statistical Analysis**

Descriptive statistics were used to calculate median and interquartile range (IQR) (due to skewed distribution of the variables). Differences between groups at baseline were tested by Mann-Whitney and chi-square tests. We used latent growth modeling (LGM) to assess change (a growth trajectory) over time. The LGM model consists of two latent factors when modeling linear trajectory: one represents the initial status called 'intercept' and the second one represents growth rate over time called 'slope' (growth factor). In LGM models, factor loadings are time scores reflecting the intervals between measurement occasions and the growth trajectory shape (e.g., linear, quadratic, cubic). By fixing factor

loadings to a certain value, they get specific meanings, i.e., specifying the factor loading of the growth factor reflects the shape of trajectory or fixing intercept factor loading to the value of one reflects baseline measurement (20).

### ***Mediation analysis***

Parallel process latent growth modeling (PPLGM) was used to evaluate how the intervention affected the growth of an outcome through changing the mediator (21). PPLGM was applied in 4 steps:

1- Preliminary analyses and unconditional LGMs were applied for the total sample, i.e., not taking into account the potential intervention effects. First of all, we assessed the relationships between the EBRBs and the adiposity measures using path analysis (using baseline scores as covariates) in Mplus. Based on the results of these path models, we decided that the subsequent mediation analyses were conducted using the first 8-month change in EBRB as a potential mediator in the LGM models. Factor loadings for the adiposity measures reflect the overall change in those variables. From the adiposity measures the growth trajectories of waist circumference and sum of skinfold thickness were non-linear. Rather than choosing a more complicated quadratic model, the growth function was linearized by square transforming of the time variable (22). The advantage of this transformation is including only a single parameter (a linear growth factor) into the mediation analysis (details on preliminary analysis and factor loadings in LGMs are explained in Supplementary File 1);

2- a) Conditional LGMs were applied to test the intervention effect on the possible mediator and outcomes. Gender and ethnicity were added as covariates;

3- The growth models for a single EBRB and a single adiposity measure were combined into one parallel process model to evaluate the association between the growth parameters of the outcomes with the mediator while adjusting for the intervention effect on outcome, gender and ethnicity;

4- The last step was testing the mediation model using the approach of Cheong et al. (21). It was tested whether intervention group status was related to the latent growth factor of the mediator (path a), and whether the growth factor of the mediator was related to the growth factor of the outcome, controlling for the intervention (path b). To identify a significant mediator, these two paths both should be statistically significant. For mediation analyses it is not required that there is a significant intervention effect on the outcome variable. As suggested by MacKinnon, the mediated or indirect effect was calculated by the product-of-coefficients method ( $a*b$ ) (6). Bias-corrected bootstrapped confidence intervals (CIs) were used to describe the uncertainty of mediated effects (23). In case that the bias-corrected 95% CIs did not include zero the mediated effect was considered as statistically significant.

In the LGM models, expected differences in the growth rates between the intervention and control group were adjusted for baseline differences of the outcome variable (i.e., changes in EBRBs and in measures of adiposity are controlled for the initial level of these variables, see Supplementary File 1). For all the models missing values were handled by the maximum likelihood procedure, which uses all available data from each parameter

and assumes that missing is at random. Due to non-normal distribution of some variables, we used a bootstrap method also for the models in step 1 and 2 (24). For the bootstrapping, 1000 replications were used with ML (25). We tested the model fit of the models by chi-square statistics and its corresponding degrees of freedom, comparative fit index (CFI) and the standardized root mean residuals (SRMR). The significant chi-square statistics ( $p < 0.05$ ) reflect a poor model fit, but it should be kept in mind that this statistic is highly influenced by sample size and non-normality. CFI values higher than 0.95 and SRMR values less than 0.08 indicate a well-fitting model (26).

Seven hundred forty five children provided complete data at four time points and 363 children had missing data on one or more time points. Logistic regression analysis was used to predict missingness using gender, intervention status and ethnicity. Gender ( $\chi^2 = 0.24$ ,  $p = 0.33$ ) and intervention status ( $\chi^2 = 2.43$ ,  $p = 0.07$ ) was not related to missingness, but Non-Western children had more missing data compared to Dutch children ( $\chi^2 = 7.03$ ,  $p = 0.006$ ).

SPSS version 15.0 and MPlus 6.1 were used for data analysis. A sample of Mplus syntax is shown in the Supplementary File 1 (available online).

## Results

### Descriptive statistics

The study sample consisted of 1108 children; 632 children in the intervention group (53% girls, mean age=12.7, 11% Non-Western ethnicity) and 476 in the control group (47% girls, mean age=12.8, 13% Non-Western ethnicity). At baseline children in the intervention group had more favorable scores of BMI, waist circumference, percentage of overweight/obese children, television (TV) viewing, computer use, screen viewing behavior and active transport to/from school ( $p < 0.05$ ) (Table 1). Supplementary File 2 (available online) shows the measures of adiposity and EBRBs at all time points for the intervention and control group.

### Step 1: Unconditional Growth Models

Supplementary File 3 (available online) shows the model fits and the growth trajectory estimates for the EBRBs and the adiposity measures for the total sample. All models fit well, or reasonably well (sugar-containing beverages consumption). BMI, waist circumference and sum of skinfolds increased over time. Sugar-containing beverages consumption, TV viewing and sweet snack consumption showed a significant decrease over time. Computer use, active transport to/from school and savory snack consumption significantly increased over time.

### Step 2: Conditional Models

All models testing intervention and mediating effects (Table 2, 3 and 4) fitted well.

#### **Overall effect, Path c**

In Table 2, 3, and 4 the columns 'Total effect' show the intervention effect on measures of adiposity in the unadjusted models. From the measures of adiposity, the DOI-intervention had a significant effect on sum of skinfolds ( $B = -0.69$ , 95% CI =  $-0.99, -0.38$ ) and

waist circumference over time ( $B=0.09$ , 95% CI= 0.01, 0.15). Both, the intervention and control group showed an increase in both adiposity measures, but this increase was smaller for sum of skinfolds and bigger for waist circumference in the intervention group (see Table 3 and 4, indicated by negative and positive effect estimates respectively). No significant intervention effect was found on BMI.

**Table 1.** Measures of adiposity and energy balance-related behaviors (EBRBs) at baseline for the intervention and control groups of DOiT-intervention.

	Intervention		Control	
	n	Median (IQR)	n	Median (IQR)
<b>Measures of adiposity</b>				
Body mass index (BMI) (kg/m <sup>2</sup> )	600	18.1 (16.5-20.2)*	453	18.8 (17.0-20.7)*
Waist circumference (cm)	599	64.7 (61.3-68.8)*	453	66.6 (62.3-71.1)*
Sum of skinfolds (mm)	590	39.3 (30.0-56.4)	450	41.3 (31.2-60.9)
Overweight/ Obese (%)	600	11.7%*	453	16.8%*
<b>EBRBs</b>				
Sugar-containing beverages consumption (l/d)	461	0.86 (0.49-1.46)	370	1.01 (0.49-1.63)
- Soft-drink (l/d)	434	0.66 (0.33-1.17)	336	0.71 (0.34-1.27)
- Fruit juice (l/d)	438	0.19 (0.04-0.51)	350	0.21 (0.06-0.54)
Screen viewing time (h/d)	520	3.43 (2.29-5.20)*	414	4.14 (2.64-6.07)*
- TV viewing (h/d)	502	2.14 (1.29-3.29)*	410	2.46 (1.57-3.57)*
- Computer use (h/d)	487	1.29 (1.00-2.14)*	375	1.64 (1.00-2.71)*
Active transport to/from school (min/d)	532	30.0 (16.0-60.0)*	417	30.0 (13.0-50.0)*
High-caloric snack consumption (portion/d)	526	1.57 (1.00-2.57)	408	1.50 (0.89-2.57)
-Savory snacks (portion/d)	490	0.43 (0.29-0.86)	378	0.43 (0.29-0.86)
-Sweet snacks (portion/d)	501	1.00 (0.57-2.00)	390	1.00 (0.57-2.00)

IQR=Interquartile range, \* Significant difference between intervention and control group ( $p<0.05$ )

### ***Intervention effect on mediator, Path a***

Conditional models showed that the DOiT-intervention resulted in a significant decrease (from baseline to post-intervention) in total sugar-containing beverages consumption ( $B=-0.14$ , 95% CI=-0.22, -0.11) in particular soft drink consumption ( $B=-0.09$ , 95% CI=-0.18, -0.004). Other putative mediators, namely screen viewing time, active transport and snacking were not significantly affected by the intervention.

### **Step 3: Parallel process LGMs**

#### ***Association between EBRBs and adiposity measures, Path b***

Table 2 shows the results from the parallel process LGMs. Total sugar-containing beverages consumption was positively associated with BMI over time ( $B= 0.10$ ; 95%CI=0.01, 0.13). The positive association between fruit juice consumption and BMI was

also significant. Computer use was positively associated with BMI over time ( $B=0.11$ , 95% CI=0.05, 0.18).

As shown in Table 3 and 4, none of the EBRBs were associated with waist circumference or sum of skinfolds.

#### **Step 4: Mediated effect**

Table 2 shows the results of the mediated effect of EBRBs (path a \* path b, ab) on the intervention on BMI via the EBRBs. Total sugar-containing beverages consumption significantly mediated the intervention effect on BMI. First, the intervention significantly decreased sugar-containing beverages consumption among participants. Second, it was found that decreasing sugar-containing beverages consumption was associated with smaller increases in BMI over time (see Table 2). The indirect effects were significant ( $ab=-0.01$ ; bias-corrected CI ranged from -0.20, -0.001). No other mediated effects could be identified, mainly because of a non-significant intervention effect on the mediators.

As shown in Table 3 and 4, none of the included potential mediators were identified as significant mediators for the intervention effect on waist circumference and sum of skinfolds.

Figure 2 illustrates one mediation model, showing the parallel process latent growth model for the mediating effect of sugar-containing beverages consumption on BMI. The significant negative intervention effect on the initial value (intercept) of the outcome (BMI) indicates that the initial BMI of children in the intervention group was significantly lower compared to the control group. The initial value of the mediators (sugar-containing beverages consumption) was significantly and negatively related to its growth factor. This indicates that children who drank more sugar-containing beverages at baseline showed a larger decrease in their consumption over time. The statistically significant paths for the mediating effect are shown in bold; the intervention was significantly negatively associated with the growth factor of sugar-containing beverages (path a) and the sugar-containing beverages' growth factor was significantly positively associated with the growth factor of BMI (path b). The figure also shows that the initial value of sugar-containing beverages consumption was significantly and positively related to the growth in BMI. This means that children who had a higher consumption at baseline showed a higher increase in BMI. The correlation between the initial values was also significant.

**Table 2.** Bootstrapped mediation effect estimates for body mass index (BMI) ( $\text{kg}/\text{m}^2$ ) of DOiT-intervention using Parallel Process Latent Growth Models

	$\chi^2$ (df)	CFI	SRMR	Intervention Effect on Mediator (path a) (95% CI)	Mediator effect on BMI (path b) (95% CI)	Indirect effect (axb) (95% CI)	Direct effect (path c) (95% CI)	Total Effect (path c) (95% CI)
								0.04 (-0.02, 0.10)
Sugar-containing beverage consumption (l/d)	204.9 (33)*	0.98	0.04	<b>-0.14 (-0.22, -0.11)</b>	<b>0.10 (0.01, 0.13)<sup>a</sup></b>	<b>-0.01 (-0.20,-0.001)</b>	<b>0.06 (0.03, 0.07)</b>	
- Soft-drink	183.4 (33)*	0.98	0.04	<b>-0.09 (-0.18, -0.004)</b>	0.15 (-0.25, 0.32)	-0.01 (-0.05, 0.01)	0.06 (-0.01, 0.13)	
- Fruit juice	277.0 (36)*	0.97	0.07	-0.01 (-0.06, 0.05)	<b>0.23 (0.06, 0.43)<sup>a</sup></b>	-0.001 (-0.02, 0.01)	0.01 (-0.07, 0.11)	
Screen viewing time (h/d)	123.0 (34)*	0.99	0.03	0.08 (-0.21, 0.36)	0.03 (-0.003, 0.07)	0.003 (-0.005, 0.02)	0.05 (-0.01, 0.12)	
- TV viewing	114.7 (34)*	0.99	0.03	0.08 (-0.11, 0.27)	0.004 (-0.06, 0.07)	0.000 (-0.01, 0.02)	0.04 (-0.02, 0.11)	
- Computer use	122.3 (33)*	0.99	0.03	0.09 (-0.10, 0.27)	<b>0.11 (0.05, 0.18)<sup>b</sup></b>	0.01 (-0.01, 0.04)	0.05 (-0.01, 0.11)	
Active transport to/from school (min/d)	126.4 (33)*	0.99	0.03	-1.21 (-3.84, 1.39)	0.001 (-0.003,0.01)	-0.002 (-0.02, 0.003)	0.05 (-0.01, 0.11)	
High-caloric snack consumption (portion/d)	161.1 (35)*	0.98	0.03	0.11 (-0.07, 0.27)	0.03 (-0.03, 0.09)	0.003 (-0.003, 0.02)	0.04 (-0.02, 0.10)	
-Savory snacks	137.3 (36)*	0.99	0.03	0.05 (-0.02, 0.11)	0.08 (-0.04, 0.20)	0.004 (-0.001, 0.02)	0.04 (-0.02, 0.10)	
-Sweet snacks	191.0 (35)*	0.98	0.03	0.05 (-0.09, 0.18)	0.02 (-0.07, 0.10)	0.001 (-0.004, 0.02)	0.04 (-0.02, 0.11)	

\* $<0.001$ , CI-confidence interval,  $\chi^2$  (df)-chi square (degrees of freedom), CFI- comparative fit index, SRMR- standardized root mean residuals.

All models were adjusted for gender and ethnicity.

**Statistically significant associations are shown in bold.**

<sup>a</sup> Positive regression coefficient indicates that a decrease in sugar-containing beverage and fruit juice consumption led to decrease in BMI (based on the growth trajectories of the variables).

<sup>b</sup> Positive regression coefficient indicates that an increase in computer use led to increase in BMI (based on the growth trajectories of the variables).

**Table 3.** Bootstrapped mediation effect estimates for waist circumference (cm) of DOiT-intervention using Parallel Process Latent Growth Models

	$\chi^2$ (df)	CFI	SRMR	Intervention Effect on Mediator (path a) (95% CI)	Mediator effect on waist circumference (path b) (95% CI)	Indirect effect (axb) (95% CI)	Direct effect (path c) (95% CI)	Total Effect (path c) (95% CI)
								<b>0.09 (0.01, 0.15)</b>
Sugar-containing beverage consumption (l/d)	260.2 (35)*	0.96	0.04	<b>-0.12 (-0.23, -0.01)</b>	0.06 (-0.07, 0.19)	-0.01 (-0.03, 0.01)	<b>0.09 (0.02, 0.17)</b>	
- Soft-drink	225.0 (35)*	0.97	0.04	-0.09 (-0.17, 0.004)	0.07 (-0.11, 0.24)	-0.01 (-0.03, 0.01)	<b>0.09 (0.01, 0.15)</b>	
- Fruit juice	219.1 (36)*	0.97	0.04	-0.01 (-0.06, 0.05)	0.09 (-0.29, 0.50)	0.000 (-0.02, 0.01)	<b>0.08 (0.01, 0.15)</b>	
Screen viewing time (h/d)	165.3 (34)*	0.99	0.03	0.07 (-0.22, 0.36)	0.01 (-0.04, 0.05)	0.000 (-0.01, 0.01)	<b>0.09 (0.01, 0.16)</b>	
- TV viewing	171.2 (36)*	0.98	0.03	0.07 (-0.13, 0.26)	-0.04 (-0.10, 0.04)	-0.002 (-0.03, 0.004)	<b>0.08 (0.01, 0.15)</b>	
- Computer use	167.6 (33)*	0.98	0.03	0.09 (-0.10, 0.27)	0.07 (-0.01, 0.14)	0.01 (-0.01, 0.03)	<b>0.09 (0.01, 0.16)</b>	
Active transport to/from school (min/d)	181.0 (33)*	0.98	0.03	-1.23 (-3.96, 1.41)	-0.003 (-0.01, 0.001)	0.004 (-0.001, 0.02)	<b>0.09 (0.01, 0.16)</b>	
High-caloric snack consumption (portion/d)	204.0 (36)*	0.97	0.03	0.11 (-0.08, 0.27)	0.03 (-0.03, 0.11)	0.004 (-0.003, 0.03)	<b>0.08 (0.000, 0.15)</b>	
-Savory snacks	168.5 (34)*	0.98	0.03	0.05 (-0.02, 0.12)	0.12 (-0.09, 0.32)	0.01 (-0.004, 0.03)	0.08 (-0.01, 0.15)	
-Sweet snacks	236.5 (36)*	0.97	0.04	0.05 (-0.10, 0.18)	0.02 (-0.07, 0.13)	0.001 (-0.004, 0.02)	<b>0.09 (0.004, 0.15)</b>	

\*<0.001, CI-confidence interval,  $\chi^2$ (df)-chi square (degrees of freedom), CFI- comparative fit index, SRMR- standardized root mean residuals.

All models were adjusted for gender and ethnicity

Statistically significant associations are shown in bold.

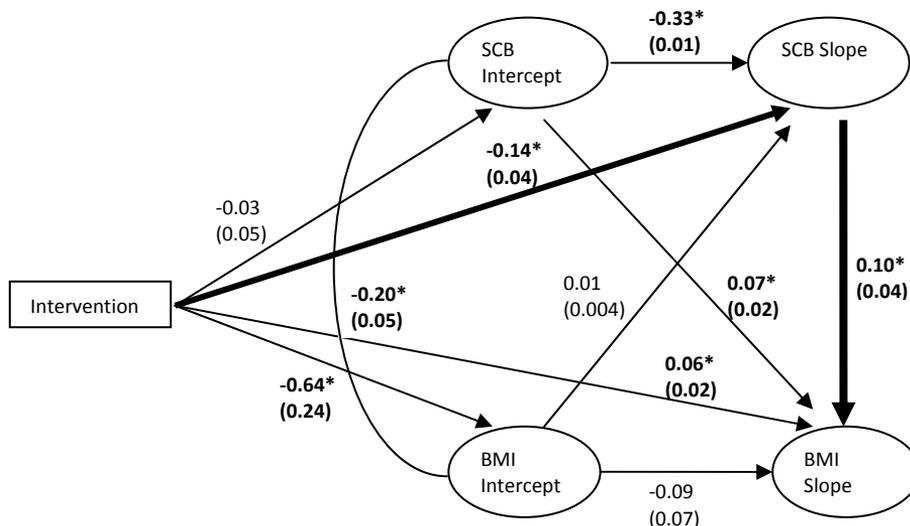
**Table 4.** Bootstrapped mediation effect estimates for sum of skinfolds (mm) of DOiT-intervention using Parallel Process Latent Growth Models

	$\chi^2$ (df)	CFI	SRMR	Intervention Effect on Mediator (path a) (95% CI)	Mediator effect on sum of skinfolds (path b) (95% CI)	Indirect effect (axb) (95% CI)	Direct effect (path c) (95% CI)	Total Effect (path c) (95% CI)
								<b>-0.69 *</b> <b>(-0.99, -0.38)</b>
Sugar-containing beverages consumption (l/d)	345.6 (33)*	0.95	0.04	<b>-0.13 (-0.24, -0.03)</b>	0.002 (-0.56, 0.61)	0.000 (-0.08, 0.08)	<b>-0.69 (-1.00, -0.36)</b>	
- Soft-drink	336.5 (34)*	0.95	0.09	<b>-0.09 (-0.18, -0.01)</b>	0.02 (-0.62, 0.77)	-0.002 (-0.09, 0.07)	<b>-0.67 (-0.98, -0.35)</b>	
- Fruit juice	339.6 (35)*	0.95	0.04	-0.01 (-0.06, 0.05)	0.15 (-1.19, 1.53)	-0.001 (-0.06, 0.03)	<b>-0.67 (-0.98, -0.36)</b>	
Screen viewing time (h/d)	269.9 (34)*	0.97	0.03	0.08 (-0.20, 0.35)	-0.06 (-0.20, 0.08)	-0.01 (-0.05, 0.01)	<b>-0.69 (-1.01, -0.37)</b>	
- TV viewing	276.0 (35)*	0.96	0.02	0.09 (-0.11, 0.27)	-0.08 (-0.31, 0.15)	-0.01 (-0.07, 0.01)	<b>-0.67 (-0.99, -0.36)</b>	
- Computer use	272.1 (33)*	0.96	0.03	0.06 (-0.11, 0.25)	0.02 (-0.26, 0.29)	0.001 (-0.02, 0.05)	<b>-0.69 (-0.99, -0.37)</b>	
Active transport to/from school (min/d)	274.3 (32)*	0.97	0.02	-0.98 (-3.58, 1.58)	0.01 (-0.01, 0.02)	-0.01 (-0.07, 0.01)	<b>-0.65 (-0.95, -0.34)</b>	
High-caloric snack consumption (portion/d)	310.7 (35)*	0.96	0.03	0.13 (-0.05, 0.29)	-0.17 (-0.41, 0.11)	-0.02 (-0.10, 0.01)	<b>-0.64 (-0.94, -0.33)</b>	
-Savory snacks	263.7 (33)*	0.96	0.03	0.06 (-0.01, 0.13)	-0.50 (-1.42, 0.36)	-0.03 (-0.12, 0.02)	<b>-0.61 (-0.91, -0.30)</b>	
-Sweet snacks	343.8 (35)*	0.95	0.03	0.06 (-0.09, 0.19)	-0.19 (-0.53, 0.19)	-0.01 (-0.08, 0.02)	-0.66 (-0.97, -0.34)	

\*<0.001, CI-confidence interval,  $\chi^2$ (df)-chi square (degrees of freedom), CFI- comparative fit index, SRMR- standardized root mean residuals

All models were adjusted for gender and ethnicity

Statistically significant associations are shown in bold.



**Figure 2.** Parallel process latent growth model for the mediating effect of sugar-containing beverages (SCB) consumption on body mass index (BMI) (*the specific factor loadings, and adjustment for gender and ethnicity are not shown in the figure for simplicity*)

## Discussion

To the best of our knowledge no study examined the longitudinal mediating effect of EBRBs on weight change in children. We tested whether the DOI-t-intervention affected the EBRBs and whether the change in EBRBs influenced the measures of adiposity over time using mediation analysis. As expected, we found that the intervention decreased the total sugar-containing beverages consumption, which, in turn led to a smaller increase in BMI over time. The intervention effect on the adiposity measures was not mediated by the other EBRBs, i.e., high-caloric snacks consumption, active transport to/from school and screen time.

The current study showed that the intervention's ability to decrease sugar-containing beverages consumption contributed to slowing down the increase in BMI among youth. Although the effect sizes for these relationships are small (standardized regression coefficient for path a=0.13 and path b=0.12), the influence of the effect in practical context, and with a high reach, might be bigger and/or accumulate over time to become larger effects. This finding is consistent with James et al. (27), who implemented a school-based educational program to reduce consumption of sugar-containing beverages among 7-11 year old children. They found that after 12 months at the end of their program, children in the intervention group significantly decreased their consumption by 0.6 glasses and this lowered the increase in their BMI compared to the control group but this latter difference was not statistically significant (27). Unfortunately, they did not conduct a

mediation analysis. Prospective observational studies confirm the positive association between sugar-containing beverages consumption and measures of adiposity such as BMI, WC and body fat among children (29,30), potentially explained by increased total energy intake, low satiety of liquid foods, and a high glycemic load (30). Recent double-blinded randomized controlled trial evaluated the effect on weight gain of masked replacement of sugar-containing beverages with non-caloric, artificially sweetened beverages among schoolchildren (31). They found that replacing sugar-containing beverages with sugar-free drinks slowed weight gain among children over the course of the 18-month study.

Our study also identified a positive association between computer time and BMI, however due to the lack of a significant intervention effect on computer time we could not confirm a significant mediating effect. Besides the significant effect on sugar-containing beverages consumption, no intervention effect on any of the other EBRBs (high-caloric snacks consumption, active transport to/from school and screen time) was found. One possible explanation for non-significant intervention effects on these EBRBs is that there was less room for improvement in these behaviors as compared to sugar-containing beverages. Furthermore, it may be that some intervention strategies targeting these behaviors were not appropriate or not well implemented. Finally, it might be that the measurement instruments were not sensitive enough to detect relatively small changes. However, the previous analyses on the long-term effectiveness of DOiT-intervention showed a significant intervention effect on screen time at some time points (9). The possible reasons for these conflicting results are the method of analysis of change, handling missing data and the stratification by gender in the study of Singh et al. (9).

Another reason for the lack of mediating effect is the lack of a significant association between the EBRBs and the adiposity measures. None of the included EBRBs were significantly associated with waist circumference or sum of skinfolds. It is known that waist circumference and sum of skinfolds are good indicators of fat mass in children (32). Although inter- and intra reliability figures were high for their measurements, the combination with moderate reliable self-reported of EBRBs might explain the difficulty in finding significant associations between EBRBs and adiposity indicators. Another possible reason for the lack of an association of the EBRBs with waist circumference and sum of skinfolds might be that other behaviors (rather than sugar-containing beverages consumption), not targeted and measured in the DOiT study, are stronger determinants of changes in waist circumference and sum of skinfolds. For instance, we did not measure total or vigorous physical activity, while these behaviors may be stronger related to changes in waist circumference and sum of skinfolds than active transport. Especially because these adiposity measures (without using prediction equations for total body fat) are indicators of regional fatness in the body rather than indicators of total fat mass (33).

This study is an example of mediation without observing a significant overall intervention effect (no significant overall intervention effect on BMI). This may occur for several reasons: in some situations mediation tests can have more power than the test for an overall intervention effect (due to highly reliable mediator measure), or an intervention may have a stronger influence on the mediator than on the outcome variable leading to stronger indirect effect (4,34). It is also possible that multiple indirect effects with

opposing signs dispose the total effect (34). Another explanation can be dilution, meaning that the intervention effect on outcome likely gets smaller when the causal chain is long (35).

To our knowledge, this is the first study exploring the mediators of a school-based intervention effect on measures of adiposity. Exploring long-term effects of an intervention provides information on the sustainability of the change and their health effect on the long term as well as on causal pathways. Overweight prevention programs should be evaluated beyond the intervention endpoint. Underlying mechanisms such as changes in EBRBs and their relationship to measures of adiposity should be investigated by using mediation analysis. Due to limited information on physical activity in the current study (only active transport to/from school), future research should also focus on mediating effects of physical activity in all dimensions in the interventions for preventing weight gain in adolescents.

### **Strengths and limitations**

When interpreting the findings, several limitations of our study need to be borne in mind. First of all, we were not able to include total PA or total energy intake and only a selection of risk behaviors were assessed. Diet and PA have complementary and interactive effects in energy balance and both should be considered in the investigation of underlying mechanisms of weight gain prevention research (36). Furthermore, this study includes children from lower secondary education and a specific age group; limiting generalizability to other youth. EBRBs were measured by self-report that suffers from recall bias and social desirability. A high number of statistical tests applied may cause a potential drawback of finding a significant result by chance alone. However, all the tests applied in this study were needed to explore mediating mechanisms. For this reason, we did not solely evaluate the significance by p values but instead we used the bias-corrected bootstrapping method to estimate confidence intervals, which is the best method for testing the mediation effects (37). Strengths of this study are the large sample size, the randomized controlled design and the theory-based and thoroughly developed intervention, the relatively long follow-up period, standardized objective measurement of measures of adiposity and the advanced analysis method. LGM is a superior method to apply longitudinal mediation analyses due to; 1) its capacity to model individual variation in growth, which is more representative of reality, 2) flexibility of the model for modeling different growth trajectories for mediator and outcome, 3) adapting ML estimation for handling missing data, which is less biased than other methods (listwise, pairwise deletion) (21).

The implications suggested by the study are that future school-based overweight prevention interventions among young adolescents in the Netherlands should aim at reducing sugar-containing beverages consumption. Since the biggest part of sugar-containing beverages consumption occurs at home, home consumption should be considered as well (38).

In conclusion, the DOiT-intervention was successful in reducing the total sugar-containing beverages, which in turn slowed down the increase in BMI among adolescents.

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## SUPPLEMENTARY FILES

### Supplementary File 1. Detailed information on the applied LGM models

Latent growth modeling (LGM) is specifically suitable for longitudinal mediation analysis when there are several time points and when a relatively large amount of individual variation at growth trajectories is expected (1). It allows examining individual differences in response to the intervention as some individuals may show faster or slower rates of growth over time (2). LGM also has the ability to use variables simultaneously in the same complex growth model, account for measurement error and incorporates a better method for handling missing data (2,3). LGM models need a considerable amount of preparation prior to estimating mediating mechanisms to get an accurate definition of factor loadings, shape of the trajectories and an accurate interpretation of the results.

**Factor loadings:** Firstly, data were analyzed cross-sectionally (e.g., regressing adiposity measures at 8 months on energy balance-related behaviours (EBRBs) measured at 8 months). The relationships were also explored longitudinally, e.g., regressing the adiposity measures at follow-up time points (12 and 20 months) on EBRBs at an earlier time point (at 8 months). These preliminary analyses showed that most of the significant relationships were between post intervention EBRBs (8 months) and the adiposity measures at a later time point (12 & 20 months) (Supplementary Table 1).

For EBRBs, factor loadings in LGM were coded as 0 for baseline, 1 for 8-month follow-up, 1 for 12-month follow-up and 1 for 20-month follow-up (Supplementary Figure 1). This coding assumes a growth/slope between the first two time points (baseline and 8 months) and assumes maintenance of the effect at later time points (12 and 20 months). For adiposity measures, we coded the time of the measurement as 0 for baseline, 1 for the 1st follow-up at 8 months, 1.5 for the 2nd follow-up at 12 months, 2.5 for the 3rd follow-up at 20 months to represent a linearly increasing growth in time (Supplementary Figure 1). With this coding we can interpret the intercept as the initial status/baseline measurement and the slope as the change in adiposity over 8 months. Due to the non-linear growth trajectories of waist circumference (WC) and sum of skinfolds, growth factors were linearized by coding the time scores for the WC and sum of skinfolds as 0, 1, 2.25 and 6.25. Parallel process latent growth modeling (PPLGM) combines two sets of individual growth models, i.e., one for the possible mediator and the other for the measure of adiposity.

**Supplementary Table 1.** Preliminary analyses of relationship between EBRBs and adiposity indicators

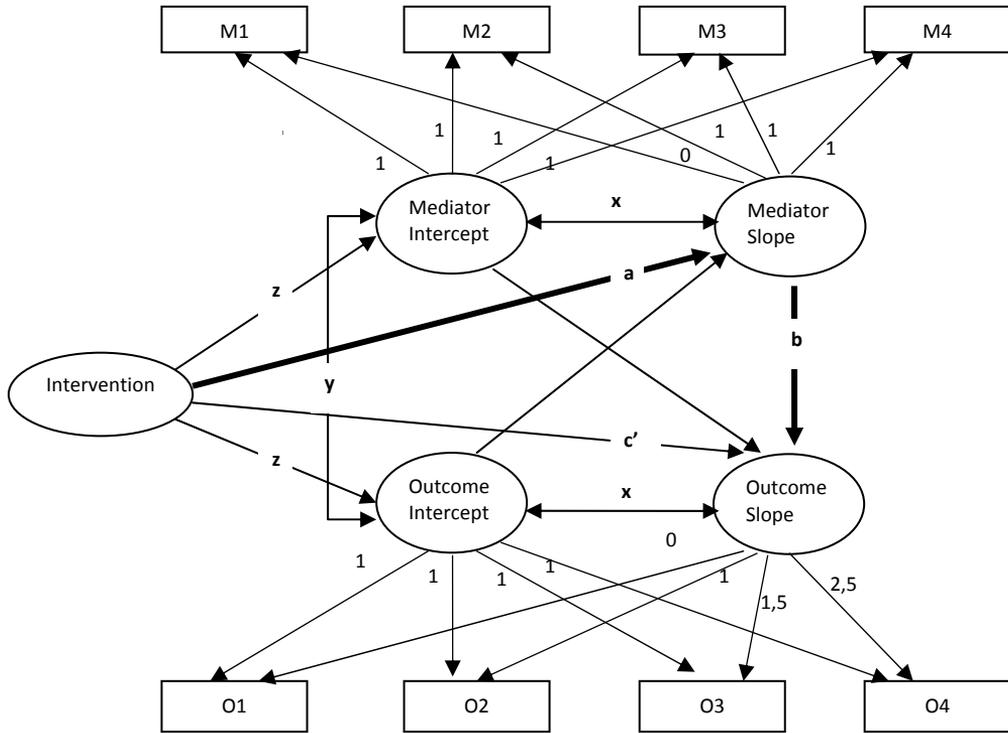
	BMI1 (SE)	BMI2 (SE)	BMI3 (SE)		BMI2 (SE)	BMI3 (SE)		BMI3 (SE)
<b>SCB1</b>	0.05 (0.04)	0.07 (0.06)	0.14 (0.07)*	<b>SCBS2</b>	0.01 (0.91)	0.09 (0.07)	<b>SCB3</b>	0.07 (0.08)
<b>-Soft drink1</b>	0.03 (0.05)	0.06 (0.07)	0.14 (0.08)	<b>-Soft drink2</b>	-0.02 (0.07)	0.10 (0.08)	<b>-Soft drink3</b>	0.01 (0.10)
<b>-Fruit juice1</b>	0.17 (0.10)	0.15 (0.14)	0.19 (0.16)	<b>-Fruit juice2</b>	0.05 (0.12)	0.10 (0.14)	<b>-Fruit juice3</b>	0.28 (0.17)

<b>Screen time1</b>	0.01 (0.01)	0.02 (0.02)	0.06 (0.02)*	<b>Screen time2</b>	-0.01 (0.02)	0.01 (0.02)	<b>Screen time3</b>	0.01 (0.02)
<b>-PC1</b>	0.02 (0.02)	0.04 (0.03)	0.12 (0.04)*	<b>-PC2</b>	0.01 (0.03)	0.07 (0.04)	<b>-PC3</b>	0.07 (0.03)*
<b>-TV1</b>	0.01 (0.02)	0.01 (0.03)	0.05 (0.04)	<b>-TV2</b>	-0.04 (0.03)	0.08 (0.09)	<b>-TV3</b>	-0.02 (0.04)
<b>Snacking1</b>	0.03 (0.03)	0.09 (0.05)	0.01 (0.03)	<b>Snacking2</b>	0.03 (0.03)	-0.00 (0.04)	<b>Snacking3</b>	0.04 (0.04)
<b>-Sweet snacks1</b>	0.02 (0.04)	0.12 (0.06)*	0.02 (0.05)	<b>-Sweet snacks2</b>	0.05 (0.04)	-0.00 (0.06)	<b>-Sweet snacks3</b>	-0.01 (0.05)
<b>-Savory snacks1</b>	0.05 (0.06)	0.14 (0.11)	-0.03 (0.09)	<b>-Savory snacks2</b>	-0.01 (0.06)	-0.01 (0.07)	<b>-Savory snacks3</b>	0.16 (0.09)
<b>Active transport1</b>	-0.00 (0.00)	0.00 (0.00)	0.01 (0.00)*	<b>Active transport2</b>	-0.00 (0.00)	0.00 (0.00)	<b>Active transport3</b>	0.00 (0.00)
	<b>WC1 (SE)</b>	<b>WC 2 (SE)</b>	<b>WC3 (SE)</b>		<b>WC2 (SE)</b>	<b>WC3 (SE)</b>		<b>WC3 (SE)</b>
<b>SCB1</b>	0.02 (0.16)	0.33 (0.21)	0.40 (0.22)	<b>SCB2</b>	-0.12 (0.17)	0.14 (0.22)	<b>SCB3</b>	0.15 (0.25)
<b>-Soft drink1</b>	-0.01 (0.18)	0.35 (0.25)	0.45 (0.27)	<b>-Soft drink2</b>	-0.18 (0.21)	0.06 (0.25)	<b>-Soft drink3</b>	0.12 (0.30)
<b>-Fruit juice1</b>	0.29 (0.37)	0.62 (0.48)	0.30 (0.53)	<b>-Fruit juice2</b>	0.02 (0.35)	0.29 (0.65)	<b>-Fruit juice3</b>	0.32 (0.54)
<b>Screen time1</b>	0.01 (0.04)	0.05 (0.07)	0.10 (0.07)	<b>Screen time2</b>	-0.04 (0.06)	-0.08 (0.08)	<b>Screen time3</b>	-0.02 (0.07)
<b>-PC1</b>	0.03 (0.07)	0.12 (0.11)	0.20 (0.11)	<b>-PC2</b>	-0.05 (0.09)	0.07 (0.12)	<b>-PC3</b>	0.12 (0.10)
<b>-TV1</b>	-0.00 (0.07)	0.01 (0.10)	0.05 (0.11)	<b>-TV2</b>	-0.05 (0.10)	-0.18 (0.13)	<b>-TV3</b>	-0.15 (0.11)
<b>Snacking1</b>	-0.06 (0.09)	0.08 (0.10)	-0.02 (0.12)	<b>Snacking2</b>	0.07 (0.09)	0.03 (0.12)	<b>Snacking3</b>	-0.05 (0.13)
<b>-Sweet snacks1</b>	-0.06 (0.10)	0.12 (0.14)	-0.00 (0.16)	<b>-Sweet snacks2</b>	0.07 (0.15)	-0.02 (0.19)	<b>-Sweet snacks3</b>	-0.17 (0.18)
<b>-Savory snacks1</b>	-0.16 (0.23)	0.02 (0.26)	-0.18 (0.28)	<b>-Savory snacks2</b>	0.07 (0.20)	0.05 (0.24)	<b>-Savory snacks3</b>	0.19 (0.26)
<b>Active transport1</b>	-0.00 (0.01)	-0.01 (0.01)	0.00 (0.01)	<b>Active transport2</b>	-0.01 (0.01)*	-0.01 (0.01)*	<b>Active transport3</b>	-0.01 (0.01)

	Sum skin1 (SE)	Sum skin2 (SE)	Sum skin3 (SE)		Sum skin2 (SE)	Sum skin3 (SE)		Sum skin3 (SE)
<b>SCB1</b>	-0.04 (0.43)	0.77 (0.49)	0.87 (0.82)	<b>SCB2</b>	0.11 (0.53)	0.08 (0.88)	<b>SCB3</b>	-0.49 (1.15)
<b>-Soft drink1</b>	-0.37 (0.50)	0.22 (0.58)	0.57 (0.96)	<b>-Soft drink2</b>	-0.57 (0.69)	0.12 (1.05)	<b>-Soft drink3</b>	0.37 (1.38)
<b>-Fruit juice1</b>	1.07 (1.09)	3.51 (1.43)*	3.37 (1.97)	<b>-Fruit juice2</b>	2.57 (1.22)*	1.47 (1.90)	<b>-Fruit juice3</b>	-2.80 (2.36)
<b>Screen time1</b>	-0.06 (0.14)	-0.03 (0.17)	-0.19 (0.27)	<b>Screen time2</b>	-0.10 (0.20)	-0.20 (0.30)	<b>Screen time3</b>	0.04 (0.30)
<b>-PC1</b>	0.07 (0.21)	0.09 (0.24)	0.04 (0.39)	<b>-PC2</b>	-0.18 (0.30)	-0.18 (0.46)	<b>-PC3</b>	0.70 (0.47)
<b>-TV1</b>	-0.27 (0.24)	-0.18 (0.31)	-0.28 (0.50)	<b>-TV2</b>	-0.03 (0.37)	0.06 (0.52)	<b>-TV3</b>	-0.55 (0.50)
<b>Snacking1</b>	-0.44 (0.24)	-0.08 (0.33)	-0.07 (0.48)	<b>Snacking2</b>	-0.14 (0.36)	-0.36 (0.47)	<b>Snacking3</b>	-0.57 (0.52)
<b>-Sweet snacks1</b>	-0.51 (0.31)	-0.23 (0.40)	0.09 (0.62)	<b>-Sweet snacks2</b>	-0.15 (0.49)	-0.32 (0.69)	<b>-Sweet snacks3</b>	-1.08 (0.77)
<b>-Savory snacks1</b>	-0.23 (0.59)	0.19 (0.78)	-0.02 (1.12)	<b>-Savory snacks2</b>	-0.77 (0.71)	-1.28 (1.07)	<b>-Savory snacks3</b>	-0.13 (1.04)
<b>Active transport1</b>	-0.02 (0.02)	-0.01 (0.02)	0.03 (0.03)	<b>Active transport2</b>	-0.04 (0.02)*	-0.03 (0.02)	<b>Active transport3</b>	0.02 (0.03)

\*p<0.05, All the models were adjusted for gender and ethnicity. BMI=Body mass index, WC=Waist circumference, SCB=Sugar-containing beverages, PC=computer time, TV=television watching

**Specific modeling issues in the parallel process LGM;** In the LGM models, dependent variable's slope is adjusted for differences in its initial status. By doing this, the LGM analyses eventually provide information when we adjust for pre-existing differences. In a fashion similar to using analysis of covariance models to compare groups of interest while adjusting for initial pretest differences, they suggest obtaining an estimate of the difference in growth rates between groups while adjusting for differences in initial status. In this way, a mediation analysis will not be confounded by initial differences between subjects in the dependent variable. To control for baseline differences between individuals, linear growth factors were correlated with their intercepts (path x, Supplementary Figure 1). The regression coefficient presents the magnitude and direction of the relationship between baseline status and growth rate (2,4). The intercepts were correlated to identify the association between baseline values (path y). Intercept was also regressed on the intervention to adjust for baseline differences between intervention and control groups (path z).



**Supplementary Figure 1.** An illustration of a parallel process latent growth model for mediation analysis.

**Mplus Syntax;** For testing the mediated effects, the ‘Model indirect’ command in combination with the ‘bias corrected interval’ command were used in Mplus. A sample of Mplus syntax for the parallel process latent growth model for mediating effect of sugar-containing beverages intake on intervention effect on BMI is shown below;

**TITLE:** PPLGM for mediating effect of sugar-containing beverages consumption

**DATA:** FILE IS DOit2\_3\_gender dummy.dat;

**VARIABLE:** NAMES ARE patnr age group school class gender ethnic  
 bmi0 bmi1 bmi2 bmi3 waist\_0 waist\_1 waist\_2 waist\_3 sumskin0 sumskin1  
 sumskin2 sumskin3 fris0 fris1 fris2 fris3 vrsap0 vrsap1 vrsap2  
 vrsap3 ssb0 ssb1 ssb2 ssb3 tv0 tv1 tv2 tv3 comp0 comp1 comp2 comp3  
 scrbeh0 scrbeh1 scrbeh2 scrbeh3 actrans0 actrans1 actrans2 actrans3  
 sporten0 sporten1 sporten2 sporten3 actief0 actief1 actief2 actief3  
 snack0 snack1 snack2 snack3 snoep0 snoep1 snoep2 snoep3  
 tussend0 tussend1 tussend2 tussend3 ssb0lt ssb1lt ssb2lt ssb3lt tv0h  
 tv1h tv2h tv3h comp0h comp1h comp2h comp3h scrbeh0h scrbeh1h  
 scrbeh2h scrbeh3h fris0lt fris1lt fris2lt fris3lt vrsap0lt vrsap1lt

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vrsap2lt vrsap3lt age_cat overwei0 overwei1 overwei2 overwei3;
USEVARIABLES ARE ssb0lt ssb1lt ssb2lt ssb3lt group gender ethnic
bmi0 bmi1 bmi2 bmi3;
MISSING = ALL (-999);
ANALYSIS: BOOTSTRAP=1000;
MODEL: i1 s1 | ssb0lt@0 ssb1lt@1 ssb2lt@1 ssb3lt@1;
          i2 s2 | bmi0@0 bmi1@1 bmi2@1.5 bmi3@2.5;
          i1 s1 ON group gender ethnic;
          i2 s2 ON group gender ethnic;
          s2 ON i1 s1;
          s1 ON i2;
          i1 WITH i2;
          group WITH gender ethnic;
          s1 WITH i1;
          s2 WITH i2;
          gender WITH ethnic@0;
MODEL INDIRECT:
          s2 IND s1 group;
OUTPUT: STANDARDIZED SAMPSTAT CINTERVAL (BCBOOTSTRAP);

```

## References

1. Von Soest T, Hagtvet KA. Mediation analysis in a latent growth curve modeling framework. *Struct Equ Modeling* 2011;18(2):289-314.
2. Duncan TE, Duncan SC. The ABC's of LGM: An introductory guide to latent variable growth curve modeling. *Soc Personal Psychol Compass* 2009;3(6):979-991.
3. Tomarken AJ, Waller NG. Structural equation modeling: strengths, limitations and misconceptions. *Annu Rev Clin Psychol* 2005;1:31-65.
4. Park I, Schutz RW. An introduction to latent growth models: Analysis of repeated measures physical performance data. *Res Quar Exerc Sports* 2005;76(2):176-192.

**Supplementary File 2.** The median and interquartile range of measures of adiposity and energy balance-related behaviors (EBRBs) at baseline and follow-ups for intervention and control groups.

	Baseline		1 <sup>st</sup> follow-up		2 <sup>nd</sup> follow-up		3 <sup>rd</sup> follow-up	
	Intervention	Control	Intervention	Control	Intervention	Control	Intervention	Control
<b>Measures of adiposity</b>								
Body mass index (kg/m <sup>2</sup> )	18.1 (16.5-20.2)	18.8 (17.0-20.7)	18.4 (17.0-20.5)	19.2 (17.4-21.3)	18.9 (17.4-21.0)	19.5 (17.7-21.7)	19.4 (17.7-21.4)	19.9 (18.1-22.1)
Waist circumference (cm)	64.7 (61.3-68.8)	66.6 (62.3-71.1)	66.0 (62.4-69.9)	67.4 (63.6-72.6)	66.5 (63.1-70.5)	67.8 (63.5-73.0)	68.8 (65.1-73.1)	69.9 (65.6-75.9)
Sum of skinfold (mm)	39.3 (30.0-56.4)	41.3 (31.2-60.9)	37.4 (28.6-55.7)	41.1 (29.4-61.6)	37.5 (28.2-55.4)	41.9 (31.3-60.4)	46.1 (32.1-65.8)	53.0 (34.4-76.7)
Overweight/obese (%)	11.7 %	16.8%	15.3%	20.5%	17.6%	24.2%	20.5%	27.1%
<b>EBRBs</b>								
Sugar-containing beverage consumption (l/d)	0.86 (0.49-1.45)	1.01 (0.49-1.63)	0.64 (0.27-1.11)	0.94 (0.46-1.51)	0.53 (0.21-0.99)	0.77 (0.36-1.31)	0.57 (0.21-0.99)	0.60 (0.23-1.17)
- Soft-drink	0.66 (0.33-1.17)	0.71 (0.34-1.27)	0.40 (0.10-0.81)	0.60 (0.23-1.19)	0.29 (0.10-0.69)	0.52 (0.17-1.01)	0.37 (0.10-0.66)	0.40 (0.10-0.82)
- Fruit juice	0.20 (0.04-0.51)	0.21 (0.06-0.54)	0.13 (0.00-0.36)	0.18 (0.00-0.44)	0.09 (0.00-0.30)	0.18 (0.00-0.40)	0.11 (0.00-0.31)	0.11 (0.00-0.34)
Screen viewing time (h/d)	3.43 (2.29-5.20)	4.14 (2.64-6.07)	3.29 (2.00-4.88)	3.70 (2.43-5.78)	3.48 (2.42-5.04)	4.00 (2.84-5.93)	3.68 (2.50-5.29)	3.86 (2.74-5.52)
- TV viewing	2.14 (1.29-3.29)	2.46 (1.57-3.57)	1.71 (1.07-2.86)	2.00 (1.21-3.00)	2.00 (1.29-2.71)	2.00 (1.29-3.00)	1.96 (1.25-2.71)	2.00 (1.29-2.93)
- Computer use	1.29 (1.00-2.14)	1.64 (1.00-2.71)	1.29 (0.82-2.29)	1.57 (0.93-2.74)	1.50 (1.00-2.57)	1.86 (1.00-3.00)	1.64 (1.00-2.61)	1.84 (1.00-2.91)
Active transport to/from school (min/d)	30.0 (16.0-60.0)	30.0 (13.0-50.0)	40.0 (20.0-60.0)	30.0 (20.0-60.0)	40.0 (20.0-60.0)	30.0 (20.0-60.0)	40.0 (20.0-60.0)	30.0 (20.0-60.0)
High-caloric snack consumption (portion/d)	1.57 (1.00-2.57)	1.50 (0.89-2.57)	1.57 (0.86-2.71)	1.71 (0.86-2.57)	1.50 (0.86-2.57)	1.43 (0.86-2.36)	1.57 (0.86-2.50)	1.29 (0.71-2.14)
-Savory snacks	0.43 (0.29-0.86)	0.43 (0.29-0.86)	0.57 (0.29-1.00)	0.57 (0.29-1.00)	0.57 (0.29-1.00)	0.43 (0.29-1.00)	0.57 (0.29-1.00)	0.43 (0.29-0.79)
-Sweet snacks	1.00 (0.57-2.00)	1.00 (0.57-2.00)	1.00 (0.57-2.00)	1.00 (0.57-2.00)	1.00 (0.57-2.00)	1.00 (0.43-2.00)	1.00 (0.57-2.00)	1.00 (0.43-1.43)

**Supplementary File 3.** Model fit indices and growth trajectories for the unconditional models.

Overall Model Fit				
	$\chi^2$ (df)	CFI	SRMR	Linear growth slope
Body mass index (kg/m <sup>2</sup> )	73.03 (5)*	0.99	0.05	<b>0.53*</b>
Waist circumference (cm)	81.99 (5)*	0.99	0.05	<b>0.65*</b>
Sum of skinfold (mm)	219.46 (3)*	0.96	0.05	<b>1.46 *</b>
Sugar-containing beverages consumption (l/d)	78.33 (3)*	0.88	0.06	<b>-0.32*</b>
- Soft-drink	62.32 (3)*	0.90	0.05	<b>-0.29*</b>
- Fruit juice	27.10 (3)*	0.95	0.04	<b>-0.10*</b>
Screen viewing time (h/d)	15.23 (4)**	0.99	0.03	-0.08
- TV viewing	8.71 (4)	1.00	0.02	<b>-0.39*</b>
- Computer use	16.37 (3)**	0.98	0.03	<b>0.21*</b>
Active transport to/from school (min/d)	14.81 (3)**	1.00	0.02	<b>6.98*</b>
High-caloric snack consumption(portion/d)	51.12 (5)*	0.95	0.05	<b>-0.11**</b>
-Savory snacks	20.86 (3)*	0.97	0.04	<b>0.09*</b>
-Sweet snacks	83.16 (5)*	0.91	0.06	<b>-0.17*</b>

\*<0.001, \*\*<0.01

$\chi^2$ (df)-chi square (degrees of freedom), CFI- comparative fit index, SRMR-standardized root mean residuals