Trajectories of change in childhood obesity prevalence across local authorities 2007/08-2015/16: a latent trajectory analysis

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Abstract

Background

We investigated differing trajectories of childhood obesity prevalence amongst English local authorities (LAs).

Methods

Data on prevalence of childhood obesity (BMI ≥95th centile) for Reception year and Year 6 for 150 LAs in England from 2006/07 to 2015/16 were obtained from the National Child Measurement Programme (NCMP). Latent class mixture modelling (LCCM) was used to identify classes of change in obesity prevalence.

Results

In Reception, most LAs showed little change across the period (Class 1; stable, moderate obesity prevalence;84%), with a smaller group with a high prevalence that fell thereafter (Class 2; high but falling obesity prevalence; 16%). In Year 6 we identified 3 classes: moderate obesity prevalence (Class 3; 43%); high and rising obesity prevalence (Class 2; 36%); and stable low obesity prevalence (Class 1; 21%). Greater LA deprivation and higher LA proportion of non-white ethnicity increased risk of being in Class 2 (Reception) or Class 2 or 3 (Year 6) compared with class 1.

Conclusions

The prevalence of childhood obesity in LAs in England follow a small number of differing trajectories that are influenced by LA deprivation and ethnic composition. LAs following a stable low obesity trajectory for Year 6 are targets for further investigation.

Background

There is considerable variation in the prevalence of childhood obesity at neighbourhood level in the UK and many other countries.[1 2] This variation has been suggested to be due to differences in compositional factors such as deprivation and ethnicity,[1 2] and may also reflect differences in local government policy and provision relating to obesity-relevant factors.

Monitoring trends in childhood obesity at local authority (LA) as well as national level is one of the aims of the National Child Measurement Programme (NCMP) in England, which measures all children in state schools in England at primary school entry at age 4-5 years (known as Reception) and at the end of primary school at age 10-11 years (Year 6). In 2017, Public Health England (PHE) published data on long-run trends in childhood BMI data for each LA in England, using data from the NCMP from its inception in 2006/07 through to 2015/16.[1] This analysis showed there was also considerable heterogeneity in longitudinal obesity trends by LA.

Such findings raise the question about whether there are subpopulations of LAs with differing trajectories of childhood BMI change over time. Latent class mixture modelling (LCCM) is a data reduction technique that identifies likely different sub-populations within a population, probabilistically assigning individuals into latent classes representing a subpopulation or a trajectory based upon similar patterns of observed longitudinal data.[3 4] Such models also allow examination of factors which influence membership of different trajectories. LCCM techniques can be applied to clusters of individuals, geographical areas or institutions as well as to individuals.

We used LCCM techniques to examine whether there are groups or subpopulations of LAs with differing patterns of change in childhood obesity, using NCMP data from 2007/08 through to 2015/16. We then examined whether area level demographic and deprivation characteristics were associated with identified LA obesity trajectories. Whilst these analyses are necessarily at the ecological level, they may be informative to identify groups of LAs doing particularly well or particularly poorly compared with the national average and thus inform future research.

Methods

Summary NCMP data on the annual prevalence of childhood obesity for all of the upper tier 152 LAs in England from 2006/07 to 2015/16 were obtained from Public Health England, the holders of NCMP data.[1] Data for 2 very small LAs were provided merged with their nearest geographical neighbour (Isles of Scilly merged with Cornwall; City of London merged with Hackney), resulting in data being available for 150 LAs. The NCMP measures children at Reception (school entry i.e. age 4-5 years) and Year 6 (age 10-11 years). Data provided included prevalence of obesity at Reception and Year 6, for both sexes combined. Whilst sex-specific data were available, we used combined data to reduce analytic burden and because it is unlikely that LA-level policies or environments impact upon obesity differentially by sex in children. Obesity was defined as BMI ≥95th centile for age and sex. No individual level data were obtained.

Data on potential predictor factors at LA level were obtained as follows:

1. Deprivation: small area measures of deprivation i.e. the Index of Multiple Deprivation (IMD) and the Index of Deprivation Affecting Children (IDACI) were obtained from the English Indices of Deprivation 2015,[5] obtained from the Department for Communities and Local Government. IMD score was used as a measure of overall deprivation at the LA level; higher score indicates greater deprivation. IDACI score was used as a measure of deprivation affecting children; scores indicate the proportion of children living in poverty within each LA, with higher score indicating greater deprivation.

2. Ethnicity: data on LA proportions by ethnic group were obtained from Census 2011 data.[6]

Analyses

We ran linear LCMMs for obesity prevalence from 2007/08 to 2015/16 separately for Reception and Year 6, using the *mixture* commands in MPlus 8.0 (www.statmodel.com). We did not include obesity data from the first NCMP year (2006/07) due to low participation by LAs for the initial year. Models used maximum likelihood estimation which account for missing data, with 1500 random starts used in each model for maxiumum likelihood optimization; this replicated the best log-likelihood ratio in all models. We began with a model with one trajectory class, and sequentially increased class number for each model. We assessed model fit criteria at each step, including Akaike Information

Criteria (AIC), sample adjusted Bayesian Information Criteria (BIC), entropy (a measure of separation of identified trajectories) and the Vuong-Lo-Mendell-Rubin test. The latter was used to test fit with k classes compared to a model with k-1 classes; a p-value <0.05 rejects the k − 1 class model in favour of the k class model.[7] We judged the best model on the basis of clinical plausibility, model fit and entropy criteria, as suggested by the literature.[3 8] Output from the models included estimates of trajectory class membership for each LA, which was imported into Stata 15 (StataCorp; College Station, TX) and merged with LA demographic and deprivation data. We then used logistic regression to examine whether LA characteristics predicted LA trajectory class membership for Reception and Year 6.

Findings

Obesity prevalence in the LAs from 2006/07 to 2015/16 are shown in Appendix Table A1 for Reception and Appendix Table A2 for Year 6.

Sequential trajectory models for obesity prevalence 2007/08 to 2015/16 for a single class through to 4-class models are shown in Table 1 for Reception and Table 2 for Year 6. For each model including from 1 to 4 classes, the Tables show first the model fit criteria (AIC, BIC and entropy); the proportions in each trajectory class (adding to 100% for each model) and the estimated intercepts and slopes for each trajectory class. The intercepts indicate the baseline starting proportion with obesity in each class, with the slope indicating the average annual change in obesity prevalence thereafter.

The 1-class model, approximating a growth model, for Reception showed an average obesity prevalence of 9.92% (SE 0.14) at baseline, had a very small negative slope consistent with a very small annual fall in obesity prevalence (by 0.072 (0.012) per year). For Year 6, the 1-class model showed an average obesity prevalence of 18.87% (0.23) with an annual rise of 0.132 (0.018).

For Reception, the 2-class model had the highest entropy and lowest AIC and BIC, indicating best model fit. For Year 6, the 3-class model had the highest entropy but similar AIC and BIC to a 4 class model. Examination of the class intercepts and slopes and the Lo-Mendell-Rubin adjusted LRT and parametric bootstrapped LRT suggested that the 4 class model offered no advantages over the 3 class model. The 3 class model was thus identified as the preferred solution for Year 6.

Membership of trajectory classes for each LA are shown in Appendix Tables A1 (Reception) and A2 (Year 6). These tables also show the probability for each LA of being in each trajectory class (1 or 2 for Reception; 1 to 3 for Year 6) together with the identified best fit for each LA i.e. the assigned trajectory class.

The 2 class model for Reception is shown graphically in Figure 1 Panel A. The modelled linear trajectories for each class are shown in a broken line together with the mean obesity prevalence across all LAs in each year for that trajectory shown in solid colour. The majority of LAs (Class 1; stable, moderate obesity prevalence; 84%) showed little change across the period, with a very small but significant negative slope (annual decrease in obesity of 0.04%). The second group of LAs (Class

2; high but falling obesity prevalence; 16%) had a high initial prevalence of obesity in 2007 which then fell approximately 0.26% per annum across the study period although prevalence amongst this class remained higher than Class 1 in 2015/2016.

Figure 1 Panel B shows the 3 class model for Year 6. The largest class (Class 3; 43%; moderate obesity prevalence) began in 2007 with average obesity prevalence but experienced a gradual rise in prevalence to 2015/16, increasing by approximately 0.12% per annum. The second largest group (Class 2; 36%; high and rising obesity prevalence) were those with high prevalence in 2007/08 and also experienced a faster rise through to 2015/16 of approximately 0.20% per annum. The final class (Class 1; 21%; stable, low obesity prevalence) had stable lower obesity prevalence throughout, with a very small although significant annual increase (0.063%).

Unadjusted associations of predictor factors with LA trajectory are shown in Table 3. For Reception, higher LA proportion of non-white ethnicity and greater deprivation (IMD and IDACI) increased the risk of being in Class 2 (high prevalence obesity) compared with Class 1. Odds ratios (OR) were higher for IDACI compared with IMD. For Year 6, higher LA proportion of non-white ethnicity and greater deprivation (IMD and IDACI) increased the risk of being in either Class 2 or 3 compared with Class 1 (stable low obesity prevalence). OR were higher for Class 2 (high obesity prevalence) than Class 3 (moderate obesity prevalence) for each predictor and again OR were slightly higher for IDACI than IMD.

Discussion

Main finding of this study

We used innovative data reduction techniques to identify differing patterns of obesity trajectories amongst English LAs over the past decade. As theorised, we identified groups of LAs that had differing trajectories in childhood obesity to the overall or mean national trends previously identified.[1]

Identified trajectories differed between Reception and Year 6 obesity trends. For Year 6 obesity, we identified 3 likely trajectories; in addition to the most common class (moderate obesity prevalence; 43%) which showed a gradual rise in prevalence, smaller groups of LAs showed a high and rapidly rising obesity trajectory (36%) or a stable low obesity prevalence (21%). In contrast, for Reception obesity, the majority of LAs demonstrated essentially little change in childhood obesity prevalence over the period (stable moderate obesity prevalence; 84%) whilst a smaller group (16%; high prevalence) had high initial prevalence but greater falls over time.

We found that higher LA deprivation levels and higher LA proportions of non-white ethnicity increased the risk of LAs being in more adverse trajectories, i.e. the Reception high but falling obesity prevalence and the Year 6 high and rising obesity prevalence classes.

What is already known on this topic

Random slope mixed effects analyses using the same dataset have identified significant variation in linear trends in childhood obesity between English LAs over the past decade.[1] Our findings that greater LA-level deprivation and non-white ethnicity were associated with more adverse childhood obesity trajectories are not surprising and likely reflect previously described associations of deprivation and non-white ethnicity with greater risk of childhood obesity at the individual level and at the LA level in the NCMP data[1] as well as at the individual level in other UK datasets.[9] It is also likely that the association with ethnicity in part or largely reflects the association with deprivation, given the very strong associations between the two in contemporary UK populations.

What this study adds

We are not aware of the use of LCMM techniques to investigate geographical variations in childhood obesity level either in the UK or elsewhere. As noted above, LA-level variation has been examined in mixed effect models, however such models merely identify LAs with random slopes that differ from the overall national average whereas LCMM techniques allow the identification of groups of LAs with discrete patterns of change over time. This technique therefore provides an alternative method to identify LAs with positive deviance in longitudinal trends for key public health indicators such as childhood obesity, and thereby facilitate analysis of LA policies and interventions that may be beneficial.

Limitations of this study

We used data from the authoritative NCMP over nearly a decade to identify plausible subpopulations of LAs following differing trajectories in childhood obesity prevalence. Data on potential predictors were obtained from routine administrative data. Methods used for LCMM followed authoritative guidance. The majority of LAs had a high (>80%) probability of being in their assigned class (Appendix), and there appears to be a good fit between these assigned classes and obesity prevalence 2007/08-2015/16 in that LA. Small numbers of LAs had notably lower probabilities for their assigned class in Reception and Year 6 suggesting that assignment of these LAs may be less accurate. Whilst our analyses were ecological, being at the LA-level rather than at the level at which data were collected (on individual children), this was appropriate as it is recognised that many important determinants of childhood obesity act at neighbourhood or school level, and as our main aim was to identify potential subpopulations of LAs. However, we cannot attribute causality to the associations identified between deprivation and ethnicity and LA trajectory class.

Our findings are subject to a number of limitations. The trajectory classes we identified are plausible; however LCMM is an exploratory data driven technique and it is possible that chance relationships in our data may influence trajectory group findings.[10] Some reassurance is provided by the fact that we were conservative in identifying most likely latent class groups and the trajectories we identified were plausible. Our data on LA deprivation and ethnicity were from a single time point towards the middle or end of the study period (2015 and 2011 respectively). It is likely that overall LA deprivation and ethnic composition were relatively stable over the 9 year study period, however it is possible that trajectory class membership may have been influenced by changes in ethnic composition or deprivation over the period. Unfortunately, we were unable to include additional time points for ethnicity (as this was only available from census data) nor for deprivation as comparable IDACI data were not available from 2007/08. We did not undertake multivariable analyses including both deprivation and ethnicity as predictors of LA trajectory due to the potential for introduction of bias in these ecological analyses. We could not examine other potential predictors of LA childhood obesity trajectories such as LA spending on public health as this was only devolved to LAs in 2012/13.

Conclusions

The prevalence of childhood obesity in LAs in England appears to follow a small number of differing trajectories. The trajectory followed appears to be influenced by LA deprivation and ethnic composition. The group of LAs following a stable low childhood obesity prevalence trajectory for Year 6 (see Appendix) are potentially worthy of further study to identify whether there are common local policies or practices that may have contributed to their positive deviance from national trends towards increase in obesity prevalence.

Conflict of interests

Both authors declare they have no conflicts of interest.

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Table 1. Latent class trajectory mixture models for obesity prevalence for 152 local authorities (LAs) from 2007/08 to 2015/16 for Reception

			1 class				**2 classes**				**3 classes**				**4 classes**	
N			150				150				150				150	
AIC			3861.473				3847.985				3850.804				3853.493	
% change AIC							-0.3%				0.1%				0.1%	
adjusted BIC			3859.314				3845.364				3850.804				3849.947	
% change BIC							-0.4%				0.1%				0.0%	
LLR			-1916.736				-1906.992				-1905.402				-1903.747	
% change LLR							-0.5%				-0.1%				-0.1%	
Entropy			N/A				0.813				0.693				0.722	
% change Entropy							N/A				-14.8%				4.2%	
Classes		N	%			N	%			N	%			N	%	
	1	150	100%			126	84%			18	12%			22	15%	
	2					24	16%			23	15%			23	15%	
	3									109	73%			10	7%	
	4													95	63%	
Trajectory class characteristics		*B*	*se*	*p*		*B*	*se*	*p*		*B*	*se*	*p*		*B*	*se*	*p*
Class 1	Intercept	9.915	0.137	<0.001	*C1*	9.417	0.147	<0.001	*C1*	10.271	0.521	<0.001	*C1*	10.507	0.328	<0.001
	Slope	-0.072	0.012	<0.001		-0.035	0.013	<0.001		0.107	0.047	0.02		0.118	0.038	0.002
Class 2	Intercept				*C2*	12.421	0.335	<0.001	*C2*	12.396	0.347	<0.001	*C2*	12.376	0.358	<0.001
	Slope					-0.257	0.033	<0.001		-0.266	0.036	<0.001		-0.269	0.037	<0.001
Class 3	Intercept								*C3*	9.271	0.217	<0.001	*C3*	8.246	0.626	<0.001
	Slope									-0.064	0.016	<0.001		-0.186	0.039	<0.001
Class 4	Intercept												*C4*	9.353	0.217	<0.001
	Slope													-0.052	0.02	0.01
Lo-Mendell-Rubin adjusted LRT			N/A				1 v. 2 classes				2 v. 3 classes				3 v. 4 classes	
							0.006				p=0.4				p=0.5	
Parametric bootstrapped LRT							1 v. 2 classes									
							<0.001				p=0.9				p=0.9	

Table 2. Latent class trajectory mixture models for obesity prevalence for 152 local authorities (LAs) from 2007/08 to 2015/16 for Year 6

			1 class				**2 classes**				**3 classes**				**4 classes**	
N			150				150				150				150	
AIC			6204.899				6186.92				6139.028				6124.606	
% change AIC							-0.3%				-0.8%				-0.2%	
adjusted BIC			6202.641				6184.098				6135.641				6120.656	
% change BIC							-0.3%				-0.8%				-0.2%	
LLR			-3086.449				-3073.46				-3045.514				-3034.303	
% change LLR							-0.4%				-0.9%				-0.4%	
Entropy			N/A				0.756				0.864				0.849	
% change Entropy							N/A				14.3%				-1.7%	
Classes		N	%			N	%			N	%			N	%	
1		150	100%			74	49%			32	21%			30	20%	
2						76	51%			54	36%			29	19%	
3										64	43%			52	35%	
4														39	26%	
Trajectory class characteristics		*B*	*se*	*p*		*B*	*se*	*p*		*B*	*se*	*p*		*B*	*se*	*p*
Class 1	Intercept	18.871	0.233	<0.001	*C1*	18.426	0.284	<0.001	*C1*	16.323	0.323	<0.001	*C1*	16.309	0.32	<0.001
	Slope	0.132	0.018	<0.001		0.129	0.031	<0.001		0.063	0.023	0.005		0.064	0.022	0.005
Class 2	Intercept				*C2*	19.292	0.4	<0.001	*C2*	21.306	0.483	<0.001	*C2*	22.437	1.255	<0.001
	Slope					0.135	0.024	<0.001		0.195	0.03	<0.001		0.149	0.111	0.2
Class 3	Intercept								*C3*	18.136	0.277	<0.001	*C3*	18.125	0.359	<0.001
	Slope									0.115	0.031	<0.001		0.095	0.037	0.01
Class 4	Intercept												*C4*	19.326	1.133	<0.001
	Slope													0.226	0.06	<0.001
Lo-Mendell-Rubin adjusted LRT			N/A				1 v. 2 classes				2 v. 3 classes				3 v. 4 classes	
							0.03				0.002				p=0.5	

Parametric bootstrapped LRT	N/A	1 v. 2 classes <0.001	2 v. 3 classes <0.001	3 v. 4 classes <0.001*

* Mplus flagged this test in this analysis as potentially not trustworthy due to local maxima

Table 3. Associations of LA sociodemographic factors with obesity trajectory class membership for Reception and Year 6

	Reception			Year 6		
	N	OR (95% CI)	p	N	OR (95% CI)	p
Ethnicity (% non-white in total population)	148			150		
Class 1		White = Reference (1)			White = Reference (1)	
Class 2		1.08 (1.05, 1.10)	<0.001		1.09 (1.05, 1.13)	<0.001
Class 3		-			1.02 (0.98, 1.06)	0.3
Index of Multiple deprivation (IMD) score	150			150		
Class 1		1			1	
Class 2		1.09 (1.03, 1.15)	0.005		1.29 (1.18, 1.42)	<0.001
Class 3		-			1.19 (1.10, 1.30)	<0.001
Index of Deprivation affecting children (IDACI) score	150			150		
Class 1		1			1	
Class 2		1.19 (1.10, 1.29)	<0.001		1.39 (1.25, 1.56)	<0.001
Class 3		-			1.21 (1.10, 1.33)	<0.001

Note: IDACI score is equivalent to proportion of children living in poverty in an LA

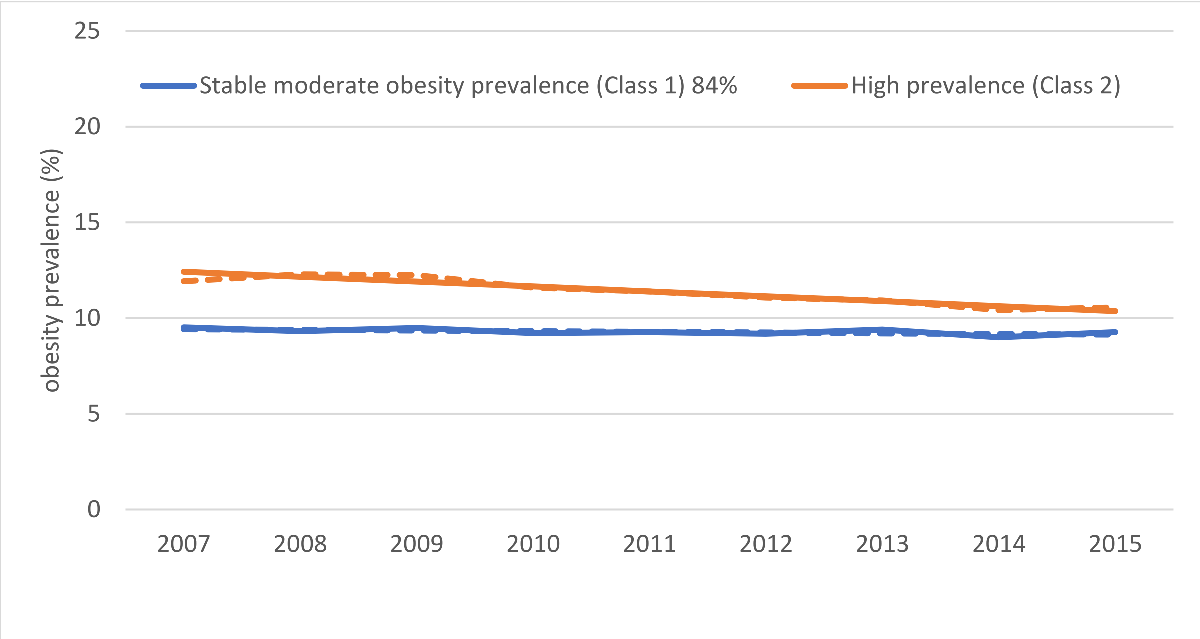
For Reception, Class 1 is stable moderate obesity prevalence; Class 2 is high prevalence.

For Year 6, Class 1 is stable low prevalence; Class 2 is high and rising prevalence; Class 3 is moderate prevalence.

Figure 1. Graphical depiction of trajectory classes for obesity prevalence

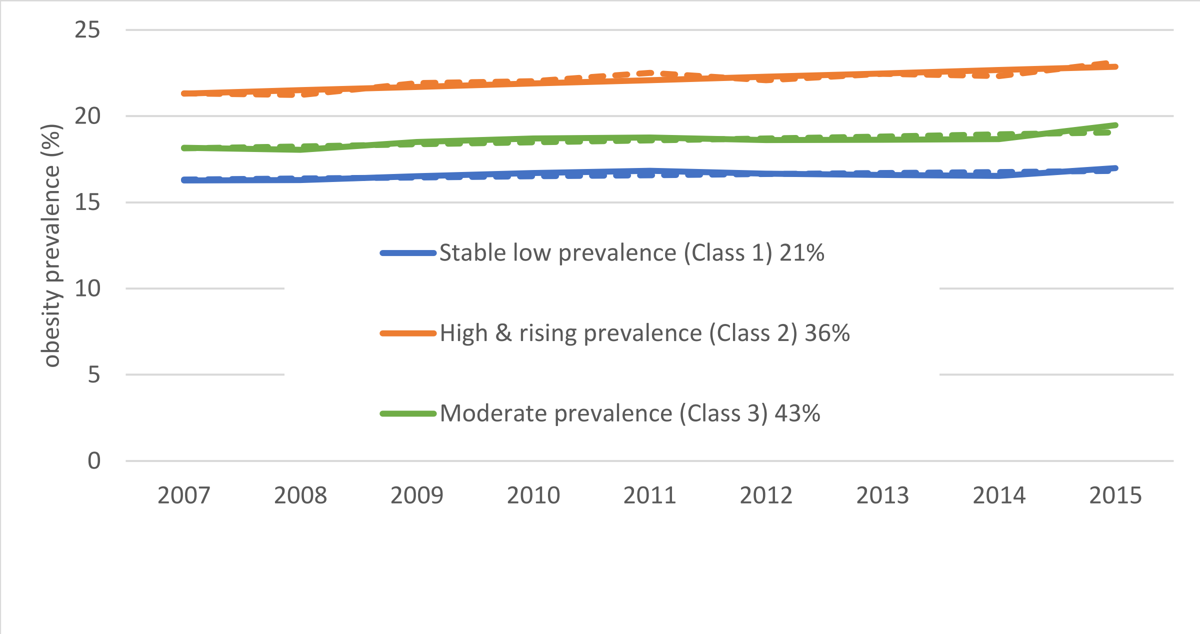
Panel A: Reception

The modelled linear trajectories for each class are shown in a broken line together with the mean obesity prevalence across all LAs in each year for that trajectory shown in solid colour.



Panel B: Year 6

The modelled linear trajectories for each class are shown in a broken line together with the mean obesity prevalence across all LAs in each year for that trajectory shown in solid colour.



References

1. Copley VR, Bray CL. National Child Measurement Programme: Changes in children's body mass index between 2006/07 and 2015/16. London: Public Health England, 2017.
2. Ells LJ, Hancock C, Copley VR, et al. Prevalence of severe childhood obesity in England: 2006-2013. *Arch Dis Child* 2015;100(7):631-6. doi: 10.1136/archdischild-2014-307036
3. Nagin DS, Odgers CL. Group-based trajectory modeling in clinical research. *Annual review of clinical psychology* 2010;6:109-38. doi: 10.1146/annurev.clinpsy.121208.131413
4. Berlin KS, Parra GR, Williams NA. An introduction to latent variable mixture modeling (part 2): longitudinal latent class growth analysis and growth mixture models. *J Pediatr Psychol* 2014;39(2):188-203. doi: 10.1093/jpepsy/jst085
5. English indices of deprivation 2015: Ministry of Housing, Communities and Local Government; 2015 [Available from: https://www.gov.uk/government/statistics/english-indices-of-deprivation-2015 accessed 9-3-2018.
6. 2001 Census: Key statistics for local authorities in England and Wales. London: Office for National Statistics, 2012.
7. Muthen L, Muthen B. Mixture modeling with longitudinal data. Mplus User's Guide, 7th Edition. Los Angeles: Muthen & Muthen 1998-2012:209-50.
8. Wickrama KAS, Lee TK, O'Neal CW, et al. HIgher-order growth curves and mixture modelling with M*Plus*. London: Routledge 2016.
9. Karlsen S, Morris S, Kinra S, et al. Ethnic variations in overweight and obesity among children over time: findings from analyses of the Health Surveys for England 1998-2009. *Pediatric obesity* 2014;9(3):186-96. doi: 10.1111/j.2047-6310.2013.00159.x
10. Ram N, Grimm KJ. Growth Mixture Modeling: A Method for Identifying Differences in Longitudinal Change Among Unobserved Groups. *International journal of behavioral development* 2009;33(6):565-76. doi: 10.1177/0165025409343765