Predicting future weight status from measurements made in early childhood: A novel longitudinal approach applied to Millennium Cohort Study data

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Abstract

Background/objective: There are reports that childhood obesity tracks into later life. Nevertheless, some tracking statistics, e.g. correlations, do not quantify individual agreement, while others, e.g. diagnostic test statistics, can be difficult to translate into practice. We aimed to employ a novel analytic approach, based on ordinal logistic regression, to predict weight status of 11-year-old children from measurements at age 5.

Subjects/methods: UK 1990 growth references were used to generate clinical weight status categories of 12 076 children enrolled in the Millennium Cohort Study. Using ordinal regression, we derived the predicted probability (percent chances) of an 11-year-old child becoming underweight, normal weight, overweight, obese and severely obese from their weight status category at age 5.

Results: The chances of becoming obese (including severely obese) at age 11 were 5.7% (95% CI: 5.2% to 6.2%) for a normal weight 5-year-old and 32.3% (29.8% to 34.8%) for an overweight 5-year-old. An obese 5-year-old child had a 68.1% (63.8% to 72.5%) chance of remaining obese at 11 years. Severely obese 5-year-old children had a 50.3% (43.1% to

57.4%) chance of remaining severely obese. There were no substantial differences between sexes. Non-deprived obese 5-year-old boys had a lower probability of remaining obese than deprived obese boys: -21.8% (-40.4% to -3.2%). This association was not observed in obese 5-year-old girls, in whom the non-deprived group had a probability of remaining obese 7% higher (-15.2% to 29.2%). The sex difference in this interaction of deprivation and baseline weight status was therefore -28.8% (-59.3% to 1.6%).

Conclusions: We have demonstrated that ordinal logistic regression can be an informative approach to predict the chances of a child changing to, or from, an unhealthy weight status. This approach is easy to interpret and could be applied to any longitudinal dataset with an ordinal outcome.

Introduction

The increasing prevalence of childhood obesity has become a major public health issue worldwide in both developing and developed countries.[1] The consequences of childhood obesity can be severe, with an increased risk of developing conditions such as, diabetes, cardiovascular disease and psychosocial disorders.[2, 3] Furthermore, there is some evidence that children who are overweight or obese are more likely to be overweight or obese adults; hence, they are more likely to suffer from comorbidities when they reach adulthood.[4] Nevertheless, most adults who are overweight or obese now were of normal weight as children.[5]

In England, approximately 1 in 5 children aged 4-5 years old and 1 in 3 children aged 10-11 are either overweight or obese[a]. These figures are from the National Child Measurement Programme (NCMP), which was introduced into England in 2006 to measure the height and weight of children in Reception (4-5 years old) and Year 6 (10-11 years old). The rationale for introducing the NCMP included the gathering of population level data on growth trends, informing service planning and delivery, and increasing awareness of weight issues in children.[6] The results from the programme are

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[a] defined using the UK90 population monitoring cut points for overweight (≥85th centile) and obesity (≥95th centile)

routinely fed back to parents via letters.[7] There is a standard template that may be used by each local authority in England; however, some areas make changes to the letter or do not use the letter at all. This variation in practice leads to a lack of consistency in how local authorities present the results and whether they offer further support to the parents/children. In some local authorities the letter suggests that children who are overweight/obese during Primary School are more likely to be overweight/obese in adulthood; some letters have previously stated that overweight or obese children are more likely to develop disorders such as cancer, diabetes and cardiovascular disease.[8] Such information can be distressing and also confusing for parents; therefore, it is important to provide parents with information that is acceptably accurate, informative and easy to understand.

The NCMP allows the annual prevalence of childhood obesity to be reported. The NCMP also has the potential to provide prognostic information, i.e. to ascertain whether an individual child is likely or not to have an unhealthy weight status when measured again later in life. Nevertheless, this issue of "tracking" is currently difficult to explore using NCMP data, which up until 2013 was anonymised before the annual upload to the national data collection system, thus prohibiting any data linkage on an individual level[9].

A statistic that is used commonly in body mass index (BMI) tracking research is the correlation coefficient. In a recent meta-analysis[10], tracking correlations were synthesised from 48 studies, which varied in their duration between initial and follow-up measurements. The authors of this review concluded that a high degree of tracking existed for follow-up durations of 1, 10 and 20 years, with respective correlation coefficients of 0.78-0.86, 0.67-0.78 and 0.27-0.47, respectively. However, a correlation coefficient does not quantify the prediction error for individual children.[11] Odds ratios, derived from binary logistic regression models, are also commonly reported in BMI tracking research. For example, in a recent secondary analysis of the NCMP data for South Gloucestershire, England,[12] multiple binary logistic models were used to derive over twenty separate odds ratios for boys, girls and the pooled sample across various weight categories. In this latter study, one odds ratio was cited to infer, incorrectly, that children who were overweight in Reception (85^{th}-94^{th} percentile, UK 1990 growth reference charts) were "13 times more likely" to be overweight or obese in Year 6, compared to children who were between the 2^{nd} to 49^{th}

percentile in Reception. It is not uncommon for odds ratios and relative risks to be misrepresented in research, rendering them difficult to translate to practitioners and patients.[13] Furthermore, the analysis by Pearce et al. (2015) only used the population monitoring cut offs for overweight and obesity; in the NCMP feedback letters the clinical cut offs are used. Pearce et al. (2015) also did not predict the odds of a child becoming severely obese, which has shown to be an increasing concern in England.[14] Lastly, BMI weight categories are clearly ordinal level data, rendering the use of many binary logistic regression models across multiple pairs of weight categories non-parsimonious.

Finally, diagnostic test statistics such as sensitivity and specificity can help ascertain the individual agreement between two different measurements of status.[15] Nevertheless, several additional statistics (e.g. positive predictive value, negative predictive value, and positive and negative likelihood ratios) are required for a full interpretation, rendering results that are sometimes difficult to explain to a layperson, such as a child's parent. Steurer et al. (2002) reported that even general practitioners can struggle to apply the statistics from the appraisal of a diagnostic test.[16]

The aim of this secondary analysis of longitudinal data was to develop a robust analytic approach to predict the individual weight status of 11-year-old children from weight status data collected at age 5, and to explore the influences of sex and deprivation.

Subjects and methods

Subjects in this secondary data analysis are from the Millennium Cohort Study (MCS), which recruited over 19 000 children born in the UK between 1st of September 2000 and 11th January 2002. Children were identified from the Child Benefit register and were recruited, along with their families, when they were approximately 9 months old.[17] The study used disproportionately stratified sampling to over-represent disadvantaged populations and areas with a high prevalence of Black and Minority Ethnic (BME) communities.[18]

Data were downloaded from the UK data archive, from sweep 1 and sweep 5 of the data collection, to select children who were of similar ages to those taking part in the NCMP (it is also possible that the children resident in England were also measured in the NCMP). The following variables were obtained: MCS research serial number, cohort member number, sex, age, BMI and index of multiple deprivation (IMD) decile (by country).[19, 20] Height and weight were measured by study investigators at each time point, and were not self-reported. Due to the sample stratification and clustering, the data needed to be set for analysis using an attrition/non response weight (whole of UK-level analysis), a Finite Population Correction factor (FPC), a stratum variable, and a ward variable to account for clustering. These variables were also obtained from the dataset.[20] Since variables were required from multiple datasets, files were merged together based on the MCS research serial number and cohort member number (used to represent twins/triplets). Raw BMI values were converted into BMI z scores/centiles using the LMS growth Microsoft Excel add-in[21] where UK 1990 growth references were selected. These centiles were then converted into weight status categories using the UK 1990 clinical cut off points: underweight ($<2^{nd}$ centile); normal weight ($\geq 2^{nd}$ but $<91^{st}$ centile); overweight ($\geq 91^{st}$ centile but $<98^{th}$ centile); and obese ($\geq 98^{th}$ centile). [22] These categories are also used in the NCMP feedback letters to parents.[6] An additional category for severely obese children was also generated using the $\geq 99.6^{th}$ centile cut off.[14] IMD scores were used to assess the level of deprivation and were presented in quintiles. Ordinal logistic regression was applied to generate the predicted probability (% chances) of a child becoming underweight, normal weight, overweight, obese and severely obese at age 11, with weight status at age 5, sex, deprivation, and their 3-way interaction as predictors. Interaction analyses presented are exploratory. All analyses were performed using Stata® software (StataCorp. 2013. *Stata Statistical Software: Release 13*. College Station, TX: StataCorp LP). Point estimates are presented together with 95% confidence intervals. These intervals are not adjusted for multiple comparisons.[23]

Three sensitivity analyses were conducted. The first simply removed the second and third born twins/triplets to explore whether these had a substantial effect on the estimates. The second relaxed the constraint of the proportional odds assumption underpinning ordinal logistic regression and repeated all analyses using generalised ordinal logistic regression.[24] This model allows the effects of the predictor variables to vary with the point at which the categories of the age 11 weight status variable are dichotomised, rather than enforcing parallel lines. Finally, we explored the effect of missing data, given that 3 116 BMI values were missing at follow up. Under a missing at random assumption, a complete case analysis – our primary analysis - is unbiased in this context and methods such as multiple imputation can only exacerbate problems by introducing additional random variation. However, multiple imputation can be used for a sensitivity analysis to examine the effects of substantial departures from the missing at random assumption. In the current study, it is plausible that those children lost to follow up had substantially higher BMI values – that is, data missing not at random. We imputed the 3 116 missing follow up BMI values predicted from baseline BMI using the Stata® 'MI' module with predictive mean matching (random selection from 10 nearest neighbours). Twenty imputations were made by sex and deprivation strata to preserve relationships for the higher order interactions in the analysis model. Using a pattern mixture modelling approach[25], each imputed follow up BMI value was then inflated by 25% to simulate data missing not at random, with higher follow up BMI in those not presenting for measurement at age 11. We then converted these inflated BMI values into weight status categories using the same method previously described. The identical ordinal logistic regression model was then applied to the 20 imputed data sets, with results combined using Rubin's rules[26].

Results

12 076 children were included in the analyses who had a BMI measurement along with complete data for sex and IMD

score. The NCMP cleaning protocol[27] was used to explore whether there were any BMI outliers; only two BMI measurements were slightly outside the acceptable ranges given in the protocol; hence, these were retained in the analysis. Half (50.3%) of the sample were boys, and 25.8% and 19.2% of children were in the most deprived (0-<20%) and least deprived (80-100%) IMD categories, respectively. The mean BMI at baseline was 16.3±1.9 kg/m^2 and the mean age was 5.2±0.3 years. The mean BMI at follow up was 19.2±3.7 kg/m^2 and the mean age was 11.2±0.3 years. At baseline (age 5) the percentage of children who were underweight, normal weight, overweight and obese (including severely obese) were as follows: 1.1% (n=127), 82.4% (n=9 954), 10.3% (n=1 249) and 6.2% (n=746). At follow up (age 11) the percentages were as follows: 1.6% (n=188), 71.0% (n=8 577), 15.1% (n=1 819) and 12.4% (n=1 492). The percentage of children who were severely obese at age 5 and 11 were 2.9% (n=347) and 4.1% (n=494), respectively. The tracking of raw BMI between age 5 and age 11 produced a correlation coefficient of 0.61.

Results from the full factorial ordinal logistic regression model are shown in Table 1, split by sex. Sex was shown to have little influence on these associations. Interestingly, overweight children had around a 1/3 chance of remaining overweight, 1/3 chance of returning to the normal weight category and 1/3 chance of becoming obese. Obese (including severely obese) children at age 5 year-old had nearly a 70% chance of remaining obese at 11 years-old.

When the analysis was performed with an additional category for severe obesity, severely obese 5-year-olds had a 52.8% (45.3% to 60.3%) chance of remaining severely obese at 11 years, and a 31.3% (27.4% to 35.1%) chance of decreasing their weight status and returning to the obese category (≥98th but <99.6th centile). There were no substantial differences between sexes: severely obese boys had 49.5% (39.4% to 59.5%) chance of remaining severely obese compared to a 56.6% (46.0% to 67.2%) chance for severely obese girls. Severely obese boys and girls had a 32.3% (28.1% to 36.5%) and 30.0% (24.1% to 35.8%) chance of decreasing their weight status and becoming obese, respectively. Boys who were obese (not severe) at age 5 had a 23.0% (17.2% to 28.8%) chance of becoming severely obese, whilst obese girls had a 27.2% (19.7% to 34.7%) chance.

Results stratified by sex and deprivation are shown in Table 2. Non-deprived obese boys had a lower chance of remaining obese at age 11 compared to deprived obese boys; a difference of -21.8% (-40.4% to -3.2%). The opposite association was found in obese girls, where non-deprived girls were more likely to remain obese than deprived obese girls; however, this difference was not substantial. The sex difference in this specific interaction of deprivation and baseline weight status was -28.8% (-59.3% to 1.6%). No other substantial differences were found between deprived and non-deprived boys/girls or when comparing boys versus girls; this was also the case when normal weight and overweight status were predicted at follow up (data not shown). We were unable to include underweight children in the analysis split by sex and deprivation as there were too few underweight children in the sample.

Table 3 shows the predicted percent chances of becoming severely obese by sex and deprivation. We also performed the analysis using the population monitoring cut points instead of the clinical cut points and found a slightly greater increase in the percent chances of becoming overweight or obese (results not shown). This was expected because the cut points are lower; hence, more children will have been categorised as overweight or obese.

When second and third born twins/triplets were removed from the analysis, there were no substantial differences in any of the predicted percent chances (data not shown). Similarly, relaxation of the constraint of the proportional odds assumption had no material effect on the findings. Results from the sensitivity analysis with missing data are shown in Table 4 for predicting obesity by sex and deprivation. When comparing the original analysis (data missing at random assumption) against the multiple imputation analysis (missing not at random assumption), no material differences were found.

Discussion

This secondary analysis of data from the MCS has shown how a robust statistical approach can be used to predict a child's future weight status in an informative way using baseline weight status, sex and deprivation as predictor variables. This technique could be applied to NCMP data and predictions could be incorporated into the parental feedback letters, to better inform parents of the chances of their child becoming or remaining an unhealthy weight status. In fact, this statistical technique could be applied to any longitudinal dataset, and additional predictor variables could be included in the model. Furthermore, as we had a considerable proportion of missing outcome data, we have demonstrated an approach to sensitivity analysis for substantial departures from the missing at random assumption.

The main findings from the MCS analysis included showing that sex does not strongly influence the tracking of weight status from age 5 and 11. However, our exploratory interaction analyses suggest that deprivation might influence whether obese boys at age 5 will remain obese at age 11, with non-deprived boys substantially less likely to remain obese. This association was not evident in girls. This finding is subject to replication and confirmation, but it suggests that non-deprived obese boys have a protective effect against remaining obese in later childhood, perhaps mediated by environmental and psychological factors.

Some of the children included in the MCS would have been measured in the English National Child Obesity Dataset (NCOD) in 2005/2006, which was then renamed the NCMP the following year after improvements were made[28]. Children in the MCS would have also taken part in the NCMP in 2011/2012 when they were in Year 6 of Primary School. Analyses of NCMP cohort trends have shown that obesity prevalence in the most deprived children is nearly double the prevalence in the least deprived children. This inequality gap has shown to significantly increase by around 0.5% every year, showing inequalities are continuing to widen[29]. Analysis of cohort trends is limited because it does not explore how the weight status of individuals changes over time, and is unable to explore the influence of sex and deprivation in depth. The analysis of individual children in the MCS identified a protective effect against obesity in more affluent obese boys, which would not have been seen in an analysis of cohort trends. Hence, this finding highlights the importance of obtaining linked NCMP data.

Following a change in NCMP legislation in 2013[30], it is now possible to upload identifiable data through an NHS number, which, if submitted, will facilitate data linkage, and future tracking analyses. Since there are seven years between the two measurements, the earliest any national tracking analyses could be undertaken is 2019. That said, NCMP data can be obtained locally in those areas where data have been stored on the Child Health System (CHIS), although there are lengthy and time consuming governance procedures to overcome in order to access these data. Examples of local authorities that have obtained data via CHIS include Hull[31] and Southampton[32]; however, not all data was collected through the NCMP as some measurements were collected before the start of the NCMP.

The main limitation to this analysis was the large amount of missing data between baseline (age 5) and follow up (age 11) where it was possible that these data might be missing not at random. However, we were able to conduct a sensitivity analysis, which showed only small differences in predicted probabilities when data was imputed under a missing not a random assumption. This finding is noteworthy, as we allowed for a large departure from the missing at random assumption, with imputed follow-up BMI values inflated by 25%. A second limitation was that some children were older than 5 years old at baseline and 11 years old at follow up; however, the majority of children were close to these ages. Also, only 1.1% of the cohort were underweight at age 5 and only 1.6% were underweight at age 11. Furthermore, only 2.9% and 4.1% of children were categorised as severely obese at age 5 and age 11, respectively. Hence, even though we analysed over 12 000 cases, a much larger sample would be required to be able to make robust predictions using these two categories. In addition, BMI may not be the most accurate measure of a child's weight status as it has shown to not always strongly correlate with body fat distribution.[(33)] However, BMI is the preferred method to use in a large sample as it is relatively quick to measure, less invasive than many other body fat assessments, and has shown to be a relatively robust measurement at a population level.[(34)] A final limitation of the analysis is that the majority of the sample was of white ethnicity; hence, we were unable to explore the influence of ethnicity, which has shown to strongly affect the likelihood of developing obesity.[35, 36] Furthermore, the majority of children were sampled from England; hence, we were unable to conduct a country-by-country analysis.

At present MCS data are only freely available up age 11; it will be interesting to explore what effect a longer follow up period has on predicting whether children will become overweight or obese in later life, especially as adolescence is anticipated to be an important predictor of adult weight status.[37] In addition, it would be worthwhile to perform further analyses looking at the effect of physical activity and nutrition on changes in BMI, and also explore what factors contribute to the protective effect against obesity in non-deprived obese boys.

To conclude, this secondary data analysis has demonstrated how weight status can be tracked robustly and informatively over time. Such methods could be applied to other longitudinal datasets such as the NCMP.

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Conflict of interests

Dr Louisa Ells is seconded to Public Health England 2 days per week as a specialist academic advisor.

Supplementary material is available on NUTD’s website.

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		Predicted percent chances of becoming each weight status category at age 11 (95%CI)			
Weight status category and sex at age 5		*Underweight*	*Normal weight*	*Overweight*	*Obese inc. severe*
Underweight	*Male*	14.2 (1.9 to 26.4)	82.2 (70.6 to 93.9)	2.6 (-0.7 to 5.8)	1.0 (-0.4 to 2.4)
	Female	29.9 (16.9 to 42.8)	68.2 (55.7 to 80.7)	1.4 (0.8 to 2.0)	0.5 (0.3 to 0.8)
Normal weight	*Male*	1.4 (1.1 to 1.7)	79.7 (78.4 to 81.0)	13.0 (12.0 to 13.9)	5.9 (5.3 to 6.5)
	Female	1.6 (1.3 to 1.9)	80.9 (79.7 to 82.0)	12.1 (11.3 to 12.9)	5.4 (4.9 to 6.0)
Overweight	*Male*	0.2 (0.2 to 0.3)	38.4 (34.5 to 42.3)	31.1 (29.5 to 32.7)	30.3 (26.7 to 33.9)
	Female	0.2 (0.1 to 0.2)	34.4 (30.7 to 38.0)	31.0 (29.4 to 32.6)	34.4 (31.0 to 37.9)
Obese inc. severe	*Male*	0.0 (0.0 to 0.1)	11.8 (8.6 to 15.1)	20.6 (17.4 to 23.8)	67.6 (61.4 to 73.7)
	Female	0.0 (0.0 to 0.1)	10.9 (7.8 to 14.0)	20.2 (16.3 to 24.2)	68.8 (61.9 to 75.8)

**numbers are rounded to 1 decimal place*

Table 1: *The predicted percent chances of child becoming underweight, normal weight, overweight and obese at age 11 based on their weight status at age 5 and sex.*

Weight status, sex and IMD (fifths) at age 5			Predicted percent chances of becoming obese (including severe) at age 11 (95%CI)
Normal weight	*Male*	*Most deprived (0-20%)*	7.4 (6.2 to 8.6)
		Least deprived (80-100%)	4.7 (3.9 to 5.5)
	Female	*Most deprived (0-20%)*	6.6 (5.5 to 7.7)
		Least deprived (80-100%)	3.9 (3.0 to 4.7)
Overweight	*Male*	*Most deprived (0-20%)*	37.2 (29.2 to 45.3)
		Least deprived (80-100%)	27.0 (20.3 to 33.6)
	Female	*Most deprived (0-20%)*	38.0 (30.7 to 45.3)
		Least deprived (80-100%)	30.9 (22.2 to 39.5)
Obese inc. severe	*Male*	*Most deprived (0-20%)*	71.4 (61.6 to 81.2)
		Least deprived (80-100%)	49.6 (34.0 to 65.2)
	Female	*Most deprived (0-20%)*	62.9 (50.9 to 74.9)
		Least deprived (80-100%)	69.9 (51.2 to 88.6)

*numbers are rounded to 1 decimal place

Table 2: *The predicted percent chances of a most and least deprived child becoming obese at age 11 based on their weight status at age 5 and sex*

Weight status, sex and IMD (fifths) at age 5			Predicted percent chances of becoming severely obese at age 11 (95%CI)
Normal weight	*Male*	*Most deprived (0-20%)*	1.5 (1.2 to 1.8)
		Least deprived (80-100%)	0.9 (0.7 to 1.1)
	Female	*Most deprived (0-20%)*	1.3 (1.0 to 1.6)
		Least deprived (80-100%)	0.8 (0.6 to 0.9)
Overweight	*Male*	*Most deprived (0-20%)*	10.2 (7.0 to 13.5)
		Least deprived (80-100%)	6.5 (4.4 to 8.5)
	Female	*Most deprived (0-20%)*	10.2 (7.2 to 13.1)
		Least deprived (80-100%)	7.6 (4.7 to 10.5)
Obese (not inc. severe)	*Male*	*Most deprived (0-20%)*	23.8 (13.1 to 34.5)
		Least deprived (80-100%)	12.9 (6.8 to 19.0)
	Female	*Most deprived (0-20%)*	18.9 (11.0 to 26.8)
		Least deprived (80-100%)	22.4 (11.3 to 33.4)
Severely obese	*Male*	*Most deprived (0-20%)*	58.7 (41.7 to 75.7)
		Least deprived (80-100%)	32.0 (-3.7 to 67.8)
	Female	*Most deprived (0-20%)*	46.5 (24.6 to 68.4)
		Least deprived (80-100%)	76.8 (52.7 to 100)

*numbers are rounded to 1 decimal place

Table 3: The predicted percent chances of a most and least deprived child becoming severely obese at age 11 based on their weight status at age 5 and sex

Weight status, sex and IMD (fifths) at age 5			Predicted percent chances of becoming obese (including severe) category at age 11 (95%CI)
Normal weight	*Male*	*Most deprived (0-20%)*	16.3 (14.5 to 18.1)
		Least deprived (80-100%)	9.1 (7.7 to 10.5)
	Female	*Most deprived (0-20%)*	13.1 (11.4 to 14.9)
		Least deprived (80-100%)	7.5 (6.2 to 8.8)
Overweight	*Male*	*Most deprived (0-20%)*	55.5 (48.9 to 621)
		Least deprived (80-100%)	37.9 (30.6 to 45.2)
	Female	*Most deprived (0-20%)*	53.1 (46.7 to 59.5)
		Least deprived (80-100%)	42.1 (33.1 to 51.1)
Obese inc. severe	*Male*	*Most deprived (0-20%)*	82.2 (75.4 to 89.1)
		Least deprived (80-100%)	52.5 (40.3 to 64.7)
	Female	*Most deprived (0-20%)*	74.1 (65.8 to 82.5)
		Least deprived (80-100%)	75.7 (59.3 to 92.0)

*numbers are rounded to 1 decimal place

Table 4: Sensitivity analysis - multiple imputation of missing data showing the predicted percent chances of a most and least deprived child becoming obese at age 11 based on their weight status at age 5 and sex