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The timing of carbohydrate intake in UK adults, using the National Dietary and Nutrition Survey (NDNS) 2008-2014 programme

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Declaration of Authorship

I, Chaochen WANG, declare that this thesis titled, "The timing of carbohydrate intake in UK adults, using the National Dietary and Nutrition Survey (NDNS) 2008-2014 programme" and the work presented in it are my own. I confirm that:

- This work was done wholly or mainly while in candidature for a MSc degree on Medical Statistics at this University.
- No part of this thesis has previously been submitted for a degree or any other qualification at this University or any other institution.
- Where I have consulted the published work of others, this is always clearly attributed.
- Where I have quoted from the work of others, the source is always given. With the exception of such quotations, this thesis is entirely my own work.
- I have acknowledged all main sources of help.
- Where the thesis is based on work done by myself jointly with others, I have made clear exactly what was done by others and what I have contributed myself.

Signed:

Date:

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I also want to express my gratitude to my family for their unconditional support, understanding, and encouragement throughout this year.

"All models are wrong, but some are useful."

George E. P. Box

Abstract

The National Dietary and Nutrition Survey (NDNS) database of detailed four-day food diaries was used to . . .

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List of Abbreviations

AIC	**A**kaike **I**information **C**riterion
aBIC	**a**djusted **B**ayesian **I**nformation **C**riterion
BMI	**B**ody **M**ass **I**ndex
BIC	**B**ayesian **I**information **C**riterion
DM	**D**iabetes **M**ellitus
EM	**E**xpectation **M**aximazation
FSA	**F**ood **S**tandards **A**gency
HbA1c	**H**emoglobin **A1c**: Glycated hemoglobin
LCA	**L**atent **C**lass **A**nalysis
LCGA	**L**atent **C**lass **G**rowth **A**nalysis
MAFF	**M**inistry of **A**griculture, **F**isheries and **F**ood
MAR	**M**issing **A**t **R**andom
MCAR	**M**issing **C**ompletely **A**t **R**andom
MLCA	**M**ultilevel **L**atent **C**lass **A**nalysis
MNAR	**M**issing **N**ot **A**t **R**andom
ML	**M**aximum **L**ikelihood
NDNS	the **N**ational **D**ietary and **N**utrition **S**urvey
OR	**O**dds **R**atio
PHE	**P**ublic **H**ealth **E**ngland
PSUs	**P**rimary **S**ampling **U**nits

Chapter 1

Introduction

Background

The widely accepted standard these days seems to be that we eat three times a day. However, whether this is really an ideal temporal eating pattern for everyone has never been answered with evidence. More importantly, the actual temporal patterns of eating in the population, proportions of people who actually manage/fail to follow this so-called doctrine have not been described thoroughly.

The importance of the circadian rhythm in regulating physiological responses has been recognised for long, while the impact of which on nutrition and metabolism is still largely unknown (Johnston, 2014; Asher and Sassone-Corsi, 2015).

Although nutritional studies have extensively examined the influence of the quantity and quality of dietary and nutrients intake and their alteration on morbidity and mortality, investigations on temporal eating patterns and their effects are still scarce. Some recent evidence have found that meal timing is associated with a wide variety of health outcomes. Skipping breakfast is associated with higher risk of type 2 diabetes (Uemura et al., 2015). Shift workers have a higher risk of developing metabolic syndrome (De Bacquer et al., 2009) and type 2 diabetes (Pan et al., 2011). Evening intake of energy is positively associated with overweight/obesity (Almoosawi et al., 2016).

More recently, discernible temporal eating patterns that differed by sociodemographic and eating profiles were revealed by latent class analysis using nutrition survey data (Leech et al., 2017; Mansukhani and Palla, 2018). Based on total energy consumption, the presence of 3 groups of eaters: grazers, early eaters, and late eaters were identified. So far, the temporal eating patterns were only based on averaging the total energy intake calculated from one or two days dietary recall, and therefore could not capture the day-to-day variation in temporal eating patterns.

(some review of articles about carbohydrate eating)

The National Dietary and Nutrition Survey (NDNS)

The National Diet and Nutrition Survey (NDNS) programme (NatCen Social Research, 2018) was initially established in 1992 and started off as a joint initiative between the Ministry of Agriculture, Fisheries and Food (MAFF) and the Department of Health. In 2008, a new continuous cross-sectional survey was started, the NDNS Rolling Programme (RP). The NDNS RP is funded by Public Health England (PHE), an executive agency of the Department of Health, and the UK Food Standards Agency (FSA). The survey covers a representative sample of around 1000 people per year. Fieldwork began in 2008 and is now beginning its eleventh year. NDNS provides essential evidence on the diet and nutrition of the UK population to enable PHE to identify and address nutritional issues in the population and monitor progress towards public health nutrition objectives.

The NDNS RP has now completed and analysed its eighth year. The sample was randomly drawn from a list of all the addresses, clustered into postcode sectors from across the UK. Overall, for years 1-8 combined, a sample of 39,300 addresses was selected from 799 (year 1-4), 323 (year 5-6), and 316 (year 7-8) postcode sectors. At each address, one household was selected at random (in cases where there were two or more households). For each household, either an adult and a child, or a child only, was selected to participate.

These individuals were asked to keep a four-day diary on their food and drink consumption on consecutive days. An interview and a nurse visit were also conducted to collect information regarding height and weight, smoking and drinking habits, physical activity, blood pressure, prescribed medicines, dietary supplements, fasting blood sample, and 24-hour urine sample.

Aims and objectives

Our goal is to explore and make use of the NDNS RP (2008/09-2015/16) database to describe and identify the potential relationship between the timing of eating within the day and specific nutrient–carbohydrate intake. We aimed at finding time patterns of consumption of carbohydrate and defining latent groups in the UK adults. Subsequently, an additional potential aim, is to investigate the association between eating time patterns with diabetes and obesity.

Chapter 2

Methods

Dietary diary collected in the NDNS RP

Participants were asked to keep a record of everything eaten or drunk over four consecutive days. Interviewers undertook three visits with each participant. At the first visit, the interviewer explained the method followed a protocol, taking participants through the sections in the diary including how to describe details of food and drink and portion size and an example day. The second was a brief visit to check for compliance, answer questions or deal with problems and review the diary to identify and edit possible omissions and missing detail. The third visit was to collect the diary and again review and edit possible omissions.

In the diary, participants were asked to record portion sizes in household measures (e.g. one tablespoon of beans, one Kit Kat finger-size), or for packaged foods to note the weight indicated on the packet. For homemade dishes, participants were asked to record on a separate page in the diary the individual ingredients and quantities for the whole dish along with a brief description of the cooking method and how much of dish they had consumed. In addition to details of what and how much was eaten, participants recorded for each eating occasion; when was it, where they were, who they were eating with. An example, used as guidance for participants, of a food diary for one day is shown in **Appendix C**.

Definition of carbohydrate intake

Detailed dairy checking was performed to code and convert the food consumption into energy and nutrients intake. Intakes of nutrients were calculated from the food consumption records using a specially adapted Nutrient Databank (Smithers, 1993), which was originally developed by the Ministry of Agriculture, Fisheries and Food (MAFF) for the Dietary and Nutritional Survey of British Adults. Further details of data coding and editing are outlined in Appendix A of the NDNS official reports

(Department of Health, 2018). Specifically, the main variables that we adopted in the current analysis were defined as:

- Total Energy intake = (protein(gramme) $\times$ 17) + (fat(gramme) $\times$ 37) + (carbohydrate(gramme) $\times$ 16) + (alcohol(gramme) $\times$ 29) kJ;
- Carbohydrate intake = total sugars (gramme) + starch (gramme);

To produce a sequence of discrete responses about the carbohydrate intake we are interested, we calculated the energy consumption per hour for each participant. The percentage of energy that contributed by carbohydrate within each hour were calculated for every every participant, each single day. Since we planed to apply latent class analysis (LCA) in the current study, in which the observed indicators for latent classes must be categorical, we then dichotomised the responses according to the carbohydrate contribution to the energy intake at cut-off value of 50%, i.e. if within an hour there is any energy intake occured, carbohydrate consumption was categorised into whether it's energy contribution was lower or higher/equal to 50% of total energy intake within that hour. Consequently, for each day of the recording, there were 24 data points generated by the dairy, each data point included one of the following responses:

- Not eating any food;
- Eating, and carbohydrate contributed less than 50% of the total energy intake;
- Eating, and carbohydrate contributed higher or equal to 50% of the total energy intake.

Survey Data

Survey Selection Method

The NDNS RP participants were drawn from the UK Postcode Address File, a list of all the addresses in the UK. The addresses were clustered into Primary Sampling Units (PSUs), small geographical areas, based on postcode sectors, randomly selected from across the UK. A list of 27 or 28 addresses was then randomly selected from each PSU.

Overall, for years 1 to 8 combined, a sample of 39,300 address was selected from 1,438 PSUs. The sampling selection process was:

- Randomly select PSUs from the Postcode Address File;
- Randomly select 27 or 28 addresses in that postcode area;

- Randomly select one household at that address;
- Selected addresses were randomly allocated to one of two groups to determine whether an adult (aged 19 years or older) and a child (aged 1.5 to 18 years), or a child only, were selected for interview.

Response rates

The response rates for completion of the food diary (three or four days) were 56%, 53%, 53%, for years 1 to 4, 5 to 6, and 7 to 8, respectively. A total of 6,155 adults aged 19 years and over were kept in our analysis.

Strata and weightings

It is necessary to apply weighting factors to the data collected in the NDNS RP for two reasons: to remove any bias in the observed results which may be due to differences in the probability of households and individuals being selected to take part; and to attempt to reduce differential non-response bias by age, sex and geographical region.

The strata that used to calibrate proportions in the sample include: age-group (1.5-3, 4-6, 7-10, 11-15, 16-18, 19-24, 25-29, 30-39, 40-49, 50-59, 60-64, 65-69, and over 70 years); sex (men or women); and regions (Northern Ireland, Scotland, Wales, and the nine regions of England).

Two steps of weighting system are designed in the NDNS RP to assure that the combined sample will be representative of the UK population:

1. An overall selection weight, which is the product of the address, dwelling unit, catering(household) unit, and individual selection weights, was generated to correct for the unequal selection probabilities. These weights are the inverse of the selection probabilities at each level of the random sampling process and they can be used to compensate for differences in the chance of selection of an individual.
2. An iterative procedure was used to adjust the selection weights until the distribution of the weighted sample matched that of the population for age-group, sex and geographical region. Population distributions were taken from the mid-year population estimates (Office for National Statistics, 2018).

Another set of weights were generated to correct for differential non-response (either due to refusal or inability) to giving a blood sample. Response to the blood sample in adults were 51%, 57%, and 50% for years 1 to 4, 5 to 6, and 7 to 8, respectively. In creating the blood sample weight, a logistic regression was used by the NDNS RP study team to model the relationship between response to giving blood sample and a set of predictor variables (socio-demographic, participant and catering/household unit characteristics). The model generated a predicted probability for each participant, which is the probability would provide blood sample, given the characteristics of the individual and the household unit. Participants with characteristics associated with non-response were under-represented in the blood sample and therefore receive a low predicted probability. The inverse of these predicted probablities were used as a set of non-response weights so that participants with a low predicted probability got a larger weight, increasing their representation in the sample. Then the blood sample weights were re-scaled so that the sum of the weights equalled the number of participants who had a nurse visit. The final blood weights should therefore make the blood sample participants representative of all eligible persons in the population.

Further details of the weighting system developed by the NDNS RP are described in the Appendix B of the reports published by Public Health England (PHE) (Bates et al., 2014; Roberts et al., 2018).

Latent Class Analysis (LCA)

Latent class analysis is a statistical technique that identifies categorical latent (unobserved) class variables on the basis of observed categorical variables (Collins and Lanza, 2010). It belongs to the family of latent variable models, and is directly analogous to the factor analysis model. The major difference is that the latent variable in LCA is categorical, not continuous as in factor analysis. The basic assumptions in LCA are independent observations, and local independence, as shown in the fundamental expression of a typical LCA model:

$$P(U_{i1} = s_1, U_{i2} = s_2, \cdots, U_{ik} = s_K) = \sum_{t=t}^{T} P(C_i = t) \prod_{k=1}^{K} P(U_{ik} = s_k | C_i = t) \quad (2.1)$$

Where,

- $P(U_{i1} = s_1, U_{i2} = s_2, \cdots, U_{ik} = s_k)$ is the probability of observing a particular vector of responses;
- $P(C_i = t)$ is the probability that a randomly selected ith observation will be in class t;
- $P(U_{ik} = s_k | C_i = t)$ is the probability of a particular observed response pattern $U_{ik} = s_k$ conditional on membership in latent class t.

Equation 2.1 indicates that responses for an observation to the measuring variables are independent of one another given its membership in latent class t. However, in the NDNS RP data set, the assumption of independent observations is violated. Each individual completed their dietary diary for four consecutive days, their diary recordings were later converted into 4 sequences of categorical responses reflecting the type of carbohydrate consumption at each hour of the day. The 4 observed sequences (observations) are nested in the participants and therefore are not independent. This nested data structure requires multilevel techniques.

Multilevel Latent Class Analysis (MLCA)

Multilevel latent class analysis accounts for the nested structure of the data by allowing latent class intercepts to vary across level 2 units and thereby examining if and how level 2 units influence the level 1 latent classes. These random intercepts allow the probability of membership in a particular level 1 (observations) latent class to vary across level 2 units (e.g., here in the current context are the individuals). Essentially this allows the probability that an observation will belong to a particular level 1 latent class to vary across Level 2 units (individuals).

Parametric approach

Proposed by Vermunt (Vermunt, 2003; Vermunt, 2008) and Asparouhov and Muthén (Muthén and Asparouhov, 2009), a traditional, parametric approach can be applied using a logistic regression model. In an unconditional logistic regression model, the probability of the outcome (i.e. being in latent class k) is constant within the 4-day survey for each individual (level 2). Therefore, say when we are fitting a model with $k(k = 1, \cdots, K)$ latent classes in level 1, then in each individual (level 2), there is a probability of being in latent class k. A random effect model consider the individual (level 2) to be drawn from a population of adults in the UK, and the probability of the outcome (i.e. being in latent class k) across individuals is considered to be a random variable (Snijders and Bosker, 2011). The 2-level random intercept effect regression model can be expressed as:

$$
\begin{aligned}
\text{logit}[P(C_{ij} = t)] &= \beta_{0j} && \textbf{(level 1)} \\
\beta_{0j} &= \gamma_0 + \gamma_1 w_j + u_{0j} && \textbf{(level 2)} \\
\Rightarrow P(C_{ij} = t) &= \frac{\exp\left(\gamma_0 + \gamma_1 w_j + u_{0j}\right)}{1 + \exp\left(\gamma_0 + \gamma_1 w_j + u_{0j}\right)}
\end{aligned}
\tag{2.2}
$$

Where we define:

- $P(C_{ij} = t)$ as the probability that the randomly selected ith observation of jth individual is belonging to latent class t;
- u_{0j} as the random intercept for jth individual;
- the random intercept are assumed be normally distributed (i.e. $u_{0j} \sim N(0, \sigma^2_{u_0})$), the magnitude of the u_{0j} variance ($\sigma^2_{u_0}$) indicates the influence of the individuals (level 2);
- w_j is the predictor for individual (level 2), such as age, and/or sex.

Same as in the typical LCA models, the latent class variable in a MLCA is defined by multiple observed indicators (here is defined by the responses of eating carbohydrate within each hour, over 24 hours and during 4 consecutive days of survey period). Considering that the latent class indicators are indicator variables (U_{ijk}), the MLCA model can be written as follows:

$$P(U_{ij1} = s_1, U_{ij2} = s_2, \cdots, U_{ijk} = s_K) = \sum_{t=1}^{T} P(C_{ij} = t) \prod_{k=1}^{K} P(U_{ijk} = s_k | C_{ij} = t) \tag{2.3}$$

Where,

- U_{ijk} represents the response of eating high/low carbohydrate on ith day of the survey ($i \in (1, 2, 3, 4)$) in subject j (level 2) at the kth hour of the day ($k \in (1, 2, 3, \cdots, 24)$);
- C_{ij} denotes the latent class membership for subject j on ith day of the survey;
- A specific latent class is referred to as t, and the total number of level 1 latent classes is denoted by T;
- $P(U_{ijk} = s_k | C_{ij} = t)$ is the probability of a specific response pattern, conditional on membership in latent class t.

The $P(C_{ij} = t)$ in equation 2.3 is what we have already defined in equation 2.2.

Non-Parametric approach

Another approach is using a non-parametric MLCA, in which separate latent class models are specified for level 1 and level 2. Similar with the parametric MLCA approach, there are $T - 1$ random intercepts, where T is the number of level 1 latent classes. However, rather than assuming the random intercepts following a normal distribution, the non-parametric MLCA assumes a multinomial (discrete) distribution of the level 2 latent classes. This approach is less computationally demanding compared with the parametric approach. These level 2 latent classes reflect differences in the probability of belonging to a specific level 1 latent class, so that clusters (i.e., individuals) that contain observations with similar probabilities for the level 1 latent classes will be grouped together. The non-parametric MLCA model can be defined as follows:

$$P(C_{ij} = t | CB_j = m) = \frac{\exp(\gamma_{tm})}{\sum_{r=1}^{T} \exp(\gamma_{tm})} \tag{2.4}$$

Where,

- CB_j is level 2 latent class membership for jth individual;
- γ_{tm} is level 1 and level 2 indicators.

According to Finch and French's simulation study (Finch and French, 2014), non-parametric approach generally resulted in more accurate recovery of the underlying latent structure of the data at both levels and provided better latent class model. Specifically, we are interested in exploring meaningful individual (level 2) latent classes rather than their daily consumption classification. Therefore, non-parametric MLCA was employed 1) to identify latent classes of observations (level 1) based on the subjects' responses to the 4-day food and drink diary and 2) to form distinct latent classes of individuals (level 2) based on the distribution of observation-level latent classes within individuals.

Strategy of conducting MLCA in the current analysis

To identify the best-fitting model, we used the following sequential modelling strategy (Henry and Muthén, 2010):

- Firstly, we ignored the multilevel structure of the data and estimated a series of traditional LC models to determine the number of classes at the observational-level;
- Next, a series of MLCA models were fitted to account for the multi-level structrure of the data. In these models, the number of observational-level classes was based on the best fitting LCA model from the first step, and the LCA model at the individual-level was estimated to identify the number of individual-level latent classes;
- Thirdly, when number of individual-level latent classes is defined based on the previous stage, observational-level classes was modified (one class lower and one class higher than in the second step), to see the effect of changing level 1 classes and confirm the best fitting model.

The number of classes in either level 1 were determined by 1) the evaluation of model fit indices, including the Akaike information criterion (AIC), Bayesian information criterion (BIC), adjusted Bayesian information criterion (aBIC) where smaller values indicate better, and entropy which is a statistic that summarizes latent class probabilities where values near 1 indicate better latent class separation; 2) the Lo-Mendell-Rubin Likelihood Ratio Test (LMR-LRT) (Lo, Mendell, and Rubin, 2001; Nylund, Asparouhov, and Muthén, 2007) which compare q vs. $q-1$ class models, where q is the number of latent classes and 3) pattern interpretability. In the step of performing multilevel LCA, where neither LMR-LRT nor BS-LRT were available, same rules of model fit indices and pattern interpretability were used to determine the optimal combination of latent classes in level 1 and level 2.

Latent Class Growth Analysis (LCGA)

LCGA is a semi-parametric technique used to identify distinct subgroups of individuals following a similar pattern of change over time on a given variable. The analysis identifies distinct subgroups of individuals following a distinct pattern of change over time. LCGA is a special type of Growth Mixture Models (GMM), in which the variance of latent slope and intercept are fixed to zero within class, and allowed to vary only across classes. LCGA assumes that all individual growth trajectories within classes are homogeneous.

In the NDNS RP data context, we considered a latent categorical variable c_i representing the unobserved subpopulation membership (latent class variable) for participant $i, (c_i = 1, 2, \cdots K)$.

Association between latent classes and other variables

Chapter 3

Results

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Subsection 1

Subsection 2

Main Section 2

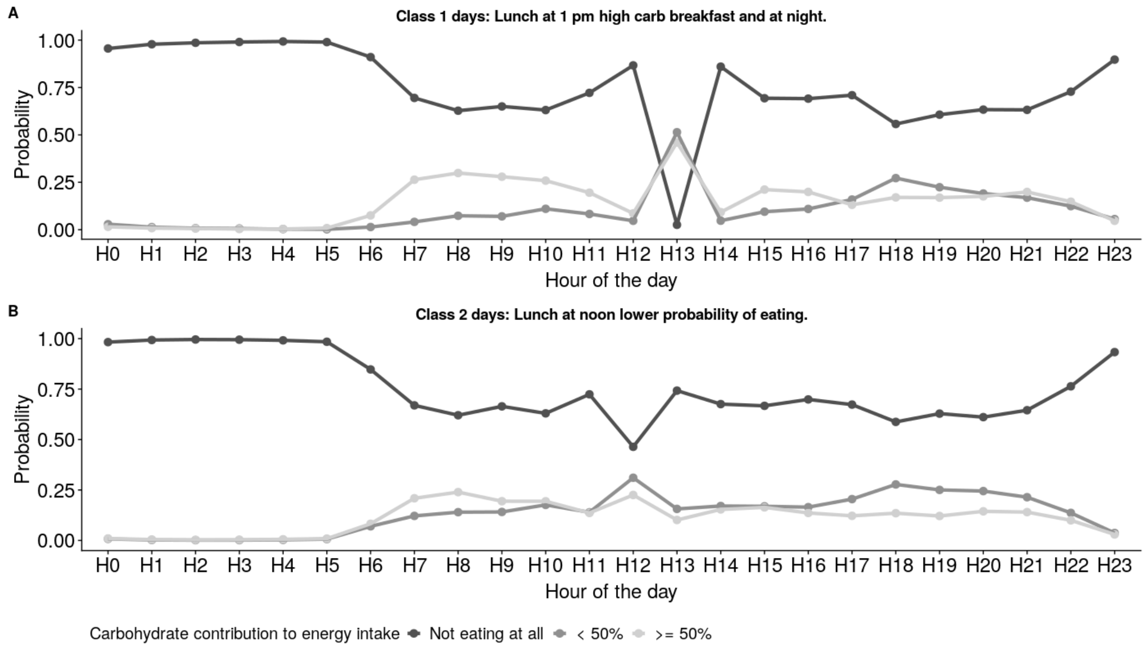

FIGURE 3.1: Carbohydrate temporal eating patterns at observational day level.

TABLE 3.1: Fit Criteria for Each Model Specification

	Number of level 1 classes				
Model	1 class	2 classes	3 classes	4 classes	5 classes
Fixed effects model					
No. of free parameters	48	97	146	195	244
Log-likelihood	-372017.293	-368913.708	-366664.971	-365528.553	-364901.166
BIC	744519.661	738807.672	734805.379	733027.723	732268.13
Lo-Mendell-Rubun LRT	—	< 0.0001	< 0.0001	0.8478	0.7602
Entropy	1	0.777	0.666	0.658	0.648
Random effects model					
2 between classes					
No. of free parameters		195	293	391	
Log-likelihood		-363460.153	-361571.164	-360297.394	
BIC		728890.925	726103.308	724546.13	
Entropy		0.834	0.798	0.784	
3 between classes					
No. of free parameters		293	440	587	
Log-likelihood		-360910.13	-358902.821	-357404.521	
BIC		724781.241	722252.166	720741.109	
Entropy		0.824	0.793	0.824	
4 between classes					
No. of free parameters		391	587	783	
Log-likelihood		-358684.859	-356668.354	-355235.955	
BIC		720078.473	719268.774	718384.699	
Entropy		0.816	0.817	0.806	

Note:
Abbreviation: No, number; BIC, Bayesian information criterion; Entropy, a pseudo-r-squared index; Lo-Mendel-Rubin LRT, likelihood ratio test comparing q classes models with $q-1$ classes models.

TABLE 3.2: Means, percentages, and 95% CIs of the characteristics of carbohydrate temporal eating patterns by MLCA memberships in the UK adults (NDNS RP 2008/09-2015/16, sample size = 6155).

	Latent class = 1	Latent class = 2	P value *
Total (%)	66.4 (64.8 , 68.1)	33.6 (31.9 , 35.2)	
Countries (%)			
England	83.1 (80.9 , 85.1)	85.4 (83.0 , 87.5)	0.203
Northern Ireland	3.0 (2.3 , 3.9)	2.3 (1.7 , 3.1)	
Scotland	8.9 (7.2 , 11.0)	7.7 (5.9 , 9.9)	
Wales	5.0 (4.1 , 6.0)	4.6 (3.6 , 6.0)	
Age (years)	47.3 (46.4, 48.2)	50.1 (49.1, 51.1)	< 0.001
Sex (%)			
Men	47.3 (45.2 , 49.5)	51.0 (48.1 , 53.9)	0.048
Women	52.7 (50.5 , 54.8)	49.0 (46.1 , 51.9)	
Survey years (%)			
1	13.1 (10.8, 15.8)	15.0 (12.1, 18.5)	0.365
2	12.3 (10.1, 14.9)	11.9 (9.4, 14.2)	
3	12.0 (9.8, 14.8)	10.4 (8.2, 13.1)	
4	13.2 (10.9, 16.0)	11.4 (9.0, 14.2)	
5	13.0 (10.8, 15.7)	13.9 (11.1, 17.3)	
6	12.0 (9.9, 14.4)	11.1 (8.8, 13.9)	
7	12.3 (10.1,14.9)	13.5 (10.9, 16.7)	
8	12.0 (9.9, 14.5)	12.8 (10.3, 15.8)	
BMI (kg/m^2)	27.2 (26.9, 27.5)	27.7 (27.5, 28.1)	0.007
WC (cm)	92.6 (91.9, 93.3)	94.2 (93.1, 95.2)	0.013
Smoking status (%)			
Current	19.8 (18.2 , 21.4)	23.8 (21.3 , 26.5)	< 0.001
Ex-smoker	22.5 (20.8 , 24.2)	28.0 (25.4 , 30.7)	
Never	57.8 (55.7 , 59.8)	48.2 (45.3 , 51.1)	
Current drinking status (%)			
Yes	23.1 (21.3 , 25.1)	11.1 (9.5 , 13.0)	< 0.001
Hypertension (%) †			
Yes	27.4 (25.0 , 29.9)	32.6 (29.3 , 36.1)	0.012
Total energy intake (KJ)	7425.7 (7323.7, 7527.8)	8149.9 (7997.3, 8302.7)	< 0.001
Carbohydrate intake (g)	226.0 (222.8, 229.3)	210 (206.1, 213.9)	< 0.001
Carbohydrate percent (%) ‡	48.3 (48.0, 48.6)	40.9 (40.6, 41.3)	< 0.001
Glucose (mmol/l)	5.13 (5.09, 5.17)	5.17 (5.11, 5.22)	0.292
A1C (%)	5.49 (5.47, 5.52)	5.47 (5.44,5.51)	0.264
DM §	4.1 (3.1 , 5.3)	5.9 (4.3 , 8.0)	0.061
Physical activity (hours/day) ¶	1.51 (1.39, 1.63)	1.64 (1.45, 1.82)	0.244

Note:
Abbreviations: CI, confidence intervals; MLCA, multilevel latent class analysis; NDNS RP, national dietary and nutrition survey rolling programme; BMI body mass index; WC, waist circumference; A1C, haemoglobin A1c;DM, diabetes mellitus; h, hour.
Variables from the blood tests (glucose and A1C) are weighted by blood sample weights, the others are weighted by individual weights.
Glucose and A1C levels are estimated in subgroups of people without diabetes.
Variables from the blood tests (glucose and A1C) are weighted by blood sample weights, the others are weighted by individual weights.
Glucose and A1C levels are estimated in subgroups of people without diabetes.
* For continuous variables, the F test was used to determine differences between latent classes. For categorical variables, differences between latent classes were assessed using the adjusted Pearson Chi-2 test for survey data.
† Hypertension was defined as either systolic blood pressure >= 140 mmHg or diastolic blood pressure >= 90 mmHg, or under treatment for hypertension.
‡ Carbohydrate percent indicates the percentage of energy from carbohydrate in total energy intake
§ DM was defined by A1C > 6.5%.
¶ Physical activity was calculated as mean time spent at moderate or vigorous physical activity during the survey.

TABLE 3.3: Means, percentages, and 95% CIs of the characteristics of carbohydrate temporal eating patterns by LCGA memberships in the UK adults (NDNS RP 2008/09-2015/16, sample size = 6155).

	Latent class = 1	Latent class = 2	Latent class = 3	P value *
Total (%)	28.4 (26.8, 30.1)	7.0 (6.2, 7.9)	64.6 (62.9, 66.2)	
Countries (%)				
England	81.4 (78.5, 84.0)	87.5 (82.9, 91.0)	84.6 (82.5, 86.4)	0.004
Northern Ireland	3.9 (2.9, 5.1)	0.6 (0.3, 1.2)	2.5 (2.0, 3.2)	
Scotland	9.5 (7.4, 12.3)	6.2 (3.5, 10.6)	8.3 (6.7, 10.3)	
Wales	5.2 (4.1, 6.6)	5.7 (3.8, 8.5)	4.6 (3.8, 5.6)	
Age (years)	43.8 (42.4, 45.1)	49.1 (47.2, 50.9)	50.1 (49.3, 50.9)	< 0.001
Sex (%)				
Men	50.6 (47.3, 53.9)	49.6 (43.7, 55.4)	47.6 (45.4, 49.7)	0.273
Women	49.4 (46.1, 52.7)	50.4 (44.6, 56.3)	52.4 (50.3, 54.6)	
Survey years (%)				
1	11.4 (8.8, 14.7)	17.1 (12.4, 23.3)	14.4 (11.9, 17.4)	0.002
2	10.1 (7.8, 13.1)	18.3 (13.3, 24.7)	12.4 (10.2, 15.0)	
3	13.9 (10.8, 17.7)	9.1 (5.7, 14.1)	10.7 (8.6, 13.1)	
4	10.9 (8.5, 13.9)	13.8 (9.7, 19.4)	13.2 (10.9, 16.0)	
5	13.5 (10.6, 17.0)	12.8 (8.4, 19.1)	13.3 (11.0, 16.1)	
6	12.8 (10.1, 16.1)	8.7 (5.7, 12.9)	11.5 (9.5, 13.9)	
7	14.3 (11.5, 17.6)	9.5 (6.5, 13.8)	12.4 (10.2, 15.0)	
8	13.2 (10.5, 16.4)	10.5 (7.4, 14.8)	12.1 (9.9, 14.6)	
BMI (kg/m^2)	27.5 (27.1, 27.9)	27.0 (26.4, 27.6)	27.4 (27.2, 27.6)	0.433
WC (cm)	93.3 (92.1, 94.5)	92.9 (90.9, 95.0)	93.1 (92.3, 93.8)	0.928
Smoking status (%)				
Current	24.1 (21.5, 27.0)	30.0 (24.8, 35.8)	18.8 (17.2, 20.6)	< 0.001
Ex-smoker	20.0 (17.6, 22.6)	27.5 (22.4, 33.2)	25.9 (24.1, 27.7)	
Never	55.9 (52.7, 59.0)	42.5 (36.6, 48.7)	55.3 (53.2, 57.4)	
Current drinking status (%)				
Yes	24.6 (21.7, 27.7)	18.3 (14.0, 23.6)	16.8 (15.3, 18.4)	< 0.001
Hypertension (%) †				
Yes	25.9 (22.3, 29.9)	31.8 (25.3, 39.1)	30.4 (27.9 32.8)	0.111
Total energy intake (KJ)	6713.8 (6575.7, 6851.8)	9256.0 (8850.8, 9661.2)	7916.9 (7814.0, 8019.9)	< 0.001
Carbohydrate intake (g)	192.9 (188.5, 197.3)	275.6 (263.4, 287.8)	226.9 (223.9, 229.9)	< 0.001
Carbohydrate percent (%) ‡	45.8 (45.3, 46.4)	47.4 (46.5, 48.3)	45.6 (45.3, 45.9)	0.001
Glucose (mmol/l)	5.16 (5.08, 5.23)	5.09 (5.00, 5.18)	5.14 (5.10, 5.19)	0.537
A1C (%)	5.47 (5.42, 5.51)	5.48 (5.42, 5.54)	5.49 (5.47. 5.52)	0.403
DM §	5.9 (4.2, 8.2)	1.1 (0.2, 5.2)	4.7 (3.6, 6.0)	0.053
Physical activity (hs/day) ¶	1.31 (1.14, 1.49)	1.82 (1.44, 2.19)	1.62 (1.49, 1.76)	0.018

Note:
Abbreviations: CI, confidence intervals; LCGA, latent class growth analysis; NDNS RP, national dietary and nutrition survey rolling programme; BMI body mass index; WC, waist circumference; A1C, haemoglobin A1c;DM, diabetes mellitus; h, hour.
Variables from the blood tests (glucose and A1C) are weighted by blood sample weights, the others are weighted by individual weights.
Glucose and A1C levels are estimated in subgroups of people without diabetes.
* For continuous variables, the F test was used to determine differences between latent classes with Bonferroni correction to account for multiple testing across >2 classes.
For categorical variables, differences between latent classes were assessed using the adjusted Pearson Chi-2 test for survey data.
† Hypertension was defined as either systolic blood pressure >= 140 mmHg or diastolic blood pressure >= 90 mmHg, or under treatment for hypertension.
‡ Carbohydrate percent indicates the percentage of energy from carbohydrate in total energy intake
§ DM was defined by A1C > 6.5%.
¶ Physical activity was calculated as mean time spent at moderate or vigorous physical activity during the survey.

Chapter 4

Discussion and Conclusion

Main Section 1

Subsection 1

Subsection 2

Main Section 2

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Appendix A

R code for importing and manipulating the data

```
# NDNS analysis, data management -----------------------------------------

# Change the data path accordingly ----------------------------------------
setwd("/home/wangcc-me/Downloads/UKDA-6533-stata11_se/stata11_se/") # in Ubuntu
library(epiDisplay)
library(plyr)
library(tidyverse)

# Read the data into memory -----------------------------------------------
library(haven)
data <- read_dta("ndns_rp_yr1-4a_foodleveldietarydata_uk.dta")
data56 <- read_dta("ndns_rp_yr5-6a_foodleveldietarydata.dta")
data78 <- read_dta("ndns_rp_yr7-8a_foodleveldietarydata.dta")
names(data)
names(data56)
names(data78)
names(data)[names(data) == "seriali"] <- "id"
names(data56)[names(data56) == "seriali"] <- "id"
names(data78)[names(data78) == "seriali"] <- "id"

# Extract the data we needed ----------------------------------------------
df14d <- data[, c(113, 1, 2, 3, 5, 6, 7, 8, 9, 21, 24, 55, 57, 58,
    59, 60, 61, 62, 63, 64)]
var <- names(df14d)
df56d <- data56 %>% select(var)
```

```
df78d <- data78 %>% select(var)
dfs1 <- rbind(df14d, df56d, df78d)
dfs2 <- dfs1[dfs1$Age >= 19, ]
rm(data, data56, data78)
dfs2

# Calculate the time (minute and hour) when they eat -----------------------

dfs2$MealTime_chr <- as.character(dfs2$MealTime)
dfs2$MealTime_hm <- unlist(strsplit(dfs2$MealTime_chr, " "))[c(FALSE,
    TRUE)]
dfs2$MealHourN <- as.numeric(unlist(strsplit(dfs2$MealTime_hm, ":"))[c(TRUE,
    FALSE, FALSE)])
dfs2$MealMinN <- as.numeric(unlist(strsplit(dfs2$MealTime_hm, ":"))[c(FALSE,
    TRUE, FALSE)])
dfs2$MealMinN0 <- (60 * dfs2$MealHourN) + dfs2$MealMinN
dfs3 <- dfs2[order(dfs2$id, dfs2$DayNo, dfs2$MealMinN0), ]
length(unique(dfs3$id))  ## number of participants = 6155

# Create a subset data with only the first observation of each
# participant --------
NDNS <- dfs3[!duplicated(dfs3$id), ]
with(NDNS, tab1(SurveyYear, graph = FALSE, decimal = 2))

# #SurveyYear :
            # Frequency Percent Cum. percent
# NDNS Year 1       801   13.01        13.01
# NDNS Year 2       812   13.19        26.21
# NDNS Year 3       782   12.71        38.91
# NDNS Year 4      1055   17.14        56.05
# NDNS Year 5       625   10.15        66.21
# NDNS Year 6       663   10.77        76.98
# NDNS Year 7       703   11.42        88.40
# NDNS Year 8       714   11.60       100.00
  # Total          6155  100.00       100.00


# create a variable combine id and day No ---------------------------------
```

```
dfs3 <- dfs3 %>%
mutate(id_dy = paste(id, DayNo, sep = "D"))

# For each subject, the total energy/carbohydrate intake for each eating
# time can be calculated --------
old <- Sys.time()
Energy <- ddply(dfs3, .(id_dy, id, SurveyYear, DayNo, Age, Sex,
                        DiaryDaysCompleted, MealHourN, DayofWeek),
                summarise,
                Tot_Energ = sum(EnergykJ),
                Tot_Carb = sum(Carbohydrateg),
                Tot_Sugar = sum(Totalsugarsg),
                Tot_Starch = sum(Starchg))
new <- Sys.time() - old
print(new)
# Time difference of 3.876385 mins

rm(df14d, df56d, df78d, dfs2)

# Calculate the energy from total carbohydrates ---------------------------
Energy <- Energy %>%
  mutate(KJcarbo = Tot_Carb * 16) %>%
  mutate(CarKJpercentage = KJcarbo/Tot_Energ) %>%
  mutate(Carbo = cut(CarKJpercentage, breaks = c(0, 0.26, 0.75, 2),
        right = FALSE)) %>% mutate(Carbo2 = cut(CarKJpercentage, breaks = c(0,
    0.26, 2), right = FALSE))
Energy0 <- Energy[!(Energy$Tot_Energ == 0), ]
          # some food consumption does not contain any carbohydrates
Energy0$Carbo <- factor(Energy0$Carbo, labels = c("Low_carb", "Med_carb",
    "High_carb"))
Energy0$Carbo2 <- factor(Energy0$Carbo2, labels = c("Low_carb", "Med_or_high_carb")

# Generate data sets for each day ---------------------------------------------
dta_day1 <- Energy0 %>%
  filter(DayNo == 1) %>%
  select(c("id", "Age",
    "Sex", "DayofWeek", "MealHourN", "Carbo", "Carbo2")) %>%
  mutate(DayofWeek = factor(DayofWeek,
```

```
    levels = c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday",
        "Saturday", "Sunday")))

dta_day2 <- Energy0 %>%
  filter(DayNo == 2) %>%
  select(c("id", "Age",
    "Sex", "DayofWeek", "MealHourN", "Carbo", "Carbo2")) %>%
  mutate(DayofWeek = factor(DayofWeek,
    levels = c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday",
        "Saturday", "Sunday")))

dta_day3 <- Energy0 %>%
  filter(DayNo == 3) %>%
  select(c("id", "Age",
    "Sex", "DayofWeek", "MealHourN", "Carbo", "Carbo2")) %>%
  mutate(DayofWeek = factor(DayofWeek,
    levels = c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday",
        "Saturday", "Sunday")))

dta_day4 <- Energy0 %>%
  filter(DayNo == 4) %>%
  select(c("id", "Age",
    "Sex", "DayofWeek", "MealHourN", "Carbo", "Carbo2")) %>%
  mutate(DayofWeek = factor(DayofWeek,
    levels = c("Monday", "Tuesday", "Wednesday", "Thursday", "Friday",
        "Saturday", "Sunday")))
vecid1 <- unique(dta_day1$id) # n = 6153
vecid2 <- unique(dta_day2$id) # n = 6153
vecid3 <- unique(dta_day3$id) # n = 6151
vecid4 <- unique(dta_day4$id) # n = 6026

Noday1 <- setdiff(vecid, vecid1)  # two subjects did not have day 1 data
Noday2 <- setdiff(vecid, vecid2)  # two subjects did not have day 2 data
Noday3 <- setdiff(vecid, vecid3)  # four subjects did not have day 3 data
Noday4 <- setdiff(vecid, vecid4)  # 129 subjects did not have day 4 data

# Transform the data shape from long to wide --------------------------------
dta_d1_wide <- dta_day1[, -7] %>%
```

```
  spread(key = MealHourN, value = Carbo)
names(dta_d1_wide)[5:28] <- paste(rep("H", 24), 0:23, sep = "")

dta_d2_wide <- dta_day2[, -7] %>%
  spread(key = MealHourN, value = Carbo)
names(dta_d2_wide)[5:28] <- paste(rep("H", 24), 0:23, sep = "")

dta_d3_wide <- dta_day3[, -7] %>%
  spread(key = MealHourN, value = Carbo)
names(dta_d3_wide)[5:28] <- paste(rep("H", 24), 0:23, sep = "")

dta_d4_wide <- dta_day4[, -7] %>%
  spread(key = MealHourN, value = Carbo)
names(dta_d4_wide)[5:28] <- paste(rep("H", 24), 0:23, sep = "")
# recode NA to not eating -------------------------------------------------
for (i in 5:ncol(dta_d1_wide))
  if (is.factor(dta_d1_wide[, i])) levels(dta_d1_wide[,
    i]) <- c(levels(dta_d1_wide[, i]), "Not_eating")

dta_d1_wide[is.na(dta_d1_wide)] <- "Not_eating"

for (i in 5:ncol(dta_d2_wide))
  if (is.factor(dta_d2_wide[, i])) levels(dta_d2_wide[,
    i]) <- c(levels(dta_d2_wide[, i]), "Not_eating")

dta_d2_wide[is.na(dta_d2_wide)] <- "Not_eating"

for (i in 5:ncol(dta_d3_wide))
  if (is.factor(dta_d3_wide[, i])) levels(dta_d3_wide[,
    i]) <- c(levels(dta_d3_wide[, i]), "Not_eating")

dta_d3_wide[is.na(dta_d3_wide)] <- "Not_eating"

for (i in 5:ncol(dta_d4_wide))
  if (is.factor(dta_d4_wide[, i])) levels(dta_d4_wide[,
    i]) <- c(levels(dta_d4_wide[, i]), "Not_eating")

dta_d4_wide[is.na(dta_d4_wide)] <- "Not_eating"
```

Appendix B

Mplus code for Multilevel LCA models

Appendix C

Example of a food diary for one day

Day EXAMPLE			**Day:** Thursday	**Date:** March 31^{st}
Time	**Where? With whom? TV on? Table?**	**What**	**Brand Name**	**Amount eaten**
How to describe what you had and how much you had can be found on pages 20-25				
6am to 9am				
7.30am	Kitchen	Orange juice, unsweetened, UHT	Tesco	Large glass
	Family	Tea	Tesco	Mug
	No TV	Milk, fresh semi skimmed	Tesco	A little
	At table	Sugar white	Silverspoon	2 level teaspoons
		Weetabix		2
		Milk as above		Drowned
		Sugar as above		2 heaped teaspoons
		Toast wholemeal, large loaf	Hovis	2 thin slices
		Butter unsalted	Anchor	thick spread on both
		Strawberry Jam	Co-op	1 teaspoon on one slice
9am to 12 noon				
11am	School playground	Coca cola diet	Coca Cola	330ml can
	With friends	Potato crisps, Salt and Vinegar	Walkers	25g packet from a multipack
12noon	School corridor	Water from water cooler		small plastic cup
	Alone	Mars Bar		1 kingsize
12 noon to 2pm				
12.45pm	School canteen	Sandwich, from home		
	With friends	White bread, large loaf	Kingsmill	2 med slices
	At table	Spread	Flora Light	thin spread on both slices
		Ham unsmoked	Tescos	1 slice
		Cheddar cheese		2 medium slices
		Branston Pickle		1 teaspoon
		Apple with skin from home		1 (left core)
		Ribena Light, Ready to Drink, Blackcurrant, from canteen		220ml carton
		Kitkat from home		2 fingers
1.50pm	School corridor			
	Alone	Chewing gum	Orbit Sugar Free	1 piece

FIGURE C.1: NATIONAL DIET AND NUTRITION SURVEY – Food and Drink Diary Example, from 6 am to 2 pm.

Day EXAMPLE			**Day:** Thursday	**Date:** March 31st
Time	**Where? With whom? TV on? Table?**	**What**	**Brand Name**	**Amount eaten**
		2pm to 5pm		
3.45pm	Bus Alone	 Wine gums	 Maynards	 140g packet
4.30pm	Home, sitting room, With family TV on Not at table	 Tea (as above) Chocolate Hob Nobs	 Mcvitites	 mug 3
		5pm to 8pm		
6.30pm	Friend's kitchen With friends No TV At table	Chicken in tomato sauce made by friend's mum Tomato fresh Sweetcorn tinned Peach yoghurt low fat Lemon squash No Added Sugar	See recipe Mullerlight Sainsbury's	3 tablespoons 3 slices 1 dessertspoon 200g pot medium glass
		8pm to 10pm		
8pm	Home, sitting room Alone TV on, Not at table	Satsuma Cream Crackers (no spread)	 Jacob's	1 4
9.30pm	Kitchen Alone No TV, At table	 Thick cut, frozen chips fried in vegetable oil Brown sauce	 McCains HP	 small portion 1 dessertspoon
		10pm to 6am		
10.30pm	Bedroom Alone TV on Not at table	Hot chocolate drink made with water	Cadbury's	Mug (made with 4 tsp powder)
2am	Bedroom (in bed) Alone No TV	Water tap		$\frac{1}{2}$ small glass

FIGURE C.2: NATIONAL DIET AND NUTRITION SURVEY – Food and Drink Diary Example, from 2 pm to 6 am.

Write in recipes or ingredients of made up dishes or take-away dishes			
NAME OF DISH: *Chicken in tomato Sauce*		***Serves:*** *4 people*	
Ingredients	***Amount***	***Ingredients***	***Amount***
Pieces of chicken	*3 pieces*	*Olive oil*	*2 tbsp*
Sauce made with:			
Tinned tomatoes	*1 tin*		
Green pepper	*1 medium*		
Onion	*1 small*		
Brief description of cooking method Chicken pieces fried in olive oil, then mixed in with tomato and vegetable sauce.			

FIGURE C.3: NATIONAL DIET AND NUTRITION SURVEY – Food and Drink Diary Example, home made food recipes.