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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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"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);

Time across a typical survey day was divided into 7 time slots in the dietary diary of NDNS RP: 6 am to 9 am, 9 am to 12 noon, 12 noon to 2 pm, 2 pm to 5 pm, 5 pm to 8 pm, 8 pm to 10 pm, and 10 pm to 6 am. To produce a sequence of discrete responses regarding the carbohydrate intake we are interested, the energy consumption within each time slot over the four days of survey for each participant were calculated. The percentages of energy that contributed by carbohydrate within each time slot were then estimated. 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 a time slot 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 time slot. Consequently, for each day of the recording, there were 7 data points generated by the diary, each data point included one of the following responses:

- Not eating any food (Energy intake = 0 kJ);
- 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 addresses 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 four sequences of categorical responses reflecting the type of carbohydrate consumption at each time slot of the day. The four observed sequences (observed days) 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 (observation days) 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 day will belong to a particular day level latent class to vary across individual levels.

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. For example, let's assume that there are two types of observation days in the dietary survey–high and low carbohydrate eating days. In an unconditional logistic regression model, the probability of the outcome (i.e. an observed high carbohydrate eating day vs. a low carbohydrate eating day) is constant within individual level which means for each person throughout his/her survey there is some probability of following a high carbohydrate eating day. A random effect model considers the individuals (level 2) to be drawn from the adult population in the UK, and the probability of the outcome (i.e. high carbohydrate eating days) across individuals is considered to be a random variable (Snijders and Bosker, 2011).

Thus, for a binary outcome $C_{ij} = 0, 1$ (low $= 0$ or high $= 1$ carbohydrate eating days), where i denotes the observation days ($i = 1, 2, 3, 4$), and j denotes the individual ($j = 1, 2, \cdots, 6155$). The 2-level random intercept logistic regression model can be expressed as:

$$
\begin{aligned}
\operatorname{logit}[P(C_{ij} = 1)] &= \beta_{0j} + \beta_1 x_{ij} \qquad \textbf{(day level)} \\
\beta_{0j} &= \gamma_0 + \gamma_1 w_j + u_{0j} \ \textbf{(individual level)} \\
\Rightarrow P(C_{ij} = 1) &= \frac{\exp(\gamma_0 + \beta_1 x_{ij} + \gamma_1 w_j + u_{0j})}{1 + \exp(\gamma_0 + \beta_1 x_{ij} + \gamma_1 w_j + u_{0j})}
\end{aligned}
\tag{2.2}
$$

Where we define:

- $P(C_{ij} = 1)$ as the probability that the randomly selected ith observation day of jth individual is a high carbohydrate eating day;
- β_{0j} as the random intercept, for outcome $C_{ij} = 1$;
- the random deviation of the individuals u_{0j} 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);
- x_{ij}, w_j is the predictors for day level (weekdays or weekends) and individual level, such as age, and sex.

Same framework can be used to consider random effects in an LCA model, but instead of saying that C_{ij} is either low or high carbohydrate eating days as if we already know, it is now replaced by a latent variable G_{ij} which indicates the typologies of carbohydrate eating patterns. Then we can use the day level data to assess the log-odds of belonging to kth type of carbohydrate eating pattern on a specific day of survey, and we allow the log-odds to vary across individuals. Therefore, for some persons the log-odds of having a kth type of carbohydrate eating pattern during the survey can be high, but for the other persons, the log-odds of following the kth type of carbohydrate eating pattern can be low.

If the day level LCA model (carbohydrate eating pattern typologies) is best defined by $T(T \geqslant 2)$ latent classes, then $T - 1$ random intercept will be specified by a two-level multinomial logistic regression model. Similar to 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 time slots, throughout 4 consecutive days of survey period). Considering the latent class indicators are indicator variables (U_{ijk}), the MLCA model can be written as follows:

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

Where,

- U_{ijk} represents the response of eating carbohydrate (one of the following: not eating any food, $< 50\%$ of the energy, or $\geqslant 50\%$ of the energy) on ith day of the survey ($i \in (1, 2, 3, 4)$) in jth individual at the kth time slot of the day ($k \in (1, 2, 3, \cdots, 7)$);
- G_{ij} denotes the latent class membership for jth individuals on ith day of the survey, the total number of day level latent class is 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 $P(G_{ij} = t)$ in equation 2.3 is what we have already defined in equation 2.2:

$$P(G_{ij} = t) = \frac{\exp\left(\gamma_0 + \beta_1 x_{ij} + \gamma_1 w_j + u_{0j}\right)}{1 + \exp\left(\gamma_0 + \beta_1 x_{ij} + \gamma_1 w_j + u_{0j}\right)} \tag{2.4}$$

Non-Parametric approach

Since the parametric approach discussed above can be extremely computationally demanding (Van Horn et al., 2008; Vermunt, 2008), an alternative approach is using a non-parametric MLCA (Davidian et al., 2008). In this approach, separate latent class models are specified for level 1 (observation days) and level 2 (individuals). 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 (individual) latent classes reflect differences in the probability of belonging to a specific day level latent class, so that individuals that contain observation days with similar probabilities for the level 1 latent classes will be grouped together. The non-parametric MLCA model can be defined as follows:

$$P(C_{ij} = t | CB_j = m) = \frac{\exp(\gamma_{tm})}{\sum_{r=1}^{T} \exp(\gamma_{tm})} \tag{2.5}$$

Where,

- CB_j is individual level latent class membership for jth individual;
- γ_{tm} is day level and individual level 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 both meaningful individual (level 2) latent classes and the daily carbohydrate consumption classification. Therefore, non-parametric MLCA was employed 1) to identify latent classes of observation days (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 LMR-LRT is available, same rules of model fit indices and pattern interpretability were used to determine the optimal combination of latent classes in observation day level and individual level. MLCA models were fitted in Mplus 7.4 (Muthén and Muthén, 2017), the Mplus codes are shown in **Appendix B**.

Day level latent classes and their characteristics

Day level latent classes identified by MLCA steps were tabulated according to whether the diary was recorded during weekdays or not. A contingency table giving the frequency of responses across the 7 time slots of the survey days was produced.

Chapter 3

Results

Model selection, and interpretation

A series of traditional LCA of the responses to carbohydrate intake within 7 time slots of day was first examined. These initial analyses ignored the clustering of observation days within participants of the survey. **Table 3.1** shows the latent class solutions for one to five classes (see rows under the Fixed effects model section). The BIC declines with the number of day level classes increases. However, the improvement of BIC dropped to less than 1000 from 3 classes to 4 classes solutions (658.9) and from 4 classes to 5 classses solutions (361.7). Entropy index indicates that the 4 classes model could explain about 51% percent of the data, while p values of Lo-Mendell-Rubun LRT suggest that the more classes we fit, the better model we will have until up to 6 classes (p = 0.06 and is not shown in the table). However, from the parsimony point of view, we extend the model with random effects building on 2 classes, 3 classes and 4 classes solutions.

The results of the random effect included models are presented in **Table 3.1** under the Random effects model section. It is obvious that the BIC improves with the addition of the random effects which account for the nested structure of the data. Entropy indicates that 4 classes in individual level and 2 classes in the day level may be the best solution mathematically. However, after these solutions were checked in more details, the potentially most substantively interpretable model was found to be the 3$\times$3 random effect model, which is the model with 3 latent classes in the day level, and 3 latent classes in the individual level. We must emphasize that different researchers may have made decision slightly different from ours, we provided the descriptions and figures for other solutions in the **Appendix xxx** for reference.

In this 3 classes solution we have chosen in the day level, there were 39.5%, 20.4%, and 40.1% classified into 3 latent groups. The overall counts and percentages for each responses within every time slot and the distributions of the solution are presented in **Table 3.2**. The trajectories illustrating the change of the probabilities of each response to carbohydrate eating during the hours of the day are shown separately by the three types of days in **Figure 3.1**.

TABLE 3.1: Fit criteria for each model specification.

	Number of day level classes				
Model	**1 class**	**2 classes**	**3 classes**	**4 classes**	**5 classes**
Fixed effects model					
No. of free parameters	14	29	44	59	74
Log-likelihood	-173793.306	-172669.771	-172039.204	-171633.941	-171377.292
BIC	347728.092	345632.608	344523.060	343864.121	343502.409
Lo-Mendell-Rubun LRT	–	< 0.0001	< 0.0001	< 0.0001	< 0.0001
Entropy	1	0.310	0.392	0.510	0.481
Random effects model					
2 individual level classes					
No. of free parameters		59	89	119	
Log-likelihood		-169331.132	-168700.96	-168366.193	
BIC		339258.502	338301.338	337934.968	
Entropy		0.581	0.569	0.555	
3 individual level classes					
No. of free parameters		89	134	179	
Log-likelihood		-166936.279	-166348.815	-166062.761	
BIC		334771.968	334051.799	333934.448	
Entropy		0.677	0.630	0.644	
4 individual level classes					
No. of free parameters		119	179		
Log-likelihood		-165441.731	-164845.696		
BIC		332086.045	331500.318		
Entropy		0.729	0.659		

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.

Class 1 days **(Figure 3.1-A)** were given the name of "high carbohydrate day" since in these days of survey, the probabilities of carbohydrate contributed higher or equal to 50% of the energy consumed were always higher than that in the other two types of days. Specifically, these days were characterised with probabilities of over 0.6 in time slots between 6 am to 9 am, 9 am to 12 am, and also 2 pm to 5 pm, during which the time slots may be interpreted as breakfast, morning snack, and afternoon snack time periods for many participants. Moreover, even during late night time period, such as 8 pm to 10 pm, and 10 pm to 6 am time slots, the probabilities of having higher carbohydrate contained food were still as high as 0.412, and 0.246, respectively.

TABLE 3.2: Day level latent class solution for three classes solution. (No Individual level Model)

Time slots of the day	Responses to carbohydrate intake	n	(%)	Class 1 (39.5%) High carbo-hydrate day	Class 2 (20.4%) Low carbo-hydrate day	Class 3 (40.1%) Regular meals day
6 am – 9 am						
	Not eating any food	7655	31.2	0.129	0.450	0.320
	Carbohydrate < 50%*	4500	18.4	0.130	0.267	0.128
	Carbohydrate ⩾ 50%†	12328	50.4	0.741	0.283	0.552
9 am – 12 am						
	Not eating any food	5447	22.2	0.237	0.079	0.401
	Carbohydrate < 50%	7227	29.5	0.158	0.492	0.173
	Carbohydrate ⩾ 50%	11809	48.2	0.605	0.429	0.426
12 noon – 2 pm						
	Not eating any food	4783	19.5	0.156	0.356	0.019
	Carbohydrate < 50%	11112	45.4	0.405	0.413	0.560
	Carbohydrate ⩾ 50%	8588	35.1	0.439	0.231	0.421
2 pm – 5 pm						
	Not eating any food	6926	28.3	0.130	0.123	0.659
	Carbohydrate < 50%	8277	33.8	0.249	0.602	0.076
	Carbohydrate ⩾ 50%	9280	37.9	0.621	0.276	0.266
5 pm – 8 pm						
	Not eating any food	3043	12.4	0.114	0.199	0.034
	Carbohydrate < 50%	14240	58.2	0.516	0.590	0.639
	Carbohydrate ⩾ 50%	7200	29.4	0.370	0.211	0.328
8 pm – 10 pm						
	Not eating any food	8722	35.6	0.322	0.291	0.480
	Carbohydrate < 50%	8898	36.3	0.266	0.551	0.212
	Carbohydrate ⩾ 50%	6863	28.0	0.412	0.158	0.308
10 pm – 6 am						
	Not eating any food	16295	66.6	0.680	0.590	0.751
	Carbohydrate < 50%	4144	16.9	0.074	0.294	0.101
	Carbohydrate ⩾ 50%	4044	16.5	0.246	0.115	0.148

Note:
* Carbohydrate < 50% indicates that within the time slot, carbohydrate contributed less than 50% total energy intake.
† Carbohydrate ⩾ 50% indicates that within the time slot, carbohydrate contributed higher or equal to 50% total energy intake.

Class 2 days **(Figure 3.1-B)** were named as "low carbohydrate day" because first of all, in these days the possibility of participants skipping breakfast was 0.45. And after 9 am, within class 2 days, the probability of having food with lower carbohydrate (contributed less than 50% of total energy intake), was always higher than having higher carbohydrate contained food. In these days, participants also turned to have morning snacks (with only 0.079 possibility of Not eating any food and similar probabilities of having either high or low carbohydrate contained food).

This phenomenon may also be interpreted as having a long and late breakfast in these mornings. The probability of Not eating any food was lowest for class 2 days during the midnights time slot (10 pm to 6 am), with about 0.590 compared with 0.680 and 0.751 during the class 1 and class 3 days.

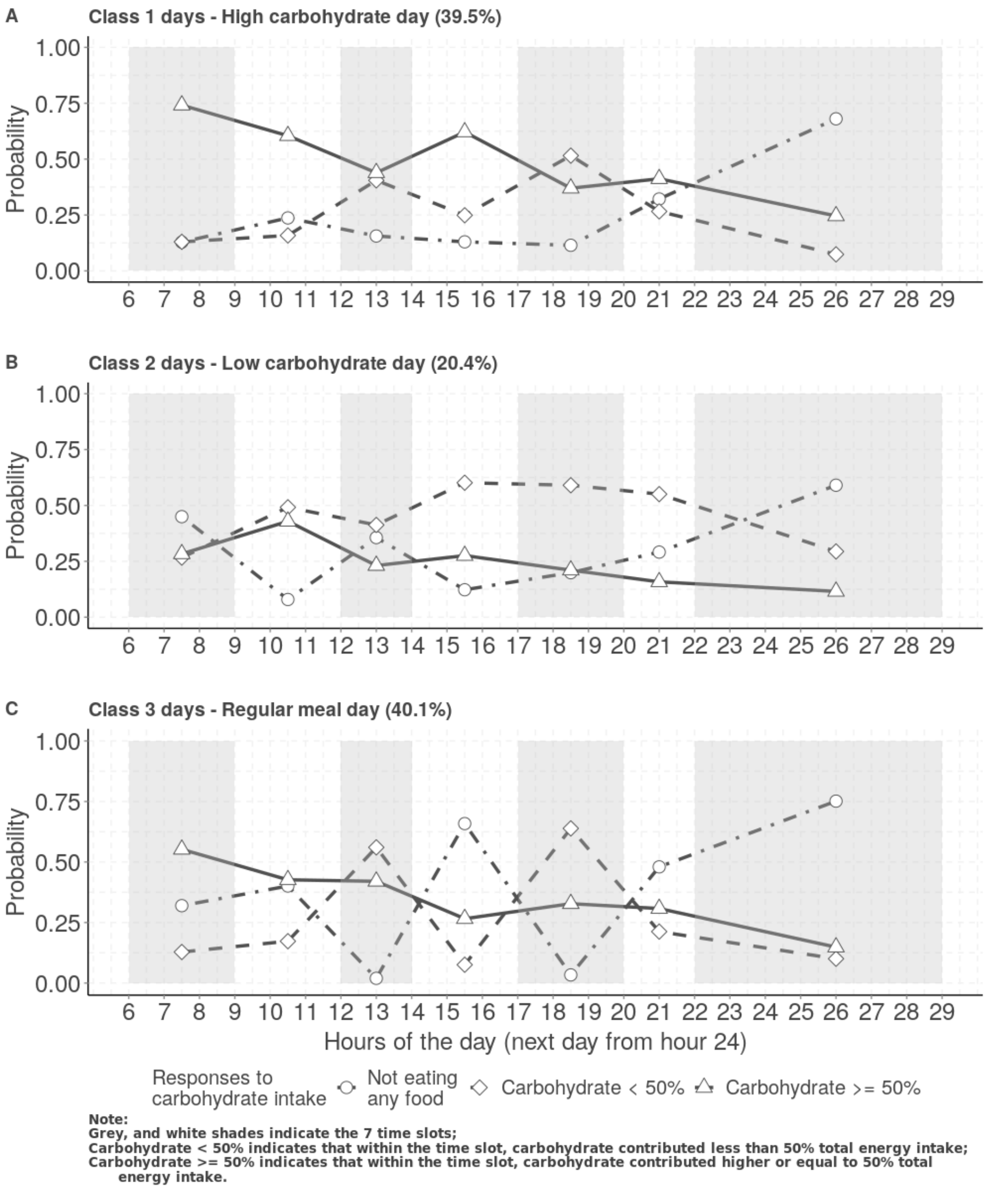

FIGURE 3.1: Day Level Latent Classes Solution.

Class 3 days **(Figure 3.1-C)** were called "regular meals day" due to the following reasons: 1) participants recordings showed that in these days there was almost 0 possibility of not eating any food at lunch (0.019 between 12 noon and 2 pm) or dinner (0.034 between 5 pm and 8 pm); 2) the probabilities of not having morning

TABLE 3.3: Means (standard deviations), and counts (%) of the characteristics of different types of days according to carbohydrate intake.

	High carbohydrate day	Low carbohydrate day	Regular meals day	*P* value*
Counts (%)	9667 (39.5)	5002 (20.4%)	9814 (40.1%)	
Country (%)				< 0.001
England	5627 (58.2)	2972 (59.4)	5291 (53.9)	
Northern Ireland	1194 (12.4)	527 (10.5)	1400 (14.3)	
Scotland	1527 (15.8)	813 (16.3)	1774 (18.1)	
Wales	1318 (13.6)	690 (13.8)	1349 (13.7)	
Day of Week (%)				< 0.001
Monday	1303 (13.5)	715 (14.3)	1370 (14.0)	
Tuesday	1266 (13.1)	674 (13.5)	1290 (13.1)	
Wednesday	1225 (12.7)	740 (14.8)	1233 (12.6)	
Thursday	1272 (13.2)	752 (15.0)	1425 (14.5)	
Friday	1458 (15.1)	797 (15.9)	1479 (15.1)	
Saturday	1537 (15.9)	703 (14.1)	1495 (15.2)	
Sunday	1605 (16.6)	621 (12.4)	1522 (15.5)	
Weekend, Yes (%)	3142 (32.5)	1324 (26.5)	3017 (30.7)	< 0.001
Total energy (kJ)	7539.98 (2875.87)	7160.22 (2922.15)	7439.68 (2978.91)	< 0.001
Carbohydrate (g)	222.79 (89.84)	209.70 (86.17)	206.59 (84.42)	< 0.001
Protein (g)	71.36 (29.79)	69.55 (30.20)	73.29 (32.94)	< 0.001
Fat (g)	65.44 (33.27)	63.94 (33.76)	67.24 (34.73)	< 0.001
Alcohol (g)	11.76 (27.31)	8.85 (24.25)	13.80 (33.00)	< 0.001
Total sugars (g)	98.63 (56.03)	88.03 (50.50)	86.39 (50.96)	< 0.001
Starch (g)	124.07 (55.84)	121.59 (56.13)	120.11 (54.62)	< 0.001
Non-milk extrinsic sugar†	59.45 (49.31)	50.07 (43.41)	50.41 (44.84)	< 0.001
Fruit (g)	107.40 (137.97)	103.15 (129.08)	92.76 (126.02)	< 0.001
Yellow Red Green Vegetables (g)	26.52 (46.44)	26.84 (47.99)	26.16 (45.99)	0.681

Note:
* *P* values were obtained from Pearson χ^2 test for categorical variables, and one-way ANOVA comparing the means in multiple groups for continuous variables;
† Non-milk extrinsic sugar is defined as: additionally added free sugar, such as table sugar, honey, glucose, fructose and glucose syrups, sugars added to food and sugars in fruit juices.

snack (9 am to 12 am) and afternoon snack (2 pm to 5 pm) were also the highest among the three types of days (0.401 and 0.659). 3) during these days, participants may have some high carbohydrate contained food between 8 pm and 10 pm (0.308), but the probability of not eating any food during 10 pm to 6 am next morning was 0.751, the highest among the three types of days.

Features of the three carbohydrate eating time patterns

The details of the characteristics of the three types of carbohydrate eating time pattern were listed in **Table 3.3**. Specifically, regular meals day turned to be recorded slightly more often in Northern Ireland, and Scotland. In terms of day of week distribution in the three types of days, there is strong evidence ($p < 0.001$) that high carbohydrate days appeared more frequently in weekends (32.5%) compared with low carbohydrate day (26.5%) and regular meals day (30.7%).

As expected, consumption of total energy (7539.98 kJ), total carbohydrate (222.79 g), total sugar (98.63 g), starch (124.07 g), and non-milk extrinsic sugar (59.45 g) were highest among high carbohydrate days (all $p < 0.0001$). On the other hand, the consumption of protein (73.29 g), total fat (67.24 g), and alcohol (13.80 g) were the highest in the so-called regular meals days. Moreover, in high carbohydrate days, participants turned to also consume the highest amount of fruit (107.40 g). There is no evidence of any difference for the consumption of yellow, red, or green vegetables across the three types of days ($p = 0.681$).

Individual level LCA solution

In the random effect models we utilized the non-parametric approach, in which we added a level 2 (individual level) latent classes based on the random means from the level 1 (day level) latent class solution. The results of the individual level LCA solution for 3 classes are presented in **Figure 3.2**, and **3.3**.

With two individual level latent classes **(Figure 3.2)**, one individual class is comprised of individuals with a relatively slightly higher proportion of having "low carbohydrate day" (22.1%) compared to the other (17.4%). This class represents nearly 65% of the individuals.

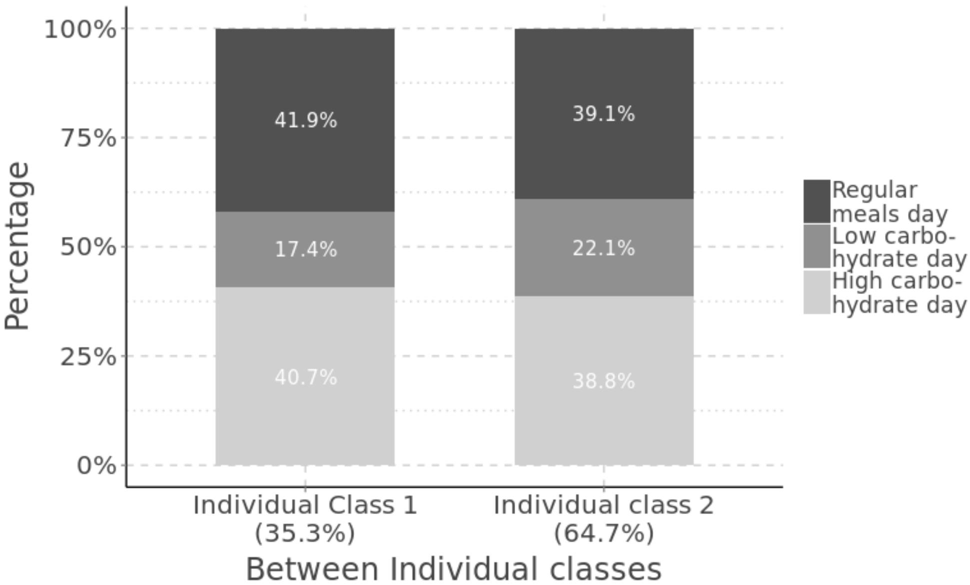

FIGURE 3.2: Multilevel Latent Class Solution, 3 classes in day level, 2 classes in individual level.

With three individual level latent classes **(Figure 3.3)**, a low-carbohydrate eaters class, moderate-carbohydrate eaters class, and high-carbohydrate eaters class emerges. 43.1% participants were identified as high-carbohydrate eaters, in these individuals, about 50% of the days (2 out of 4 days) in the survey, they were classified as having high carbohydrate days.

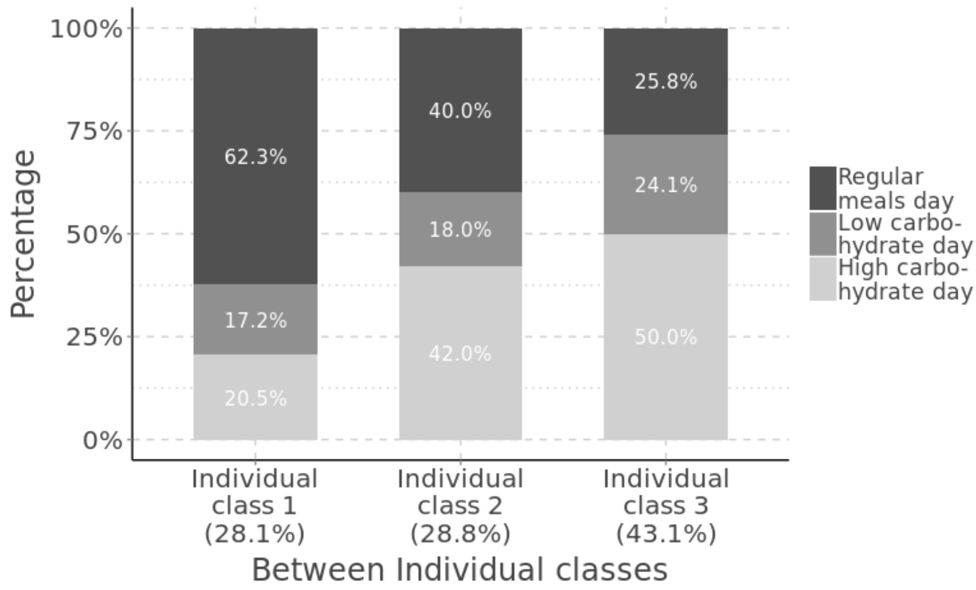

FIGURE 3.3: Multilevel Latent Class Solution, 3 classes in day level, 3 classes in individual level.

TABLE 3.4: Weighted means, percentages, and 95% CIs of the social, economical characteristics by latent class memberships in the UK adults. (NDNS RP 2008/09-2015/16, sample size = 6155)

Variables	**Individual class 1 (n = 1730)**	**Individual class 2 (n = 1772)**	**Individual class 3 (n = 2653)**	***P* value** *
Total (%)	28.4 (26.9, 29.9)	28.7 (27.1, 30.3)	43.0 (41.3, 44.7)	
Countries (%)				0.007
England	84.5 (81.7, 86.9)	82.0 (79.3, 84.5)	84.7 (82.3, 86.8)	
Northern Ireland	2.1 (1.6, 2.8)	4.2 (3.2, 5.6)	2.2 (1.7, 3.0)	
Scotland	9.1 (7.0, 11.8)	8.6 (6.7, 11.1)	8.0 (6.3, 10.2)	
Wales	4.3 (3.3, 5.6)	5.1 (4.0, 6.4)	5.1 (4.0, 6.4)	
Age (years)	51.0 (49.9, 52.1)	40.3 (39.1, 41.6)	51.7 (50.7, 52.7)	< 0.001
Sex (%)				0.119
Men	50.0 (46.9, 53.1)	50.2 (47.0, 53.5)	46.6 (44.0, 49.1)	
Women	50.0 (46.9, 53.1)	49.8 (46.5, 53.0)	53.4 (50.9, 56.0)	
Survey years (% in rows)				0.015
1	32.5 (28.4, 36.9)	26.3 (21.9, 31.2)	41.2 (36.6, 46.0)	
2	26.8 (22.6, 31.3)	22.6 (18.6, 27.3)	50.6 (45.8, 55.4)	
3	22.6 (18.8, 26.9)	33.7 (28.6, 39.2)	43.6 (38.7, 48.7)	
4	27.9 (24.1, 32.2)	27.6 (23.8, 31.8)	44.4 (40.2, 48.7)	
5	27.9 (24.2, 32.0)	28.7 (24.4, 33.5)	43.3 (38.2, 48.6)	
6	28.0 (24.0, 32.4)	31.5 (26.9, 36.6)	40.5 (35.8, 45.3)	
7	29.1 (25.2, 33.4)	29.0 (24.5, 34.0)	41.8 (37.1, 46.7)	
8	31.1 (27.3, 35.3)	30.5 (25.9, 35.5)	38.4 (34.1, 42.8)	
Paid employment† (%)				0.907
Yes	40.3 (37.0, 43.6)	40.8 (37.1, 44.5)	39.8 (37.1, 42.6)	
No	59.7 (56.4, 63.0)	59.2 (55.5, 62.9)	60.2 (57.4, 62.9)	
Live with partner‡ (%)				< 0.001
Yes	56.9 (53.6, 60.1)	38.4 (35.2, 41.8)	61.3 (58.7, 63.7)	
No	43.1 (39.9, 46.4)	61.6 (58.2, 64.8))	38.7 (36.3, 41,3)	
Household Income, £/year	36558.53 (34800.21, 38316.84)	27180.80 (25597.95, 28763.65)	32171.58 (31024.96, 33318.2)	< 0.001
Ethnicity (%)				
White	94.2 (92.4, 95.6)	79.5 (76.4, 82.3)	91.9 (90.1, 93.4)	< 0.001
Non-White	5.8 (4.4, 7.6)	20.5 (17.7, 23.6)	8.1 (6.6, 9.9)	
Education (%)				
Degree or higher	29.0 (26.1, 32.1)	23.3 (20.5, 26.3)	26.2 (24.1, 28.5)	0.019
Lower than degree	71.0 (67.9, 73.9)	76.7 (73.7, 79.5)	73.8 (71.5, 75.9)	

Note:

Abbreviations: CI, confidence intervals; NDNS RP, national dietary and nutrition survey rolling programme. Variables were weighted by individual weights.

* 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 χ^2 test for survey data.

† Paid employment was defined as being in paid employment during the last 4 weeks prior to the survey.

‡ Live with partner was defined as either living with a married husband/wife or a legally recognised civil partnership.

TABLE 3.5: Weighted means, percentages, and 95% CIs of the anthropometric measurements, average main nutrients intake and biochemical characteristics by latent class memberships in the UK adults. (NDNS RP 2008/09-2015/16, sample size = 6155).

Variables	**Individual class 1 (n = 1730)**	**Individual class 2 (n = 1772)**	**Individual class 3 (n = 2653)**	***P* value** *
BMI (kg/m^2)	27.8 (27.4, 28.2)	27.2 (26.7, 27.7)	27.3 (26.9, 27.6)	0.006
WC (cm)	94.6 (93.5, 95.6)	92.3 (91.0, 93.5)	92.2 (91.4, 93.1)	0.001
Smoking status (%)				
Current	20.4 (18.0, 23.0)	27.8 (25.0, 30.9)	17.1 (15.4, 19.0)	< 0.001
Ex-smoker	29.3 (26.5, 32.2)	16.8 (14.6, 19.2)	26.1 (24.9, 28.3)	
Never	50.3 (47.2, 32.2)	55.4 (52.2, 58.6)	56.8 (54.3, 59.3)	
Current drinking status (%)				
Yes	11.8 (10.0, 13.8)	24.0 (21.2, 27.1)	20.6 (18.7, 22.8)	< 0.001
Hypertension† (%)				
Yes	33.4 (29.9, 37.1)	21.1 (17.7, 24.9)	31.2 (28.3, 34.2)	< 0.001
Total energy intake (kJ)	7985.8 (7823.3, 8146.295)	7341.8 (7825.3, 8146.3)	7677.0 (7555.8, 7799,8)	< 0.001
Carbohydrate percent‡ (%)	203.8 (199.8, 207.8)	218.3 (212.9, 223.7)	233.4 (229.6, 237.2)	< 0.001
Carbohydrate percent (%)	40.6 (40.2, 41.0)	47.3 (46.8, 47.8)	48.3 (47.9, 48.6)	< 0.001
Protein intake (g)	79.9 (77.9, 81.8)	69.3 (67.6, 71.0)	73.7 (72.5, 74.8)	< 0.001
Protein percent (%)	17.2 (16.9, 17.5)	16.3 (16.0, 16.6)	16.5 (16.3, 16.6)	< 0.001
Fat intake (g)	74.7 (73.1, 76.4)	63.8 (62.1, 65.5)	65.7 (64.4, 67.0)	< 0.001
Fat percent (%)	35.4 (34.9, 35.8)	32.5 (32.1, 32.9)	32.0 (31.7, 32.3)	< 0.001
Glucose (mmol/l)	5.20 (5.15, 5.26)	5.09 (5.02, 5.17)	5.13 (5.09, 5.12)	0.051
A1C (%)	5.49 (5.45, 5.52)	5.44 (5.40, 5.48)	5.52 (5.49, 5.55)	0.012
DM §	6.9 (5.0, 9.3)	3.5 (2.3, 5.3)	4.1 (2.9, 5.6)	0.011
Physical activity (hours/day) ¶	1.63 (1.43, 1.83)	1.32 (1.15, 1.49)	1.65 (1.49, 1.81)	0.016

Note:
Abbreviations: CI, confidence intervals; NDNS RP, national dietary and nutrition survey rolling programme; BMI body mass index; WC, waist circumference; A1C, haemoglobin A1c; DM, diabetes mellitus.
Variables from the blood tests (glucose and A1C) were weighted by blood sample weights, the others were weighted by nurse visiting 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 accountfor multiple testing across > 2 classes. For categorical variables, differences between latent classes were assessed using the adjusted Pearson χ^2 test for survey data.
† Hypertension was defined as either systolic blood pressure $\geqslant$ 140 mmHg or diastolic blood pressure $\geqslant$ 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 including both work-related and recreational activities during the survey.

Association between individual level latent classes and hypertension

Association between individual level latent classes and obesity

Association between individual level latent classes and diabetes

Chapter 4

Discussion and Conclusion

- MLCA ignored the order of observation days.
- We used the maximum probability rule and ignored that these are just probabilities.

Main Section 1

Subsection 1

Subsection 2

Main Section 2

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Appendix A

R code for importing and manipulating the data

```r
# 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 and output for Multilevel LCA models

```
Mplus VERSION 7.4
MUTHEN & MUTHEN
07/28/2018   9:55 AM

INPUT INSTRUCTIONS

TITLE:    3-class at level 1 (CW), 3-classes at level 2 (CB) random effects model
ordered polytomous variables for carb intake at each time slot over four
days of NDNS survey 2008/09 - 2015/16
variable 0 = not eating
1 = eating & carb provided < 50% calorie
2 = eating & carb provided >= 50% calorie

DATA:     File is H:\summer_project\Mplus\TimeSlots\NDNS_Tslots.dat;


VARIABLE: NAMES = id id_dy Age Sex H6_9 H9_12 H12_14 H14_17 H17_20
H20_22 H22_6;

USEVAR = H6_9 H9_12 H12_14 H14_17 H17_20
H20_22 H22_6;

auxiliary = Age Sex;

CATEGORICAL =  H6_9 H9_12 H12_14 H14_17 H17_20
H20_22 H22_6;
```

```
CLUSTER = id;

IDVARIABLE = id_dy;

BETWEEN = CB;

WITHIN = H6_9 H9_12 H12_14 H14_17 H17_20
H20_22 H22_6;

CLASSES = CB(3) CW(3);

MISSING are .;



ANALYSIS:
type = mixture twolevel;
starts = 50 25;
process = 8(starts);


MODEL:
%within%
%overall%
%between%
%overall%
CW ON CB;



Savedata:
file is H:\summer_project\Mplus\TimeSlots\Multilevel\NDNSslot_CW3CB3.txt;
save is cprob;
format is free;
```

```
3-class at level 1 (CW), 3-classes at level 2 (CB) random effects model
ordered polytomous variables for carb intake at each time slot over four
days of NDNS survey 2008/09 - 2015/16
variable 0 = not eating
1 = eating & carb provided < 50% calorie
2 = eating & carb provided >= 50% calorie

SUMMARY OF ANALYSIS

Number of groups                                                 1
Number of observations                                       24483

Number of dependent variables                                    7
Number of independent variables                                  0
Number of continuous latent variables                            0
Number of categorical latent variables                           2

Observed dependent variables

Binary and ordered categorical (ordinal)
H6_9        H9_12       H12_14      H14_17      H17_20      H20_22
H22_6

Observed auxiliary variables
AGE         SEX

Categorical latent variables
CB          CW

Variables with special functions

Cluster variable      ID
ID variable           ID_DY

Within variables
H6_9        H9_12       H12_14      H14_17      H17_20      H20_22
H22_6
```

```
Estimator                                                        MLR
Information matrix                                          OBSERVED
Optimization Specifications for the Quasi-Newton Algorithm for
Continuous Outcomes
Maximum number of iterations                                   100
Convergence criterion                                    0.100D-05
Optimization Specifications for the EM Algorithm
Maximum number of iterations                                   500
Convergence criteria
Loglikelihood change                                   0.100D-02
Relative loglikelihood change                          0.100D-05
Derivative                                             0.100D-02
Optimization Specifications for the M step of the EM Algorithm for
Categorical Latent variables
Number of M step iterations                                      1
M step convergence criterion                             0.100D-02
Basis for M step termination                             ITERATION
Optimization Specifications for the M step of the EM Algorithm for
Censored, Binary or Ordered Categorical (Ordinal), Unordered
Categorical (Nominal) and Count Outcomes
Number of M step iterations                                      1
M step convergence criterion                             0.100D-02
Basis for M step termination                             ITERATION
Maximum value for logit thresholds                              15
Minimum value for logit thresholds                             -15
Minimum expected cell size for chi-square                0.100D-01
Maximum number of iterations for H1                           2000
Convergence criterion for H1                               0.100D-03
Optimization algorithm                                           EMA
Integration Specifications
Type                                                      STANDARD
Number of integration points                                    15
Dimensions of numerical integration                              0
Adaptive quadrature                                             ON
Random Starts Specifications
Number of initial stage random starts                           50
Number of final stage optimizations                             25
```

```
Number of initial stage iterations                              10
Initial stage convergence criterion                      0.100D+01
Random starts scale                                      0.500D+01
Random seed for generating random starts                         0
Parameterization                                             LOGIT
Link                                                         LOGIT
Cholesky                                                       OFF

Input data file(s)
H:\summer_project\Mplus\TimeSlots\NDNS_Tslots.dat
Input data format  FREE


SUMMARY OF DATA

Number of missing data patterns             1
Number of y missing data patterns           0
Number of u missing data patterns           1
Number of clusters                       6155



COVARIANCE COVERAGE OF DATA

Minimum covariance coverage value   0.100


UNIVARIATE PROPORTIONS AND COUNTS FOR CATEGORICAL VARIABLES

H6_9
Category 1    0.313         7655.000
Category 2    0.184         4500.000
Category 3    0.504        12328.000
H9_12
Category 1    0.222         5447.000
Category 2    0.295         7227.000
Category 3    0.482        11809.000
H12_14
```

```
Category 1    0.195         4783.000
Category 2    0.454        11112.000
Category 3    0.351         8588.000
H14_17
Category 1    0.283         6926.000
Category 2    0.338         8277.000
Category 3    0.379         9280.000
H17_20
Category 1    0.124         3043.000
Category 2    0.582        14240.000
Category 3    0.294         7200.000
H20_22
Category 1    0.356         8722.000
Category 2    0.363         8898.000
Category 3    0.280         6863.000
H22_6
Category 1    0.666        16295.000
Category 2    0.169         4144.000
Category 3    0.165         4044.000


RANDOM STARTS RESULTS RANKED FROM THE BEST TO THE WORST LOGLIKELIHOOD VALUES

Final stage loglikelihood values at local maxima, seeds, and initial stage start nu

-166348.815  153942          31
-166348.815  573096          20
-166348.815  253358          2
-166348.816  318230          46
-166348.816  246261          38
-166348.873  285380          1
-166348.908  903420          5
-166349.394  120506          45
-166349.394  966014          37
-166349.394  207896          25
-166349.395  195873          6
-166349.513  68985           17
-166349.514  366706          29
```

```
-166352.737  76974           16
-166357.057  127215          9
-166482.723  533738          11
-166495.844  645664          39
-166668.918  372176          23


THE BEST LOGLIKELIHOOD VALUE HAS BEEN REPLICATED.  RERUN WITH AT LEAST TWICE THE
RANDOM STARTS TO CHECK THAT THE BEST LOGLIKELIHOOD IS STILL OBTAINED AND REPLICATED.


THE MODEL ESTIMATION TERMINATED NORMALLY



MODEL FIT INFORMATION

Number of Free Parameters                    134

Loglikelihood

H0 Value                     -166348.815
H0 Scaling Correction Factor      1.8182
for MLR

Information Criteria

Akaike (AIC)                  332965.630
Bayesian (BIC)                334051.799
Sample-Size Adjusted BIC      333625.950
(n* = (n + 2) / 24)



MODEL RESULTS USE THE LATENT CLASS VARIABLE ORDER

CB  CW
```

```
Latent Class Variable Patterns

CB        CW
Class     Class

1         1
1         2
1         3
2         1
2         2
2         3
3         1
3         2
3         3


FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASS PATTERNS
BASED ON ESTIMATED POSTERIOR PROBABILITIES

Latent Class
Pattern

1  1      4050.97975        0.16546
1  2      1561.55249        0.06378
1  3      1286.46696        0.05255
2  1      2746.94031        0.11220
2  2      3011.00217        0.12298
2  3      1341.59686        0.05480
3  1      2748.25320        0.11225
3  2      4770.55950        0.19485
3  3      2965.64876        0.12113


FINAL CLASS COUNTS AND PROPORTIONS FOR EACH LATENT CLASS VARIABLE
BASED ON ESTIMATED POSTERIOR PROBABILITIES

Latent Class
Variable    Class
```

```
CB            1      6898.99902          0.28179
2      7099.53906          0.28998
3     10484.46094          0.42823
CW            1      9546.17285          0.38991
2      9343.11426          0.38162
3      5593.71240          0.22847


FINAL CLASS COUNTS AND PROPORTIONS FOR THE LATENT CLASS PATTERNS
BASED ON THEIR MOST LIKELY LATENT CLASS PATTERN

Class Counts and Proportions

Latent Class
Pattern

1  1             4262          0.17408
1  2             1406          0.05743
1  3             1178          0.04812
2  1             2807          0.11465
2  2             2946          0.12033
2  3             1260          0.05146
3  1             2745          0.11212
3  2             5315          0.21709
3  3             2564          0.10473


FINAL CLASS COUNTS AND PROPORTIONS FOR EACH LATENT CLASS VARIABLE
BASED ON THEIR MOST LIKELY LATENT CLASS PATTERN

Latent Class
Variable    Class

CB            1            6846          0.27962
2            7013          0.28644
3           10624          0.43393
CW            1            9814          0.40085
```

```
2             9667          0.39485
3             5002          0.20431


CLASSIFICATION QUALITY

Entropy                          0.630


Average Latent Class Probabilities for Most Likely Latent Class Pattern (Row)
by Latent Class Pattern (Column)

Latent Class Variable Patterns

Latent Class         CB        CW
Pattern No.       Class     Class

1             1         1
2             1         2
3             1         3
4             2         1
5             2         2
6             2         3
7             3         1
8             3         2
9             3         3

1        2        3        4        5        6        7        8        9

1   0.720    0.091    0.073    0.016    0.032    0.004    0.005    0.033    0.025
2   0.183    0.609    0.098    0.005    0.002    0.030    0.040    0.005    0.027
3   0.211    0.084    0.629    0.008    0.005    0.007    0.011    0.036    0.009
4   0.019    0.004    0.002    0.692    0.184    0.051    0.011    0.034    0.003
5   0.042    0.001    0.001    0.158    0.709    0.045    0.001    0.035    0.009
6   0.012    0.037    0.013    0.065    0.084    0.702    0.042    0.003    0.042
7   0.011    0.029    0.004    0.012    0.002    0.022    0.641    0.126    0.153
8   0.026    0.003    0.009    0.025    0.024    0.001    0.115    0.675    0.123
9   0.046    0.024    0.004    0.003    0.010    0.018    0.079    0.174    0.642
```

```
MODEL RESULTS

Two-Tailed
Estimate       S.E.  Est./S.E.    P-Value

Within Level

Latent Class Pattern 1 1

Thresholds
H6_9$1            -0.718      0.218     -3.294      0.001
H6_9$2             0.973      0.299      3.258      0.001
H9_12$1           -2.516      0.463     -5.433      0.000
H9_12$2            0.675      0.132      5.118      0.000
H12_14$1          -1.025      0.145     -7.057      0.000
H12_14$2           1.240      0.116     10.725      0.000
H14_17$1          -1.566      0.149    -10.520      0.000
H14_17$2           1.090      0.100     10.909      0.000
H17_20$1          -1.998      0.125    -16.000      0.000
H17_20$2           1.549      0.100     15.556      0.000
H20_22$1          -0.933      0.085    -10.914      0.000
H20_22$2           1.829      0.103     17.770      0.000
H22_6$1            0.253      0.083      3.046      0.002
H22_6$2            2.308      0.117     19.691      0.000

Latent Class Pattern 1 2

Thresholds
H6_9$1            -4.021      1.788     -2.249      0.025
H6_9$2            -0.115      0.259     -0.445      0.656
H9_12$1            0.167      0.373      0.448      0.654
H9_12$2            2.142      0.586      3.657      0.000
H12_14$1          -3.210      1.518     -2.115      0.034
H12_14$2           0.858      0.167      5.124      0.000
H14_17$1           0.044      0.384      0.114      0.909
```

```
H14_17$2              1.617        0.293        5.509        0.000
H17_20$1             -2.109        0.390       -5.409        0.000
H17_20$2              1.399        0.196        7.126        0.000
H20_22$1             -0.367        0.174       -2.109        0.035
H20_22$2              2.347        0.382        6.151        0.000
H22_6$1               0.754        0.259        2.912        0.004
H22_6$2               2.542        0.264        9.646        0.000

Latent Class Pattern 1 3

Thresholds
H6_9$1              -15.000        0.000      999.000      999.000
H6_9$2                2.357        0.783        3.011        0.003
H9_12$1              -1.433        0.372       -3.850        0.000
H9_12$2              -0.604        0.279       -2.166        0.030
H12_14$1             -1.988        0.257       -7.749        0.000
H12_14$2              0.524        0.125        4.209        0.000
H14_17$1             -1.027        0.232       -4.436        0.000
H14_17$2              0.274        0.131        2.087        0.037
H17_20$1             -2.665        0.310       -8.605        0.000
H17_20$2              0.707        0.112        6.322        0.000
H20_22$1             -0.527        0.152       -3.462        0.001
H20_22$2              0.702        0.138        5.102        0.000
H22_6$1               1.119        0.185        6.062        0.000
H22_6$2               1.748        0.183        9.544        0.000

Latent Class Pattern 2 1

Thresholds
H6_9$1                1.663        0.199        8.370        0.000
H6_9$2                1.839        0.198        9.274        0.000
H9_12$1              -2.150        0.281       -7.643        0.000
H9_12$2              -0.869        0.140       -6.190        0.000
H12_14$1             -1.978        0.191      -10.349        0.000
H12_14$2              0.323        0.078        4.139        0.000
H14_17$1              0.237        0.183        1.293        0.196
H14_17$2              0.782        0.123        6.352        0.000
H17_20$1             -2.936        0.428       -6.853        0.000
```

```
H17_20$2            0.632       0.081       7.807       0.000
H20_22$1            0.028       0.142       0.194       0.846
H20_22$2            0.868       0.086      10.145       0.000
H22_6$1             0.658       0.109       6.010       0.000
H22_6$2             1.326       0.100      13.215       0.000

Latent Class Pattern 2 2

Thresholds
H6_9$1              1.640       0.171       9.619       0.000
H6_9$2              1.906       0.179      10.678       0.000
H9_12$1            -1.954       0.347      -5.636       0.000
H9_12$2            -0.360       0.127      -2.842       0.004
H12_14$1           -0.016       0.189      -0.084       0.933
H12_14$2            0.948       0.135       7.029       0.000
H14_17$1           -1.906       0.301      -6.327       0.000
H14_17$2            0.371       0.080       4.614       0.000
H17_20$1           -0.812       0.116      -7.030       0.000
H17_20$2            0.910       0.089      10.259       0.000
H20_22$1           -0.742       0.089      -8.318       0.000
H20_22$2            0.998       0.085      11.705       0.000
H22_6$1             0.298       0.083       3.608       0.000
H22_6$2             1.337       0.099      13.475       0.000

Latent Class Pattern 2 3

Thresholds
H6_9$1             -1.072       0.500      -2.144       0.032
H6_9$2             -0.309       0.346      -0.892       0.372
H9_12$1             2.441       1.044       2.339       0.019
H9_12$2             3.599       1.983       1.815       0.069
H12_14$1           -1.029       0.211      -4.880       0.000
H12_14$2            0.603       0.123       4.913       0.000
H14_17$1           -0.010       0.243      -0.041       0.967
H14_17$2            0.784       0.157       4.977       0.000
H17_20$1           -0.953       0.203      -4.684       0.000
H17_20$2            0.779       0.135       5.784       0.000
H20_22$1           -0.105       0.210      -0.500       0.617
```

```
H20_22$2            1.203       0.135       8.914       0.000
H22_6$1             0.582       0.299       1.950       0.051
H22_6$2             1.370       0.206       6.653       0.000

Latent Class Pattern 3 1

Thresholds
H6_9$1             -4.593       1.699      -2.703       0.007
H6_9$2             -2.975       0.428      -6.957       0.000
H9_12$1            -0.322       0.207      -1.553       0.120
H9_12$2             0.398       0.363       1.095       0.274
H12_14$1           -5.060       3.668      -1.380       0.168
H12_14$2            0.307       0.100       3.080       0.002
H14_17$1            0.186       0.530       0.351       0.726
H14_17$2            0.317       0.245       1.295       0.195
H17_20$1           -4.019       0.957      -4.199       0.000
H17_20$2            0.747       0.093       7.987       0.000
H20_22$1           -0.233       0.132      -1.767       0.077
H20_22$2            0.607       0.109       5.571       0.000
H22_6$1             1.304       0.146       8.918       0.000
H22_6$2             1.850       0.160      11.579       0.000

Latent Class Pattern 3 2

Thresholds
H6_9$1             -1.232       0.195      -6.305       0.000
H6_9$2             -0.858       0.169      -5.068       0.000
H9_12$1            -4.377       1.937      -2.260       0.024
H9_12$2            -1.488       0.316      -4.717       0.000
H12_14$1           -1.727       0.227      -7.611       0.000
H12_14$2            0.302       0.082       3.666       0.000
H14_17$1           -1.834       0.237      -7.730       0.000
H14_17$2           -0.294       0.186      -1.582       0.114
H17_20$1           -2.588       0.487      -5.313       0.000
H17_20$2            0.631       0.062      10.187       0.000
H20_22$1           -0.920       0.078     -11.852       0.000
H20_22$2            0.462       0.073       6.308       0.000
H22_6$1             0.640       0.119       5.361       0.000
```

```
H22_6$2              1.162       0.129       9.039       0.000

Latent Class Pattern 3 3

Thresholds
H6_9$1              -4.941       5.813      -0.850       0.395
H6_9$2              -2.680       0.887      -3.024       0.002
H9_12$1             -0.765       0.640      -1.195       0.232
H9_12$2              1.164       0.920       1.265       0.206
H12_14$1            -1.415       0.439      -3.226       0.001
H12_14$2             0.566       0.085       6.626       0.000
H14_17$1            -2.052       0.650      -3.158       0.002
H14_17$2             0.612       0.210       2.909       0.004
H17_20$1            -1.627       0.427      -3.810       0.000
H17_20$2             0.713       0.103       6.935       0.000
H20_22$1            -0.850       0.329      -2.585       0.010
H20_22$2             0.685       0.134       5.104       0.000
H22_6$1              1.237       0.195       6.349       0.000
H22_6$2              1.893       0.179      10.582       0.000

Between Level

Categorical Latent Variables

Within Level

Intercepts
CW#1                -0.076       0.366      -0.208       0.835
CW#2                 0.475       0.309       1.539       0.124

Between Level

CW#1       ON
CB#1                 1.223       0.473       2.585       0.010
CB#2                 0.793       0.441       1.796       0.073

CW#2       ON
CB#1                -0.282       0.535      -0.526       0.599
```

```
CB#2                0.333      0.455      0.733      0.464


Means
CB#1               -0.417      0.100     -4.178      0.000
CB#2               -0.386      0.067     -5.770      0.000


QUALITY OF NUMERICAL RESULTS

Condition Number for the Information Matrix              0.428E-04
(ratio of smallest to largest eigenvalue)


SAVEDATA INFORMATION



Save file
H:\summer_project\Mplus\TimeSlots\Multilevel\NDNSslot_CW3CB3.txt

Order of variables

H6_9
H9_12
H12_14
H14_17
H17_20
H20_22
H22_6
ID_DY
AGE
SEX
CPROB1
CPROB2
CPROB3
CPROB4
CPROB5
CPROB6
CPROB7
```

```
CPROB8
CPROB9
CB
CW
MLCJOINT
ID

Save file format           Free

Save file record length    10000


DIAGRAM INFORMATION

Mplus diagrams are currently not available for Mixture analysis.
No diagram output was produced.


Beginning Time:  09:55:10
Ending Time:  10:02:01
Elapsed Time:  00:06:51



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Appendix C

Example of a food diary for one day

Day EXAMPLE			Day: Thursday	Date: March 31st
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 Family No TV At table	Orange juice, unsweetened, UHT Tea Milk, fresh semi skimmed Sugar white Weetabix Milk as above Sugar as above Toast wholemeal, large loaf Butter unsalted Strawberry Jam	Tesco Tesco Tesco Silverspoon Hovis Anchor Co-op	Large glass Mug A little 2 level teaspoons 2 Drowned 2 heaped teaspoons 2 thin slices thick spread on both 1 teaspoon on one slice
9am to 12 noon				
11am 12noon	School playground With friends School corridor Alone	Coca cola diet Potato crisps, Salt and Vinegar Water from water cooler Mars Bar	Coca Cola Walkers	330ml can 25g packet from a multipack small plastic cup 1 kingsize
12 noon to 2pm				
12.45pm 1.50pm	School canteen With friends At table School corridor Alone	Sandwich, from home White bread, large loaf Spread Ham unsmoked Cheddar cheese Branston Pickle Apple with skin from home Ribena Light, Ready to Drink, Blackcurrant, from canteen Kitkat from home Chewing gum	 Kingsmill Flora Light Tescos Orbit Sugar Free	 2 med slices thin spread on both slices 1 slice 2 medium slices 1 teaspoon 1 (left core) 220ml carton 2 fingers 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		½ 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.