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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:

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- I have acknowledged all main sources of help.
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Signed: ______________________________

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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
cAIC	**c**onsistent **A**kaike **I**nformation **C**riterion
BIC	**B**ayesian **I**information **C**riterion
EM	**E**xpectation **M**aximazation
FSA	**F**ood **S**tandards **A**gency
LCA	**L**atent **C**lass **A**nalysis
LTA	**L**atent **T**ransition **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

Chapter 1

Introduction

Background

The widely accepted norm these days seems to be that we eat three times a day. However, is this really an ideal temporal eating pattern for everyone? 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).

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 rolling programme 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

Chapter 2

Methods

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:

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

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:

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

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 carbohydrates 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 carbohydrates 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.

Survey Data

Survey Selection Method

Response rates

Chapter 3

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Main Section 1

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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

SAS code for mixed effect LCA analysis

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.