

Exposure to food environments, diet and weight status in children

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“The causes of overweight and obesity are multifactorial, complex, and not fully understood. Yet the alarming prevalence compels us to use evidence based interventions and act, at individual and population levels, even while research into the underlying causes continues... individual action on diet must be supported by population level interventions that tackle the obesogenic environment... Otherwise the consequences of the increased burden of disease could be extreme.”

*- Simon J Howard, public health specialty registrar & Sally C Davies, chief medical officer for
England, 27 March 2014.*

Abstract

There is a growing interest in understanding how the built food environment influences health behaviours. Whilst policy interest in the influence of food environments on diet and body weight is growing, the evidence base is limited, particularly for environments beyond the home neighbourhood. Research in children is of particular importance, as it is known that dietary behaviours and weight tend to track into adulthood.

This thesis addresses the gap in knowledge surrounding the influence of exposure to the food environment on weight and diet in children. It also takes into consideration the interactions with socio-economic status. Existing research exploring the environmental influences on diet and weight in children is reviewed, and a conceptual framework of key determinants identified is presented. Three studies are presented which investigate associations between different measures of exposure to the food environment and diet and weight. A systematic review investigating the use of GPS in studies of the food environment is also conducted. Additionally, a novel method for assessing environmental exposure is presented.

The results from this research suggest that unhealthy food environments measured at an area level are generally conducive to weight gain and poorer diet, while the opposite is true for healthier food environments. Furthermore, this thesis supports the hypothesis that diet, weight and access to food are patterned by social class, and that the food environment partially mediates the well-known association between socio-economic status and weight status. However, findings were equivocal when using measuring exposure to the food environment at an individual level. This suggests that correctly measuring the characteristics of the food environment is important in order to disentangle their effects on health outcomes, and calls for efforts to attempt to reduce the heterogeneity in measures of the food environment employed.

Declaration

The research reported in this thesis is my own original work which was carried out in collaboration with others as follows:

Chapter 1 was written by Andreea Cetateanu. Andy Jones reviewed drafts of the chapter.

Chapter 2- Andreea Cetateanu was the lead author. She reviewed the literature, designed the framework and wrote the manuscript. Andy Jones reviewed drafts of the manuscript.

Chapters 3- Andreea Cetateanu was the lead author. She carried out statistical analyses and wrote the manuscripts. Andy Jones reviewed drafts of the manuscript and assisted with advice on statistical analysis. All the datasets used in this chapter were freely available: the NCMP dataset was freely available on the National Obesity Observatory website (www.noo.org.uk), which provided information on: IDACI scores for each MSOA, area of greenspace, area of domestic gardens, and prevalence of obesity and normal weight of Reception and Year 6 children in British schools. Information on population age, occupation and ethnicity was downloaded at MSOA level from the 2001 UK Census (freely available at <http://census.edina.ac.uk/>). Information on location of food outlets in England was requested from The Ordnance Survey and was supplied in the form of their Points of Interest dataset. Andreea Cetateanu requested or downloaded these three datasets, cleaned and put them into usable format and linked them according to the MSOA codes.

Chapter 3 has been published as:

Cetateanu A, Jones AP. (2014). Understanding the relationship between food environments, deprivation and childhood overweight and obesity: evidence from a cross sectional England-wide study. *Health & Place*; 27:68-76.

Chapter 4- Andreea Cetateanu was the lead author. For the SPEEDY-1 baseline study presented in this thesis, she carried out statistical analyses and wrote the manuscript. While Andreea Cetateanu assisted in the primary data collection and questionnaire design for the SPEEDY-3 follow up study, data from the SPEEDY-1 baseline study was provided as a secondary data source, as this was conducted before the start of this PhD in 2007. The creation of buffers around the home and school, the density of food outlets within these buffers, BMI, daily dietary intake and other variables used were therefore provided as a result of requesting this dataset. The SPEEDY study has been led by Dr Esther van Sluijs at the

Medical Research Council Epidemiology Unit in Cambridge. Andy Jones reviewed drafts of the manuscript and assisted with advice on statistical analysis.

Chapter 4 to be submitted as:

Cetateanu A, Jones AP. Exposure to the food environment, food consumption and weight in children aged 9-10 years: evidence from the SPEEDY study

Chapter 5- Andreea Cetateanu was the lead author. Andy Jones reviewed drafts of the manuscript.

Chapter 5 has been submitted to Social Science and Medicine as:

Cetateanu A, Jones AP. How can GPS technology help us better understand the food environment? A systematic review

Chapter 6- Andreea Cetateanu was the lead author. She assisted in the design of the algorithm, carried out statistical analyses and wrote the manuscript. Andy Jones reviewed drafts of the manuscript and assisted with advice on statistical analysis. Andrei Alin Popescu and Bogdan Luca from the Computer Science department at UEA developed the suite of Python programs that automatically processed the GPS data and assisted with drafts of the manuscript.

Chapter 6 has been submitted to Applied Geography as:

Cetateanu A, Luca, B., Popescu A.A., Page, A., Cooper, A., Jones A.P. Identifying travel mode and trips from raw GPS data: a novel methodology applied to assess exposure to the food environment

Chapter 7- Andreea Cetateanu was the lead author. She performed statistical analyses and wrote the manuscript. Andy Jones reviewed drafts of the manuscript. Professor Ashley Cooper and Dr Angie Page from the University of Bristol led the PEACH study. They provided the data from the food frequency questionnaire (detailed in Appendix 7.1.) that was collected in 2007/8, before the start of the PhD.

Chapter 7 has been submitted to Health and Place as:

Cetateanu A, Jones AP, Cooper A, Page A: Food consumption, weight, socio-economic status and exposure to the food environment in children aged 11-12 years: the PEACH project

Chapter 8 was written by Andreea Cetateanu. Andy Jones reviewed drafts of the chapter.

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ABBREVIATIONS

ANGELO= Analysis Grid for Environments Leading to Obesity

BMI= body mass index

EMA= Ecological Momentary Assessment

EST= Ecological Systems Theory

FFQ= food frequency questionnaire(s)

FS= Food Stores

GIS= geographic information system(s)

GPS= global positioning system(s)

MSOA= Middle Layer Super Output Area

NCMP =National Child Measurement Programme

NPPG= National Planning Practice Guidance

NSP= Non-starch polysaccharides

PALMS= Physical Activity Location Measurement System

PEACH= Personal and Environmental Associations with Children's Health

PoI= Points of Interest

SD= Standard Deviation

SES= socio-economic status

SPEEDY= Sport, Physical activity and Eating behaviour: Environmental Determinants in Young people

UK= United Kingdom

US(A)= United States of America

Chapter 1

General introduction

The environment and health: implications for obesity and diet

We live in what has been termed an ‘obesity era’, where the ‘technological revolution’ is a major cause of weight gain¹. The speed of the recent rise in the prevalence of obesity suggests that some components of the social or physical environment may have an aetiological role². The term ‘obesogenic environment’ has been coined to describe environments which may promote obesity^{3,4}. The environment can be broadly defined to mean anything that is external to the individual⁵. Obesity is known to be determined by a complex system of factors that interact with each other⁶⁻¹¹. However in the vast majority of cases, obesity is due to lifestyle rather than pathology¹², and food habits, sedentariness and physical activity have been shown to be key¹³. Although physical activity behaviours are a key determinant of weight status, food systems play a significant role.

Behavioural determinants research and behavioural nutrition interventions have focused mostly on individual-level motivational factors. However, the previous belief that obesity is simply a result of a lack of willpower and an inability to discipline eating habits is no longer satisfactory¹⁴. The case has therefore been made recently that the focus on pharmacological, educational and behavioural interventions have had limited overall success, and that a novel and longer term approach would be to investigate the environments which promote high energy intake and sedentary behaviour¹⁵. For example, the UK Department of Health recently funded the development of the Healthy Foundations Life-Stage Segmentation¹⁶, a toolkit for profiling individuals by their health behaviours, as part of the ‘Healthy Towns’ lifestyle survey initiative; it was designed to target behaviour change across seven domains, including obesity. However, this has been criticised to not represent deprived populations well and to being weighted towards psychological and behavioural constructs rather than the environments and cultures which people inhabit.

It is therefore vital to investigate the built (physical)^{17,18} and socioeconomic^{19,20} contexts in which health behaviours occur, as it has been argued that these may be the main determinants of nutrition behaviours. The built environment has been defined to be the sum of a range of physical and social elements that make up the structure of a community, or otherwise all aspects of an individual’s surroundings which are human-made⁵. It has in particular been

hypothesised to play an important role in influencing obesity by promoting a climate that stimulates increased energy consumption and decreased energy expenditure⁵. Indeed, a Public Health England 2014 report on ‘Obesity and the environment: regulating the growth of fast food outlets’²¹ stressed that obesity is a complex problem that requires action from individuals and society across multiple sectors, and that one important action is to modify the built environment so that it does not promote sedentary behaviour or provide easy access to energy-dense food. This plays into the current context whereby one of the dietary trends in recent years has been an increase in the proportion of food eaten outside the home, which is more likely to be high in calories²².

Despite this, the theoretical basis and empirical evidence for environmental determinants of nutrition behaviours are not strong. Evidence regarding the mechanisms through which the built environment may influence obesity is only just beginning to emerge^{5 17 23}. To this end, a call for better theory and evidence on environmental determinants of healthy eating and obesity has been made²⁴.

The importance of action on obesity in children

Investigating determinants of obesity and diet in young people is of particular concern given that increasing global obesity trends over the last years¹⁹ are also apparent among children, and this leads to not only an increased risk of disease (such as hypertension, asthma)²⁵, but also discrimination and stigmatisation²⁶. There is a growing body of evidence that highlights an epidemic of obesity that is affecting children and adolescents worldwide, with trends that have been particularly pronounced in highly industrialised countries²⁷. In the UK for example, although healthy eating concerns are increasing among consumers²⁸ current predictions suggest further increases in the prevalence of obesity in young people. A 10.1% obesity prevalence in UK boys and 8.9% in girls has been predicted by 2015²⁹, with similar trends being reported in other countries^{30 31}.

Most research in the area of environmental influences on health outcomes has however focused on adults³². The case has been made³³ for focusing more on children as the population of interest. Dietary factors in children are important because early-life health behaviours predict both health behaviours and health status later in life³⁴, with approximately 70% of obese children or adolescents becoming obese adults¹². What is more, children relate to their food environment in their own way³⁵ or through their parents³⁶, and the food environment may therefore have a different importance in this population. There is therefore a need to

identify behavioural factors that support the susceptibility to excess energy intake in young people³⁷. The health problems associated with obesity, and the evidence that it tracks from childhood to adulthood¹² mean that the prevention of excess weight gain in children in particular is a public health priority.

The role and importance of the food environment in the current context

Researchers are increasingly investigating associations between exposure to the food environment and weight and weight-related behaviours (i.e., diet) and how these might be patterned by social class. The food environment, broadly conceptualized to include any opportunity to obtain food, is becoming more recognized as critical to health³³, because it is perceived as increasingly of an obesogenic nature, being characterized by inexpensive, palatable, energy-dense food³⁸. In the literature, the food environment has been generally defined to mean availability and accessibility to food, as well as food advertising and marketing³², or any opportunity to obtain food that includes physical, socio-cultural, economic and policy influences at both micro and macro levels^{1 15}. This has also been referred to as the ‘foodscape’³⁹⁻⁴² and it generally represents the multiplicity of sites where food is found and/or consumed. This thesis will generally focus on the retail food environment aspect (i.e., availability of and access to food obtained outside the home or school settings, represented by food outlets). For the purpose of this thesis therefore, the ‘retail food environment’ will simply be referred to as ‘the food environment’.

It has been suggested by some findings that exposure to food in the neighbourhood⁴³ or in the daily activity space⁴⁴ influences diet and is associated weight status⁴⁵. Some researchers argue that “food deserts”⁴⁶, areas with little or no provision of fresh and healthy food, may contribute to disparities in obesity and related health problems, such as diabetes or hypertension⁴⁷. One of the goals of their research has been to shape effective strategies to improve access to healthy foods or decrease access to unhealthy foods to help tackle the obesity epidemic that has been particularly pronounced in highly industrialised countries²⁷, and on the rise in poorer countries as well^{48 49}. Such evidence has led to a number of targeted interventions and policy activities. Some recommend increasing the number of supermarkets and grocery stores in neighbourhoods or improving access to these facilities^{50 51}. Others aim to reduce the number of fast food outlets and convenience stores⁵¹⁻⁵³, especially those to which children may be readily exposed.

Yet despite the efforts with regard to policy development, research into the link between food availability or exposure and obesity is relatively undeveloped, with most evidence coming from the US and less from the UK⁵⁴. Moreover, the associations found in the literature are equivocal^{45 55-58}, which can make drawing up policy recommendations from across-the-board challenging. Some studies find associations between access to food and weight^{54 59 60} or diet^{43 61}, but some are counterintuitive⁶², while other studies find no associations^{55 63}. Furthermore, it has been hypothesised that there is a social class gradient in diet⁶⁴, weight⁸ and access to food^{65 66}, even in children⁶⁷. However, results are also equivocal in this respect. For example, some studies find associations between social class and access to food^{66 68}, while others find none^{66 69}. The mixed results across the literature may largely be due to issues such as sample size, sample heterogeneity, use of unreliable diet or weight measures, or the fact that there is no gold standard as of yet on how to measure exposure to the food environment. In the current context where almost two thirds of adults and a third of children are overweight or obese⁷⁰, it is becoming more critical to establish how these associations interplay.

Changing the obesogenic food environment: the policy context

The diseases that obesity can cause (such as diabetes, strokes, kidney failure) are rising. The World Health Organisation predicts that they will be the leading causes of death in all countries, including the poorest⁷¹. One of the gravest consequences of this is the enormous burden on the health-care systems. A major determinant of this is the current food system, which is tilting the body's system in favour of fat storage: it is not just the fact that diets are energy dense, but also they alter the biochemistry of fat metabolism and change insulin signalling, which affects how the body processes carbohydrates. According to the 'thrifty gene hypothesis' put forth by James Neel in 1962³⁸⁰, genes that predispose to obesity in the current environment enable individuals to efficiently collect and process food to deposit fat during periods of food abundance in order to provide for periods of food shortage. While these were historically advantageous for people who lived in times of privation when food was only sporadically available, such as hunter-gatherers³⁸¹, they have become detrimental in the modern world, where we have access to cars, technology and processed food. Policy makers should therefore be reforming the current food system in which people are embedded and develop policies that regulate commercial interests and promote access to nutritious food for everyone.

As research in the food environment area is gaining increasing momentum, policy makers are becoming more aware of the importance of changing the current foodscape in order help combat obesity. A few examples would be New York City's recent attempt to ban large-size cups for sugary soft drinks, the city of Detroit's zoning of fast food around schools (requiring a minimum distance of 500 ft between the two), or Denmark's short-lived tax surcharge on foods that contain more than 2.3 per cent saturated fat. In the UK, the National Planning Practice Guidance (NPPG)⁷² recognizes the importance of promoting access to healthier food in newly launched national guidance. According to a recent Public Health England report²¹, a number of local authorities have drawn up planning documents to restrict the development of new fast food premises near schools (most of them using a distance of 400 meters exclusion zone, and some even 800 meters). However, these are recognised to take a long time to be put in action and require planning permission.

Children are a population group that is especially susceptible to their environment. In qualitative research children have identified availability/choice, cost and time/effort in obtaining food as barriers to eating a healthful diet⁷³. To this end, planning authorities can influence the built environment to improve health and reduce the extent to which it promotes obesity in children. It is therefore important to inform policy in this respect by providing evidence-based recommendations. An example is the recent Public Health England report²¹ on regulating the growth of fast food environment which suggests that formal recommendations should be developed on reducing the proximity of fast food outlets to schools and other places where children gather.

Another population group that is particularly sensitive to the current obesogenic food environment are lower social-class communities. According to Public Health England²¹, the prevalence of obesity in children in the 10% most deprived groups is approximately double that in the 10% least deprived. In rich nations obesity and poor diet is concentrated amongst the least well-off and less educated. This has started to be the case even in even in poorer nations^{48 49}, phenomenon termed as the 'nutrition transition'. What is more, according to the National Obesity Observatory⁷⁴, there is a strong association between deprivation and the density of fast food outlets. Policy makers should therefore give special attention to deprived communities.

The obesity epidemic has attracted attention at all levels, not just policy makers but also health practitioners and urban planners. Shaping the environment to better support healthful

decisions has the potential to be a successful obesity prevention intervention¹⁵. In this respect, planning authorities have the power to influence the built environment in order to improve health-related behaviours and reduce the extent to which it promotes obesity-related behaviours⁷⁵.

Limitations of existing research

In spite of progress that research has made towards understanding the most important environmental determinants of obesity and dietary behaviours in children and adults, there are several challenges still to be overcome. The need to strengthen the evidence in the food environment area is becoming increasingly recognised, with the emergence of new technologies for measuring exposure to the food environment.

There are multiple geographical settings which people operate within including the home, school, work, or neighbourhood environments. Therefore, individual dietary choice and health may be influenced by factors within one or more of these environments. It is therefore important to gain an understanding of the drivers which operate within different environments in order to fully understand the influences on behaviour and enable effective interventions to be designed⁷⁶. Most research has been limited on focusing on the importance of one type of environment and not others.

Moreover, it is important to assess if research findings are transferable to different settings. Research to date has been mostly conducted in urban areas in the US⁷⁷, a country where contrasts in urban design and neighbourhood segregation may lead to a different importance of the food environment compared to the UK²³. Hence, the importance of environmental factors should be interpreted within context.

There is further a lack of standardised definition and assessment of the food environment. Many of the mixed results regarding associations between food environment characteristics and diet/weight have been suggested to be in part due to the differences in methodologies used⁷⁶. Most literature to date has relied on assuming exposure to the food environment in residential neighbourhoods with the help of GIS (Geographic Information Systems)^{43 78 79}, and only recently have researchers begun to investigate personal exposures in the spaces where people conduct their daily activities with the help of GPS (Global Positioning Systems)^{44 80 81}. For studies that use GIS, there is a wide variation in buffer sizes used, ranging from 160 to 300 meters as reported by a recent systematic review³³. For studies that use GPS, there

is not a standardised way of how many days of tracking would be sufficient to capture regular food behaviours^{17 48}. According to two recently conducted systematic reviews, studies that employed GIS-based measures were more common than those using other measures, however these studies less consistently reported a significant relationship between the food environment measure and dietary outcomes in the expected direction^{33 82}. One of the reviews³³ found that among studies that relied on GIS-based measures to characterize the food environment, measures of accessibility were somewhat less consistent in finding significant expected associations with dietary outcomes compared to measures of availability.

While both methods have strengths and limitations, combining them can provide an unprecedented opportunity to move forward in better disentangling the determinants of obesity and food intake. It has further been suggested that the integration of such objective (GIS-based or GPS-based) measures with perceived measures³³ of the environment might be important^{44 83 84}, as they may operate on behaviour through different mechanisms. It can therefore be useful to survey residents about availability of food in their neighbourhoods, as they might provide information on foods that actually exist, which is not captured by data on locations of food outlets. A limitation of this approach is the reporting bias.

However, research often includes only one of these types of measurements, often operationalised in different ways.

This thesis attempts to overcome some of the limitations of existing research by investigating associations between different objective measures of the food environment (GIS and GPS-based) and weight and diet, if different measures show different associations with outcomes, as well as how these are related to socio-economic status.

Data used in this thesis

The NCMP dataset

The NCMP (National Child Measurement Programme) measures the weight and height of children in reception class (aged 4 to 5 years) and year 6 (aged 10 to 11 years) and was designed to assess the prevalence of overweight and obese children within schools in the UK. Local Authorities are asked to collect data on children's height and weight from all state maintained schools within their area, and participation in the programme is not compulsory. The data is available at different geographical levels, and in this thesis data for

6781 geographical areas across England known as Middle Super Output Areas (MSOAs) was used. The MSOA is a UK Census geography designed for small-area statistical analyses⁸⁵. Aggregate area-level data from the NCMP sweeps for the years 2007/8 and 2009/10 was used, which provides data for approximately 3 million children across England.

The SPEEDY-1 study

The SPEEDY study (Sport, Physical activity and Eating behaviour: Environmental Determinants in Young people) was set up to quantify levels of physical activity and dietary habits and the association with potential correlates in 9–10 year old British school children. SPEEDY-1 is the baseline data collected over the summer of 2007. The methods of recruitment, sampling and overall sample representativeness of the study have been described in more detail elsewhere⁸⁶. Children were sampled through schools in the county of Norfolk, which were selected based on urban-rural status and Healthy School status. Healthy School status is awarded to schools who meet the national criteria for promoting healthy eating, physical activity, personal and social education and emotional wellbeing⁸⁷. Teams of research assistants visited participating schools between April and July 2007 and children were collected from 92 schools. Research assistants collected a range of data according to standard operating procedures including anthropometry, demographic information, school-level information, and details of children's home and neighbourhood environment. Children completed a 4-day food diary, and a questionnaire was also completed by a parent or main carer of each child.

The PEACH-2 study

PEACH (Personal and Environmental Associations with Children's Health) is a longitudinal study undertaken in Bristol, UK which investigates how the environment can influence eating and physical activity behaviours in children aged 10-11 (1307 children from 23 primary schools) and 11-12 years old (953 children from 19 secondary schools), from 2006/7 to 2007/8. PEACH-2 represents the first follow up of data collection from the baseline, representing children who moved up from last year of primary school into first year of secondary school. Only a subsample of the children wore a global positioning system (GPS) device which provided the exact location of children over 4 days (including one weekend day). The children were also asked to complete a diet screener, which recorded self-reported eating and lifestyle behaviours. The cross-sectional data for the years 2006/7 and 2007/8

combined used in this thesis was for a sub-sample of 688 secondary school children who completed the diet screener and also wore a GPS device.

Thesis structure

Using data collected from the NCMP, SPEEDY and PEACH studies, this thesis investigates the role the food environment might play in obesity causation and prevention and in dietary intake in children, as well as what role socio-economic status might have (Figure 1.1.). Associations between different measures of exposure to the food environment and weight status (Chapters 3, 4, 7) and diet (Chapters 4, 7) are explored, as well as between socio-economic status and exposure to the food environment, weight status and/or diet (Chapters 3, 4, 7). Furthermore, the potential of role of exposure to the food environment as a mediator in the association between socio-economic status and weight status has also been explored (Chapters 3, 4). Having different scale studies with different measures of the food environment and diet offered the opportunity to evaluate if these varied measures might lead to divergent findings, and if this might in part explain the equivocal results across the literature to date. In the NCMP study, exposure to the food environment is measured as GIS-derived counts of food outlets within a census administrative area, in the SPEEDY study it is measured as density of food outlets within predefined home and school neighbourhoods, and in the PEACH study GIS-derived measures of food exposure within home and school neighbourhoods are compared against measures of personal proximity to food outlets derived from GPS locations (Figure 1.2.). This thesis is presented as a series of papers (each its own chapter) that build on each other. One paper has been published, and the rest have either been submitted for publication (and are either in print, in press, or under review) or are about to be submitted at the time of or shortly after thesis submission.

Figure 1.1. Overall analysis flow

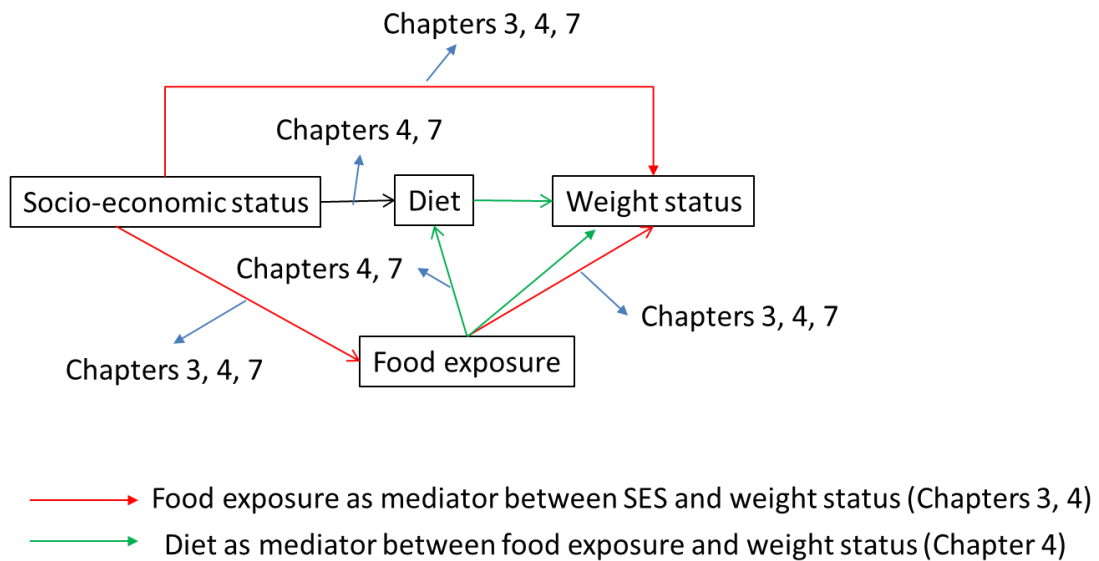
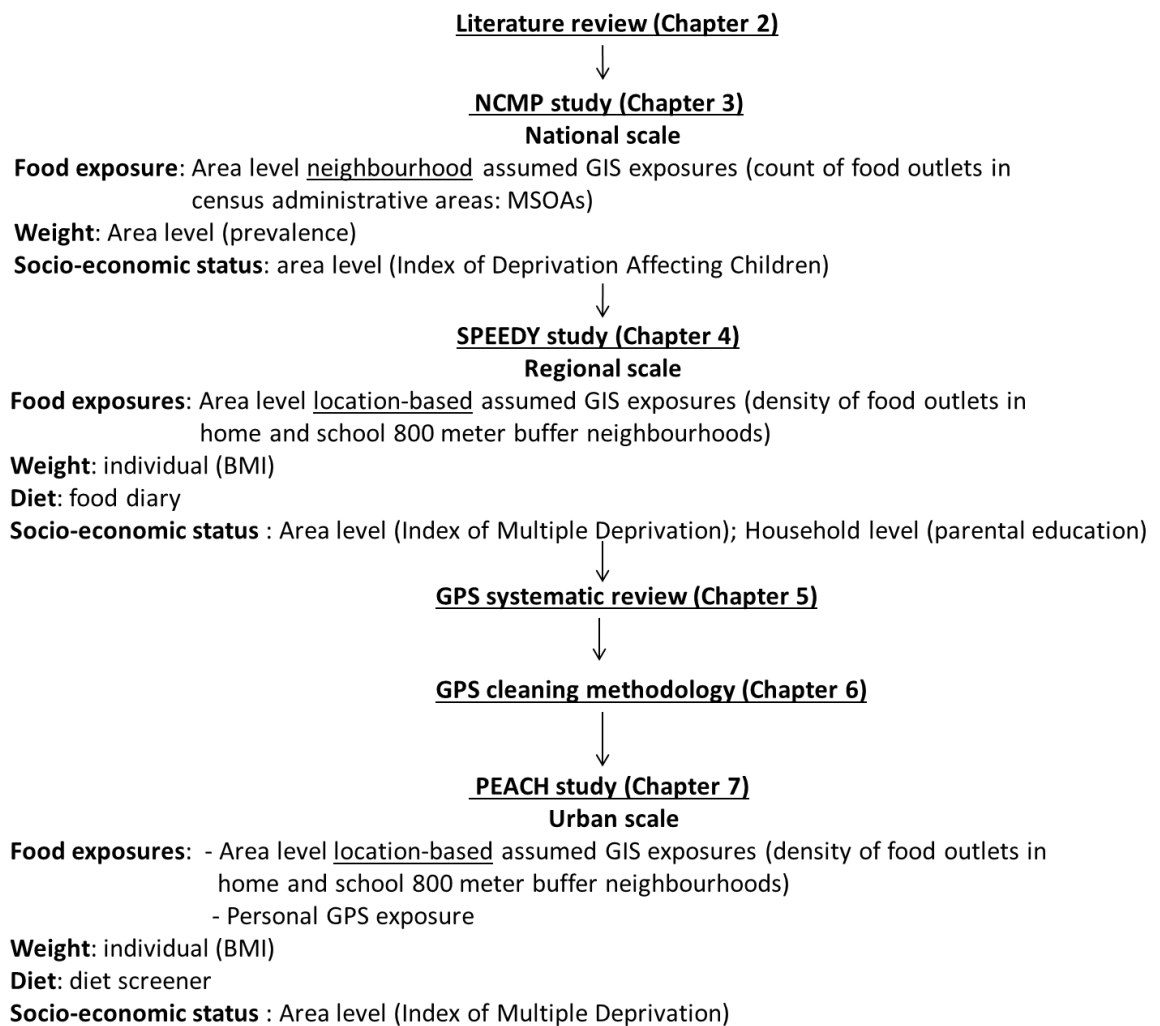


Figure 1.2. Structure of analytical chapters



Chapter 2 provides a general context of the food-related environmental correlates of diet and weight, particularly in youth (physical activity-related correlates are not examined in this thesis). It reviews the existing literature and identifies components of the food, social, production and consumer environment which have been examined previously and used to create a new system map and a conceptual framework. The system map has been useful in illustrating the complexity of the food system, from which a set of key determinants of weight and diet that drive the whole food system have been extracted. These key determinants have been used to develop a simpler conceptual framework. However, it would not be possible to analyse all determinants identified in one thesis. Therefore, this thesis focuses on one aspect of the conceptual framework, i.e. the retail food environment, as it has been identified in Chapter 2 that this area has received relatively little attention and it is a growing and important area of research.

Chapter 3 investigates associations between neighbourhood assumed exposure to the food environment (based on census administrative areas) with the help of geographical information systems (GIS) and weight prevalence and area level deprivation in both primary and secondary school children at national level. The work used data from the National Child Measurement Programme (NCMP) and hence benefited from data from a large sample of children across the whole of England.

Chapter 4 assesses the associations between assumed exposure to food in location centred environments (around the home and the school) and individual weight, diet and household socio-economic status in secondary school children, using the SPEEDY (Sport, Physical activity and Eating behaviour: Environmental Determinants in Young people) study based in Norfolk. For the analysis in chapter 3 we had no information on the home location of children, individual/household level variables (such as socioeconomic status or individual weight), and dietary intakes. We have therefore built on the previous analysis in chapter 3 and further unpicked the relationship between socioeconomic status, the food environment, and weight in children, and additionally diet. When chapter 3 was published as a paper, a key issue that arose in the press was related to schools, whereby because NCMP was school based catchment, it was interpreted that fast food outlets around schools are conducive to children having elevated weight status. However NCMP being a study conducted in schools, it was not possible to differentiate between home and school exposures, so SPEEDY offers us the opportunity to investigate if there is evidence of a differential importance of home vs. school.

Chapter 5 collates and appraises in a systematic way the evidence available regarding the use of Global Positioning Systems (GPS) to study and measure the food environment. Previous studies have mostly relied on assumed exposure to the food environment in a GIS, and that has been built on in chapters 3 and 4. However it has been argued in the literature that there is a need to also investigate exposures beyond the residential neighbourhood and move away from place based assumed exposures to people based exposures with the help of GPS. We have therefore conducted a systematic review to bring together and quality assess the evidence on the use of GPS to study food environments.

Chapter 6 sets out the methodology used to clean the raw GPS data which was used to perform analysis in chapter 7. One of the aims in chapter 7 was to calculate on foot (or slow cycling- not considered separately here) exposure to the food environment from the cleaned GPS data, as it is considered that participants in motorised vehicles would not have the opportunity to access food. Chapter 6 therefore presents the methodology used to construct a robust algorithm based on the Hidden Markov Model (HMM) and various other criteria, which is used to strip out noises and motorised vehicle trips from the GPS data.

Chapter 7 assesses associations between both assumed neighbourhood and personal exposure to the food environment and diet, weight and socio-economic status (SES) in children in an urban setting, using data from the PEACH (Personal and Environmental Associations with Children's Health) study. The assumed location based exposure was derived with the help of GIS in a similar way to chapter 4, while the individual on-foot exposure was derived with the help of GPS (cleaned with the help of the algorithm set out in Chapter 6).

Chapter 8 summarises the findings from this thesis, considers the implications for exposure to the food environment in influencing weight and diet, and highlights areas for future research.

In Appendix A. a glossary of technical terms can be found, and the reader is referred to that for definitions of the specialty terms used throughout this thesis.

Chapter 2

Understanding determinants of diet and weight in young people: a new framework

Abstract

It has been widely acknowledged that the complex network of factors that influence weight, coupled with a lack of strong evidence on many putative associations between the food environment and dietary behaviours, means there is a need for a better theoretical understanding of the environmental determinants of weight and diet behaviours.

There are studies that have researched the influence on diet and weight of environmental factors such as the built environment, the socio-cultural environment, the policy environment and so on, and research in the food area in particular has been growing over the past few years. Building on this, an evidence-based food system map was constructed in this chapter as part of an initial scoping exercise that describes food-related drivers of weight and diet in children. Drawing on a similar process to that of the UK Foresight Obesity System Map, the map details the relationships between its component factors. While it was useful in illustrating the complexity of the obesogenic food system, this complexity can arguably detract from its practical application. Hence, it was used as a basis for a simplified version that allowed identification of key determinants of weight and diet.

This review and the developed framework have formed the theoretical basis for this thesis and highlighted areas where further research evidence is needed. A particular growing area of interest identified is in understanding how exposure to the food environment influences health outcomes. The literature in this area is relatively new, with diverse and emerging ways of measuring the food environment, which suggests that better understanding the ways the measurement of the food environment might influence study outcomes is important. It is also hoped that the framework will help guide those wishing to undertake interventions in children.

Introduction

Although health related lifestyle choices such as food intakes are arguably within the individual's responsibility, the past 30 years have seen dramatic changes in the food and physical activity environments, both of which contribute to the changes in human behaviour that could explain obesity^{33 88}. Modern environments generally promote energy-dense food and offer little incentive for an active lifestyle, particularly in low-income neighbourhoods³³. Investigating determinants of diet and weight in children is particularly important, as the development and long-term health of children are linked to nutritional habits from early life onward³⁸.

Several authors have developed conceptual frameworks in an attempt to better understand the manner by which the environment might contribute to childhood obesity. An important early example of a conceptual framework is ANGELO (Analysis Grid for Environments Leading to Obesity)⁴, which has been adapted by many authors⁸⁹, and includes macro and micro physical, economic and socio-cultural environments that influence energy balance. Another framework focusing on both adults and children was the "Causal Web" of the International Obesity Task Force⁹⁰, based on social-ecological theory⁹¹ which organised causal factors into proximal (e.g. those associated with the school) and distal (e.g. national or international), with unidirectional relationships between them. Similarly, based on ecological systems theory (EST)⁹², Davison and Birch⁹³ presented an ecological model of predictors of childhood overweight, categorised into three main areas: child characteristics and child risk factors; parenting styles and family characteristics; and community, demographic and social characteristics. Pearce and Witten¹⁰ have published a framework also based on social-ecological theory which incorporates economic, political and socio-cultural influences and the reciprocity between them for understanding food choices in the three food environments (home, school and community) that children use. The marketing and public policy framework developed by Goldberg and Gunasti⁹⁴ makes the distinction between four marketing mix components (product, price, promotion and place) in the importance of the food marketing system, while Rosenkranz and Dzewaltowski⁹⁵ propose a model of child obesity based on a home food environment conceptualized as overlapping fields made of built, natural, socio-cultural, political, and economic influences. Furthermore, Livingstone and Helsper⁷ present a model of factors which influence children's food choice, habits and health. Glanz et al⁹⁶ have also developed a model of community nutrition environments which affect eating patterns, and which includes four environments: community nutrition environment (e.g., location and

accessibility of food outlets); consumer nutrition environment (e.g., price, promotion, and placement of food choices); organizational nutrition environment (access to food in other settings such as workplaces and schools); and information environment (marketing, media, advertising).

Despite the existence of such frameworks, it has been argued that we have rather little understanding of the interaction between key factors that influence health outcomes^{52 97 98}, and their living settings such as schools and homes¹⁰.

One high profile attempt to depict the complexity of the energy balance mechanism in both children and adults is the 2007 UK Government Foresight Obesity System Map^{99 22}. The map remains the most comprehensive investigation into obesity and its causes by describing the complex relations between the social, economic and physical environments and individual factors that underlie the development of obesity. It has been widely used by both the policymaker and academic communities and has been effective in illustrating the complexity of influences on energy balance as well as stimulating new research and debate. However by attempting to depict the complete system in a single diagram, the Foresight map is necessarily broad. Indeed it has been suggested that this may detract from its practical application, as not only is the obesogenic environment a concept that is difficult to conceptualise, but attempting to consider every possible environmental contribution to energy balance can be overwhelming³⁸². One way forward is to unpack this complexity into more manageable pieces relevant to certain programmes or policy interventions¹⁰⁰. Furthermore the map is based on evidence published over half a decade ago, a long time in such a fast-moving research field.

Building on the Foresight framework, a scoping exercise was undertaken that resulted in the development of a new system map that describes the complex manner by which different components of the food environment may influence dietary behaviours and implicitly weight of children. The map, which is presented in the chapter, is only focused on aspects related to the food, and does not take into consideration physical activity-related determinants. It draws on the available evidence as well as hypothesised relationships between the different aspects of the food environment and diet/ weight. Based on this, a simplified version conceptual framework was further developed that included the key determinants identified in the system map. This framework has helped identify areas that have received rather little attention and which are further investigated in the subsequent chapters of this thesis.

Methodology

In the first stage of the work, a comprehensive non-systematic scoping review was undertaken of the available scientific evidence on the correlates of children's diet and weight status. The Scopus, PubMed, Medline and Ovid databases were searched and search terms included obesity, children, food marketing, neighbourhood, food environment, food deserts, food outlets, dietary behaviour, neighbourhood deprivation, consumption, price, income, food access, and food security. Many of the terms used, with the exception of some such as 'allowance', 'parental control' or 'pester power', were applicable to adults as well as children although this review focussed only on studies of children (which are defined here as individuals up to 16 years old). Studies were included in this review if they referred to dietary behaviours or weight/obesity as dependent variables and included at least one environmental or food exposure factor as causal variables, proposed policy interventions, or components of theoretical frameworks for obesity prevention. The reference lists of identified studies were also reviewed for additional references.

This scoping review was used to design a comprehensive system map (Figure 2.1.) of food-related determinants of weight and diet, which was designed using DIA, a software program for drawing entity relationship diagrams¹⁰¹. Relationships between variables were denoted using two types of lines: continuous lines which indicate positive relationships and dotted lines for negative relationships. The proposed direction of effect is indicated by an arrow, where a change in the tail variable leads to a change in the head variable. Unbroken lines with no arrows represent categories of a particular variable (e.g. types of promotion). All the variables are interconnected through various causalities, be they linear or circular feedback loops. The circular causalities can be positively reinforcing (amplifying or leading to exponential growth) or negatively reinforcing (stabilizing, balancing, or pushing the system towards equilibrium). In the map, the proportion of arrows leaving and entering a cluster shows the balance of linkages between it and others. Furthermore, the proportion of variables from one thematic cluster influencing another cluster's patterns shows how strongly the two are connected.

Using a similar methodology to that employed in the original Foresight map and building on the literature reviewed and relevant system dynamics theory^{102 103}, the 'nodal' variable was first defined, which is the variable aimed to be understood and around which the whole system revolves. Given that the health outcome of interest, weight status, is associated with

physical activity in addition to dietary behaviours and that physical activity is not explicitly addressed, 'weight and diet' were chosen as the nodal variables.

Next the 'core engine' or 'foundational loop' was designed. This is a central, limited set of interconnected feedback loops which drives the dynamics of the system. The core engine consists of eleven variables forming three feedback loops, the relationships between them being represented through thick coloured arrows:

- A core balancing loop linking five variables: 'promotion', 'persuasion processing', 'food exposure', 'pester power', 'pressure to improve food offerings'
- A reinforcing loop, where 'family disposable income' is positively driven by 'economic growth', and in turn drives an increase in 'purchasing power', which leads to more 'access' to food, which in turn pushes up 'food security'.
- A second reinforcing loop, whereby having 'access' to food leads to an increased 'desire to maximise volume', which in turn increases the 'pressure to improve food offerings'.

The approach taken was then to build from the core towards the periphery. Leverage (or key) variables were identified; these have an important effect on the system's dynamics and drive the core engine, having several arrows entering and leaving⁹⁹. Eleven such key variables from each cluster were identified: price, food availability, neighbourhood deprivation, portion size, food preference, parental consumption, parental control, child autonomy, peer interaction, nutritional knowledge and food literacy. The relationships between the key variables and the variables of the 'core engine' are represented through coloured arrows. Two other important variables (represented in bold-italics) are education (which directly influences food literacy and persuasion processing) and cultural norms (which directly influence preferences and portion size). Finally, the map was segmented into four general thematic clusters: 'food production', 'food consumption', 'food environment' and the 'social environment' (or socio-economic). Each relevant factor identified in a reviewed study was assigned to an appropriate cluster.

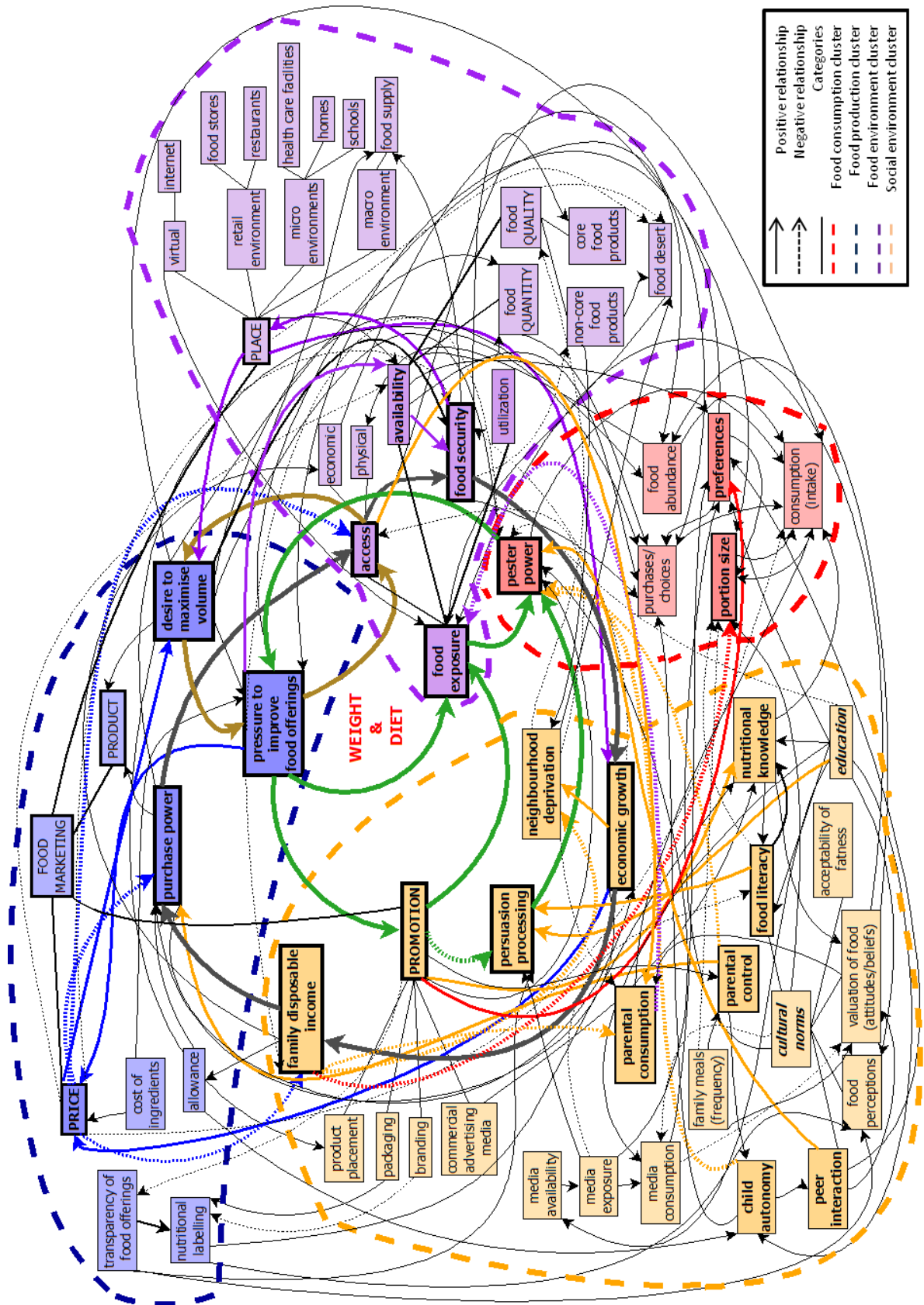


Figure 2.1. Food system map of understanding determinants of weight status

It would not be possible to discuss in this chapter each of the relationships illustrated in the system map. Rather than individually deconstructing all relationships in the system map, these have been presented to illustrate the complexity of the food system, as well as to identify the most important determinants of weight and diet that drive the whole system. Based on these, a simpler conceptual framework was developed (Figure 2.2.) that only included these key determinants and the determinants of the core engine: the conceptual framework therefore contains the eleven variables of the core engine, the eleven leverage variables and the other two variables identified as important above (a total of 24 variables). The conceptual framework thus conceptualised was divided into four more refined relevant environment clusters that interact with each other: (1) production (supply) environment; (2) community environment (2.1. (retail) food environment; 2.2. economic environment; 2.3. socio-cultural environment); (3) home environment; (4) consumer environment (Table 2.1). The supply, retail and economic environment are macro-environments, while the socio-cultural, home and consumer environment are micro-environments.

Table 2.1. Simplification from Figure 2.1. to Figure 2.2.

Core engine variables	Figure 2.1. (Food system map)		Cluster	Figure 2.2. (Simpler conceptual framework)	
	Key (leverage) variables	Other important variables			
Pester power					
	Food preferences Portion size		Food consumption		Consumer environment
Purchase power Desire to maximise volume Pressure to improve food offerings Price			Food production		Production environment
Food exposure Food access					Community environment (retail food environment)
	Food availability		Food environment		
Food security Deprivation Economic growth					Community environment (economic environment)
			Social environment		
Promotion Persuasion processing					Community environment (socio-cultural environment)
	Food literacy Nutritional knowledge Peer interaction		Social environment		
		Cultural norms			
Income					
	Parental consumption Parental control Child autonomy		Social environment		Community environment (home environment)
		Education			

Components of the identified clusters

In this section the evidence base behind the key determinants of the conceptual framework in Figure 2.2. is discussed.

1. Production environment

The four key variables in the production cluster are: price, purchase power, desire to maximise volume (sold) and pressure to improve food offerings.

Obesity is promoted by ‘powerful profit-led manipulations of the global supply and quality of food’¹⁰⁴, who actively seek to minimise cost and maximise volume sold, while at the same time being under pressure to improve access to food offerings and cater for acquired tastes⁹⁹. While common sense might tell us that we are free to choose not to participate in the fattening system, food companies maximise their profits precisely by restricting our choices, which involves encouraging people to choose foods that are most profitable to produce and sell.

Since demand for specific food products is a function of their price (which implicitly drives the purchase power for those products), changes in the prices of food thus affect the demand for particular foods¹⁰⁵ and implicitly dietary behaviours. A notable change in recent years has been the steep decline in the price of food for processed foods that are high in saturated fat and sugar¹⁰⁶; it has been shown that there is a growing price disparity between nutrient-dense foods and less nutritious foods, which may pose a barrier to the adoption of healthier diets¹⁰⁷. When it comes to branded products, marketers can establish their own price depending on the consumer segment they wish to target.

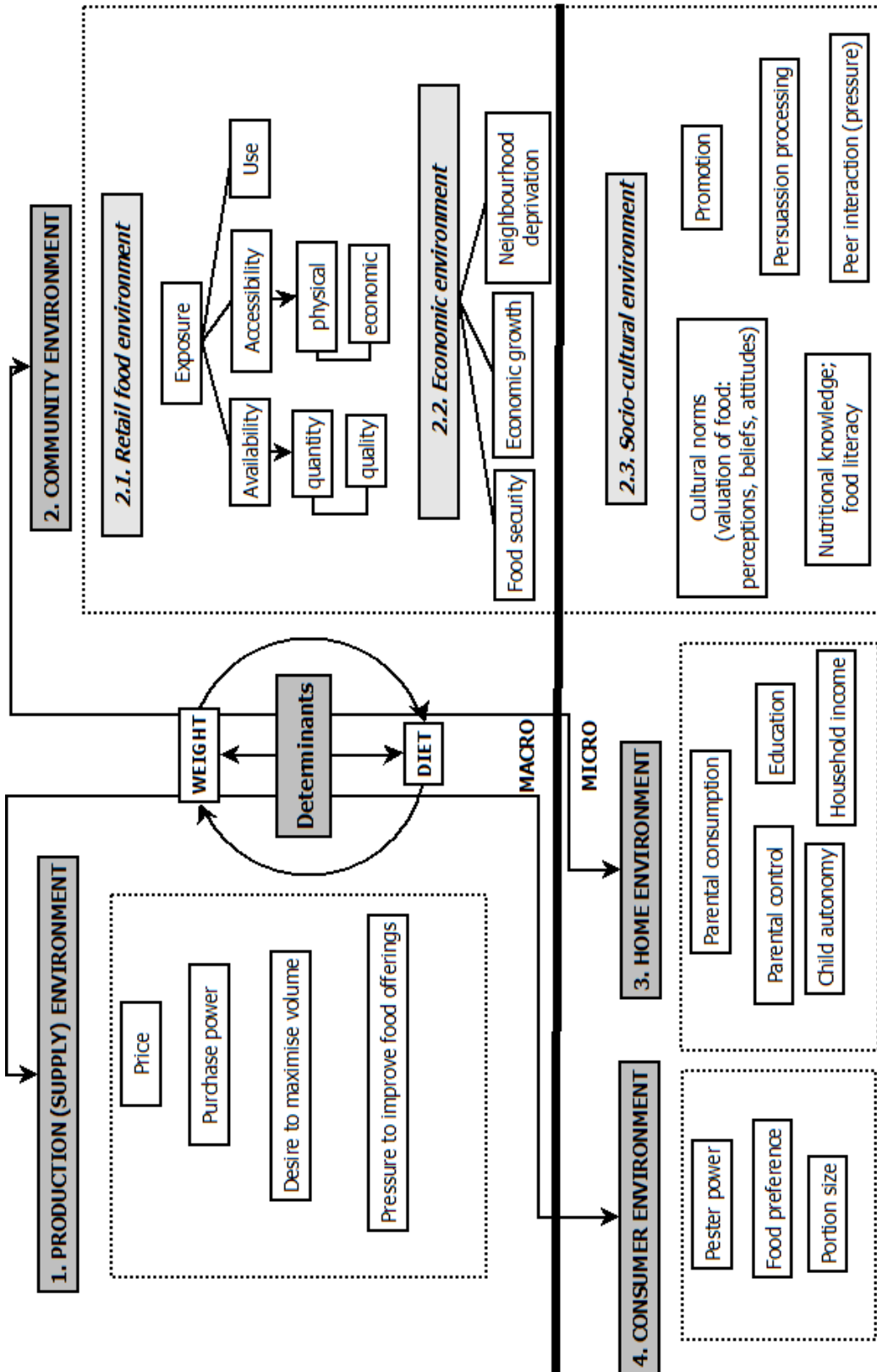


Figure 2.2. Simplified conceptual framework of key food-related determinants of weight and diet

A particularly vulnerable segment in this respect is represented by low social class communities. Price (as well as perceived price and availability), is a recurrent obstacle to fruit and vegetable consumption amongst low-income households. This can explain why fruit and vegetables may be perceived as poorer value for money than more energy-dense foods. This is of concern because of evidence that lower fruit and vegetable prices, higher fast food prices, and greater supermarket availability are related to higher fruit and vegetable consumption and lower BMI⁶⁸. Similarly, a US study performed amongst elementary school children reported that lower prices of fruit and vegetable predicted significantly higher intake frequency¹⁰⁸. Another study amongst 2 to 9 year old children¹⁰⁹ reported that higher fast food prices were associated with lower fast food consumption, healthier eating and higher fruit and vegetable consumption, and that there was an association between higher fruit and vegetable prices and higher BMI.

Despite these relationships however, it has been shown that diets high in fruits and vegetables cost more^{110 111}. Few studies have addressed the relationship between purchasing power, diet cost and diet quality^{112 113}. It has been argued that the ability to adopt healthier diets may have less to do with psychological factors or readiness to change than with economic resources and purchasing power¹¹⁴. Continuing to recommend costly foods to low-income families can therefore be ineffective, and simply improving nutrition awareness amongst these groups might not be enough if the cost of a healthy diet is high.

2. Community environment

The community environment cluster has been split into three relevant sub-clusters: the retail food environment (which includes exposure to food outlets, operationalised through availability, access and use); the economic environment (which includes food security, economic growth and neighbourhood deprivation); and the socio-cultural environment (general cultural norms in which individuals are embedded, which can be represented by the behaviours and attitudes of peers or messages promoted by the media; and the persuasion processing and food literacy abilities of individuals).

2.1. Retail food environment

While factors such as parental practices, individual preferences or financial resources affect food choice, increasingly these determinants are likely to be mediated by the food environment to which people are exposed. Parents traditionally encourage children to eat in

order to grow and be healthy, but in the current obesogenic food environment this can promote overeating and weight gain³⁸. Physical proximity to fast food outlets has been one of the most commonly identified elements of an obesogenic environment^{89 115 116}. There is increasing evidence that the characteristics of the retail food environment influence behaviours and weight status not only of adults, but also of even very young children^{11 33 77 82}.

A recent example is an England-wide study⁵⁴, whereby it was found that area exposure to fast food and other unhealthy outlets is associated with higher overweight and obesity prevalence in children, with the reverse being observed for outlets traditionally containing healthy food. Another UK study⁴³ found that neighbourhood availability of unhealthy outlets was inversely associated with body weight and positively associated with unhealthy food intake, with the opposite being observed for healthy food outlets availability. A recent UK study in adults¹¹⁷ found that exposure to takeaway food outlets around the home and work environments was positively associated with takeaway-type food consumption and BMI. On the other hand, supermarkets and grocery stores have been assumed to enable individuals to access a wider variety of healthy food, which would improve diet quality and lower the risk of obesity⁸⁹. Research all over the world (Australia¹¹⁸, USA¹¹⁹, UK^{120 121}, New Zealand¹¹⁸) particularly suggests that fast food outlets are more numerous in deprived neighbourhoods as compared to their affluent counterparts. Conversely, it has been suggested that deprived communities have poorer physical access to supermarkets and grocery stores⁶⁶. This type of research has its roots in the ‘poor pay more’ and ‘food deserts’ debates that have been around a while, and which suggest that poorer people pay more and have poorer access to food outlets and other facilities essential for daily life^{122 123}.

The evidence in the literature is however not always consistent, which points to a complex interaction between the retail food environment and weight and diet. For example, one US study¹²⁴ found no association between the density of fast food outlets and childhood obesity in a low-income preschool sample, while another⁴⁵ found no association between counts/densities of food outlets inside home/school neighbourhoods and consumption. In the UK, White et al¹²⁵ found no independent relationship between most indicators of healthier eating and local retail environment factors. Furthermore, a UK study¹²⁶ found that deprived neighbourhoods had better access to grocery stores, and another UK study⁵⁶ has found that better access to supermarkets is associated with higher obesity. While research on access to food has been fairly clear cut in the USA, suggesting the existence of ‘food deserts’, in part explained by the higher ethnic residential segregation of the country, research in the UK and

Australia have become more equivocal over time, suggesting that such patterns may vary by nation⁸⁹. Nevertheless, there is still a suggestion that residents in deprived areas might benefit from policies aimed at increasing their access to healthier food alternatives²³. Similarly, evidence that supermarkets protect against obesity is stronger in the US⁵¹.

Such equivocal results may be in part be explained by the different ways of measuring exposure to the food environment, with no consistent measure across studies¹²⁷. Measures of exposure to the retail food environment are conventionally: access, availability or use of food (outlets). Access to food can be either economic (having enough money to buy appropriate food), or physical (often operationalized as distance to the nearest food outlets), with the two factors commonly interacting. While economic models hypothesise that food purchase is influenced by the price of food, ecological models posit that food demand is a function of physical access to food¹⁰⁵. Availability is commonly measured by the number or density of food outlets present in a geographic space and/or the quality of food present in a food outlet.

It has however recently been suggested that proximity to food might not be the best measure to indicate access to healthy food, as low-income families for example tend to shop little and often at discount stores even when provision to better quality food is available in their neighbourhood^{128 129}. Furthermore, while density measures investigate the food opportunities that people have, there is a growing interest in activity modelling, through the use of activity diaries and evaluation of activity spaces and patterns⁵. The case has hence been made to complement conventional place-based perspectives in health research (i.e., predefined spatial units, circular buffers, polygon-based road network buffers) with people-based perspectives which integrate the space-time dynamics of human behaviour. That is now possible due to the ability to track individuals as they make decisions (with the help of wearable Global Positioning Systems (GPS) and other Location-aware technologies (LATs)), which may prove to be a fundamental advance^{127 130}. However, while using such technologies may be suitable for relatively small-scale studies, they may not be feasible (i.e. too expensive, time consuming, or too much data to manage) at a larger level. Several methods that move away from fixed neighbourhoods have been developed, such as standard deviation ellipse, minimum convex polygon or kernel density estimations. Such technological developments provide an opportunity to measure an individual's exposure to multiple contexts and to compare these measures against exposures derived from conventional place boundaries¹²⁷. Nevertheless, both measures raise important methodological concerns, such as conceptually

choosing the right size of an activity space or a neighbourhood, or creating metrics appropriate to rural vs. urban areas, just to name a few.

In 2005, Glanz et al⁹⁶ were making the case that more research is needed in the food environment area, as it is the most under-studied and is likely to have the largest impact on nutritional health; while studies in the area have significantly increased since, a recent systematic review³³ made the case that there continue to be major gaps in understanding. One of the gaps relates to the fact that most studies have focused on adults, and it is known that children relate to their food environment in their own way³⁵, therefore it is important to understand the impact of the food environment on children's outcomes so that interventions can be tailored to prevention in this population group. The influence of place for example changes over the life course, and children are more likely to get attached to locations closer to their places of residence¹³⁰. Moreover, most studies have focused on weight⁷⁷, and less on dietary outcomes³³. Another problem is that because of the variation in measures of the local food environment, overall reproducibility is lacking because there is no gold standard across studies as of yet on how to measure food access. Many measurement challenges thus remain unaddressed⁸².

2.2. Economic environment

The availability of food outlets in an area, combined with socio-economic indicators such as income, price or food security, materializes in the literature in the form of discussions of typologies of areas such as 'food-deprived neighbourhoods' or 'food deserts'^{46,47}, which are defined as areas characterised by poor access to healthy and affordable food⁴⁶. The availability of food in a neighbourhood commonly interacts with its socio-economic characteristics. Overall, it is thought that poor people are more affected by their environments because of their smaller activity spaces and restricted mobility³⁷², which can have implications for their ability to make healthful food purchases.

For example, Cunmins and colleagues¹²⁰ found that the prevalence of McDonalds restaurants in England increased with increasing area deprivation. Another study¹³¹ found a significant positive association between the density of fast food outlets, socioeconomic deprivation, and the prevalence of overweight and obesity in children aged 3-14 years old in Leeds, England. In Australia, food store variety and accessibility to healthy foods was generally better for advantaged neighbourhoods⁶⁶. A US study⁶⁵ found that the biggest factor contributing to higher grocery costs in poor neighbourhoods was that large chain stores where prices are

lower were not located in these neighbourhoods. A possible explanation for the observed links between poverty and obesity involves the low cost of energy dense foods^{112 114}.

A closely related factor to food access is food security, which means people having “physical and economic access to sufficient food to meet their dietary needs for a productive and healthy life”¹³² (p.4). The ‘food insecurity-obesity’ paradox¹³³ or the ‘obesity-hunger’ paradox¹³⁴ are an increasingly important research area. They acknowledge that socioeconomic deprivation and obesity can coexist, the paradox being that food insecurity has a double burden as it can not only lead to under nutrition, but also over nutrition via the consumption of cheap energy dense foods³¹. The evidence regarding an association between food insecurity and overweight status in children is however mixed. For example, one US study found an association between food insecurity and overweight in children below 5 years old¹³⁵, while another detected no association in 10-15 year old children¹³⁶.

It has been suggested that policy initiatives to satisfy the need for food security can speed economic growth in low-income countries in particular¹³². In the current capitalist climate, it has been argued that the technological advances driven by unrestricted economic growth and free producer access to markets however have little concern for health effects¹³⁷, and in particular it brings a range of risks to public health for low income countries³¹. Developments in industry, stemming from economic growth, serve to enhance consumption, and yet they are contributing to the obesity epidemic^{104 138}. The relationship between economic growth and food security hence seems to switch from positive to negative over the course of development¹³². If economic growth does not attend to its environmental and health impacts, it is not necessarily the best measure of success for a country¹³⁹. Simply restoring economic growth without reducing socio-economic inequalities (such as income inequality) will not reduce health inequalities.

2.3. Socio-cultural environment

The socio-cultural setting in which an individual is embedded influences eating habits, both in terms of the types of food consumed and the energy density of one’s diet⁸⁹.

A study of social networks has shown that the risk of obesity of an individual increased by 57% if they had a friend who became obese¹⁴⁰. It may therefore be that the relationships people form with their peers play a role in their health behaviours. The evidence in the literature is however mixed regarding the importance of the role that peers play on children’s

dietary behaviour. Some studies have reported associations between peer interaction and dietary behaviours^{141 142}, while others have found no significant associations with dietary intake, only with physical activity^{143 144}. An US study¹⁴⁵ found a differential influence of peer interaction on food intake and food selection by gender, suggesting that adolescent girls may be more influenced by their peers than boys.

Promotion of food is another important determinant of diet in children. We are embedded in general development trends leading to increasingly advanced methods of food marketing¹⁴⁶, and children and adolescents are especially susceptible to the high energy density food¹⁴⁷ to which they are exposed to through different media channels. A systematic review produced evidence that advertising to children has an effect on their food knowledge, preferences and behaviour¹⁴⁸. There is considerable evidence that television advertising influences food and beverage preferences and purchase requests of smaller children (2 to 11 years old)^{94 149}. A study¹⁵⁰ across several countries showed a significant association between the proportion of children who were overweight and the number of adverts per hour on children's television, in particular those that advertised energy-dense foods that were poor in micronutrients. In recent years however the amount of time children spend watching TV has decreased, having been replaced with new media channels, such as computer games^{37 97 151}. The evidence base to date for these new emerging forms of promotion is small. Yet early evidence for their potential importance comes from an assessment of the content of food industry websites and 'advergames' targeting children which concluded that these sites almost exclusively promoted high sugar and fat items¹⁵². However, it has been argued⁹⁴ that while the current food landscape has contributed to the child obesity problem, it can potentially be part of the solution. For example, marketing could be used as a method of effectively persuading children to make healthier choices in their dietary habits and to sustain those habits over time¹⁵³⁻¹⁵⁵.

The stage of discernment or the persuasion processing phase is important as there is obvious concern regarding children's ability to understand the nature, purpose and appropriateness of food advertising. The literature¹⁵⁶ identifies four age groups of discernment: early childhood (less than 5 years old), characterised by no awareness or processing abilities; middle childhood (6 to 9 years old), characterised by increased information processing and understanding, or moving towards the so called 'heuristic persuasion processing'; late childhood (10 to 12 years old), where children begin to evaluate advertising systematically and have increased autonomy; and adolescence (13 to 16 years old), where children move into

the ‘systematic persuasion processing’ phase, where their cognitive processing capacity reaches adult-like levels and they become more critical. Evidence in the literature suggests that children learn from behaviours symbolically modelled in the media. It would hence be expected that children exposed to eating behaviour patterns modelled as prevalent and favourable in food advertisements will adopt such behaviours themselves¹⁵⁷. Persuasion processing is an important media literacy skill, as it can mediate the effects of promotion to children. This translates into their ability to analyse and evaluate media messages in various contexts⁷ and it is associated with child age. The rise of new advertising practices means there is a need for better understanding how children process persuasive messages¹⁵⁶, particularly as the literature to date is based mostly on adults.

Researchers have classified food items in ‘core’ (healthy: nutrient dense, low in energy) and ‘non-core’ (unhealthy: high in undesirable components: sugar, salt, fat and energy), as defined by dietary standards^{158 159}. The food promotion directed at children often strongly favours ‘non-core’ foods, a matter of considerable concern¹⁶⁰. Survey evidence also shows that children worldwide have extensive recall of food advertising¹⁵¹. Considering most products advertised to children are non-core, and that age is inversely related with persuasion processing abilities¹⁵⁶, it is unsurprising that children mostly demand unhealthy food products. For example, a UK study¹⁶¹ found that packaging influences children’s preferences, particularly with respect to unhealthy foods.

Food literacy is another key variable in influencing dietary behaviours in children. It has been hypothesised that the more food literacy children have, the greater their persuasion processing is, and this may improve dietary behaviours. Food literacy is a consequence of greater nutritional knowledge. For example, a recent cluster randomised control trial in UK schools found that improving nutrition knowledge in primary school children leads to changes in attitudes to healthy eating¹⁶², although how this may result to improved eating behaviours is not yet known. As parental and child behaviours are closely inter-connected, parental nutritional knowledge directly affects that of their children; for example, a lack of knowledge of appropriate serving sizes may lead parents to overfeed their children⁹³.

3. Home environment

The five key home environment factors that influence diet and weight in children in the present framework are: parental consumption, parental control (and implicitly child

autonomy), and the two commonly used proxies for socio-economic status: (parental) education and household income.

The home environment has a crucial role in influencing obesity¹⁶³ and diet^{164 165} in children, with parents being key moderators of food availability and consumption in children¹⁶⁶. Children's dietary patterns evolve within the context of the family⁹³, and consistent similarities have been noted in child and parent patterns of food acceptance, preference and dietary intake^{167 168}, in particular with that of mothers^{142 159}. The various pathways by which parents may shape children's dietary patterns include nutritional knowledge¹⁶⁹ - which can translate into the kind of education children receive, and in turn the nutritional knowledge that children themselves are equipped with, parental modelling^{170 171} (including feeding practices¹⁷² and parental control¹⁷³) or parental perceptions, beliefs and behaviours on diet¹⁷⁰. More restrictive practices and authoritarian feeding styles for example have been associated with higher weight and higher preference for and overconsumption of the 'forbidden foods', while authoritative (a balance between authoritarian and permissive) parental styles have been associated with a more positive perception about fruit and vegetable consumption¹⁴². Evidence relating parents' use of restriction in feeding to child weight is however equivocal¹⁷⁴, with some studies showing no association with weight¹⁷⁵, others showing it as a predictor of increased weight¹⁷⁶, and others to have a protective effect against changes in weight¹⁷⁷.

It must be noted that determinants of diet may differ in preschool children (2-5 years) from those in older samples¹⁵⁹, the latter having more autonomy. While parents have greater power during earlier childhood years, this tends to decrease in strength and other forces such as peer pressure¹⁷⁸ and the media become more important as children age¹⁷⁹. Furthermore, children from lower socio-economic status backgrounds^{70 180 74} (measured by low household income and/or low parental education) have been shown to have poorer diets and more elevated weight compared to their counterparts^{19 67 93 181 182}, in part because their families avoid wasting food, learn to eat fast and tend to overeat when food is available, because of the food insecurity they experience. A review on the importance of parental involvement in obesity prevention programmes concluded that greater involvement was associated with improved intervention success.¹⁸³ Furthermore, a randomised controlled trial¹⁸⁴ found that children who received parent-child nutrition education significantly improved their overall diet quality. Higher parental education has been associated with health consciousness in food choices¹⁴², whereby children with more educated parents had higher intakes of protein, fibre and

carbohydrates¹⁸¹. Maternal education in particular has a strong influence on children's dietary habits, being inversely associated with children's sugar¹⁸⁵ and fat¹⁸⁶ intake.

Household economic resources have a major influence on the foods purchased and consumed¹⁰. However, the influence of income on obesogenic dietary behaviours is not linear, because as wealth increases, the proportion of income spent on food will decline to the point of being insignificant as will the perceived financial attractiveness of cheap energy dense foods. Choice is generally more meaningful for higher social classes, and children are very dependent on their family's income⁹. A US study for example, reported that children and adolescents from higher household income groups had significantly greater fruit and vegetable consumption and lower BMI despite also eating more fast food than their lower income counterparts¹⁰⁹.

Evidence in the literature suggests that some potentially modifiable features of the home food environment are associated with BMI¹⁷⁴, and this calls for the development of childhood obesity family-based prevention programs as a primary public health goal⁹⁵. The literature for example suggests that increasing efficacy among mother to promote healthier diets are likely to be important targets for future obesity prevention initiatives, especially in deprived communities¹⁷⁴. A systematic review by Pinard and colleagues¹⁶³ looking at measures of the home food environment related to childhood obesity have identified 19 studies looking at some aspect of parenting specific to food, 20 studies looking at the food physical environment, 8 studies looking at the media physical environment, 12 studies looking at feeding styles and 8 studies looking at parenting related to screen time. The authors argue that many of the measures of the home food environment focus on one or two constructs and more comprehensive measures are necessary in order to capture the influences of the home on children's eating behaviour.

4. Consumer environment

The key determinants of diet and weight in the consumer environment cluster are preferences, portion size and pester power. Food preferences are the product of an interplay between genetic and environmental factors that result in substantial individual differences^{38 373}; there is however also substantial similarity in children's preferences which transcend cultural variations, whereby children tend to prefer high-fat and sweet foods and dislike vegetables, which suggests the existence of innate predispositions of tastes^{374 375}. This might be because in the past the innate tendency to reject sour and bitter foods may have protected individuals

from toxins. However, it has been suggested³⁸ that preferences can be malleable through a combination of modelling and taste exposure, therefore a dislike for fruits and vegetables for example can be reduced or even reversed³⁷⁶.

Pester power represents a child's influence over family shopping choices. It is widely acknowledged as being consequential of advertising exposure^{187 188}, although additional factors such as interaction with peers and the family environment can also be notable^{10 189}. As influencers on their parents' decision making and as potential future adult consumers¹⁹⁰, children constitute a primary market for advertisers. To illustrate the role they can play in a family's food choice, a UK consumer study performed by CWS¹⁹¹ found that 73% of children ask their parents to buy after seeing crisps and sweets advertised. If they were told 'no', various pester power strategies were used by over four fifths of children.

Another key factor which influences dietary behaviours in children is portion size, or the mean quantity in grams consumed in one eating occasion¹⁹². Portion size is known to be associated with weight in children. For example, a positive association has been reported between portion size for non-core foods and overweight in 3-6 year old French children¹⁹³. Portion size also predicts food consumption and has significantly increased over the past decades¹⁹⁴, playing a role in the obesity epidemic⁹⁵, as larger portions influence children's eating by promoting intake¹⁴². The choice of portion is frequently influenced by marketing practices (such as price) and cultural norms. A clear example is the 'value for money' concept associated with 'super-size' portions in some cultures³⁷. Portion sizes are also predicted by parental characteristics and the amounts parents serve themselves¹⁶⁸. There is evidence to show that the issue of larger portion sizes may be particularly pertinent to low income families, even in very young children³⁷.

Discussion

This review suggests that understanding food-related determinants of weight and diet requires a prior understanding of a complex landscape of intertwining factors. More research in children of different age groups is particularly needed, as it emerged from this review that most research conducted is on adults. Childhood obesity is associated with adult obesity and it is very difficult to treat once developed, putting affected children at risk of lifelong health problems. Furthermore, exposure to the food environment may have a different importance in children as compared to adults, as children interact differently with their environment³⁵. This

review also highlighted the fact that lower socio-economic groups are generally more affected by obesogenic determinants of weight and diet across all clusters of the framework. The subsequent chapters of this thesis will focus on children and also consider the role of social class.

It is primarily noteworthy that this review has identified that assessing exposure to the food environment in particular is a new research area where findings are equivocal, possibly in part due to the wide variety of methodologies used to measure characteristics of the food environment. The Association for the Study of Obesity¹⁵ has recently suggested that more robust methods are required to establish which aspects of the food environment (often operationalised through accessibility and availability of food) are relevant to food choice and adiposity. Traditionally, as highlighted in Section 2.1., studies have used GIS-based measures which assume exposure to the food environment at an area level. However, just because a food opportunity exists in a neighbourhood, that does not mean that individuals are actually exposed to it or use it. Therefore, in order to more closely relate environmental exposures to actual behaviours, new ways of measuring exposure to the food environment have emerged. These employ new technologies such as GPS, which provide the opportunity to investigate exposures in the spaces where people actually move. Studies detailing the application of GPS in the food area are very few. Moreover, this also means there is substantial variation and technical and methodological challenges in the measures used, which will be considered in Chapters 5, 6 and 7. The rest of this thesis will focus on measuring exposure to the retail food environment (referred to simply as the 'food environment' in the following chapters). Both traditional methods and newer GPS-based methods are employed, and how this relates to weight and diet in children is investigated.

There are a number of limitations to the framework and the evidence review underpinning it. Although it is focused on a complex matrix of etiological factors, it is not exhaustive. The scoping review undertaken when developing the system map was extensive although it was not systematic in that the quality of studies was not graded or systematically screened for inclusion. This was intentional as the purpose was to provide a narrative of a wide body of very diverse literature. Furthermore, although articles not written in English were not specifically excluded, the use of English search terms means relevant literature written in other languages may have not been considered. Whilst the map is evidence based as far as possible, there is an inevitable element of subjectivity in its construction; some of the relationships illustrated are hypothesised, and for others there is debate in the literature. It is

acknowledged there may not be perfect agreement amongst all readers with all of the elements of the map, yet if this fact leads to renewed discussion and debate then one of the primary objectives of this work will be met. What is more, for the purpose of this thesis, the map was merely presented to illustrate the complexity of the food system and used as a basis to extract the key determinants that drive the whole system and on which the conceptual framework was developed. It would not have been possible to discuss in detail all the complex relationships between its components.

In terms of overall learnings and recommendations for potential interventions from the key determinants assessed, at a micro-level parents have a crucial role in shaping their children's diets, and it is recommended that they choose meal times, propose adequate food and portion sizes, and promote social interaction and role modelling for eating behaviours³⁸.

Unfortunately few parents receive guidance on how to promote a healthy diet. Not only parents but also children need to be educated in this respect, as food nutrition education should be received from an early age, when food habits form and tend to perpetuate into adulthood^{11 195}. Parents should understand that children who are self-regulated in diet may better handle the current food-surplus environment³⁸.

Potential important macro-level areas for intervention include improved urban planning of local food systems¹⁹⁶, regulation of marketing messages that promote unhealthy eating to children¹⁹⁷, effective government policies to reflect the discrepancy in development between self-regulation and statutory regulation¹⁹⁸ and the development of effective school policies that involve parents in children's dietary behaviours^{11 198}. Nevertheless, substantial resources have been invested in a food production system that does not promote better health, resulting in an obesogenic economy, with children being the primary target¹³⁷. In 2005 the European Commission, set up the Platform for Action on Diet, Physical Activity and Health³⁷⁷ to encourage the food industry to address the ways in which their products contribute to obesity, and gave a one year deadline for them to improve labelling and to stop advertising non-core food to children. Such efforts have yet to show significant results¹⁹⁹ and this highlights the importance of a heightened focus on key intervention points in the obesity system. One of these is exposure to the retail food environment.

Chapter 3

Understanding the relationship between food environments, deprivation and childhood overweight and obesity: evidence from a cross sectional England-wide study

Abstract

Using a large cross sectional English sample, this chapter quantified the association between weight status in children aged 4–5 and 10–11 year, characteristics of the food environment, and area deprivation. A positive association was observed between the number of unhealthy food outlets in a neighbourhood and the prevalence of overweight and obesity in children. An association in the opposite direction was observed for other types of food outlets, although after adjustment this was only statistically significant for younger children. The prevalence of fast food and other unhealthy food outlets explained only a small proportion of the observed associations between weight status and socioeconomic deprivation. Children's weight status may be influenced by their local environment, particularly older children, but associations between obesity and deprivation do not appear strongly due to local food environment characteristics.

Introduction

There is a growing body of evidence that points towards an epidemic of obesity amongst children, particularly in highly industrialised countries²⁷. Children are an especially important group as early-life behaviours may track into adulthood and influence weight status later in life, with approximately 70% of obese children or adolescents becoming obese adults¹².

Obesity in children is a particular concern as it may lead to the development of asthma, psychosocial morbidity, orthopaedic and cardiovascular problems, and diabetes in childhood as well as an increased risk of obesity persistence in adulthood¹². The causes of the obesity epidemic are undoubtedly multifactorial^{99 100}. Nevertheless, much attention has recently focussed on how changes to the built environment may be drivers via their influence on physical activity and dietary behaviours²⁰⁰⁻²⁰².

One aspect of the environment that may be particularly important in children is the availability of outlets selling low-cost energy dense foods, which particularly appeal to the young pallet¹⁴⁷. Within the UK, as elsewhere, the prevalence of obesity in children is known to show a gradient with social class, with obese children being more likely to come from socioeconomically deprived populations^{131 203}. It is also noteworthy that there is evidence of fast food and other unhealthy food outlets being more common in deprived areas in the UK^{120 131 204} and abroad^{118 205}. On the other hand environments that are supportive of a wider range of food choice, including healthy food as defined by dietary standards¹⁵⁸, are more common in higher social-class neighbourhoods⁶⁶. These social gradients are particularly pertinent given the evidence that features of the food environment are associated with both the dietary behaviours and weight status of children¹⁸.

Despite the presence of evidence for the importance of the food environment in children, the findings from many studies are null or equivocal^{1 10}. While some have found associations between food outlet density and weight status in children¹³¹, or with both diet and weight⁴³, and weight and deprivation²⁰⁶, others have failed to find associations between neighbourhood food outlet density and BMI in children⁵⁵, or with diet⁴⁵. This may partly be due to methodological limitations of previous work. A key factor is that many previous studies have relied on relatively small population samples drawn from large urban areas, limiting heterogeneity in access to different types of food outlets and statistical power to detect associations. Furthermore, much of the evidence comes from the USA, a country where contrasts in urban design and neighbourhood segregation may lead to a different importance

of the food environment compared to the UK²³. Indeed, the presence of stronger residential segregation in the US²⁰⁷ suggests that the local food environment may contribute more to socioeconomic differences in health²⁰⁸.

In England the recent availability of data from the National Child Measurement Programme (NCMP) provides an opportunity to offer new information on the importance of the food environment for children's weight status. A recent study of NCMP data²⁰³ showed that childhood overweight and obesity rates were strongly associated with deprivation, but did not attempt to explain the reasons why this might be so. Using the whole-England sample of the NCMP for children aged 4-5 and 10-11, the present study tests a series of hypotheses. These are, firstly, that area characteristics of the food environment are associated with weight-status of children in England; secondly, that the strength of association will be greater for 10-11 year old children who will have more independence in their purchasing decisions^{156 209}, and thirdly that area characteristics of the food environment mediate the association between area deprivation and child weight-status.

Methods

Study population

The NCMP is an England-wide cross-sectional dataset containing measured weight status recorded at school for Reception (4 to 5 year old) and Year 6 (10 to 11 year old) children²¹⁰. The data has been collected on an annual basis since 2005. It provides weight status measurements, recorded using anthropometric procedures by trained staff, for approximately one million children each year attending the majority of state schools in England²¹¹. For the purpose of this study the data for children in primary and secondary state maintained schools and some independent and special schools in England during the 2007/08 (n=973,073), 2008/09 (n=1,003,849) and 2009/10 (n=1,026,366) school years was used.

Outcome, predictor and confounding variables

The variables generated for this study are described in Table 3.1. Aggregate area-level data from the NCMP sweeps for the years 2007-8 and 2009-10 were utilised. These two periods were combined to maximise the sample size whilst restricting the period studied such that substantial changes in the food environment were unlikely to have taken place. Two outcomes were used; the prevalence of children who were overweight or obese, and the prevalence of

children who were obese for 6781 geographical areas across England known as Middle Super Output Areas (MSOAs). The MSOA is a UK Census geography designed for small-area statistical analyses⁸⁵ with an average population of 7500. In our sample for analysis there was an average of 192 4-5 year old and 186 10-11 year old children in each MSOA. Based on standard procedure, overweight was defined as body mass index (BMI) greater than or equal to the 85th percentile and obese as a BMI greater than or equal to the 95th centile of the UK90 BMI reference^{12 212}.

Measures of the food environment were computed in a Geographical Information System (GIS) (ArcGIS 9.3 (ESRI Inc, Redlands, CA, USA)) using the UK Ordnance Survey Points of Interest (PoI) dataset²¹³. The PoI contains the location of all commercial facilities across England. Although concerns have been expressed regarding the accuracy of this type of facility dataset²¹⁴ recent work to validate PoI against more detailed data provided by local government for the county of Cambridgeshire, UK, concluded that PoI provided a viable alternative to other such data sources²¹⁵. Hence it was chosen for use here.

Table 3.1. Outcome and explanatory variables generated for Middle Super Output Areas

Variable description	Data source	Mean	SD	Min	Max
Outcome variables (weight status):					
Percentage of 4-5 yr. old children who are overweight or obese	NCMP ¹	23.61	4.47	7.7	40
Percentage of 4-5 yr. old children who are obese	NCMP ¹	9.53	2.95	2.4	21
Percentage of 10-11 yr. old who overweight or obese	NCMP ¹	33.87	5.56	14	53.9
Percentage of 10-11 yr. old who are obese	NCMP ¹	18.19	4.71	4.1	36.5
Potential covariates (neighbourhood characteristics):					
Area (square meters (adjacent MSOAs added together)	EDINA ²	166.3	290.9	2.1	4106.8
Income deprivation affecting children (IDACI) scores, 2010	DCLG ³	0.21	0.14	0	0.8
Percentage area domestic gardens, 2005	ONS ⁴	19.48	13.57	0.1	67.9
Percentage area green space, 2005	ONS ⁴	51.35	27.98	1.3	98.6
Percentage of population aged under 7 years old	Census ⁵	9.68	2.03	1.9	20.6
Percentage of population aged between 10-14 years old	Census ⁵	6.56	1.23	1.3	11.6
Percentage of population age 16-74 who are managers, senior officials or in a professional occupation	Census ⁵	25.84	9.44	7	62.7
Percentage of population of mixed ethnicity	Census ⁵	1.31	1.19	0	11.3
Percentage of population of not white or mixed ethnicity	Census ⁵	7.63	13.44	0	87.1
Primary exposure variables (food environment):					
Counts of fast food outlets	Ordnance Survey ⁶	30.38	18.06	0	266
Counts of other unhealthy food outlets	Ordnance Survey ⁶	29.68	14.26	0	239
Counts of mixed food outlets	Ordnance Survey ⁶	101.51	89.15	4	2255

1 National Child Measurement Programme, <http://www.noo.org.uk/NCMP>

2 DIGIMAP <http://edina.ac.uk/ukborders/>

3 Department for Communities and Local Government, <http://www.communities.gov.uk/communities/research/indicesdeprivation/deprivation10/>

4 Office for National Statistics, <http://www.neighbourhood.statistics.gov.uk/dissemination/>

5 UK Census of Population <http://casweb.mimas.ac.uk/>

6 Ordnance Survey, Points of Interest, <http://www.ordnancesurvey.co.uk>

For the purpose of this study, we extracted information on the location of all food outlets and grouped them into three categories: ‘fast food outlets’, ‘other unhealthy outlets’ and ‘mixed food outlets’. The ‘fast food outlets’ category included the PoI categories: fast food and takeaway outlets, fast food delivery services, and fish and chip shops, whilst the ‘other unhealthy outlets’ category included newsagents, convenience and general stores, and confectioners. The ‘mixed food outlets’ contained everything else and thus included: cafes, pubs, restaurants, bakeries, butchers, delicatessens, fishmongers and frozen foods, green and ‘new age food outlets’, green grocers and markets, organic, cash and carry, independent supermarkets and supermarket chains. The development of the typologies was based on the

evidence on associations with diet from the literature^{18 81 118 216} as well as fieldwork visits made by the authors to a sample of outlets falling within each category. These visits were made to ensure the classifications were appropriate to the products being sold.

Using the GIS, a count was made of the number of outlets of each type falling within the boundaries of each MSOA plus those with which it shared a boundary and this formed the primary exposure. Neighbouring MSOAs were included as the MSOA of residence was felt to represent a too restricted measure of the food environment for children. Zenk et al⁴⁴ have shown that most people conduct their day-to-day activities outside their residential neighbourhood. Urban MSOAs are smaller and with a higher population density compared to rural ones, and therefore by taking these units to construct our food neighbourhoods the size of a neighbourhood is associated with population density and hence the propensity of the population to travel further for food purchase, as suggested in the literature²¹⁷.

In order to determine a robust set of relationships between weight status and the food environments, a number of covariates are considered in statistical analyses. These included the area of the food neighbourhood in square kilometres, IDACI (Income Deprivation affecting Children Index) scores that measure the proportion of children aged under 16 living in low income households²¹⁸, measures of gardens and green space both of which have been associated with physical activity in children^{219 220}, the number of similar age children as an indicator of potential social networks²²¹, population ethnicity, and various indicators of area socioeconomic status.

Statistical analysis

Unadjusted associations between the weight status outcomes and measures of the food environment were examined using Analysis of Variance (ANOVA) and error-bar plots. So that any trends were apparent, the counts of outlets in the food environments were represented as quartiles. Stepwise linear regression models were fitted to examine the relationship between the four weight status outcomes and food outlet availability scores while controlling for various covariates. All the potential covariates in Table 3.1. were initially included within the regression models. Those that did not show a statistically significant associations (at least at the $p=0.05$ level) with each outcome were dropped in a stepwise manner until the final models retained only statistically significant variables. To determine the effect of this adjustment on the unadjusted associations observed, the quartile based measures of food

outlet availability were then added to the models, and tests for trend across quartiles were made.

In order to examine associations between food outlet availability and area deprivation the Mantel-Haenszel general linear test for trend across quartiles of deprivation was used. Next, in order to examine the role of food outlet availability as a potential mediator of the relationship between area deprivation and weight status, mediation analysis was performed using the Preacher and Hayes indirect effect method²²². From this, effect ratios were computed that represent the percentage of the total effect of the independent variable on the dependent variable that is explained by the mediator²²³. All statistical analyses were performed using SPSS version 19 (IBM Corp, Armonk, NY, USA).

Results

In total 279 (4.1%) of MSOAs had missing data for Reception obese, 190 (2.8%) for Reception overweight and obese, 246 (3.6%) for Year 6 obese and 239 (3.5%) for Year 6 overweight and obese. Missingness was due to data suppression associated with low numbers of children participating in the NCMP²²⁴ in some areas. The missing MSOAs were excluded from the corresponding analyses.

Before adjustment there was a statistically significantly ($p < 0.01$) increasing prevalence of overweight and obesity with a greater number of both 'fast food' and 'other unhealthy' outlets in food neighbourhoods (Figure 3.1.). For 'mixed food outlets' the direction of association was reversed. The effect size for secondary school children was greater (over 4% difference in overweight and obesity prevalence comparing the highest to lowest quartile) compared to primary school children (1.5%). Similar trends were observed for obesity alone (results not presented).

Table 3.2. shows the multivariable models containing the covariates that were found to be statistically significantly associated with the four outcomes. As anticipated, the prevalence of overweight and obesity was positively associated with deprivation, with a positive association with IDACI scores, and a negative association with professional employment for all outcomes. Prevalence was elevated in areas with higher non-white populations, whilst a negative association was apparent with the area of green-space and domestic gardens in each MSOA, as with the percentage of the population who were same age group peers.

Table 3.3. shows the associations with the four outcomes across quartiles of the food environment exposure measures after adjustment for the covariates in Table 3.2. For the older children there remained a statistically significant positive trend between overweight and obesity and the number of both ‘fast food’ and ‘other unhealthy food’ outlets. Furthermore, there was a negative association with the availability of ‘mixed food outlets’, although the trend was somewhat attenuated from that before adjustment. For the younger children however, whilst the associations with ‘mixed food outlets’ remained unchanged as compared to the unadjusted, no association with ‘other unhealthy food’ outlets remained after adjustment. For fast food outlets, a statistically significant association remained with the percentage of children who were overweight or obese, although this was in the opposite direction to that observed before adjustment, with the lowest prevalence being observed in the areas with the most outlets of this type.

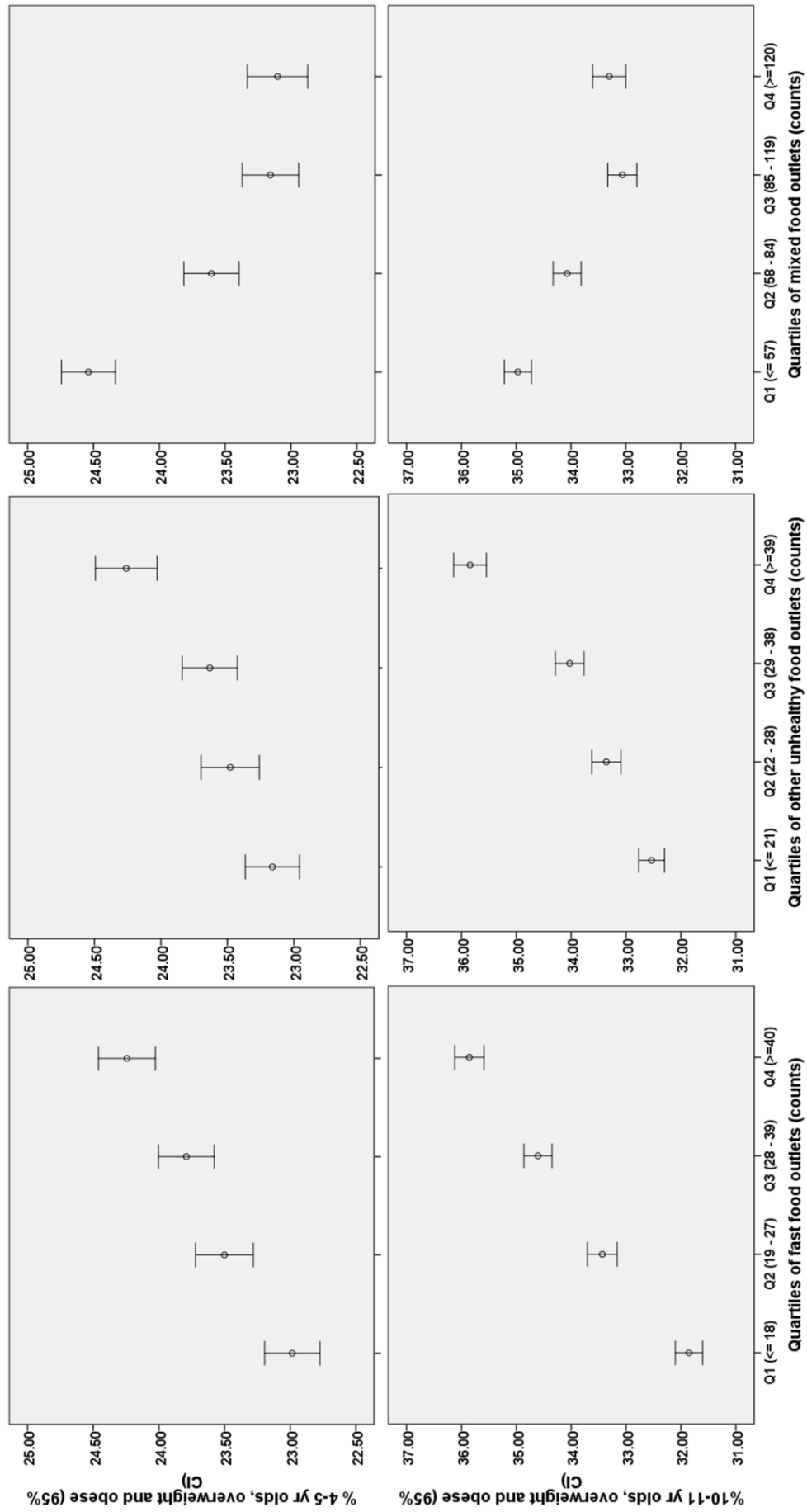


Figure 3.1. Unadjusted associations between weight status and food outlets prevalence (error bars, 95% CI)

Table 3.4. shows the unadjusted associations between the food environment measures and deprivation levels, as represented by IDACI scores. The values in the table portray, for each quartile of deprivation, the percentage of MSOAs falling within each quartile of food outlet availability. For example, 42.2% of MSOAs falling in the top quartile of fast food outlet prevalence lie in the most deprived quartile of IDACI scores, whilst just 14.1% lie in the least deprived quartile. The Mantel-Haenszel test for trend revealed a significant trend in the prevalence of all food outlets across levels of deprivation, whereby prevalence of fast food and other unhealthy food increase with area deprivation. A trend in the opposite direction was apparent for mixed food outlets.

The mediation analysis (Table 3.5.) suggested that fast food outlets and other types of unhealthy food outlets availability partially mediated the relationship between deprivation and obesity and overweight/obesity in older children. The effect ratio is however very small, suggesting that between just 1% and 2% of the total effect of deprivation on obesity and overweight/obesity in secondary school children in England was explained by the availability of fast food and other unhealthy food outlets in the food environment. No evidence of mediation was found for mixed food outlets.

Discussion

This study found that geographical variations in measured characteristics of the food environment were associated with the prevalence of overweight and obesity in English children participating in the National Child Measurement Programme. The association was stronger for 10-11 year olds than for 4-5 year olds. There was little evidence that food environment characteristics mediated the known association between deprivation and weight status in this age group.

The association between deprivation and weight has been well researched, with studies consistently showing in the UK^{120 203 204 225}, Canada¹⁸⁰, US²⁰², New Zealand¹¹⁸ and Europe in general²²⁶, that overweight and obese children are more likely to come from more socio-economically deprived areas.

Table 3.2. Associations between weight status in children and area characteristics

Covariates	% 4-5 years old, overweight or obese				% 4-5 years old, obese				% 10-11 years old, overweight or obese				% 10-11 years old, obese			
	B	LB	UB	sig	B	LB	UB	sig	B	LB	UB	sig	B	LB	UB	sig
(Constant)	27.838	26.852	28.824	<0.001	11.298	10.669	11.926	<0.001	40.685	39.587	41.783	<0.001	23.309	22.419	24.199	<0.001
Income deprivation affecting children (IDACI) scores, 2010	9.511	8.288	10.734	<0.001	7.254	6.478	8.029	<0.001	10.098	8.740	11.456	<0.001	11.688	10.587	12.789	<0.001
Percentage area domestic gardens, 2005	-0.020	-0.032	-0.007	0.002	-0.016	-0.024	-0.009	<0.001	-0.039	-0.054	-0.025	<0.001	-0.026	-0.037	-0.014	<0.001
Percentage area green space, 2005	-0.002	-0.009	0.005	0.624	-0.006	-0.010	-0.002	0.008	-0.027	-0.035	-0.019	<0.001	-0.018	-0.025	-0.011	<0.001
Percentage of population aged under 7 years old	-0.192	-0.246	-0.137	<0.001	-0.086	-0.121	-0.051	<0.001								
Percentage of population aged 10-14 years old									-0.325	-0.429	-0.220	<0.001	-0.334	-0.418	-0.249	<0.001
Percentage of population of mixed ethnicity	0.157	0.032	0.282	0.014	0.246	0.167	0.326	<0.001	0.697	0.560	0.833	<0.001	0.415	0.304	0.525	<0.001
Percentage of population of not white or mixed ethnicity	0.018	0.010	0.026	<0.001	0.017	0.012	0.022	<0.001	0.047	0.039	0.056	<0.001	0.037	0.030	0.044	<0.001
Percentage of population age 16-74 who are senior officials or in a professional occupation	-0.164	-0.179	-0.150	<0.001	-0.089	-0.099	-0.080	<0.001	-0.230	-0.247	-0.213	<0.001	-0.186	-0.200	-0.172	<0.001

Note 3.2.: B- B slope representing the direction of effect; LB, UB- lower and upper bound of the 95% Confidence Interval (CI); sig- significance (p value)

Table 3.3. Associations between weight status in children and food outlets prevalence, after adjustment for area characteristics

	% 4-5 years old, overweight or obese			% 4-5 years old, obese			% 10-11 years old, overweight or obese			% 10-11 years old, obese						
	B	LB	UB	sig	B	LB	UB	sig	B	LB	UB	sig				
Counts of fast food outlets Q2 (19-27)	0.058	-0.197	0.313	0.655	0.119	-0.044	0.281	0.153	0.695	0.415	0.975	<0.001	0.479	0.252	0.707	<0.001
Counts of fast food outlets Q3 (28-39)	-0.254	-0.510	0.002	0.051	-0.094	-0.256	0.069	0.260	0.880	0.599	1.160	<0.001	0.643	0.415	0.871	<0.001
Counts of fast food outlets Q4 (>=40)	-0.597**	-0.874	-0.320	<0.001	-0.151**	-0.328	0.025	0.093	0.846**	0.541	1.152	<0.001	0.584**	0.336	0.832	<0.001
Counts of other unhealthy food outlets Q2 (22-28)	0.016	-0.240	0.271	0.903	0.048	-0.114	0.211	0.561	0.372	0.092	0.653	0.009	0.245	0.018	0.473	0.034
Counts of other unhealthy food outlets Q3 (29-38)	0.066	-0.191	0.322	0.617	0.107	-0.056	0.270	0.200	0.628	0.346	0.910	<0.001	0.461	0.232	0.690	<0.001
Counts of other unhealthy food outlets Q4 (>=39)	-0.111	-0.391	0.170	0.439	0.018	-0.161	0.196	0.847	0.721**	0.413	1.029	<0.001	0.511**	0.262	0.761	<0.001
Counts of mixed food outlets Q2 (58-84)	-0.275	-0.534	-0.017	0.037	-0.119	-0.283	0.045	0.154	-0.019	-0.303	0.266	0.896	-0.094	-0.324	0.137	0.426
Counts of mixed food outlets Q3 (85-119)	-0.274	-0.544	-0.004	0.047	-0.211	-0.382	-0.039	0.016	-0.281	-0.579	0.017	0.065	-0.234	-0.476	0.008	0.058
Counts of mixed food outlets Q4 (>=120)	-0.432**	-0.732	-0.133	0.005	-0.282**	-0.473	-0.091	0.004	-0.205	-0.535	0.126	0.225	-0.225	-0.493	0.043	0.101

Note 3.3.: Q1, Q2, Q3, Q4 represent quartiles of food outlets, with quartile 1 being the reference category in the linear regression model; B- B slope representing the direction of effect;

LB, UB- lower and upper bound of the 95% Confidence Interval (CI); sig- significance (p value). Each set of food outlet quartiles has been introduced into the best fit model in turn.

**p<0.01, *p<0.05 represent the significance levels of the test for trend for each predictor

Table 3.4. Unadjusted association between food environment measures and area-level deprivation

	IDACI Q1 (≤.093)	IDACI Q2 (.094-.164)	IDACI Q3 (.165-.294)	IDACI Q4 (.295+)
Counts of fast food outlets Q1 (≤18)	35.2	32.3	19.8	12.8
Counts of fast food outlets Q2 (19-27)	29.3	25.5	26.5	18.8
Counts of fast food outlets Q3 (28-39)	20.5	24.0	27.7	27.8
Counts of fast food outlets Q4 (≥40)	14.1	17.4	26.2	42.2**
Counts of other unhealthy food outlets Q1 (≤20)	27.5	28.9	27.0	16.7
Counts of other unhealthy food outlets Q2 (21-27)	24.2	27.7	26.9	21.2
Counts of other unhealthy food outlets Q3 (28-36)	25.2	24.1	25.2	25.4
Counts of other unhealthy food outlets Q4 (≥37)	22.9	19.1	20.6	37.5**
Counts of mixed food outlets Q1 (≤59)	17.5	21.7	31.0	29.7
Counts of mixed food outlets Q2 (60-85)	23.4	26.9	27.7	22.0
Counts of mixed food outlets Q3 (86-121)	28.0	27.5	23.8	20.6
Counts of mixed food outlets Q4 (≥122)	25.0	25.0	25.0	25.0**

Note 3.4.: the cells represent row percentages (the percentages of food outlets in each quartile across quartiles of deprivation; Mantel-Haenzel test for trend (** $p < 0.001$)

Another UK study also found positive associations between density of fast food outlets, deprivation and overweight and obesity, this time in children aged 3 to 14 years¹³¹. A Canadian study found that children from more deprived schools have a poorer dietary intake and sit in front of the television and computer more, however there was no difference between weight status in deprived vs. the affluent schools²⁰⁶. While data on actual dietary intake was not available in our study, it was found that children from less affluent areas do have higher weight status compared to their more affluent counterparts, and there was evidence that this may be mediated by the fast food environment. It could be that the school is hence an inappropriate level at which to measure deprivation. One English study has reported associations between neighbourhood availability of unhealthy food outlets and weight and dietary intake in a sample of children aged 9 to 10 years⁴³. Additionally, unhealthy food intake was associated with availability of unhealthy food outlets, which is consistent with our findings, although we did not have information on actual intakes in our analysis. Unlike our study which was based amongst an environmentally heterogeneous population, most studies have majorly relied on urban and relatively small population samples^{131 166}. Where no association has been observed between food outlet density and weight status in children, this may be explained by a lack of variation in the types of environment study populations are exposed to⁵⁵.

Table 3.5. How neighbourhood food outlets prevalence may mediate the association between area deprivation and child weight-status (after adjustment for area characteristics)

Mediator	DV	IV	Indirect effects	Coefficient	SE	Bootstrapping		Mediation diagnosis	Effect ratio
						BCa 95% CI Lower	Upper		
Counts of fast food outlets	% 4-5 yrs old, overweight and obese	IDACI	Total effects	9.51	0.6	-	-	Inconsistent mediation	-0.02*
			Direct effects	9.68	0.6	-	-		
			Indirect effects	-0.17	0.1	-0.3	-0.07		
Counts of fast food outlets	% 4-5 yrs old, obese	IDACI	Total effects	7.25	0.4	-	-	Inconsistent mediation	-0.01*
			Direct effects	7.32	0.4	-	-		
			Indirect effects	-0.07	0	-0.15	-0.02		
Counts of other unhealthy food outlets	% 4-5 yrs old, overweight and obese	IDACI	Total effects	9.51	0.6	-	-	No	
			Direct effects	9.6	0.6	-	-		
			Indirect effects	-0.09	0.1	-0.23	0.1		
Counts of other unhealthy food outlets	% 4-5 yrs old, obese	IDACI	Total effects	7.25	0.4	-	-	No	
			Direct effects	7.26	0.4	-	-		
			Indirect effects	-0.01	0.04	-0.09	0.08		
Counts of mixed food outlets	% 4-5 yrs old, overweight and obese	IDACI	Total effects	9.51	0.6	-	-	No	
			Direct effects	9.58	0.6	-	-		
			Indirect effects	-0.07	0.1	-0.26	0.12		
Counts of mixed food outlets	% 4-5 yrs old, obese	IDACI	Total effects	7.25	0.4	-	-	No	
			Direct effects	7.25	0.4	-	-		
			Indirect effects	0.001	0.1	-0.12	0.15		
Counts of fast food outlets	% 10-11 yrs old, overweight and obese	IDACI	Total effects	10.1	0.7	-	-	Yes, partial	0.01
			Direct effects	9.98	0.7	-	-		
			Indirect effects	0.12	0.1	0.04	0.26		
Counts of fast food outlets	% 10-11 yrs old, obese	IDACI	Total effects	11.69	2.6	-	-	Yes, partial	0.01
			Direct effects	11.6	2.6	-	-		
			Indirect effects	0.08	0.7	0.03	0.19		
Counts of other unhealthy food outlets	% 10-11 yrs old, overweight and obese	IDACI	Total effects	10.1	0.7	-	-	Yes, partial	0.02
			Direct effects	9.88	0.7	-	-		
			Indirect effects	0.22	0.1	0.1	0.4		
Counts of other unhealthy food outlets	% 10-11 yrs old, obese	IDACI	Total effects	11.69	0.6	-	-	Yes, partial	0.01
			Direct effects	11.56	0.6	-	-		
			Indirect effects	0.13	0.1	0.04	0.25		
Counts of mixed food outlets	% 10-11 yrs old, overweight and obese	IDACI	Total effects	10.1	0.7	-	-	No	
			Direct effects	10.14	0.7	-	-		
			Indirect effects	-0.04	0.1	-0.23	0.17		
Counts of mixed food outlets	% 10-11 yrs old, obese	IDACI	Total effects	11.69	0.6	-	-	No	
			Direct effects	11.74	0.6	-	-		
			Indirect effects	-0.06	0.1	-0.22	0.13		

Note 3.5.: DV- dependent variable; IV- independent variable; SE- standard error; BCa- Bias Corrected and accelerated confidence interval; * inconsistent mediation

Whilst there are studies acknowledging the impact of various environment or area characteristics (such as advertisement^{156 227}, family intake²²⁸ or deprivation²⁰³) on younger compared to older children, to our knowledge there are no studies assessing the impact of the food environment on children's weight or diet that differentiate by the age of children. Our study has shown that there seems to be different effects of the food environment characteristics, most obvious for availability of fast food outlets in the neighbourhood, across children's age groups, with clear associations for older children, but less so for younger children.

Our study has a number of strengths and limitations. The strengths of the study include the large sample size, which provides adequate statistical power. The fact that the study covered the whole population meant that there was substantial heterogeneity in both the socio-demographic characteristics of the sample as well as types of food environment to which they were exposed. The work also benefitted from the availability of an extensive number of potential confounders, and the fact that the anthropometric outcomes were measured rather than self-reported. In addition, this is one of the few studies to undertake a mediation analysis in an attempt to understand how exposure to the food environment may sit on the causal pathway between socioeconomic disadvantage and obesity. Nevertheless, there are a number of limitations to the work. The cross sectional design of the study means that caution must be taken when inferring causality of association, as with any ecological study. It is known that obese children are underrepresented in the NCMP²¹⁰ and this participation bias could reduce the heterogeneity of the outcome, thus attenuating the strength of observations. We had no information on where participants in the NCMP or their families purchased food, and hence our food neighbourhoods may not represent the locations used to actually buy food, although they do provide a measure of local purchasing potential. Indeed, childhood obesity results from an interplay of various factors which yet remain to be fully understood²⁰³ and we did not have information on other potentially important correlates such as the physical activity levels of the children. Although continually updated, it is likely that, in common with all such products, the Points of Interest database we used may not represent all food outlets present and may contain some that have subsequently closed. Nevertheless, recent evidence suggests that it provides an adequate representation of the food environment²¹⁵ and it is unlikely that any omissions would have a substantial impact on the measure given the large differences in outlet density observed across the country.

We chose counts of food outlets as our outcome measure rather than density, because we were interested in looking at the number of opportunities that children have, rather than how they were spatially organised. Nevertheless, to examine the impact of this decision, we performed a sensitivity analysis with counts of food outlets per unit area as the primary food exposure measures in the regression models. For fast food and other unhealthy outlets, these models were largely similar to those presented here, although a statistically significant positive association was observed between weight status and exposure to ‘mixed food outlets’ amongst Year 6 children. A comparison between the impact of different methodological choices of measuring the food environment has been described elsewhere²²⁹. For each food outlet type, we also tested for presence of the other types of food outlets in the area as potential confounders by including them as explanatory variables in the regression models, but again our results were not substantively changed and are hence not repeated here. The typology of food outlets we developed inevitably meant that difficult decisions had to be made about in which category to place some food outlets. More detailed measures such as food quality ratings or store inventories might be more predictive for health outcomes, but these are costly and time consuming or do not exist on a national scale⁴⁵.

Various methods are available for performing mediation analysis, but all have advantages and disadvantages. The classic Baron and Kenny method²³⁰ which has been used by researchers as the standard toolkit has been recently criticised²³¹ and hence we chose that developed by Preacher and Hayes²²². However, in common with other techniques, this method cannot accurately estimate the mediation effect ratio for regression models with covariates. Hence values for the indirect effects should be interpreted with caution as the method can return negative values which cannot legitimately be interpreted as a proportion; in this case, there is still mediation but the mediator acts as a suppressor variable, a situation which is referred to as inconsistent mediation²³². It is also noteworthy that, whilst we found evidence of statistically significant mediation in this work, the effect ratios were small. It is likely that the level of statistical significance attained is somewhat driven by the large sample size, and therefore the findings regarding mediation should be treated accordingly.

Whilst this study supports findings in the literature that there is a direct association between area level deprivation and availability of unhealthy food, making the case for ‘food deserts’ at national level, we recognise that evidence for their presence in the literature is equivocal^{23 46}

^{120 233 234} and most comes from the US, where there is greater neighbourhood segregation.

Our findings that certain characteristics of the food environment mediated the association

between deprivation and weight status in older, but not younger children might be explained by the fact that younger children do not directly interact with their food environment as much, but they do so mostly through their parents who make choices for them, as compared with older children, who have more autonomy. Furthermore, evidence of higher provision of unhealthy food outlets in more deprived areas suggests that deprived children have more physical and economic (price of food vs. income) access to unhealthy food, a phenomenon known as the ‘obesity-hunger paradox’ or the ‘food insecurity-hunger paradox’¹³⁴. We believe our findings are applicable to other parts of the developed world, as the association between deprivation and obesity has also been observed in other developed countries^{202 226}. Studies undertaken in less developed countries report mixed associations with poverty, although it seems that by contrast, obesity in children is often a problem of the rich²³⁵. How the associations we have observed may play out in such contexts is unknown.

We suggest this study highlights the importance of considering different aspects of the food environment when assessing the environmental causes of childhood obesity. Public health in the UK is changing, and some public health functions have been recently transferred from Primary Care Trusts to Local Authorities. This may present an opportunity as it will directly bring together public health practitioners and planners into the same offices for the first time. It is therefore important to better understand the association between location and health related outcomes for population health gain, as some solutions might lie in the planning domain, with fiscal and legal implications.

We suggest that public health policies to reduce obesity in children incorporate strategies to prevent high concentrations of fast food and other unhealthy food outlets. Evaluations carried out regarding zoning of food outlets around schools in New Zealand²³⁶ and the US²³⁷⁻²³⁹ for example, found that food environments within walking proximity to schools are characterized by a high density of fast foods or other inexpensive and energy-dense food providers, and that this is particularly so in more deprived areas. Interventions for tackling childhood obesity and creating environments that are more supportive for both physical activity and better dietary choices should however nevertheless be part of the bigger picture looking at the whole obesity system, and strategies should also address the wide spectrum of factors that contribute to the obesogenic environment.

In conclusion, this study has reported evidence that, in a large and geographically diverse sample of children, whilst the number of fast food and other unhealthy food outlets in the

neighbourhood may only very partially account for the observed association between childhood deprivation and childhood obesity, a higher presence of food outlets selling unhealthy food is linked to higher levels of children who are overweight and obese, while the opposite is true for food outlets selling a range of healthier food.

Chapter 4

Exposure to the food environment, food consumption and weight in children aged 9-10 years: evidence from the SPEEDY-1 study

Abstract

Objective: There is a need to determine which components of the environment may be contributing to the recent rise in obesity rates. This may happen through the avenue of poor diets and exacerbated by low socio economic class. In this cross-sectional study we examined associations between weight, diet, socio-economic class and characteristics of food environments around homes and schools among 2064 9-10 year old children in Norfolk, UK.

Methods: Availability of food outlets was computed in GIS for each child's unique neighbourhood. Outlets were grouped into healthy, unhealthy, and fast food. Weight status measurements were objectively collected, and food intake was recorded using 4-day food diaries.

Results: BMI of children increased with increasing exposure to unhealthy food outlets in the home environment, and consumption of fast food increased with increasing exposure to fast food outlets in the home and school environments. Furthermore, fibre intake increased with increasing exposure to healthy food outlets in the home environment, and energy density of diet increased with and increasing exposure to fast food in the school environment. Children from lower social class backgrounds were more likely to have a higher BMI, a poorer and more energy dense diet, and they were more likely to be exposed to a higher density of food outlets in their neighbourhoods. There was no clear evidence of an effect modification by food knowledge or preference, or of mediation.

Conclusion: Exposure to unhealthy food in the home or school neighbourhood may be conducive to weight gain and poorer and more energy dense diets in children. There is a social class gradient in weight status, diet and access to food. Exposure to food environments should be taken into consideration when targeting policies and interventions to reduce childhood obesity.

Introduction

The obesity pandemic highlighted the importance of the environment in relation to eating and physical activity behaviours. To this end, obesity prevention initiatives have been characterised by calls to modify the environment. Despite this, there is still little empirical data investigating associations between environmental factors and eating behaviours that might impact obesity risk¹. This is particularly the case with children, who have less control of use of their environments than adults. In Chapter 3 the relationship between food environments and obesity was investigated, but no information was available on eating patterns.

The number of studies examining the association between the local food environment and diet has been growing in recent years. A recent systematic review⁸² reported 38 studies; however, some of them included perceived measures of availability, and most of them dealt with adults, while only seven with children. An earlier systematic review²⁴⁰ on the environmental correlates of obesity-related dietary behaviours amongst children and adolescents found that while the majority of studies focused on sociocultural and household factors, few studies examined food accessibility, availability or affordability in local neighbourhoods. With the rise of the fast food industry and the desire for convenience, more consumers are choosing fast food over home cooking alternatives²⁴¹, thereby potentially increasing their levels of fats, sugars, and overall obesity²⁴². It is therefore important to investigate the effect the obesogenic environment might have on the types of food consumed, but also on macro-nutrient intake.

Socio economic status^{142 243} also plays an important role in the promotion of weight loss/gain in children. A heightened consciousness concerning socio-economic influences on the health of individuals and the population at large has emerged over the last few years.

Epidemiological studies have shown an association between leading an unhealthy lifestyle and being in a lower socio-economic class²⁴⁴. It has been reported²⁴⁵ that the obesity prevalence among children increases with socioeconomic deprivation, and indeed the obesity prevalence of the most deprived 10% of the child population in England has been found to be approximately twice that of the least deprived 10%. The results of studies are however not always consistent, which points to a complex interaction between socio-economic status and food choices¹⁶⁶. It has however been shown that unhealthy food outlets are more common in deprived areas in the UK^{54 120 131 204} and abroad^{118 205}, so it might be that the relationship between socio-economic status and obesity could be explained by the mediating effect of

exposure to unhealthy food environments. Indeed this has indeed been shown to be the case, albeit to a small extent, in the previous chapter (Chapter 3), but only for older children.

While the work in Chapter 3 benefited from data from a large sample of children across the whole of England⁵⁴, it had a number of limitations. One was that the home location of children was not available, only the school they attended. There was also no information on individual/household level variables such as socioeconomic status or individual weight, only area level deprivation and obesity prevalence. A particular limitation of Chapter 3 was the fact that no information on dietary intakes in the children was available and hence it was not possible to determine what role diet played in the tested associations. This chapter aims to build on that previous analysis and further unpick the relationship between socioeconomic status, the food environment, weight and additionally diet in older children at an individual level and observe if the ecological associations uncovered in the previous chapter might be different than associations at an individual level, when having the same data. The SPEEDY study (Sport, Physical activity and Eating behaviour: Environmental Determinants in Young people) utilised in this chapter offered the possibility to investigate such associations further by providing both home and school locations of children, household and neighbourhood socio-economic status, individual weight, as well as finely measured dietary intake derived from food diaries.

Using the baseline data of the SPEEDY study, this chapter therefore aims to identify how exposure to particular types of food in the children's environments and socio-economic status might be associated with food intake and individual weight. We aim to explore various mediation models to investigate how these factors interplay. The following questions will be investigated:

1. Is there a relationship between the food environment around the school and home and weight status and diet in SPEEDY children?
2. Is there a relationship between socioeconomic status and diet/weight, the food environment in SPEEDY children?
3. Does diet mediate any associations between the food environment and weight status?
4. Does the food environment mediate any associations between socio-economic deprivation and weight status?

Methods

Study population and sampling

The SPEEDY 1 study was set up to quantify the potential correlates of levels of physical activity and dietary habits in 9 to 10-year-old schoolchildren (Year 5) in the county of Norfolk, England. The children were recruited from 92 primary schools during the summer term (April to July) of 2007, and the schools were purposively sampled to achieve maximum environmental heterogeneity. Participating children at baseline (n=2064) were visited at school by teams of two or more trained research assistants. They collected a range of data according to standard operating procedures including anthropometry, demographic information, school-level information, and details of children's home and neighbourhood environment. A questionnaire was also completed by a parent or main carer of each child. A description of the methods adopted and participant recruitment procedures has been published in more detail elsewhere^{2 43 61 86}.

Measures

The variables generated for this analysis are described in Table 4.1. The outcome variables of interest are weight status and diet. Weight status was measured using BMI (weight divided by height squared), whilst diet was measured through daily intake of key food groups, nutrient intake and energy density of diet.

Food intake was recorded using a 4-day food and drink diary where children, with assistance from their parents, were asked to record everything they ate and drank. Diaries were completed over four consecutive days; either Thursday to Sunday or Saturday to Tuesday depending on when measurement took place at a child's school. A 4 day diary was deemed sufficient to determine mean dietary intake without overburdening participants, while also covering equal numbers of weekdays and weekend days²⁴⁶. A short questionnaire at the beginning of the food diary asked children about their usual dietary habits, preferences and knowledge. The diary required children to record all food and drink consumed by time of consumption, and to include estimates of portion size (small, medium or large, or specific unit such as a packet of crisps). Guidance on the completion of the diary was given to the children by the research assistants and full written instructions were included for parents. Weights of portions were then estimated using published values, including those specific to children²⁴⁷ and mean intakes from key food groups, plus nutrient intakes, were estimated using the WISP

nutritional analysis software version 3.0 (Tinuviel Software, Warrington, UK). More details about the measurement methods are reported elsewhere^{43 246}.

For the analyses with diet as an outcome, only those with 4 days' worth of data were included. From the data available, the following macronutrients were extracted: mean intakes of protein and fibre (NSP: Non-starch polysaccharides); percentage of energy from saturated fat and carbohydrates (including sugars). Additionally, the energy density of the diet (kcal per gram, solids only) was also extracted. The decision to include only solids in this measure was based on evidence in the literature²⁴⁸, as it has been argued that beverages, which have a high water content, tend to have a lower energy density than most foods and may disproportionately influence dietary energy density values. It has been shown²⁴⁸ that calculations based on energy-containing beverages may diminish associations with outcome variables.

The intakes of key food types were estimated as mean daily intake in grams of food. For the purpose of this study, key food groups were grouped into three categories of interest: healthy, unhealthy and fast food. The 'healthy' food category included fruit, vegetables and unsweetened fruit juice. The 'unhealthy' food category included items such as sweet and savoury snacks, puddings and desserts, carbonated drinks, soft drinks, squash and cordials. For the fast food category, as there was no information on where the children actually bought the food, a range of food items were used as a proxy for fast food: pizzas, chips and burgers, based on practice in previous studies¹¹⁷.

Table 4.1. Characteristics of the study population and their neighbourhood environments

	Overall	Boys	Girls	<i>p-value for diff by sex</i>
N (%)	2064	926 (44.9)	1138 (55.1)	
Individual characteristics of sample:				
BMI, mean \pm SD	18.22+3.19	17.88+2.89	18.50+3.38	<0.001
Age, mean \pm SD	10.25+0.31	10.24+0.31	10.26+0.31	0.28
IMD, mean \pm SD	17.12+11.70	17.33+14.62	16.95+11.58	0.409
Physical activity (counts per minute), mean \pm SD	672.67+224.64	716.97+223.68	637.26+219.15	<0.001
Under-reporters***, mean \pm SD	86.07+18.53	86.08+18.87	86.07+18.26	0.99
Energy (kcal)**	1748.52+363.916	1813.35+377.347	1696.60+344.289	<0.001
Ethnicity, % white:	96.2	96.2	96.2	0.97
SES:				
Parental level of educational attainment, %				0.46
None or school leaving certificate	7.4	7.1	7.7	
GCE or equivalent	51.2	50.3	51.9	
A level or equivalent	24.9	24.5	25.1	
University/postgraduate degree	16.5	18.1	15.3	
Food preference, % highest score*	54.4	52.5	55.9	0.17
Food knowledge, % highest score*	50.6	47.9	52.6	0.06
Diet outcome variables**:				
Daily healthy food intake (g), mean \pm SD	333.87+208.79	332.36+212.24	335.09+206.09	0.79
Daily unhealthy food intake (g), mean \pm SD	390.31+280.48	428.51+301.36	359.71+258.68	<0.001
Daily fast food intake (g), mean \pm SD	36.46+36.13	36.57+36.47	36.38+35.87	0.91
Daily protein intake (g), mean \pm SD	61.92+13.85	64.76+14.61	59.65+12.76	<0.001
Daily fibre intake (g), mean \pm SD	10.78+2.87	11.03+3.04	10.59+2.72	0.002
% energy from carbohydrates, mean \pm SD	48.66+5.01	48.69+5.19	48.64+4.87	0.59
% energy from saturated fat, mean \pm SD	13.88+2.64	13.88+2.72	13.87+2.58	0.97
Energy density of diet (kcal/g), mean \pm SD	2.03+0.32	2.05+0.32	2.01+0.31	0.04
Primary assumed food exposure variables (density of food outlets within 800 meter buffers around the home):				
Healthy food				0.866
% highest exposure	13.6	13.8	13.4	
% middle exposure	13.8	13.4	13.4	
% no exposure	72.6	72.8	72.4	
Unhealthy food				0.58
% highest exposure	17.6	16.7	18.4	
% middle exposure	20.2	20.5	20	
% no exposure	62.1	62.8	61.6	
Fast food				0.421

% highest exposure	18.9	19.2	18.7	
% middle exposure	18.9	17.7	20	
% no exposure	62.1	63.1	61.3	
Primary assumed food exposure variables (density of food outlets within 800 meter buffers around the school):				
Healthy food				0.437
% highest exposure	16.3	15.2	17.2	
% middle exposure	16.9	16.7	17.1	
% no exposure	66.8	68.1	65.7	
Unhealthy food				0.453
% highest exposure	27.8	28	27.6	
% middle exposure	28.5	27.2	29.6	
% no exposure	43.7	44.8	42.8	
Fast food				0.013
% highest exposure	24.5	24.9	24.2	
% middle exposure	27.2	24.1	29.8	
% no exposure	48.2	51	46	

** Data is for the 1718 children out of 2064 who filled in all diary days

*** Under-reporting defined as reported energy intake < 71% of estimated energy requirements.

Note 4.1.: Abbreviations: SD: standard deviation; BMI: body mass index; IMD: Index of Multiple Deprivation. The reported sig. value is for sex differences: **Mann-Whitney U** test for IMD, physical activity, food groups. **t-test** for BMI, age, under-reporters, macronutrients and energy density; **ChiSquare** test for ethnicity, parental education, food exposures. Food exposure predictors have been split in 3 categories according to their frequency distribution as follows: zero (no food outlets present), one food outlet, more than one food outlet

Under-reporting of energy intake was assessed by calculating the ratio of reported energy intake (EI) to estimated energy requirements (EERs) and has been described in more detail elsewhere⁴³. For the SPEEDY data the 95% confidence interval for EI:EER was 0.71, 1.30; therefore those reporting an EI of less than 71% of EER were defined as under-reporters. So as not to distort dietary intake data by excluding children who under-reported energy intake, the EI:EER ratio was included as a continuous variable in all statistical models with dietary variables as outcomes²⁴⁹. This adjustment was therefore done to account for those who do not record everything they eat in the food diary, and it may be that participants who eat more of certain types of foods are the ones who are worse at reporting; it cannot be known what the impact of excluding cases based on a minimum reporting criteria would be (it might produce bias or not).

A neighbourhood was constructed around each child's home and school in ArcGIS (ESRI Inc., Redlands, CA, USA) by choosing an 800 metre zone along pedestrian networks as a definition for a suitable neighbourhood for children. This threshold was based on previous literature⁴³ and on the fact that parents report this as a safe walking distance for children²⁵⁰, roughly equating to a 10 minute walk⁶¹. An on-foot grounds audit was undertaken at all participating schools²⁵¹, and this identified the location of all entrances to the school grounds. For this analysis, the entrance closest to the main school building was used as the school's location for the purpose of defining the school neighbourhood.

Availability of food outlets in children's neighbourhoods (which is a measure of assumed exposure to the food environment) were computed using the Ordnance Survey "Points of Interest" database (PoI), which provides data on the location of geographic and commercial facilities across Great Britain. The data for food outlets in the database has been reported to be reliable²¹⁵, and 95% of the PoI contained in a sample have been reported to have a positional accuracy of within 17.51 meters of the real-world features they represent²⁵². In order to measure the quality of the local environment, food outlets were classified into healthy, unhealthy and 'fast food' following similar procedures to the previous chapter⁵⁴, which has shown these to be associated with weight status in children. Healthy food outlets included grocers, farm shops and supermarkets; unhealthy food outlets included convenience stores, general stores, and newsagents and tobacconists, and fast food included fast food and takeaway outlets, fast food and delivery services and fish and chip shops. For each outlet type, information was generated on the number of units in the child's neighbourhood (expressed as number of outlets per km²). For the purposes of analysis these measures were transformed

into three-category variables: no exposure (no food outlets), middle exposure and highest exposure, with the less and more time spent categories being derived using a median split.

For this chapter, access to food was operationalised as availability of food within home and school neighbourhoods, measured as density of food outlets within the 800 meter buffers, which takes into account the fact that these neighbourhoods can vary in size. Using a density measure allows comparison with previous studies that have employed a similar measure of the food environment when investigating associations between the food environment and individual diet and/or weight^{43 55}. This density measure of access to food was chosen over a proximity measure (i.e. distance to the nearest food outlet of a given type), as it has previously been shown that distance measures in rural and more densely populated areas are not comparable²⁵³. Unlike density measures, distance-based measures do not indicate the presence of multiple facilities²⁵⁴.

A number of covariates were considered in the statistical analyses: age, gender, ethnicity, socio-economic status, physical activity in mean daily counts per minute (only for the BMI models), mean daily energy intake (kcal) and under reporting estimate (only for the diet models). Household socio-economic status was represented by parent's educational attainment in this study. Information on this was obtained by parental self-report. Area level deprivation was represented by Index of Multiple Deprivation (IMD) scores²⁵⁵ (in this analysis the total IMD score using all domains was used). A higher IMD score reflects a higher level of deprivation.

Interaction effects were tested with nutritional knowledge and food preference, as it was hypothesised that the impact of any environmental exposures on the outcomes might be moderated by food preference and nutritional knowledge of the child, which were found to be potential important factors in influencing children's diet in Chapter 2. Food knowledge/preference scores were based on individual variables from a set of questions completed as part of the food diary for which missing cases had been imputed. Where answers were missing for the "How much do you like each of these foods?" (such as pizza, sausages, fish, rice etc.) and "How healthy do you think these foods are?" questions, they were coded to the central value = e.g. "They're ok" or "neither good nor bad". However imputations were made only if the child had actually answered 75% of the questions themselves. The rationale for coding to the central value was that it is a kind of null response – it doesn't bias the score one way or the other.

Statistical analysis

Descriptive data were summarised as means with standard deviations or percentages. Gender differences were determined using Student's t test, Mann-Whitney U test or the χ^2 test.

Statistical models were fitted using linear regression to examine the relationship between the food environment and food consumption and individual weight status (BMI) in the SPEEDY children. The lowest exposure category (no exposure, i.e. zero density of food outlets in the area) represented the reference category in the regression models. The models were investigated with and without the influence of the confounding variables. The BMI and key food groups models were additionally represented as error-bar plots and tests for trend across the three food exposure categories.

The macronutrients and energy density models were presented in tables with the unadjusted and adjusted mean values, confidence intervals and p value of the test for trend. Because there is virtually no precedent in the literature with regards to exposure to food environments and macronutrients as outcomes, it was hypothesised that exposure to healthy foods would be associated with a higher intake of fibre and exposure to unhealthy foods would be associated with a higher intake of saturated fat and carbohydrates. Therefore, associations were investigated between fibre and healthy food exposure only, and between saturated fat/carbohydrates and unhealthy/fast food exposure only. Associations with protein were tested for all food exposure predictors. Similarly, associations were tested between energy density of diet and all three food exposure predictors.

Also explored was whether there was an association between socio-economic status (parental education) and BMI, diet and access to food in the neighbourhoods. SES differences were determined using Student's t test or Mann-Whitney U test (mean and SD), or the χ^2 test.

In order to investigate if there was evidence of an effect modification by food preference or food knowledge, interaction effects were also tested for between the food environment predictors and food knowledge/preference scores. Finally, in order to examine the role of diet as a potential mediator in the relationship between the food environment and weight, as well as that of the food environment as a potential mediator between socio-economic status and weight, mediation analysis was performed using the Preacher and Hayes indirect²²², and respectively the mediate²⁵⁶ method. All statistical analyses were conducted in SPSS (version 21, IBM Corp, Armonk, NY, USA).

Results

The mean age of the study participants was 10.25 years ($SD \pm 0.31$), and 55% were girls (Table 4.1). There was a small amount of missing data where the child did not complete the relevant question. Not all children provided an address, which was requested on the consent form, or the address that was given did not match the available address database, and could therefore not be located. That meant that IMD could not be calculated for some children (2%). 8.8% of children were missing data on SES, 4.4%, on physical activity, 7.3% on ethnicity, and 8.8% on the food knowledge/preference scores. Data for BMI (0.6%) could be missing because a child did not want to be weighed on the day, but still completed other measurements, or there could have been a fault with the machine which invalidated their reading. EIEER (9.9 % missing) is dependent on a valid BMI reading, so could implicitly not be calculated for anyone missing BMI data; it also was not calculated for anyone who did not fill in the food diary. The diet outcome variables had 9.9% missing cases, and the food environment predictors had 2% missing data.

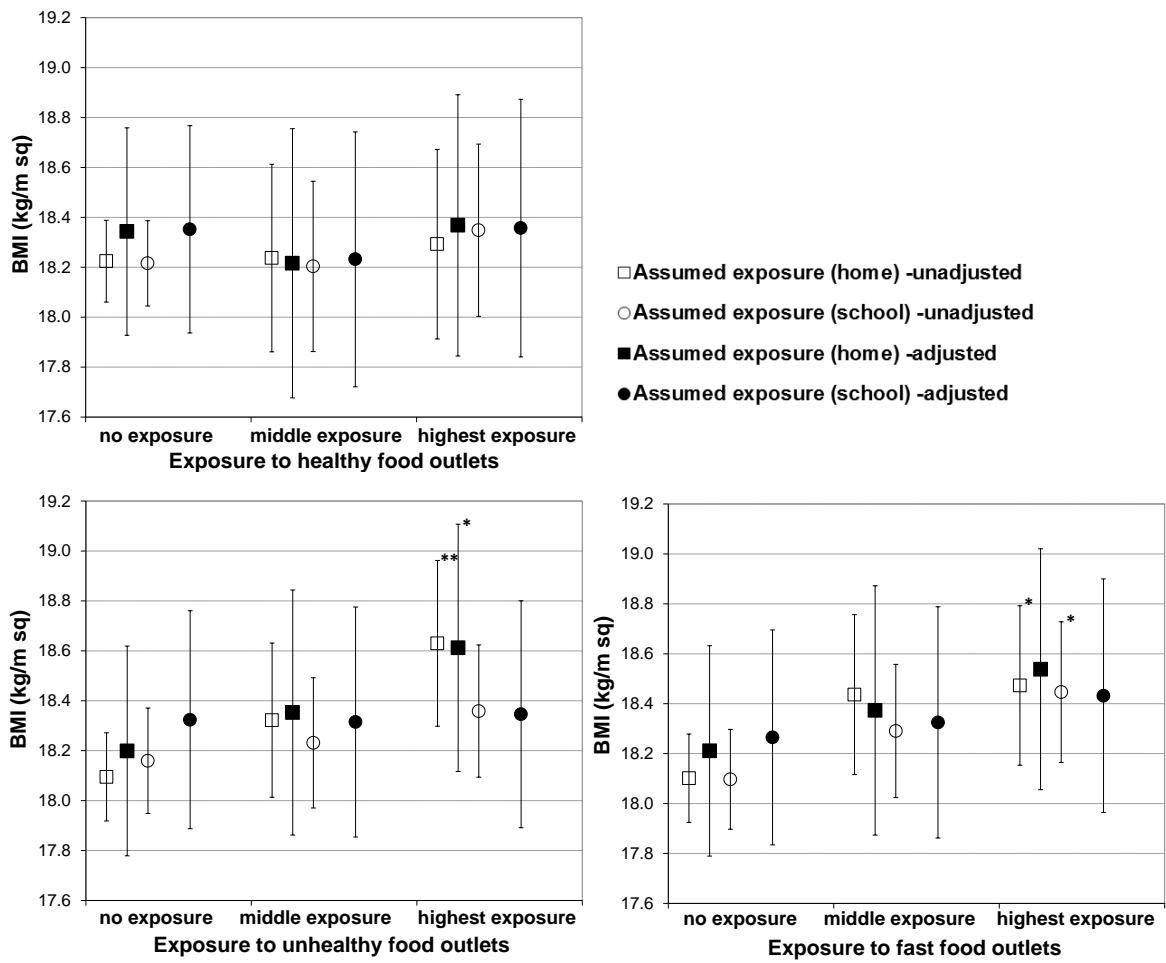
Of the 2064 children recruited in the SPEEDY study, 1859 had valid diet data (i.e. did not send back empty food diaries), and 1718 completed all four days of the diary; therefore the remaining 346 were excluded from the models with diet as an outcome in order to minimise the risk of bias by having incomplete data. Furthermore, BMI data was missing for 12 children. The final samples were therefore 2052 children for the models with BMI as an outcome, and 1718 for the models with diet as an outcome, with all children attending 92 schools. There was no difference between those included and excluded in terms of sex, BMI and SES ($p > 0.05$). Those excluded did however report lower energy intake and had lower estimated under-reporting ($p < 0.01$).

Characteristics of the pupils included in the analyses are reported in Table 4.1. Girls generally had a higher BMI than boys ($p < 0.01$), but there were no significant gender differences in SES or under-reporting. Participants reported consuming an average of 1749 ($SD 364$) kcal/day, with 48.66 ($SD 5.01$) % of energy coming from carbohydrates and 13.88 ($SD 2.64$) % from saturated fat. Average daily intake of protein was 61.92 ($SD 13.85$) g and of NSP fibre was 10.78 ($SD 2.87$) g.

When considering the associations between the density of different food outlet types and BMI (Figure 4.1.), there was no significant trend across categories of healthy food exposure around the home or school, either before or after adjustment. There was a significant increasing trend

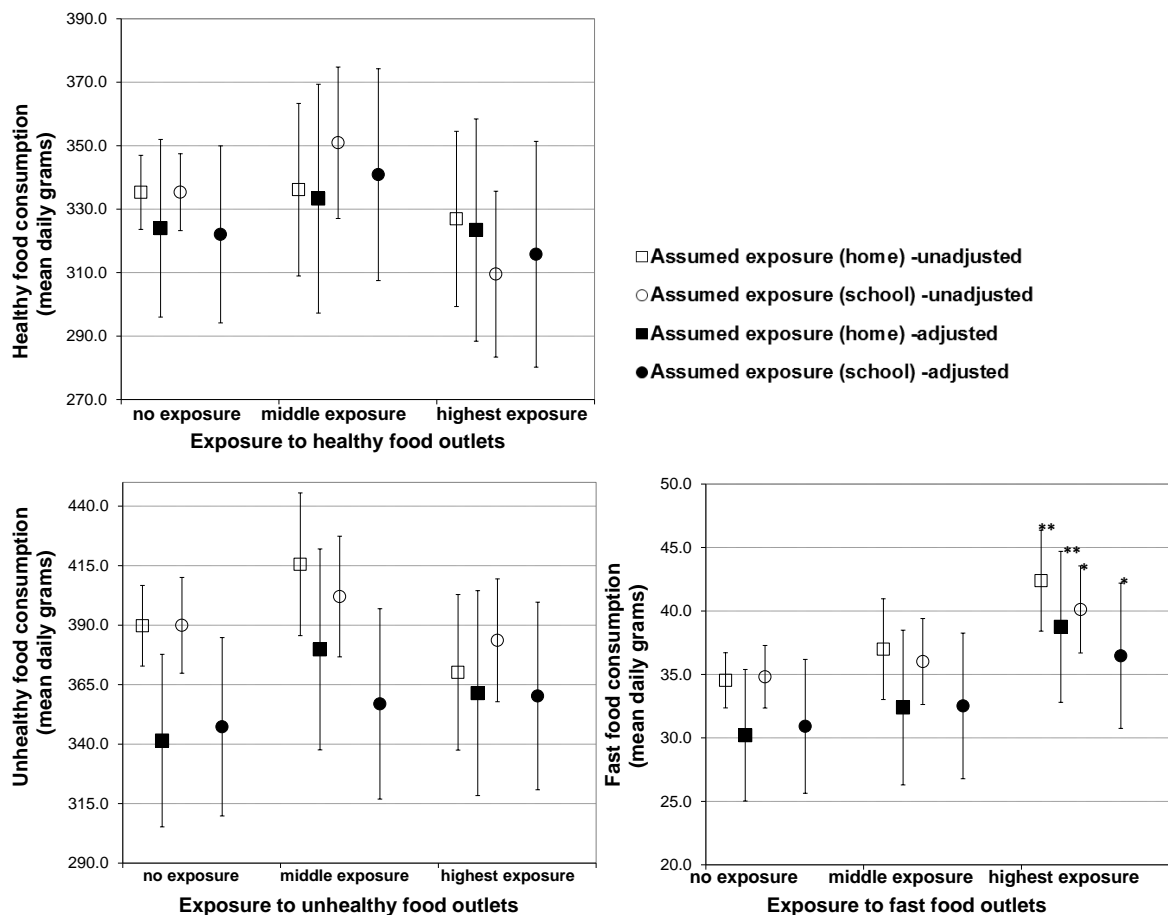
across categories of unhealthy food exposure around the home only, both before ($p < 0.01$) and after ($p < 0.05$) adjustment. The trend in BMI over categories of fast food exposure was only statistically significant before adjustment, in both the home and school neighbourhoods. In terms of the associations between density of each food outlet type and intake of relevant key food groups (Figure 4.2.), again there was no significant trend across categories of healthy food exposure around the home or school, either before or after adjustment. The same was true for unhealthy food exposure. There was however a statistically significant increasing trend of fast food consumption across categories of fast food exposure in both the home and school neighbourhoods, whereby more exposure to fast food in these environments was associated with more reported consumption of fast food-type items.

Figure 4.1. Associations between food exposure and BMI



Note 4.1 (fig).: Adjusted models control for age, gender, ethnicity, parental education, physical activity; Error Bars with 95% Confidence Intervals; significant test for trend across food exposure categories (* $p < 0.05$; ** $p < 0.01$)

Figure 4.2. Associations between food exposure and diet (food groups)



Note 4.2. (fig): Adjusted models controlled for age, gender, ethnicity, parental education, under reporting estimate, and mean daily energy intake (kcal); Error Bars with 95% Confidence Intervals; test for trend across food exposure categories (* p<0.05; ** p<0.01)

For associations with fibre intake (Table 4.2.), while there was no significant trend across categories of healthy food exposure before adjustment, there was a significant ($p<0.01$) increasing trend after adjustment, whereby more exposure to healthy food in the home neighbourhood only was associated with greater intake of fibre. While there was a significant decreasing trend of protein intake across all food exposure categories (with the exception of healthy food exposure around the home) before adjustment, no significant trend remained after adjustment (Table 4.2.). There was no evidence of a significant trend in saturated fat or carbohydrate intake over the unhealthy or fast food exposure categories, either before or after adjustment (Table 4.3.). Finally, no evidence was found before or after adjustment of a significant trend of energy density of diet for healthy and unhealthy food exposure (Table 4.4.). The same was true for fast food exposure in the home neighbourhood. There was however a significant increasing trend ($p<0.05$) over categories of fast food exposure in the school environment, both before and after adjustment), whereby more exposure to fast food around schools was associated with more energy dense diets.

In order to test if associations between nutrient intake/key food groups and food environment exposure might act to mediate the known SES related gradients in dietary intake and obesity, associations with the individual SES measures were examined. Tables 4.5. and 4.6. present the associations between SES and the outcomes and predictors. There was a significant difference ($p<0.01$) in BMI amongst SES categories, whereby children whose parents were less educated generally had a higher BMI. There was also a significant SES related gradient ($p<0.01$) in diet, whereby generally the less educated parents were, the less healthy food and the more unhealthy (except the lowest SES category) and fast food children consumed. Regarding macronutrients, the less educated parents were, the less protein children consumed ($p<0.01$) in general (with the exception of GSCE attainment as a measure of SES). Furthermore, the less educated the parents, the less fibre ($p<0.01$) children consumed, and the more energy dense their diets were ($p<0.01$). There was no SES difference in carbohydrates and saturated fat consumption amongst the SPEEDY children (Table 4.5.).

Table 4.2. Associations between food exposure and overall intake of fibre and protein (mean daily grams)

	Fibre						Protein							
	unadjusted			adjusted			unadjusted			adjusted				
	Mean	LB	UB	P	Mean	LB	UB	P	Mean	LB	UB	P		
Home:														
Density of healthy food outlets				0.659				0.009				0.072		0.430
no exposure	10.783	10.622	10.944		10.268	9.915	10.620		62.390	61.616	63.163		61.958	64.633
middle exposure	10.717	10.341	11.092		10.461	10.007	10.916		61.523	59.721	63.324		61.673	65.122
highest exposure	10.914	10.532	11.295		10.736	10.294	11.177		60.674	58.844	62.504		60.958	64.308
Density of unhealthy food outlets								0.009						0.588
no exposure									62.546	61.713	63.380		61.918	64.617
middle exposure									62.276	60.801	63.752		61.635	64.776
highest exposure									59.917	58.308	61.526		61.292	64.498
Density of fast food outlets								0.004						0.251
no exposure									62.662	61.826	63.499		62.006	64.718
middle exposure									62.019	60.494	63.544		61.936	65.125
highest exposure									60.020	58.490	61.550		60.955	64.066
School:														
Density of healthy food outlets				0.076				0.468				0.007		0.984
no exposure	10.846	10.679	11.014		10.340	9.988	10.693		62.644	61.841	63.447		61.926	64.595
middle exposure	10.888	10.558	11.218		10.544	10.123	10.966		61.265	59.683	62.846		61.076	64.269
highest exposure	10.418	10.057	10.779		10.402	9.953	10.852		60.210	58.477	61.942		61.823	65.225
Density of unhealthy food outlets												0.032		0.463
no exposure									62.539	61.549	63.529		61.868	64.651
middle exposure									62.623	61.376	63.870		62.025	64.996
highest exposure									60.643	59.374	61.913		61.308	64.237
Density of fast food outlets												<0.001		0.183
no exposure									63.215	62.272	64.158		61.832	64.579
middle exposure									62.289	60.995	63.584		62.631	65.621
highest exposure									59.536	58.223	60.848		60.710	63.693

Note 4.2. : Adjusted models controlled for age, gender, ethnicity, parental education, under reporting estimate, and mean daily energy intake (kcal); 95% Confidence Intervals; test for trend across food exposure categories (p)

Table 4.3. Associations between food exposure and overall intake of saturated fat and carbohydrates (% energy from)

	Saturated fat						Carbohydrates					
	Unadjusted			adjusted			unadjusted			adjusted		
	Mean	LB	UB	P	Mean	LB	UB	P	Mean	LB	UB	P
Home:												
Density of unhealthy food outlets												
no exposure	13.938	13.778	14.097	0.078	13.852	13.471	14.234	0.252	48.661	48.358	48.964	0.574
middle exposure	13.916	13.633	14.198		13.848	13.404	14.293		48.274	47.738	48.809	
highest exposure	13.593	13.286	13.901		13.616	13.162	14.07		49.02	48.436	49.604	
Density of fast food outlets				0.438				0.607				0.673
no exposure	13.918	13.758	14.078		13.846	13.462	14.23		48.617	48.313	48.921	
middle exposure	13.799	13.507	14.091		13.662	13.21	14.114		48.605	48.051	49.159	
highest exposure	13.808	13.515	14.101		13.803	13.363	14.244		48.772	48.216	49.328	
School:												
Density of unhealthy food outlets				0.635				0.91				0.718
no exposure	13.894	13.705	14.084		13.818	13.423	14.212		48.58	48.221	48.94	
middle exposure	13.905	13.666	14.144		13.761	13.34	14.182		48.714	48.261	49.167	
highest exposure	13.813	13.57	14.056		13.807	13.392	14.222		48.675	48.213	49.136	
Density of fast food outlets				0.805				0.797				0.65
no exposure	13.87	13.689	14.052		13.761	13.371	14.15		48.819	48.475	49.162	
middle exposure	13.944	13.695	14.192		13.884	13.46	14.31		48.162	47.69	48.633	
highest exposure	13.814	13.561	14.066		13.782	13.359	14.21		48.8	48.322	49.278	

Note 4.3. : Adjusted models controlled for age, gender, ethnicity, parental education and under reporting estimate; 95% Confidence Intervals; test for trend across food exposure categories (p)

Table 4.4. Associations between food exposure and energy density of diet

	Energy density of diet							
	unadjusted				adjusted			
	Mean	LB	UB	P	Mean	LB	UB	P
Home:				0.176				
Density of healthy food outlets	2.032	2.014	2.049					0.366
no exposure	2.023	1.982	2.065		2.028	1.983	2.072	
middle exposure	2.000	1.958	2.041		2.031	1.974	2.089	
highest exposure					2.003	1.947	2.058	
Density of unhealthy food outlets				0.604				0.861
no exposure	2.025	2.006	2.045		2.019	1.974	2.063	
middle exposure	2.047	2.013	2.081		2.045	1.993	2.097	
highest exposure	2.005	1.968	2.042		2.013	1.960	2.066	
Density of fast food outlets				0.742				0.886
no exposure	2.029	2.010	2.049		2.026	1.981	2.071	
middle exposure	2.016	1.981	2.051		2.008	1.955	2.061	
highest exposure	2.026	1.991	2.061		2.028	1.977	2.080	
School:								
Density of healthy food outlets				0.196				0.425
no exposure	2.032	2.014	2.050		2.026	1.982	2.070	
middle exposure	2.025	1.989	2.062		2.026	1.973	2.079	
highest exposure	2.002	1.962	2.041		2.005	1.949	2.062	
Density of unhealthy food outlets				0.116				0.100
no exposure	2.006	1.984	2.029		2.003	1.957	2.049	
middle exposure	2.054	2.026	2.083		2.047	1.998	2.096	
highest exposure	2.031	2.002	2.060		2.029	1.981	2.078	
Density of fast food outlets				0.042				0.025
no exposure	2.010	1.989	2.032		2.003	1.957	2.049	
middle exposure	2.037	2.008	2.067		2.038	1.988	2.087	
highest exposure	2.047	2.016	2.077		2.042	1.993	2.092	

Note 4.4.: Adjusted models controlled for age, gender, ethnicity, parental education and under reporting estimate; 95% Confidence Intervals; test for trend across food exposure categories (*p*); Energy density is measured as kcal per gram

In terms of associations between SES and the food exposure predictors, the values represent, for each category of SES, the percentage of children falling in each category of food outlet density. The results generally show that children of less educated parents were more likely to reside in areas with highest exposure to fast food and other unhealthy food outlets.

Furthermore, children of less educated parents were also more likely to go to school in areas with highest exposure to fast food outlets: for example, 21.9% of children falling in the top category of fast food outlet density around the school lie in the most educated category, whilst 38.4% lie in the least educated category ($p < 0.01$) (Table 4.6.).

Similar results can be seen for associations between SES and healthy food exposure however, which is opposite to what we would expect.

We also tested for some interactions between the food exposure predictors and food preference/food knowledge, but found no evidence of a significant effect modification, except for one (density of healthy food outlets around the school and food preference, $p = 0.04$, however the trend was not clear).

Finally, the mediation analysis suggests that in this sample, diet did not act as a mediator in the association between neighbourhood exposure to the food environment and weight status (Table 4.7.). Similarly, there was no clear evidence that the food environment sits on the causal pathway in the association between socio-economic status and weight status (Table 4.8.), except for one instance, where it was found that exposure to unhealthy food around the home partially explains the observed relationship between household SES (parental education) and BMI.

Table 4.5. Associations between socio-economic status (parental education) and the outcomes

Outcomes:	Parental education				p for trend
	Degree or higher	A-levels or equivalent	GCSE or equivalent	None or school leaving certificate	
BMI, mean \pm SD	17.97 \pm 2.90	17.85 \pm 3.03	18.34 \pm 3.14	19.28 \pm 3.94	<0.001
Healthy (mean daily grams), mean \pm SD	406.79 \pm 230.92	330.64 \pm 218.43	320.91 \pm 194.55	293.79 \pm 185.81	<0.001
Unhealthy (mean daily grams), mean \pm SD	339.90 \pm 257.83	397.67 \pm 285.02	415.99 \pm 286.81	375.43 \pm 276.67	<0.001
Fast food (mean daily grams), mean \pm SD	28.93 \pm 33.73	34.26 \pm 36.60	38.22 \pm 35.92	43.93 \pm 34.70	<0.001
Protein (mean daily grams), mean \pm SD	64.46 \pm 14.77	61.91 \pm 13.46	62.11 \pm 13.16	59.16 \pm 15.19	<0.001
Fibre (mean daily grams), mean \pm SD	11.52 \pm 3.18	10.77 \pm 2.75	10.71 \pm 2.80	10.39 \pm 2.85	<0.001
Percentage energy from carbs, mean \pm SD	49.08 \pm 4.86	48.72 \pm 5.03	48.49 \pm 5.02	48.87 \pm 5.11	0.512
Percentage energy from sat fat, mean \pm SD	13.74 \pm 2.67	13.72 \pm 2.46	13.99 \pm 2.76	13.81 \pm 2.50	0.400
Mean energy density (kcal/gram) of diet (solids), mean \pm SD	1.93 \pm 0.30	2.03 \pm 0.30	2.05 \pm 0.32	2.06 \pm 0.30	<0.001

Table 4.6. Associations between socio-economic status (parental education) and the predictors

	Parental education				p for trend
	Degree or higher	A-levels or equivalent	GCSE or equivalent	None or school leaving certificate	
Predictors :					
Healthy food - home					0.001
% highest exposure	11.3	13.2	12.4	24.6	
% middle exposure	14.6	11.1	14.9	9.4	
% no exposure	74.1	75.7	72.7	65.9	
Healthy food - school					0.002
% highest exposure	15.9	13.7	15.6	26.8	
% middle exposure	15	16.1	16.4	15.9	
% no exposure	69.1	70.3	68	57.2	
Unhealthy food- home					0.001
% highest exposure	22.9	12.8	17	23.9	
% middle exposure	14.3	21	21.8	18.8	
% no exposure	62.8	66.2	61.2	57.2	
Unhealthy food- school					0.402
% highest exposure	27.6	25.2	28	34.1	
% middle exposure	25.9	29.9	29.5	26.1	
% no exposure	46.5	44.9	42.5	39.9	
Fast food- home					0.001
% highest exposure	18.6	15.4	19.4	26.1	
% middle exposure	14.6	18.7	19.6	27.5	
% no exposure	66.8	65.9	61	46.4	
Fast food- school					0.004
% highest exposure	21.9	23.2	23.6	38.4	
% middle exposure	25.2	29.5	28	19.6	
% no exposure	52.8	47.3	48.4	42	

Discussion

This chapter investigated associations between food environment exposure, diet, individual weight and household socio-economic status in older children. While measures of exposure to the food environment were assumed at an area level just like with the previous chapter, they were more refined in the sense that they were based on known locations of both the home and school of participants. Furthermore, measures of weight and deprivation were also known at an individual and household level respectively rather than at an area level.

In the previous chapter, it was found that higher exposure to fast food and other types of unhealthy food outlets in the neighbourhoods was associated with higher overweight and obesity prevalence in the area in older children. In the sample of similar age children in this chapter, while no significant associations were found between fast food exposure and weight status, there was evidence that a higher density of unhealthy food outlets in the home (but not the school) neighbourhoods was associated with a higher BMI. As with the previous chapter, no evidence was found in this chapter either that exposure to healthier types of food outlets might have an impact on weight status in older children. It might therefore be the case that policies aimed at reducing childhood obesity should focus on reducing the prevalence of food outlets that sell unhealthy food. It might be that children are more likely to get attached to locations closer to their places of residence¹³⁰ and hence these appear to have an impact.

Unlike the previous chapter, where information on diet was not available, in this study associations with diet could be explored. In the present sample of children from the SPEEDY study, while no evidence was found that exposure to healthy or unhealthy food might significantly impact food intake, it was found that children exposed to more fast food in both their home and school neighbourhoods have a higher consumption of fast food-type items. Furthermore, while no evidence was found to suggest that exposure to unhealthy or fast food outlets in the neighbourhoods might increase intake of carbohydrates, saturated fat or protein in this sample, it was found that those exposed to a higher density of fast food outlets around their school had a higher energy density of diet overall. Additionally, children with a higher density of healthy food outlets around their home had a higher intake of fibre. It must be noted however that the increase in effect sizes in these models was relatively small, so it is a matter of debate as to whether the effect was likely to be meaningful from a public health perspective

Table 4.7. Mediation of diet in the association between the food environment and weight

Mediator	DV	IV	Indirect effects	Coefficient	SE	Bootstrapping		Mediation diagnosis
						Bca 95% CI Lower	Upper	
healthy food intake	BMI	density of healthy food (home)	Total effects	-0.0767	0.0696			
			Direct effects	-0.0779	0.0696			
			Indirect effects	0.0012	0.0027	-0.0019	0.0100	No mediation
healthy food intake	BMI	density of healthy food (school)	Total effects	0.0452	0.0819			
			Direct effects	0.0437	0.0820			
			Indirect effects	0.0015	0.0031	-0.0019	0.0135	No mediation
unhealthy food intake	BMI	density of unhealthy food (home)	Total effects	0.0934	0.0571			
			Direct effects	0.0939	0.0571			
			Indirect effects	-0.0005	0.0032	-0.0081	0.0051	No mediation
unhealthy food intake	BMI	density of unhealthy food (school)	Total effects	0.0158	0.0514			
			Direct effects	0.0173	0.0513			
			Indirect effects	-0.0015	0.0031	-0.0109	0.0031	No mediation
fast food intake	BMI	density of fast food (home)	Total effects	0.0405	0.0317			
			Direct effects	0.0407	0.0318			
			Indirect effects	-0.0002	0.0022	-0.0053	0.0038	No mediation
fast food intake	BMI	density of fast food (school)	Total effects	0.0392	0.0288			
			Direct effects	0.0392	0.0288			
			Indirect effects	-0.0001	0.0013	-0.0031	0.0024	No mediation

Note 4.7.: DV = dependent variable; IV = independent variable; SE = standard error; Bca = Bias corrected and accelerated

Table 4.8. Mediation of the food environment in the association between the socio-economic status and weight

Mediator	DV	IV	Indirect effects	Omnibus*	SE	Bootstrapping		Mediation diagnosis
						Bca 95% CI	Lower	
density of healthy food (home)	BMI	SES	Total effects		0.0142			
			Direct effects		0.0145			
			Indirect effects	-0.0003	0.0007	-0.0019	0.0008	No mediation
density of healthy food (school)	BMI	SES	Total effects		0.0142			
			Direct effects		0.0140			
			Indirect effects	0.0002	0.0008	-0.0014	0.0023	No mediation
density of unhealthy food (home)	BMI	SES	Total effects		0.0142			
			Direct effects		0.0136			
			Indirect effects	0.0005	0.0006	0.0001	0.0023	Mediation
density of unhealthy food (school)	BMI	SES	Total effects		0.0142			
			Direct effects		0.0142			
			Indirect effects	0.0000	0.0003	-0.0005	0.0008	No mediation
density of fast food (home)	BMI	SES	Total effects		0.0142			
			Direct effects		0.0136			
			Indirect effects	0.0002	0.0003	-0.0002	0.0011	No mediation
density of fast food (school)	BMI	SES	Total effects		0.0142			
			Direct effects		0.0137			
			Indirect effects	0.0002	0.0003	-0.0002	0.0009	No mediation

***Note 4.8.:** An omnibus test of the *direct effect* of the IV is conducted by ascertaining whether the addition of the independent variable to the model containing only proposed mediators and covariates improves the fit of the model, as indexed by a change in the squared multiple correlation that results when the IV is added. This test is equivalent to a test of mean group differences in analysis of covariance, controlling for the covariates and the proposed mediators. An omnibus test for the *total effect* ascertains whether the inclusion of the IV improves the estimation of the DV when added to a model containing only the covariate. When X is a multi-categorical variable, the omnibus total effect test answers the question as whether there is a difference between the groups of the IV on the DV on average independent of any covariates in the model²⁵⁷.

In terms of associations with social class, there was a social class gradient in BMI and type of food consumed, as expected and as shown previously in the literature^{180 226}: children with less educated parents had a higher BMI, consumed less healthy food and fibre and more unhealthy and fast food, and their diet was more energy dense. There was also a social class gradient in neighbourhood food availability, with lower social class being associated with more exposure to unhealthy and fast food, but also to healthy food, the latter being counterintuitive. No evidence was found to indicate that SES affects macronutrient composition of diet such as saturated fat, carbohydrates or protein intake, which is consistent with findings from a previous systematic review on social class and diet quality⁶⁴.

Although the literature review in Chapter 2 suggests that food preference and nutritional knowledge are two key factors that influence diet, there was no clear evidence of an effect modification by food knowledge/preference in this sample. It could be that these factors act through different untested mediation or moderation mechanisms other than the food environment.

Furthermore, it is interesting that the hypothesis that diet might mediate the association between the food environment and weight status was not supported in this study. It could be that other key factors presented in the framework in Chapter 2 act as mediators, such as individual preferences or portion size. In concordance with the previous chapter, the only significant mediation found was whereby exposure to unhealthy food in the residential neighbourhood was found to mediate the known association between SES and weight status in older children. However, due to the large number of tests performed, this may well be due to chance. The ‘mediate’²⁵⁶ Preacher and Hayes method was used in this analysis, which has been recently developed to deal with multi-categorical predictors. The omnibus test²⁵⁷ is used in this case in order to specify if there is an overall mediation effect without specifying which of the categories of the multi-categorical independent variable (SES in this case) is responsible for the effect. It therefore investigates the nature of the difference between group means that is responsible for the effect the predictor has on the outcome²⁵⁷ (Note 4.8.), but this statistic is flagged up as being a work in progress on the author’s webpage²⁵⁸. An effect ratio could therefore not be calculated as for Chapter 3, as the independent variable is multi-categorical, not continuous. Therefore, while the results show that exposure to unhealthy food in the home acts as a mediator in the relationship between SES and BMI, it cannot be concluded exactly how much of that association is explained by the mediator.

After a scoping of the literature, it was concluded that this is most likely the first study to investigate the associations between measures of exposure to the food environment and consumption of key food groups, a range of macronutrients and energy density of diet in one single study. A previous study²⁴⁶ on the same SPEEDY sample looked at food/drink groups, macronutrients and energy density of diet, but in relation to food and drink consumption at school lunchtime. A recent review²⁵⁹ looked at macronutrients and food consumption, but these were considered as predicting weight change in adults, not as outcomes. Another UK study¹⁴⁷ has reviewed the literature regarding a possible mechanistic link between fast foods, energy density and obesity; it found that fast foods have an extremely high energy density, and that children and adolescents may be especially vulnerable to this because they have not yet developed the necessary cognitive dietary restraint. Systematic reviews reveal that most studies investigate associations with key food groups, and associations with macronutrients⁸² or energy density¹⁴⁷ as an outcome are very scarce. This is of particular importance given that researchers have found that for example children who consume fast food have higher intakes of total energy, fat, sugar, carbohydrates and carbonated soft drinks²⁶¹. The types of foods commonly consumed as snacks are often high in fat or high in carbohydrates including sugar and starch²⁶².

The work presented in this chapter has a number of strengths and limitations. In terms of strengths, a large number of schools and pupils were recruited to the study, and a range of measurements was collected from them. The SPEEDY schools and children were broadly representative of the Norfolk population, although with a slightly higher proportion of girls and a lower proportion of obese children taking part⁸⁶. Schools in Norfolk however have a low proportion of non-white pupils which may limit generalizability of the findings of this study to more ethnically diverse populations. Dietary intake was assessed using detailed diet diaries over four whole days and included two weekend days and two weekdays. The food diaries offered the possibility to extract not only information on consumption of key food groups, but also nutrient and calorie intake. Although food diaries have the potential to provide a valid measure of food intakes in this age group²⁶³, the diary used in the SPEEDY study was not validated. The children were not asked to weigh their the food and drink they consumed and children have been seen to experience difficulty in estimating portion sizes²⁶⁴. Under-reporting is often a problem in self-reported diary assessment, but in this study under-reporting of energy intake was adjusted for.

A key issue is that there was no way of knowing if the fast-food dietary outcome extracted from the food diary that was matched with the exposure to fast-food outlets represented fast-food items that were actually prepared and consumed at home, or if they were actually purchased from another food outlet other than a fast-food outlet. In order to test for the latter, as with Chapter 3, for each food outlet type, we performed a sensitivity analysis whereby we also tested for the presence of the other types of food outlets in the area as potential confounders by including them as explanatory variables in the regression models, in order to account for food environment ‘context’, based on previous practice in the literature¹¹⁷.

However the results were not substantially changed and are hence not repeated here, although it must be noted that some associations attenuate when including other food outlets in the models. This might be because indeed it is likely that the items considered in the fast-food category in this chapter were actually purchased from other types of food outlets.

CONCLUSION

Overall, this study supports findings in the literature and in the previous chapter that exposure to unhealthy food in the neighbourhood and low social class might be conducive to weight gain and/or poorer and more energy dense diets. It might also be that exposure to unhealthy food sits on the causal pathway in the association between low socio-economic status and weight gain. It can however be observed that not all ecological associations found to be significant in Chapter 3 are also significant when tested at an individual level in this Chapter. This might in part be because the different way of measuring exposure to the food environment, or the lower geographical heterogeneity in this sample.

Improving food environments and targeting low-social class groups are nevertheless likely to be important in targeting policies and interventions to reduce childhood obesity. This should be further tested at different scales and geographical contexts.

Chapter 5

How can GPS technology help us better understand the food environment? A systematic review

Abstract

Purpose: Global Positioning Systems (GPS) are increasingly being used to objectively assess the spatial locations of features in the environment or movement patterns of people related to health behaviours. However research detailing their application to the food environment is scarce. This systematic review examines the application of GPS in studies of food environments and their potential influences on health.

Results: 18 studies met the inclusion criteria, which were appraised to be of moderate quality. When validating secondary food databases, ground-truthing studies had the highest quality. Associations between observed mobility patterns in the food environment and diet related outcomes were equivocal.

Conclusions: The use of GPS to measure aspects of the food environment is still in its infancy. There are considerable variations and challenges in developing and standardising the methods used to assess exposure.

Introduction

Understanding the food environment, its use and the link with health related outcomes and behaviours

Environmental factors have been shown to influence health behaviours^{45 76}, and understanding their importance has formed a growing area of research, driven by the emergence of social-ecological theory and a shift of focus from individual-level influences on health^{265 266}. Studies have researched the influence on health behaviours of factors associated with features of the natural and built environments (including physical activity and leisure facilities, green space²⁶⁷, food outlets^{54 117}); the socio-cultural environment (such as media exposure²⁶⁸, familial characteristics⁹⁵ such as education and parenting style^{243 269 270}, and societal characteristics such as peer interaction¹⁴⁵); and the policy environments^{11 271} (public policy, and regulatory efforts to promote enhanced well-being at organizational, municipal, regional, and international levels)^{76 266}. One area of particular interest has been the influence of the macro-level food environment on weight and associated dietary behaviours, food intake, and food purchasing^{47 229}.

Motivated by concerns over rising obesity rates^{30 54 272}, researchers have begun mapping the food environment and relating it to relevant health outcomes. The food environment can encompass a variety of features, such as the location of outlets selling food in the residential, school, work, or activity spaces, with the latter defining the places people go to purchase food or the food they are exposed to while doing their daily activities⁸⁰. There are various hypotheses in the literature that link these food environments to diet, weight, and other health-related outcomes⁴⁵. Yet, despite the fact that conceptually it is evident that less supportive environments for health lead to worse diets and elevated weight, the findings reported in the literature are equivocal^{45 55-58}, with studies reporting mixed associations between various food environment measures and health outcomes^{44 80 81}. Some studies find associations with relevant outcomes^{54 117 131}, whilst others find none^{45 63 273}. It is pertinent that two systematic reviews on the environment and obesity suggest that the great heterogeneity across studies limits what can be learned from this body of evidence^{274 275}. It has recently been suggested that such equivocal results might be because of imprecision in measurement of the environment; for example, facilities being present in an area does not necessarily mean that people will use them.

Researchers are increasingly using geospatial technologies^{276 277} to model the environment or how people interact with it. These include GIS (geographical information systems)²¹⁶, GPS (global positioning systems)⁴⁴, smartphones^{278 279}, tablets²⁷⁸, PDAs (handheld personal digital assistants)²⁸⁰, Google maps²⁸¹, and smart card technology²⁸². Much of the evidence in the literature is however based on the use of GIS to compute measures of assumed exposures to the food environment based on the location of facilities²²⁹ and typically focussed on residential neighbourhoods with indicators of proximity/density used to describe retail food accessibility⁸⁰. Despite their popularity, these methods however have several limitations. In particular, they typically fail to account for daily movements of individuals. This is pertinent given that it has been shown that people conduct only a small proportion of their daily activity within the residential neighbourhood²⁸³. As a result, arguments have been made of the need for future research to consider food environments outside of residential neighbourhoods and also to consider how individuals interact with these environments⁵. This has led to a recent increase in studies using GPS¹²⁷, applied to either looking at the ‘activity space’ of people²⁷⁶ or to identifying locations of facilities in the environment²⁹⁵.

What does GPS contribute?

GPS is a satellite-based global navigation system that provides an accurate location of any point on the Earth’s surface²⁸⁴. It thus provides a means to objectively assess the spatial location of features in the environment or people’s behaviours while moving in the environment. Outdoor GPS rely on being able to receive a signal from four or more satellites in order to triangulate a person’s position, and a GPS data point will typically consist of a time stamp and longitude, latitude and altitude coordinates. GPS therefore is a valuable tool for field auditors in environment and health work, as it facilitates the accurate acquisition of the location of features within the built environment. Furthermore, when worn by study participants, it enables investigators to track the mobility patterns of individuals and therefore measure environmental exposures and activity spaces²⁸⁵.

Despite the potential of GPS to help us better understand food environments, it is noteworthy that the existing literature detailing its application comes largely from the physical activity domain^{284 286 287} or studies that focus on travel behaviours^{83 288 289}, with very little from the food and diet area^{44 80 290}. Little is therefore known about how actual use of the environment is associated with food related behaviours⁴⁴, and this raises the need for a better understanding of how GPS can refine current knowledge of the influence of food environments on diet and

weight²⁹⁰. This is particularly the case given that has been shown that correlations between residential neighbourhoods and the places people actually visit are weak⁴⁴.

The potential applications of GPS for food environments extend beyond investigating human exposure to food: researchers have been using GPS technology to characterise the retail food environment by mapping the actual location of food outlets. Food stores are the most frequently used measure of the constantly changing food environment, but methods used to identify them still have technical challenges^{291 292}. Researchers and government programs have mainly relied on GIS based secondary retail food outlet databases for location information. When using commercial listings for food outlets, there may be problems associated with the fact that the validity of common data sources used to characterize the food environment can be limited²⁹³ and the literature suggests only limited to fair agreement between commercial data and field observations^{294 295 45}. There is thus the potential to introduce bias into studies if these databases provide an inaccurate representation of current food outlet locations and if accuracy is associated with area characteristics such as material deprivation²⁹⁶.

Improving access to healthy foods is a promising strategy to prevent nutrition-related diseases; however the equivocal evidence base to date to inform such decisions begs the question of whether researchers have been measuring the food environment in the right way. This systematic review has therefore been undertaken to examine the application of GPS in studies of food environments and their potential influences on health. As far as we are aware this is the first review to specifically focus on the use of GPS in this field.

Methods: search strategy and data extraction

An initial scoping exercise was undertaken in June and July 2013. Studies were deemed to be eligible for inclusion in the scoping exercise if: (1) they were written in English and (2) they were related to the use of GPS to measure factors associated with the food environment. From this initial scoping, two main patterns in the use of GPS for food environments emerged: (1) studies using GPS for identifying actual *location of people* (and linking that to diet, weight, and related behaviours); and (2) studies using GPS for identifying actual *location of food outlets* (as an audit tool to characterise the food environment). The scoping exercise informed the present systematic review and suggested the studies were too heterogeneous to permit meta-analysis.

The full systematic review involved searching four electronic databases (Scopus, Medline, PubMed, and Web of Science), including reference lists of retrieved papers, and manual searches of key authors and key journals to identify relevant studies related to GPS and the neighbourhood food environment. The search keywords were: (food OR diet) AND (“global positioning systems” OR “global positioning system”). The inclusion and exclusion criteria for the systematic review were formulated as a result of the scoping exercise (Table 5.1.). They were based on the two patterns identified, and were cross-checked by both authors. Studies were therefore included if they were written in English and if they used GPS to identify location of food facilities or that of individuals in relation to food. No restriction based on publication year, comparator or study design was applied.

Table 5.1. Criteria for inclusion and exclusion of studies in the review

Inclusion	Exclusion
- Studies using GPS for evaluating the use of / exposure to the food environment by humans	- Studies conducted in animals and/or using GPS for other purposes than measuring use of / exposure to food environment (such as agriculture and farming, physical activity and sports, alcohol behaviours, travel behaviours other than to purchase/consume food, general clusters of activities/travel behaviours etc.)
- Studies that use GPS to map/assess the food environment (location of food outlets)	- Studies using GPS for other purposes than mapping the food environment
- Papers and documents written in English	- Papers not written in English

The included studies were appraised on quality (Tables 5.2., 5.3.). The studies mapping the food environment were appraised against nine quality criteria: (1) number of data sources used; (2) if the study area size was reported (if appropriate); (3) if statistics of agreement between primary data collection and secondary data sources were reported; (4) the number of food outlet types considered; (5) any pre-testing or post-canvassing- the latter represent a thorough re-examination of a defined geographical setting in order to look for retail food outlets identified via secondary sources that did not match those identified via primary data²⁹⁵- of the retail food environment (if applicable); (6) the food classification system used; (7) if GPS positional accuracy was reported; (8) if the paper reflected on data quality (such as signal loss); and (9) if peer review had been undertaken. The food exposure studies were also appraised against a set of nine quality criteria: (1) representativeness of the sample population; (2) sample size; (3) length of GPS recording period; (4) how many food outlet types were assessed; (5) if a dietary or (6) an anthropometric measure was included; (7) if

positional accuracy was reported; (8) data quality (such as whether the dietary outcome was linked to the GPS location); and (9) if the study had been subjected to peer review. These criteria were developed from those previously used in a systematic review of the use of GPS in physical activity research²⁸⁴.

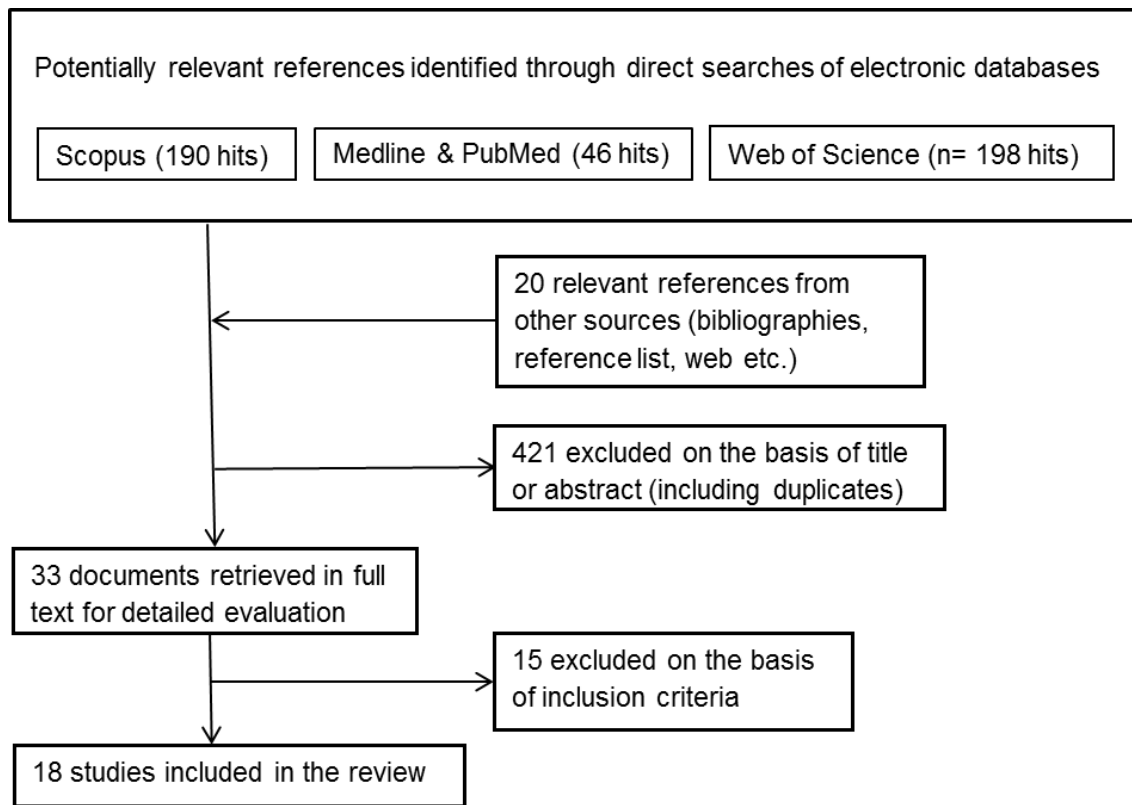
The quality of each paper was depicted by a score summarising the metrics to provide an overall impression of the quality of the available evidence. A weighting system was employed whereby the score for each metric was divided by the maximum possible value so that each metric had the same weighting in the overall quality score. The scores were initially assigned by the first author (AC) and cross-checked by the second (APJ) with disagreements being resolved by discussion.

Results: Evidence synthesis

Study selection

Overall, 434 potentially relevant publications were identified based on title and an additional 20 were found by checking the reference lists of the included papers (Figure 5.1.).

Examination of abstracts resulted in the exclusion of 421 articles. The full text of 33 papers was assessed, and 15 were found not to meet the inclusion criteria. This was mostly because there was either no mention of GPS or GPS was briefly mentioned but not used in the study, no mention of food, diet, or other related health behaviours, or the studies were simply describing the literature in a conceptual way rather than mapping the environment or examining associations with health outcomes. The review process ultimately identified a small number of final relevant studies (n=18) that were published between 2008 and 2013 (Appendix 5.1., 5.2.).

Figure 5.1. Study flowchart

The identified studies were classified into categories according to the two patterns identified after the scoping exercise: (category 1) studies mapping the location of food outlets in relation to secondary food outlet sources or health outcomes (n=14, Table 5.2.), and (category 2) studies mapping the location of people in relation to food outlets and linking that to health outcomes (n=4, Table 5.3.). Studies mapping or assessing the location of food outlets were split into two sub-categories according to their primary objective: (1.1) those validating accuracy of secondary retail food data, based on type and location of food outlets, by comparing them with data collected in the field (n=10, Table 5.2.)^{214 217 291 293 295-300}; and (1.2) other food mapping studies (n=4, Table 5.2.)³⁰¹⁻³⁰⁴ which use GPS for identifying location and type of food outlets without comparing this to secondary data sources, but rather to explore various associations with health or health related behaviours. Those studies that used GPS for understanding the use of and exposure to the food environment by humans were not subdivided due to their small number (n=4, Table 5.3.)^{44 80 81 305}.

Quality of studies

The overall quality score for each study had the potential to range between 0 and 12 for sub-category (1.1) and 0 and 10 for sub-category (1.2) of food mapping studies, and between 0 and 14 for studies of use and exposure to food environments. Actual scores ranged from 4 to 9 for category 1.1, from 3 to 5.333 for category 1.2 (Table 5.2.), and from 2.500 to 4.667 for category 2 (Table 5.3.). For category 1.1, one study had a total score within the upper tercile of the scale, eight studies within the middle tercile, and one study within the lower tercile. For category 1.2, no studies scored highest quality, three studies scored middling quality, and one scored lowest quality. While no studies were situated in the upper tercile of the scale for category 2, one study was in the middle tercile and three studies in the lower tercile. Overall, the studies included in this review can be regarded as being of moderate quality.

Description of studies:***General description of studies***

Unsurprisingly, most studies were recent, with two thirds (n=12)^{44 80 214 217 293 297-301 303 305} published in 2011 or 2012. One study was published in 2008²⁹⁶, one in 2009³⁰⁴, three in 2010^{291 295 302} and one in 2013⁸¹ (Appendix 5.1. and 5.2.). Most studies came from the USA (83%)^{44 80 81 214 217 291 293 295-297 300 302-305}, two were from Canada^{298 301} and one from Denmark²⁹⁹. Garmin models were the most commonly used GPS receivers used (4 studies)^{44 298 300 301}, with Qstarz BT-1000XT being the second most employed (3 studies)^{80 81 305}, followed by the Bluetooth Wide Area Augmentation System (WAAS) enabled portable GPS receiver (2 studies)^{296 304} and Trimble Juno ST (1 study)²⁹⁵. The eight remaining studies did not report the exact model of GPS used. Over two thirds of the studies (78%)^{44 80 81 214 217 293 295-299 302-304} used between one to three food data sources, 2 studies (11%) used six databases^{291 300}, whilst two studies used none^{301 305} (Table 5.4.).

Table 5.2. Quality appraisal- Category 1: Studies of mapping of the food environment

STUDY	Number of data sources used ^a		Reporting agreement with/ secondary data sources ^c		Variety of food outlet types mapped ^d		Pre-testing/post-canvassing ^e		Food classification system used ^f		Positional accuracy reported ^g		Data quality ^h		Peer reviewed ⁱ		Total weighted score
	Study area size	reported	secondary data sources	validity of secondary data sources	mapped	outlet types	pre-testing/post-canvassing	post-canvassing	classification system used	accuracy reported	quality	reviewed	score				
(1.1.) Studies validating secondary data sources in the field- primary objective:																	
1. Liese (2010) ²⁹⁵ , US	3	1	1	1	3	1	1	1	1	1	1	1	1	1	1	1	9
2. Sharkey (2008) ²⁹⁶ , US	3	1	1	1	3	1	1	1	1	1	0	0	0	0	1	1	7
3. Fleischhacker (2012) ³⁰⁰ , US	3	1	1	1	3	1	1	1	1	1	0	0	1	1	1	1	8
4. Powell (2011) ²¹⁴ , US	2	1	1	1	3	1	1	0	1	1	0	0	0	0	1	1	7.667
5. Toft (2011) ²⁹⁹ , Denmark	1	0	1	1	1	1	0	0	0	0	1	1	1	1	1	1	4.667
6. Longacre (2011) ²⁹³ , US	2	1	1	1	3	1	1	1	1*	0	0	0	0	0	1	1	6.667
7. Hosler (2010) ²⁹¹ , US	3	0	1	1	3	1	0	0	0	0	0	0	0	0	1	1	4
8. Seliske (2012) ²⁹⁸ , Canada	2	0	1	1	3	1	0	0	1	1	0	1	1	1	1	1	6.667
9. McGuiert (2011) ²⁹⁷ , US	2	1	1	1	3	1	1	1	1	1	0	0	0	0	1	1	5.667
10. Gustafson (2012) ²¹⁷ , US	2	0	1	1	3	1	0	0	1	1	0	0	0	0	1	1	4.667
(1.2.) Other studies:																	
1. O'Connell (2011) ³⁰³ , US	1	0	n.a.	n.a.	2	n.a.	n.a.	n.a.	1	1	0	0	0	0	1	1	3
2. Gasevic (2011) ³⁰¹ , Canada	0	0	n.a.	n.a.	3	n.a.	n.a.	n.a.	1	1	0	0	1	1	1	1	4
3. Lopez (2010) ³⁰² , US	3	0	n.a.	n.a.	3	n.a.	n.a.	n.a.	1	1	0	0	0	0	1	1	4
4. Sharkey (2009) ³⁰⁴ , US	1	1	n.a.	n.a.	3	n.a.	n.a.	n.a.	1	1	1	1	0	0	1	1	5.333

Quality criteria for food mapping studies:

^a Number of data sources used: 0=0; 1=1; 2=2; 3= 3 or more sources (1.1.); n.a. (not applicable) (1.2.)

^b Geographical area size and other area specifics reported: 0=no; 1= yes

^c Reporting agreement with/evidence for validity of secondary data sources used: 0=no; 1=yes (kappa statistics ; PPV (positive predictive value); sensitivity; 95% CI, FischerTest (Liese, 2010)) (1.1.); n.a. (not applicable) (1.2.)

^d Identify, assess and report a variety of food outlets: 1= 1 food outlet type; 2= 2 to 4 food outlet types; 3= 5 or more food outlet types

^e Pre-testing and/or re-canvassing: 0=no; 1=yes (1.1.); n.a. (not applicable) (1.2.)

^f Food classification system used: 0=own definition or classification system; 1= pre-existing government classification system (NAICS; SIC; NEMS etc.)

^g Positional accuracy of the GPS device reported: 0= no, 1= yes

^h Data quality: 0= not discussed; 1= data quality discussed (does the paper reflect on GPS issues such as signal loss, difference between actual location and recorded location)

ⁱ Peer reviewed: 0= no; 1= yes

* Did not specify NAICS or SIC codes

Table 5.3. Quality appraisal- Category 2: Studies of the use of/exposure to the food environment

STUDY	Representativeness ^a	Sample size ^b	Length of recording ^c	Variety of food outlet		Dietary component ^e	Anthropometric component ^f	Positional accuracy reported ^g		Peer reviewed ^h	Total weighted score ⁱ
				types ^d	outlet types ^d			Data quality ^h	accuracy reported ^g		
1. Christian (2012) ⁸⁰ , US	0	2	1	2	0	0	0	0	0	1	3.167
2. Gustafson (2013) ⁸¹ , US	0	2	1	3	0	0	0	0	0	1	3.5
3. Huang (2012) ³⁰⁵ , US	1	0	1	3	n.e.	n.e.	n.e.	0	0	1	2.5
4. Zenk (2011) ⁴⁴ , US	0	2	2	2	0	n.e.	n.e.	0	1	1	4.667

Quality criteria for use of / exposure to the food environment studies:

^a The sample was representative of the selected target group: 0= no, 1= yes

^b Sample size for the GPS study: 0= <=50, 1= 51-100, 2=>100

^c Recording period: 0= <=2 days, 1= 3-4 days, 2=>4 days

^d Asses a variety of food outlet types: 1= 1 food outlet type; 2= 2 to 4 food outlet types; 3= 5 or more food outlet types

^e Measure of dietary outcome: 0=frequency questionnaire (consumption (FFQ) or habitual food purchase), 1=food diary, 2 = objective measure (nutrient intake etc.)

^f Anthropometric measures: 0= self-reported; 1= measured

^g Positional accuracy of the device used was reported: 0= no, 1= yes

^h Data quality: 0= not discussed, 1= data quality discussed (does the paper reflect on GPS issues such as signal loss, is dietary outcome linked to GPS location?)

ⁱ The study was published in a peer-reviewed journal/book: 0= no, 1= yes

This criteria was adapted from Krenn et al⁴⁴

n.a.= not applicable; n.e.= not examined;

In terms of the system used to classify the types of food outlets, 16 out of the 18 included studies used a pre-established validated classification system, with the most popular one being NAICS (North America Industry Classification System) used by 12 studies^{81 214 217 293 295 296 298 300-304}. Eight studies^{44 80 81 291 297 299 302 305} developed their own classification system (two of the studies used both NAICS and their own classification, so they fit in both categories). In terms of the variety of food outlet types assessed, one study looked at one type of food outlet²⁹⁹, another looked at two types⁴⁴, whilst most studies at over three types: 44% of the studies (n=8)^{80 214 296-298 300 302 303} looked at between 3 and 7 types of food outlets, and 45% (n=8)^{81 217 291 293 295 301 304 305} at between 8 and 13 types. The types of food outlets identified were: supermarket or grocery store (15 studies)^{44 80 81 214 217 293 295-297 300-305}, specialty store (7 studies)^{81 214 293 295 296 300 301}, fast food outlet (9 studies)^{44 81 214 217 293 297 299 304 305}, full service restaurant (7 studies)^{214 293 295 298 300 301 305}, farmers' market (4 studies)^{81 217 291 305}, convenience store (including gas stations) (15 studies)^{80 81 214 217 291 293 295-298 300-303 305}, markets (2 studies)^{80 301}, general store (3 studies)^{217 293 301}, supercentre (2 studies)^{81 304}, farm or produce stand (3 studies)^{81 293 302}, and other food outlet types (such as discount stores, beverage stores, food bank) (13 studies)^{80 214 217 291 293 295 296 298 300-302 304 305} (Table 5.4.).

Category 1: Mapping/assessing the food environment

These studies differed considerably in various aspects including the type of GPS unit used, the classification criteria used for defining types of food outlets examined, the portion of study area canvassed, the type of geographic area (e.g.: county or census block), whether they use pre-testing and/or re-canvassing, the settings included (urban and/or rural), reporting agreement with secondary data sources, and the geographic unit of analysis used. These aspects were included in the quality appraisal criteria (Table 5.2.) and described in Appendix 5.1.

Most of the studies (n=11) come from the US^{214 217 291 293 295-297 300 302-304}, with two from Canada^{298 301} and one from Denmark²⁹⁹. The primary objective of all was to compare the validity of secondary food outlet data sources with data collected in the field by researchers. One study²¹⁷ additionally used the data obtained to explore the association between deprivation and the food environment. Out of the 14 studies in this category, only 7^{214 293 295-297 300 304} reported the size of the study area covered, with four reporting it in square miles, one in square kilometres (after transforming this one in square miles as well for comparison purposes, these ranged from 651.80 to 5575 square miles), and two studies in road miles

(ranging from 1500 to 26507 road miles). Four studies^{291 299 300 302} included predominantly urban areas, 3 studies^{217 293 296} were predominantly rural, 5 studies^{214 295 297 298 301} encompassed both, and 2 studies^{303 304} did not directly specify setting (O’Connell et al³⁰³ studied 22 American Indian reservations (tribes) in Washington state, and Sharkey et al³⁰⁴ included 197 census block group (CBG) area of Hidalgo County). While about half of the studies (43%) did not report if they used a hand or vehicular GPS to canvass the study area, 4 studies^{293 298 302 303} (29%) report using a handheld GPS device, 2 studies^{297 300} (14%) a vehicular GPS, and 2 studies^{291 299} (14%) report using both types. Additionally, 3 studies^{296 300 301} involved taking photographs of the food environment, 2 studies^{296 297} performed windshield surveys (i.e., a form of direct observation conducted by driving through a community of interest to directly observe and to describe its physical and social characteristics²⁹⁷), and 4 studies^{214 291 293 303} undertook an additional in-store survey (Table 5.5.).

Table 5.4. General description of studies

Attribute	N (count)	Studies
Year of publication:		
2008-2010	5	(Hosler and Dharssi, 2010 ²⁹¹ ; Liese et al., 2010 ²⁹⁵ ; Lopez-Class and Hosler ³⁰² , 2010; Sharkey and Horel, 2008 ²⁹⁶ ; Sharkey et al., 2009 ³⁰⁴)
2011	7	(Gasevic et al., 2011 ³⁰¹ ; Longacre et al., 2011 ²⁹³ ; McGuirt et al., 2011 ²⁹⁷ ; O'Connell et al., 2011 ³⁰³ ; Powell et al., 2011 ²¹⁴ ; Toft et al., 2011 ²⁹⁹ ; Zenk et al., 2011 ⁴⁴)
2012	5	(Christian, 2012 ⁸⁰ ; Fleischhacker et al., 2012 ³⁰⁰ ; Gustafson et al., 2012 ²¹⁷ ; Huang et al., 2012 ³⁰⁵ ; Seliske et al., 2012 ²⁹⁸)
2013	1	(Gustafson et al., 2013) ⁸¹
Setting:		
USA	15	(Christian, 2012 ⁸⁰ ; Fleischhacker et al., 2012 ³⁰⁰ ; Gustafson et al., 2013 ⁸¹ ; Gustafson et al., 2012 ²¹⁷ ; Hosler and Dharssi, 2010 ²⁹¹ ; Huang et al., 2012 ³⁰⁵ ; Liese et al., 2010 ²⁹⁵ ; Longacre et al., 2011 ²⁹³ ; Lopez-Class and Hosler, 2010 ³⁰² ; McGuirt et al., 2011 ²⁹⁷ ; O'Connell et al., 2011 ³⁰³ ; Powell et al., 2011 ²¹⁴ ; Sharkey and Horel, 2008 ²⁹⁶ ; Sharkey et al., 2009 ³⁰⁴ ; Zenk et al., 2011 ⁴⁴)
Canada	2	(Gasevic et al., 2011 ³⁰¹ ; Seliske et al., 2012 ²⁹⁸)
Denmark	1	(Toft et al., 2011) ²⁹⁹
Model (type) of GPS receiver used:		
Garmin	4	(Fleischhacker et al., 2012 ³⁰⁰ ; Gasevic et al., 2011 ³⁰¹ ; Seliske et al., 2012 ²⁹⁸ ; Zenk et al., 2011 ⁴⁴)
Qstarz BT-1000XT	3	(Christian, 2012 ⁸⁰ ; Gustafson et al., 2013 ⁸¹ ; Huang et al., 2012 ³⁰⁵)
Bluetooth Wide Area Augmentation System (WAAS) enabled portable GPS receiver	2	(Sharkey and Horel, 2008 ²⁹⁶ ; Sharkey et al., 2009 ³⁰⁴)
Trimble Juno ST	1	(Liese et al., 2010) ²⁹⁵
Number of secondary food databases used:		
One to three	14	(Christian, 2012 ⁸⁰ ; Gustafson et al., 2013 ⁸¹ ; Gustafson et al., 2012 ²¹⁷ ; Liese et al., 2010 ²⁹⁵ ; Longacre et al., 2011 ²⁹³ ; Lopez-Class and Hosler, 2010 ³⁰² ; McGuirt et al., 2011 ²⁹⁷ ; O'Connell et al., 2011 ³⁰³ ; Powell et al., 2011 ²¹⁴ ; Seliske et al., 2012 ²⁹⁸ ; Sharkey and Horel, 2008 ²⁹⁶ ; Sharkey et al., 2009 ³⁰⁴ ; Toft et al., 2011 ²⁹⁹ ; Zenk et al., 2011 ⁴⁴)
Six	2	(Fleischhacker et al., 2012 ³⁰⁰ ; Hosler and Dharssi, 2010 ²⁹¹)
None	2	(Gasevic et al., 2011 ³⁰¹ ; Huang et al., 2012 ³⁰⁵)
System used to classify the types of food outlets:		
NAICS (North America Industry Classification System)	12	(Fleischhacker et al., 2012 ³⁰⁰ ; Gasevic et al., 2011 ³⁰¹ ; Gustafson et al., 2013 ⁸¹ ; Gustafson et al., 2012 ²¹⁷ ; Liese et al., 2010 ²⁹⁵ ; Longacre et al., 2011 ²⁹³ ; Lopez-Class and Hosler, 2010 ³⁰² ; O'Connell et al., 2011 ³⁰³ ; Powell et al., 2011 ²¹⁴ ; Seliske et al., 2012 ²⁹⁸ ; Sharkey and Horel, 2008 ²⁹⁶ ; Sharkey et al., 2009 ³⁰⁴)
NEMS (Nutrition Environment Measures Survey)	1	(Fleischhacker et al., 2012) ³⁰⁰
SIC (Standard Industrial Classification)	1	(Powell et al., 2011) ²¹⁴
NACE (European Business Codes- Nomenclature des Activités Economiques)	1	(Toft et al., 2011) ²⁹⁹
Other: IMI (Irvine-Minnesota Inventory)	1	(Gasevic et al., 2011) ³⁰¹
Other: Lexington-Fayette County Health Department	1	(Christian, 2012) ⁸⁰
Own	8	(Christian, 2012 ⁸⁰ ; Gustafson et al., 2013 ⁸¹ ; Hosler and Dharssi, 2010 ²⁹¹ ; Huang et al., 2012 ³⁰⁵ ; Lopez-Class and Hosler, 2010 ³⁰² ; McGuirt et al., 2011 ²⁹⁷ ; Toft et al., 2011 ²⁹⁹ ; Zenk et al., 2011 ⁴⁴)
Number of food outlet types assessed:		
One to four	5	(Christian, 2012 ⁸⁰ ; O'Connell et al., 2011 ³⁰³ ; Seliske et al., 2012 ²⁹⁸ ; Toft et al., 2011 ²⁹⁹ ; Zenk et al., 2011 ⁴⁴)
Five to nine	12	(Fleischhacker et al., 2012 ³⁰⁰ ; Gasevic et al., 2011 ³⁰¹ ; Gustafson et al., 2013 ⁸¹ ; Gustafson et al., 2012 ²¹⁷ ; Hosler and Dharssi, 2010 ²⁹¹ ; Liese et al., 2010 ²⁹⁵ ; Longacre et al., 2011 ²⁹³ ; Lopez-Class and Hosler, 2010 ³⁰² ; McGuirt et al., 2011 ²⁹⁷ ; Powell et al., 2011 ²¹⁴ ; Sharkey and Horel, 2008 ²⁹⁶ ; Sharkey et al., 2009 ³⁰⁴)
Thirteen	1	(Huang et al., 2012) ³⁰⁵
Types of food outlets:		
Supermarket or grocery store	15	(Christian, 2012 ⁸⁰ ; Fleischhacker et al., 2012 ³⁰⁰ ; Gasevic et al., 2011 ³⁰¹ ; Gustafson et al., 2013 ⁸¹ ; Gustafson et al., 2012 ²¹⁷ ; Huang et al., 2012 ³⁰⁵ ; Liese et al., 2010 ²⁹⁵ ; Longacre et al., 2011 ²⁹³ ; Lopez-Class and Hosler, 2010 ³⁰² ; McGuirt et al., 2011 ²⁹⁷ ; O'Connell et al., 2011 ³⁰³ ; Powell et al., 2011 ²¹⁴ ; Sharkey and Horel, 2008 ²⁹⁶ ; Sharkey et al., 2009 ³⁰⁴ ; Zenk et al., 2011 ⁴⁴)
Specialty store	7	(Fleischhacker et al., 2012 ³⁰⁰ ; Gasevic et al., 2011 ³⁰¹ ; Gustafson et al., 2013 ⁸¹ ; Liese et al., 2010 ²⁹⁵ ; Longacre et al., 2011 ²⁹³ ; Powell et al., 2011 ²¹⁴ ; Sharkey and Horel, 2008 ²⁹⁶)
Fast food outlet	9	(Gustafson et al., 2013 ⁸¹ ; Gustafson et al., 2012 ²¹⁷ ; Huang et al., 2012 ³⁰⁵ ; Longacre et al., 2011 ²⁹³ ; McGuirt et al., 2011 ²⁹⁷ ; Powell et al., 2011 ²¹⁴ ; Sharkey et al., 2009 ³⁰⁴ ; Toft et al., 2011 ²⁹⁹ ; Zenk et al., 2011 ⁴⁴)
Full service restaurant	7	(Fleischhacker et al., 2012 ³⁰⁰ ; Gasevic et al., 2011 ³⁰¹ ; Huang et al., 2012 ³⁰⁵ ; Liese et al., 2010 ²⁹⁵ ; Longacre et al., 2011 ²⁹³ ; Powell et al., 2011 ²¹⁴ ; Seliske et al., 2012 ²⁹⁸)
Farmers' market	4	(Gustafson et al., 2013 ⁸¹ ; Gustafson et al., 2012 ²¹⁷ ; Hosler and Dharssi, 2010 ²⁹¹ ; Huang et al., 2012 ³⁰⁵)
Convenience store (including gas stations)	15	(Christian, 2012 ⁸⁰ ; Fleischhacker et al., 2012 ³⁰⁰ ; Gasevic et al., 2011 ³⁰¹ ; Gustafson et al., 2013 ⁸¹ ; Gustafson et al., 2012 ²¹⁷ ; Hosler and Dharssi, 2010 ²⁹¹ ; Huang et al., 2012 ³⁰⁵ ; Liese et al., 2010 ²⁹⁵ ; Longacre et al., 2011 ²⁹³ ; Lopez-Class and Hosler, 2010 ³⁰² ; McGuirt et al., 2011 ²⁹⁷ ; O'Connell et al., 2011 ³⁰³ ; Powell et al., 2011 ²¹⁴ ; Seliske et al., 2012 ²⁹⁸ ; Sharkey and Horel, 2008 ²⁹⁶)
Markets	2	(Christian, 2012 ⁸⁰ ; Gasevic et al., 2011 ³⁰¹)
General store	3	(Gasevic et al., 2011 ³⁰¹ ; Gustafson et al., 2012 ²¹⁷ ; Longacre et al., 2011 ²⁹³)
Supercentre	2	(Gustafson et al., 2013 ⁸¹ ; Sharkey et al., 2009 ³⁰⁴)
Farm or produce stand	3	(Gustafson et al., 2013 ⁸¹ ; Longacre et al., 2011 ²⁹³ ; Lopez-Class and Hosler, 2010 ³⁰²)
Other food outlet types (such as discount stores, beverage stores, food bank)	13	(Christian, 2012 ⁸⁰ ; Fleischhacker et al., 2012 ³⁰⁰ ; Gasevic et al., 2011 ³⁰¹ ; Gustafson et al., 2012 ²¹⁷ ; Hosler and Dharssi, 2010 ²⁹¹ ; Huang et al., 2012 ³⁰⁵ ; Liese et al., 2010 ²⁹⁵ ; Longacre et al., 2011 ²⁹³ ; Lopez-Class and Hosler, 2010 ³⁰² ; Powell et al., 2011 ²¹⁴ ; Seliske et al., 2012 ²⁹⁸ ; Sharkey and Horel, 2008 ²⁹⁶ ; Sharkey et al., 2009 ³⁰⁴)

Most studies included in this category (n=12) (Table 5.2.) use objective analysis using GIS software to geocode addresses of food stores from secondary sources in order to compare them with the GPS locations collected in the field, or for other types of not clearly specified analysis^{292 299}. The geocoding was undertaken in different ways. Out of the 14 food mapping studies, 10 used GPS to assess the location and type of food outlets, with the main purpose of reporting agreement with pre-existing secondary data sources that list the food outlets observed in the field (Table 5.2., category 1.1.).

There were 4 studies that did not use GPS to measure individual exposure to food, or for assessing validity of secondary retail food outlet data (Table 5.2., category 1.2.). The common feature of all is assessment of access to and availability of nutritious food, especially in low income communities. The purpose of one study³⁰¹ was to assess various features of the obesogenic built environment, including food outlets, by comparing two different existing audit tools. The other three studies³⁰²⁻³⁰⁴ were mainly concerned with aspects of food security, including spatial access and affordability, in predominantly low income communities of American Indians³⁰³, Latinos³⁰², and Colonias³⁰⁴. Only one study in this category reported positional accuracy of the GPS device²⁹² (<3 meters).

Category 2: Understanding use of and exposure to the food environment

Only 4 studies were identified that tracked daily movement patterns through GPS as a way to understand how individuals move within the food environment (Table 5.3., Appendix 5.2.). All four were located in the USA. Sample sizes ranged from 35 to 131 (n=35,121,121,131 respectively) participants. All the studies were focused on adults, with the age of participants being over 18. One of the studies looked only at people aged over 45 and one looked at people over 50 with mobility disabilities. Only two studies^{44 81} reported recruitment rates; one study⁸¹ reported an 11% response rate, and the other⁴⁴ a 28% enrolment rate. Most studies recruited participants through flyers^{80 81 305} (3 studies), other recruitment channels reported were neighbourhood association meetings⁸⁰, announcements in relevant organisational e-newsletters³⁰⁵, and telephone⁴⁴.

The GPS recording period varied from 3 days (3 studies)^{80 81 305} to 7 days (1 study)⁴⁴. In 3 studies^{44 81 305}, GPS measurement was made on both weekdays and weekend days, whereas one study⁸⁰ trimmed the GPS data to the first three weekdays only (the reasons given for limiting the activity space data to three days being that it eliminates the need for participants to charge the GPS and it facilitates measurement of a set of local retail food opportunities,

rather than actual food shopping behaviours). Three of the studies reported the number of participants that remained from the initial sample size to the analysis stage: between 2% and 17% of people were lost in the process. The various reasons why data was excluded from the analysis were: trips without eligible GPS data, participants did not wear the GPS for the entire required length of time^{80 81} or at all⁴⁴, there were unknown routes between destinations due to reception issues⁸⁰, the participants travelled outside the study area^{44 80}, there were data collection errors by staff⁴⁴, or data was “suspicious”, a term not clarified in the paper but confirmed by the authors to represent sparse data⁴⁴. While studies commented on issues such as battery life^{44 80} (n=2), time to first fix⁸⁰ (n=1), and interval of time at which GPS records location^{44 80} (n=2) ranging between 3 to 30 seconds, none of the four studies reported positional accuracy of the GPS device. Two studies^{44 80} gave additional detail on the GPS data, such as how the participants were instructed to wear the device, how many points the device yielded, how these were treated and analysed.

Food and weight related outcomes

Retrospective questionnaires and immediate diary records of an individual’s dietary behaviours are attractive because they offer simple and inexpensive estimates of habitual behaviours. Most studies looking at dietary behaviours to date rely on such reports^{306 307}, and the majority of the studies included in this category (n=3) used food consumption or food purchase frequency questionnaires^{44 80 81}, with the exception of one study³⁰⁵ which used semi-structured interviews. Three of the studies^{44 80 81} assessed self-reported dietary outcomes; frequency of consumption of specific foods^{44 80 81}, mean daily saturated fat intake in grams⁴⁴ and servings of specific foods⁴⁴. Two of these^{80 81} also assessed frequency of purchase, and one⁸¹ studied food venue choice.

While three studies^{44 80 81} were focused on how measures of food accessibility relate to weight and weight related behaviours, one³⁰⁵ focused on how older people with mobility disabilities access locations, travel mode, and what the facilitators and barriers to accessing locations outside the home may be. Two studies did not examine any anthropometric measures^{44 305}, whilst two included self-reported BMI^{80 81}. Christian et al⁸⁰ reported weight status as a categorical outcome (underweight/normal for BMI < 25, overweight for 25 ≤ BMI < 30, and obese for BMI ≥ 30). Gustafson et al⁸¹ also reports BMI as categorical (underweight, normal weight, overweight, obese), but it is used to describe the sample rather than as an outcome. None of the studies used objectively measured weight.

Environmental exposure assessment

All four studies were concerned with access to food venues in the activity space, meaning the space where people conduct their day to day activities. The activity space was measured in different ways. Zenk et al⁴⁴ adapted two measures from the existing literature, calculating a one standard deviation ellipse and a daily path area. The daily path area was calculated by buffering all GPS points by 0.5 mile and merging these separate features into one space. Two papers published after Zenk et al⁴⁴ use the same distance when calculating activity space based on daily path area^{80 81}; the reason for using this distance was that Zenk et al⁴⁴ noted significant associations using it, and preliminary analysis in one of the studies⁸⁰ found no associations when using a 0.25 mile buffer. One study³⁰⁵ did not use a direct measure of activity space; GPS locations were used as a discussion starting point for where study participants went while wearing the GPS. The authors reported that GPS provided additional objective information on what types of facilities and venues people access most.

Most studies (n=3)^{44 80 81} utilised the ArcGIS software package for calculating spatial access to and availability of environmental characteristics. Environmental attributes measured ranged from counts, proportions and density of food outlets within the daily activity space^{44 80 81} to audits of food stores⁸¹. Some looked beyond food environments at environmental attributes related to physical activity, such as neighbourhood walkability³⁰⁵ and park land use⁴⁴. While all studies focused on the activity space environment, two^{44 80} also compared the activity with the neighbourhood based food environment. In Zenk et al⁴⁴, the neighbourhood food environment was defined as the number of food outlets of each type in each residential neighbourhood (0.5 mile street-network buffer around the census block centroid). Christian et al⁸⁰ calculated a neighbourhood-level measure defined as either density (food outlets of each type per square mile or per ten square miles) or proportion (percentage of food outlets among all food stores).

Discussion

Main findings of studies and data quality

Category 1: Mapping/assessing the food environment studies

In this review, it was found that earlier year of publication was generally associated with poorer data quality, as defined by the data quality weighted score. There was a positive

relationship between the primary data gathering approach for food validation studies identified according to the Fleischhacker typology²⁹⁵ (see Appendix 5.1.) and data quality, with ground-truthing studies having the highest quality and targeted observation the poorest.

Most studies (n=16)^{80 81 214 217 291 293 295-298 300-305} examined at least 3 food outlet types. Given that the relative availability of healthy and unhealthy foods differ by food outlet^{308 309}, it is important for researchers to be able to examine availability by store and restaurant type, otherwise results may suggest a greater or lesser nutritious food supply than actually exists²¹⁴. However there was no relationship between the number of food outlet types investigated and data quality in this review.

The studies that did not report whether the area canvassed was rural or urban had the lowest quality scores. Indeed, a pattern that emerges is that public directories can particularly misrepresent the actual distribution of food outlets in small towns and rural areas²⁹³ due to the fact that they are more likely to be incomplete³⁰⁸ or inaccurate²⁹¹ in these settings. The lower percent agreement for rural areas might be because of difficulty in obtaining addresses²¹⁴, lower precision of geocoding^{310 311}, greater presence of locally owned food procurement food establishments²⁹³, or higher rates of closure and population change over time²¹⁷.

Four studies were identified that use GPS for identifying food outlets locations for other reasons than establishing agreement with secondary data sources. Their main purpose was to pair actual location of food outlets with health variables, or to simply characterise the built environment. One study³⁰¹ reported the challenges in assessing the obesogenic built environment, including food outlets, using both perceived and objective GPS derived measures. The other three studies³⁰²⁻³⁰⁴ show that there are significant disparities in access to and cost of foods in the retail food environment within low income communities, with limited availability and access to nutritious food in such settings.

Category 2: Use of the food environment studies

In this small sample of studies, there was no relationship between the number of days for which participants were asked to wear the GPS and data loss (measured in number of participants lost from the initial sample). Furthermore, year of publication, sample size, participant age, GPS manufacturer, number of food outlet types and anthropometric component were not related to data quality.

The two studies^{44 80} that examined the differences in relationship between GPS measured activity-space and GIS measured residential food environment exposures and dietary outcomes reported only weak associations between environmental features of residential neighbourhoods and those in the activity space. This highlights how the residential neighbourhood is likely to be a poor proxy for the food environment to which individuals are exposed through the course of their day-to-day activities. Indeed, one study⁸⁰ showed that individuals encountered very different food environments in their daily travel than that within or near their neighbourhood. This suggests that neighbourhood-level studies of food environments are likely to encounter substantial misclassification bias.

Associations between activity space as well as neighbourhood food environment and diet related outcomes were equivocal across the studies included in this review. Two studies found associations between activity based food environment measures based on the daily path area and some dietary components^{24 25}, but not others²⁵⁻⁸¹; there was an inverse association reported between the identification of unhealthy food dense activity spaces and whole grain intake^{44 80}, with a positive association with saturated fat intake⁴⁴, but no significant associations were found with fruit and vegetable intake⁴⁴, added sugar, red meat or fried potatoes⁸⁰. Activity space measures of environmental use were also associated with the availability of specific foods in a food venue⁸¹, which suggests it is not merely the presence of food outlets that influence behaviour, but the availability within that outlet. Additionally, greater accessibility of calorically dense, ready-to-eat foods in the activity space was associated with higher weight status⁸⁰. In the only study that also tested associations between neighbourhood based food exposures and diet, no associations were found with residential fast food density⁴⁴.

Issues and considerations in the use of GPS in food environment studies

Characterising features and usage of the retail food environment as accurately as possible is important for many reasons, including identifying areas with limited retail access and therefore pushing policy strategies to reduce inequalities and nutrition-related diseases by improving access to healthy food. To this end, GPS technologies have proven to be increasingly useful. However, their use should be carefully weighed against their limitations depending on the study scale and context.

Physical activity studies typically temporally link information on activity levels recorded with accelerometer devices with the locations people visit throughout the day. There is the

potential to improve specificity of measurement using similar methods in studies of the food environment if foods diaries or momentary assessment techniques can be used to derive time-dependent measures of eating occasions or food purchases. Linking the GPS position with photographs of food outlets may be also be useful, as it provides the researcher with a later visual reference and allows the potential for a better classification of a food outlet type or food group found inside a food outlet, which is something few studies attempt (Table 5.5.).

While GPS is becoming the gold standard for geospatial accuracy, Liese et al ²⁹⁵ call for caution as GPS is also subject to error that can arise from satellite-related errors, signal propagation errors and receiver errors. It is noteworthy that physical activity studies appear more likely to discuss issues such as location precision, data loss and GPS data quality²⁸⁴; in this review only three studies touch upon GPS data loss and reasons why. The collection of GPS data also requires technical knowledge, and challenges such as signal loss, slow location detection, precision of the device, battery power, or participants forgetting to switch on the device remain²⁸⁵. For these reasons, cleaning protocols have been developed to try and counteract these issues^{312 313}.

Table 5.5. Category 1: Mapping/assessing the food environment

	GPS		Area type				Photos taken	Windshield survey	In store survey
	handheld	vehicular n.r.	Model specified	n.r. rural	urban	both			
1.1. Studies validating secondary data sources on the field- primary objective:									
2. Liese (2010) ²⁹⁵ , US	✓	✓	✓	✓	✓	✓	✓	✓	✓
3. Sharkey (2008) ²⁹⁶ , US			✓	✓			✓	✓	✓
4. Fleischhacker (2012) ³⁰⁰ , US	✓		✓				✓		
5. Powell (2011) ²¹⁴ , US		✓		✓	✓	✓			✓
6. Toft (2011) ²⁹⁹ , Denmark	✓			✓	✓	✓			
7. Longacre (2011) ²⁹³ , US	✓*			✓	✓	✓			✓
8. Hosler (2010) ²⁹¹ , US	✓				✓				✓
9. Seliske (2012) ²⁹⁸ , Canada	✓		✓						
10. McGuiert (2011) ²⁹⁷ , US	✓		✓						✓
11. Gustafson (2012) ²¹⁷ , US**		✓		✓					
1.2. Other food mapping studies:									
2. O'Connell (2011) ³⁰³ , US	✓			✓				✓	✓
3. Gasevic (2011) ³⁰¹ , Canada		✓		✓					✓
4. Lopez (2010) ³⁰² , US	✓			✓					
5. Sharkey (2009) ³⁰⁴ , US		✓		✓					

* Not specified in the paper that they use GPS, but authors confirmed they use handheld GPS devices and geolocated any new outlets or relocated any of the outlets that were miss-located based on where the secondary data sources placed them

** Although primary goal is food outlet validation, it also explores other secondary objectives such as association between deprivation and the food environment
n.r.= not recorded

Caution must be taken in inferring causality when studying human behaviour with the help of GPS, as it cannot be determined if food related activity patterns in the neighbourhood are a cause or consequence of the food environment⁴⁴. Despite this, characterizing the space within which people move or travel during the course of their day-to-day activities rather than only where they live, work or study, clearly offers the potential to provide a more comprehensive and accurate assessment of the environment to which individuals are exposed and utilize⁴⁴ and facilitates the detection of temporal and spatial patterns of behaviours that relate more closely to health outcomes of interest²⁷⁶.

Strengths and limitations

To our knowledge this is the first systematic review to identify studies that investigate the food environment with the help of GPS. The strengths of this review include the systematic methods used for assessing the quality of studies by more than one reviewer. It provided an overall summary of the quality of evidence available and reported important technical aspects of the GPS assessment in detail. A limitation is the fact that only papers written in English were considered and relevant material written in foreign languages may be omitted. Furthermore, conclusions need to be interpreted in the context of the small number of studies retrieved, which also contributed to the fact that no meta-analysis was possible in this instance.

Conclusion

This review has shown that the use of GPS to measure aspects of the food environment is still in its infancy and there are considerable variations in the methods and techniques used. There are clearly also a number of outstanding methodological and practical issues associated with their application. It was apparent from the review that collection of GPS data can be problematic in certain contexts such as rural areas or low income communities. However the findings from the few studies that have attempted to use the technology illustrate the potential added value that can be obtained from being able to record and analyse actual use of the food environment. This may be enhanced in the future by the further development of techniques such as momentary dietary assessment.

Chapter 6

Identifying travel mode and trips from raw GPS data: a novel methodology applied to assess exposure to the food environment

Abstract

Aim: The previous chapter synthesised the literature on the use of GPS for measuring exposure to the food environment, and what the value added of this might be, but also the challenges. While studies using GPS have the potential to refine measures of exposure to the food environment, one of the challenges is that they do not provide information on how these exposures differ when erroneous data points due to signal noise or journeys performed in vehicles are stripped out. The aim of this chapter is to present and test a methodology to explore these issues.

Methods: Using the PEACH dataset presented in Chapter 7, a computational algorithm was employed in order to infer two transport states: motorised vehicle and non-vehicle, on the basis of which trips were extracted. Additional criteria are imposed in order to improve robustness of the algorithm. The aim was to clean the raw GPS data in order to be able to extract measures of on-foot or slow cycling exposure to the food environment in chapter 7, where associations between these and weight and diet are explored.

Results: After stripping out noise in the GPS data and motorised vehicle journeys, 82.43% of the initial GPS points remained, on which analysis presented in Chapter 7 has been performed. After comparing a sub-sample of trips classified visually of vehicle, non-vehicle and mixed mode trips with the algorithm classifications, it was found that there was an agreement of 88%. The measures of exposure to the food environments of interest calculated before and after algorithm classification were strongly correlated.

Conclusion: Identifying on-foot exposures to the food environment makes little difference to exposure estimates in urban children but might be important for adults or rural populations who spend more time in cars. Extracting travel mode of interest and stripping out noise in the GPS data can help to better measure true exposure to the environment and more accurately reflect likely interactions with environmental features.

Introduction

As it has been observed in the previous chapter, a recent criticism³¹⁴ of many neighbourhood and health studies published to date has been that they have not adequately taken into account actual exposures to the food environment that individuals experience in their daily activity patterns. Rather, they tend to assume exposures based on home and/or school/work locations. There are also studies that infer exposures from travel surveys or diaries, but these provide subjective declarative data based on participants' recall⁸³. There is also a third type of studies that use passive tracking of study participants, which yield objective data. To this end GPS (Global Positioning Systems) are increasingly being used to measure daily activity space and investigate behaviours that relate more closely to health outcomes of interest. This daily mobility is of particular interest in environment–health research, as both a potential source of transportation-related physical activity and of a measure of exposure to certain geographic environments⁸³, such as food environments. However, such multi-place measures must be carefully constructed in order to make sure true exposures of interest are assessed.

While logging travel patterns using GPS measurements has become increasingly commonplace in recent years, managing the considerable volumes of GPS data collected to extract value has become a major problem. Furthermore, since GPS technologies are still new and under development, with different qualities of GPS software and hardware, even if the device is working at peak performance, there will always be error in the accuracy of location recording. Such errors can emerge from factors such as: (1) satellite signal loss; (2) propagation delays or slow location detection (initialization and start-up, whereby the GPS receiver needs some time to first acquire signals from satellites); (3) precision of the device (the most accurate GPS devices, at their best performance, are accurate to around three meters); (4) battery power; (5) participants forgetting to switch on the device²⁸⁵; (6) a person forgetting the GPS device in the car or in bag instead of wearing it; (7) signal obstruction by nearby buildings, trees, tunnels, or even clothing; (8) multipath error (when signals from the GPS satellites bounce off buildings).

Additional to such technical or usability issues, other issues that arise with GPS data are related to how it is interpreted when extracting exposures of interest. For example, in studies investigating exposures to the retail food environment and linking them to health-related outcomes, researchers may be interested only in GPS points that represent on-foot or even slow cycling trips, as it is considered that people within moving vehicles would not have the

opportunity to access food outlets to purchase food without the vehicle stopping and them getting out. This consideration has typically been ignored in the literature, in part because of some of the problems inherent in identifying the travel modes of study participants. For example, GPS points that in reality represent a car slowing down at intersections, traffic calming measures or due to the presence of other traffic may be wrongly interpreted as walking, because they register low speeds. Those studies that have attempted to make such differentiations typically use either crude criteria (such as identifying walking as GPS points under a certain speed threshold)³¹⁵, or they clean GPS data manually³¹⁶, which can be very time consuming. A physical activity study¹²⁷ has used a platform called PALMS (Physical Activity Location Measurement System) to manage GPS data, but such platforms have also proved to be problematic; the authors report that misclassification of trips included stationary trips classified as vehicles, bicycle and walking, mixed trips classified as a single type and vice versa, and recommend that further research is needed to overcome problems in data treatment.

To date a small number of researchers have attempted to produce more robust algorithms for cleaning GPS data and extracting useful information from it such as travel mode^{313 317-321}, however there is no uniform standard across disciplines. Most methods have several commonalities among them. They each attempt to split the raw GPS data into smaller relevant segments (i.e. journeys or trips) on which further analysis is carried out (e.g. determining transport mode for each segment). Usually some form of pre-processing is carried out to remove outliers and de-noise the data, after which a main algorithm is applied for analysis, and subsequently post-processing is used to further improve classification accuracy. These main algorithms used can be split into supervised and unsupervised methods.

Supervised methods^{313 318 321} rely on manually classified data in order to make inferences about unknown data. In such cases, features (average speed, maximum speed, acceleration etc.) are extracted from each segment, and supervised classifier models such as decision trees are used to make inference about new data based on previously observed values. An obvious drawback of such methods is the requirement of training data, which is usually obtained by manual classification and can hence be time consuming and costly to generate. A further limitation is that models trained on one dataset may perform poorly when applied to a different dataset.

Unsupervised methods^{322 323} overcome this disadvantage by not relying on training data for predictions. Such methods could work for example by using some expert-chosen rules (e.g. speeds below a certain threshold are considered walking) to analyse segments. These methods can however be problematic if the expert chosen rules are not correct, or for cases in which noise could affect a segment's adherence to these rules. More sophisticated unsupervised methods rely on an underlying model for predictions. An example would be the work of Feng et al³¹⁹, which uses Bayesian Belief Networks (BBN) to predict transportation mode of a segment. They typically require much additional information (e.g. data from accelerometers that provide information on physical activity) to aid their model. The work of Lin et al³²⁰ assume that each transport mode generates speeds from a certain distribution. They use the raw GPS data to estimate the parameters of these distributions and conduct statistical tests to determine the differences between these distributions across different segments. Based on these inferred differences, they then use hierarchical clustering to group segments into major groups which correspond to transport modes. Unreliable segments are classified based on proximity to relevant locations such as bus stops. Most of these methods are therefore data intensive and require additional information (such as relevant landmark positions), and would not work as well for studies that do not have such information available.

The method presented here falls in the category of unsupervised methods and is applied on the PEACH (Personal and Environmental Associations with Children's Health) dataset containing the GPS locations of a sample of children in Bristol. The development and testing of the methodology presented in this chapter arose from the need to extract only non-motorised vehicle trips from the PEACH dataset in order to calculate exposure to the food environment, on the basis of which analysis in Chapter 7 is performed. The method presented is innovative in that it requires no additional information except the registered timestamp of each GPS point and the distance between two consecutive points, on the basis of which speed can be easily calculated. In this method a model known as a Hidden Markov Model (HMM)³²⁴ was used to model the differences in speeds from raw GPS data generated by two transport modes: walking or slow cycling (not considered separately in this study) and in a motorised vehicle. These states will further be referenced as *non-vehicle* and *vehicle* state. The present chapter investigates how accurately the method presented here differentiates between the transport modes, and if the post-processing exposure estimates to the food environment differ to those before processing.

Methodology

Dataset

The dataset used in developing the model presented here was obtained from PEACH, a study undertaken in Bristol, UK which investigates how the environment can influence physical activity and dietary behaviours in children. Characteristics of the PEACH study sample have been described in more detail elsewhere^{267 315} and in the next chapter. In brief, this dataset provides 4 days of GPS data recorded in the morning (8am-9am), evening (3pm-10pm), and additionally weekend (8am-10pm). The analysis in this thesis is performed on a subsample of 688 children in their first year of secondary school who wore a Garmin Foretrex 201 GPS receiver recording data at 10-s intervals (i.e., epochs). The GPS has limited battery life, and participants were asked to switch the GPS on at the end of school, and off at bedtime. Research staff charged the units after the first two days of use.

GPS data from this study (cleaned using the methodology presented in this chapter) was used to measure personal exposure to the food environment and its association with diet and weight, analysis which forms the content of the next chapter. The personal exposures were calculated as the percentage of time spent in the vicinity (within 50 meters) of different retail food outlet types, merged into three categories: time spent near healthy food outlets, time spent near unhealthy food outlets and time spent near fast food outlets. Calculation of these exposure measures is detailed in the next chapter. As explained in the introduction, in order to better measure true environmental exposures to food, the aim of this chapter was to identify for later removal any points that might represent time spent in a motorised vehicle such as a car or a bus, or spurious GPS points. The following theoretical model was used and some prior and subsequent criteria have been developed to differentiate between walking/cycling and other vehicle modes, as well as eliminate noise in the data due to location imprecision associated with a poor satellite signal.

Theoretical model

Frequently in real life applications, one can observe a sequence of emissions (i.e. the speed of a person, measured at specific intervals of time), generated by a process (i.e. the movement of the person) with a finite number of states (i.e. the travel modes). The states that gave rise to the observed emissions are usually unknown to the observer, thus are referred to as *hidden*

states. One of the common tasks in these cases is that given a sequence of observations, to infer the most likely sequence of states that generated the observations.

One of the theoretical models that can be used to model the above behaviour and which has been used as a basis for the method presented here is called the Hidden Markov Model (HMM)³²⁴. As stated in Ghahramani³²⁵, HMM is a statistical tool used to model the probability distributions of a sequence of observations (emissions) $Y_{1:N}$. The model works on the assumption that every observation Y_i , $1 \leq i \leq N$ is generated by a hidden state S_i of a process with K possible states. An important property of the model is that given the state S_{i-1} , S_i is independent of all the states before $i - 1$. Also, any observation Y_i is independent of all the previous states and observations and depends only on the state S_i , by which it was generated (Figure 6.1.). Using these characteristics of the model, the joint distribution of a sequence of observations and states is given by:

$$P(S_{1:N}, Y_{1:N}) = P(S_1)P(Y_1|S_1) \prod_{i=2}^N P(S_i|S_{i-1})P(Y_i|S_i),$$

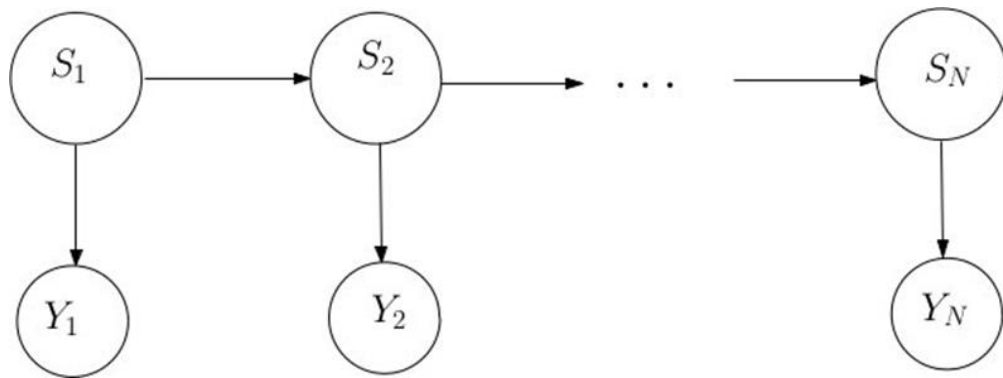
where $P(S_1)$ represents the probability distribution over the initial states (the generation of a sequence of observations can start in any of the K possible hidden states with a certain probability for each state), called the *initial probabilities*. $P(S_i|S_{i-1})$, the short form of $P(S_i = w|S_{i-1} = v)$, is the *transition probability* from the given state v to any of the other possible states w (note that v can equal w , meaning that the process generated the emissions Y_{i-1} and Y_i from the same state). The transition probabilities are defined by the $K \times K$ transition matrix (T) associated with the model, with $T_{v,w}$ representing the transition probability from the state v to the state w , $1 \leq u, v \leq K$. This is referred to in the literature as ‘changing points’³²⁰, which indicate a change of transportation modes or remaining in the same state. $P(Y_i|S_i)$ represents the *emission probability* of the observation Y_i from the state S_i .

To infer these parameters (the initial probabilities, the transition probabilities and the emission probabilities) based on the sequence of observations only, a version of the Expectation-Maximisation³²⁶ algorithm, known as the Baum-Welch algorithm³²⁷ is used. This algorithm starts with some random values for the above parameters, then with each iteration it estimates new values based on the data, until a stopping criterion is met. Full details of this

algorithm are beyond the scope of this paper and the reader is referred to ‘Machine Learning, a probabilistic perspective’ by Kevin P Murphy³²⁴ for more detail.

Once these parameters have been inferred, using the joint probability of observations and emissions $P(S_{1:N}, Y_{1:N})$, the most likely sequence of states given a sequence of observations, $S_{1:N}^* = \operatorname{argmax}_{S_{1:N}} P(S_{1:N} | Y_{1:N})$, can be easily determined using the Viterbi algorithm³²⁸.

Figure 6.1. The workings of a HMM: S_i represent the hidden states, while Y_i represent the emissions of those states.



Trip and travel mode detection, data cleaning and smoothing

Stage 1: Pre-processing

In the first instance several criteria have been developed to mark points for later removal that would not represent true exposures. These included GPS drift (i.e., GPS records which suggest that a child has moved an implausible amount in a short space of time, meaning there has been some inaccuracy in the GPS locations, often as the signal was obstructed by buildings or trees), as well as short participant reads (i.e. participants registering a very low number of GPS points overall), which typically represented poor device wear compliance.

The criteria developed are as follows:

- 1.1. Marking isolated points: for each participant, select the list of points that are further than 500m from any other GPS points belonging to them.
- 1.2. Marking aberrant speed: all points having more than 100 kph.
- 1.3. Marking short participant reads: all participants with less than 1 minute total GPS wear time.

Stage 2: Processing

For each participant, the points were ordered according to their timestamp and the obtained series of GPS points were subsequently divided into segments (trips). A segment (trip) was considered to be a number of consecutive points for which the time difference between every two consecutive points is less than 5 minutes. If the time difference between two consecutive points in time is greater than 5 minutes, this marks the beginning of a new segment or trip.

For each segment, the transportation mode (*non-vehicle* or *vehicle*) that generated the observed GPS points is aimed to be inferred. A trip or segment can therefore be a *vehicle* trip or a *non-vehicle* trip. It is however of course possible that several transportation modes have been used during one trip, and such a trip will be referred to as a *mixed* trip (i.e., it includes both vehicle and non-vehicle states).

To model these behaviours, consecutive speed reads from a segment are considered to be the sequence of emissions $Y_{1:N}$ of the HMM. The transportation modes (walking/cycling vs motorised vehicle) represent the only possible states of the model. The aim is to infer the most likely transport modes that generated the sequence of speeds. For the HMM model, this means to infer the most likely sequence of states that generated the emissions. The event of changing the transportation mode is modelled by the HMM by transitioning from one state to the other.

The non-vehicle state is likely to give rise to speeds that are much lower than the vehicle state. To model this in the HMM, it is assumed that each state will emit observation from a different Gaussian distribution, with the mean of the distribution corresponding to the *vehicle* state, higher than the one corresponding to the *non-vehicle* state.

To infer the parameters of the model, we used all the segments from all participants as input for the Baum-Welch. Then, for each segment, the most likely sequence of states has been determined using the Viterbi algorithm.

Stage 3: Post-processing

Some post-processing steps are needed in order to correct some issues as detailed below.

Firstly, short segments (for which the overall duration is less than 1 minute in total GPS time) were marked separately with the purpose of later being eliminated from the raw GPS data.

This was based on the hypothesis that it is very unlikely that such short segments would represent actual walking/cycling trips.

Furthermore, instances have been observed whereby in a segment there is an isolated point adjacent to two points of a different state. It was considered that a change of transportation mode that spans only one point is very unlikely. This was thus corrected by changing the state of the isolated point to the state of its neighbours. To address situations where the wearer was in a vehicle that was slowing down, an additional criteria was developed whereby if *non-vehicle* segments spanned less than 2 minutes and were surrounded by *vehicle* points, these were marked as *vehicle* points. Furthermore, there were instances where within a segment (trip) some points were classified as *vehicle* and some as *non-vehicle*, but the *vehicle* points represented a very small proportion of the whole segment, which was mostly dominated by *non-vehicle* points. An additional criterion was therefore imposed whereby if less than 5% or less than 5 of the points in a segment are classified as *vehicle* and the rest are *non-vehicle*, all the points in that segment are considered as *non-vehicle*.

After processing, there were still some points over 15 kph classified by the model as *non-vehicle*. This was because the speeds were not high enough for the model to suggest them as motorised vehicle points given their surrounding points were mostly non-vehicle. An additional criterion was therefore imposed by marking all of these points as *vehicle*. This was based on previous practice in studies that have used the same dataset^{15 16}, where travel speeds above 15kph were judged to be journeys in vehicles.

The accuracy of the algorithm in classifying the two hidden states was further tested on a sub-sample of randomly selected segments and comparing the algorithm classification with visual classification undertaken by A.C. The difference between the algorithm classification and the visual classification was determined using a χ^2 test. How similar the exposure measures to the food environment were when calculated on the raw GPS data as opposed to the cleaned GPS data was investigated using Pearson's correlation coefficients. All statistical analysis was done in SPSS (version 21, IBM Corp, Armonk, NY, USA). The algorithm was written in the Python programme (Appendix 6.1.).

Results

Before any processing there were 366432 GPS points in the PEACH dataset that was used to train the HMM model, which represented a total of 4018 trips or segments. Out of these, 2488

were non-vehicle only trips, 443 were vehicle and the rest were mixed trips (including both vehicle and non-vehicle points).

The Baum-Welch algorithm converged to the parameters illustrated in Figure 6.2. It can be observed that the emission distribution corresponding to a *non-vehicle* state is centred around 2.14 kph, while for the *vehicle* state it is centred around 26.86 kph, consistent with the initial assumption, that the speeds should be able to differentiate well between the two transportation modes.

In terms of transition probabilities, the probability of moving from non-vehicle to vehicle is 0.0232 and the probability of moving from vehicle to non-vehicle state is 0.1223. These low values reflect the fact that the likelihood of two consecutive points corresponding to different travel modes is much lower than that of them being the same. The probability of remaining in the *non-vehicle* state is about 10% percent higher than the probability of remaining in the *vehicle* state. This is explained by the fact that the data is highly right skewed (skewness= 3.4099124, Figure 6.3.), thus increasing the probability that if in a *non-vehicle* state, one remains in a *non-vehicle* state.

Out of the 366432 GPS points in the PEACH dataset used to train the HMM model, 64385 were marked for removal during the pre-processing, processing and post-processing stages. This meant that 17.57 % of the original GPS points have been marked for removal, which represented: 0.37% (n= 1347) isolated points, 0.08% (n= 282) aberrant speed, 0.006% (n= 21) participants with less than 1 minute worth of GPS data, 15.94% (n= 58409) motorised vehicle points, 0.30% (n= 1087) points representing trips below one minute total duration, and 0.88% (n= 3239) points registering speeds over 15 kph. (Figure 6.4.). As a result, 302047 GPS points (82.43%) remained representing non-vehicle points.

Figure 6.2. The HMM model after training. The purple vertices represent the states of the model, the numbers on arrow from state u to state v represent the transition probability from the state u to the state v and the distributions in the yellow rectangles represent the emission probabilities.

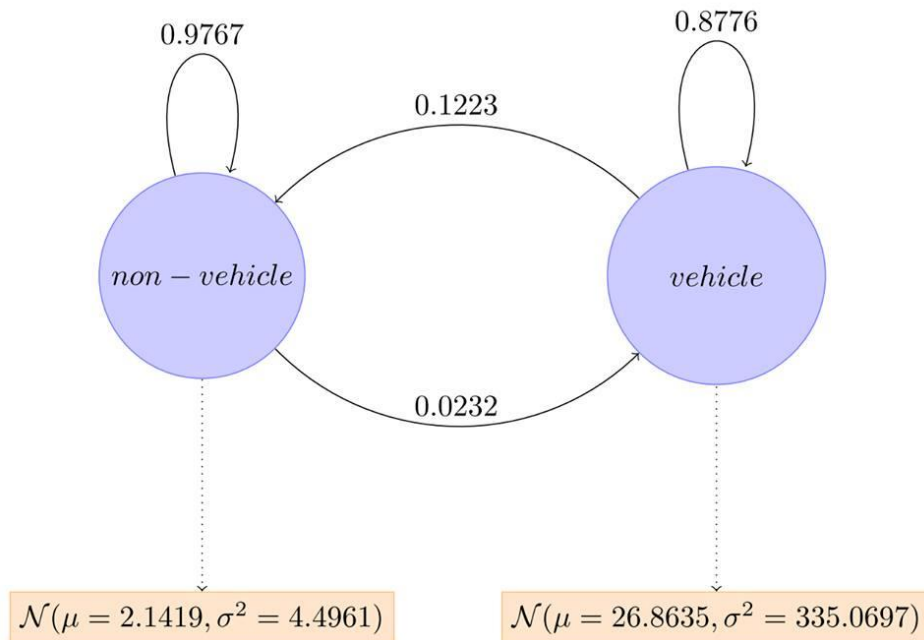


Figure 6.3: Histogram of speeds

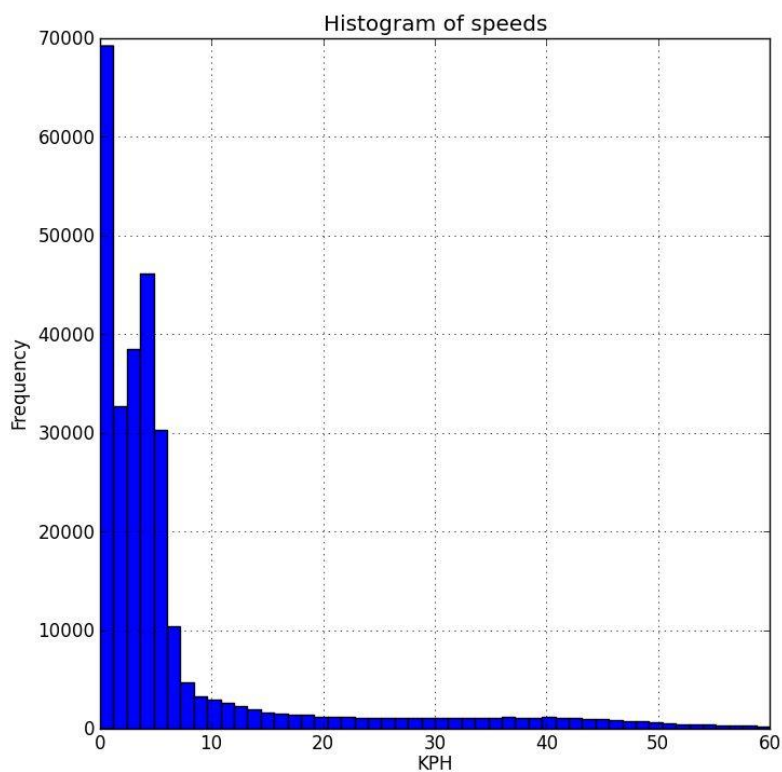
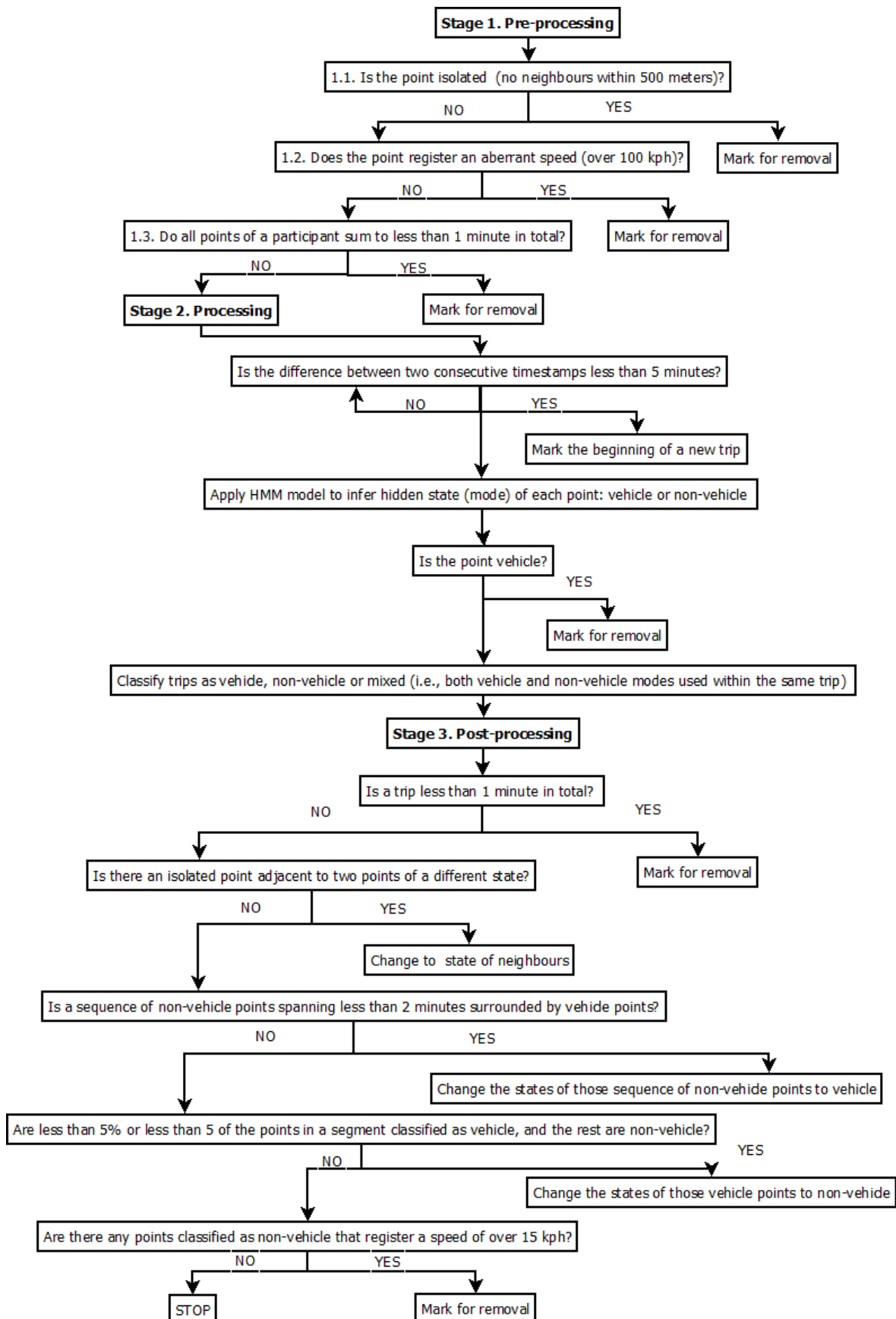


Figure 6.4. Flow diagram of steps



In order to visually represent results from the model, plots were generated to represent all 4018 pairs of segments before and after post-processing. Figures 6.5., 6.6. and 6.7. represent three such examples, whereby the left-hand side graph represents the classification of GPS points during the processing stage, and the right hand side graph represents the classification of points at the post-processing stage. In Figure 6.5., which represents one segment, the algorithm classifies some points as *non-vehicle* (the blue points), and other points as *vehicle* (the red points) at the processing stage. Some points are considered as *non-vehicle* because when a car slows down, the speeds are considered by the model as too low to be *vehicle* points. However, the number of consecutive points marked as *non-vehicle* spanned less than 2 minutes and were surrounded by *vehicle* points. Therefore, these were changed to *vehicle* points in the post-processing stage. In Figure 6.6. the *vehicle* points represented only 5 points of the whole segment, which was mostly dominated by *non-vehicle* (blue) points. These points are therefore marked as *non-vehicle* at the post-processing stage. In Figure 6.7., less than 5% of GPS points in the segment are *vehicle*, and therefore at post-processing these are marked as *non-vehicle*; however, some of these points register speeds of over 15 kph, because the speeds were not high enough for the model to suggest them as motorised *vehicle* points given their surrounding points were mostly *non-vehicle*. Therefore, these are marked (black points) for later removal.

The validity of the algorithm was tested by visually inspecting a sub-sample of 99 randomly selected segments (33 *vehicle* segments, 33 *non-vehicle* segments and 33 segments containing both *vehicle* and *non-vehicle*, termed here as *mixed*) for manual classification by overlaying the segments on a base map. Each of these was compared against the segments classified by the algorithm, and the percent agreement obtained was 88% ($p < 0.001$), indicating a close match (Table 6.1.).

Table 6.1. Comparison of algorithm classification with manual classification of trips (segments) on a sub-sample of 99 segments

		Algorithm classification			Total
		vehicle	non-vehicle	mixed	
Manual classification	vehicle	30	2	6	38
	non-vehicle	0	31	1	32
	mixed	3	0	26	29
Total		33	33	33	99

Note 6.1.: *mixed-* represents mixed mode trips, i.e. where participants have been classified to have used both vehicle and non-vehicle transportation modes within the same trip

When comparing the absolute differences in measures of exposure to the food environment before and after processing (Table 6.2.), it can be observed that the exposure measures calculated on the raw GPS data were statistically significantly higher than the post-processing values. However, when correlating the GPS points to compare classification before and after processing, for all the exposure measures (in both absolute time and percentage time) the correlation coefficient was of 0.98 or above ($p < 0.001$). This shows that children who had high levels of exposure before processing also had high levels of exposure after processing. Therefore the processing led to lower levels of estimated absolute exposure but did not substantially modify the ordering of children in terms of their exposure.

Table 6.2. Comparison of before with after processing exposures

	<i>Pre- processing</i>	<i>Post- processing</i>	<i>p-value for diff</i>
Percentage of time spent within 50 meters of food outlets			
healthy food outlets (mean \pm SD)	0.20 \pm 0.48	0.16 \pm 0.46	<0.001
unhealthy food outlets (mean \pm SD)	0.57 \pm 1.44	0.47 \pm 1.41	<0.001
fast food outlets (mean \pm SD)	0.40 \pm 1.32	0.31 \pm 1.28	<0.001
Absolute time spent within 50 meters of food outlets (hours)			
healthy food outlets (mean \pm SD)	0.04 \pm 0.11	0.04 \pm 0.10	<0.001
unhealthy food outlets (mean \pm SD)	0.11 \pm 0.18	0.08 \pm 0.17	<0.001
fast food outlets (mean \pm SD)	0.07 \pm 0.16	0.05 \pm 0.14	<0.001

Note 6.2.: The reported *p-value* is for before-after processing differences, calculated with Wilcoxon signed-rank test

Discussion

The method presented in this chapter aims to refine current understanding of measuring environmental exposures in studies using GPS that do not require other information than the speed of each GPS point. The model used is applied on a health study that aims to investigate associations between individual on foot (or slow cycling) exposure to the food environment and weight-related outcomes (analysis presented in the next chapter). It was found that for this particular application, the model works with high accuracy (88%) as reported on a subset of the data which has been manually classified. Approximately 18% of the raw GPS data points were marked for removal, which represented motorised vehicle journeys or GPS device inaccuracies. The exposures to the food environment measured before and after processing were strongly correlated.

As detailed in the introduction, one of the strengths of the model presented here is the fact that it is an unsupervised model, and hence it does not require manually classified data for the

training of the model, as the supervised models do. Therefore, using individual speed instances to judge the transportation mode does not suffer from the fact that any spurious changes in speeds could affect the inferred modes, as is the problem with supervised methods³²⁰. Furthermore, HMM is a mature statistical model that has been extensively and successfully used in many fields.

While there are various attempts and methods of identifying travel mode in the literature, it was concluded that using a Gaussian-based model such as HMM and some additional pre and post-processing criteria has rendered promising results for the experimental data used. While other methods³¹⁹ have differentiated between different modes (walk, car, bus, bike etc.), the researchers had access to more information than available with the dataset used here, such as bus station location for finding bus trips.

Indeed, one of the major advantages of the approach presented here is that it requires minimal user interaction or additional data, and can work very well on just time-stamped GPS points. For this method, the user interaction consisted of visually inspecting a sub-sample of the data at the post-processing stage in order to test the robustness of the algorithm classification. For example, in order to test the hypothesis that segments less than 1 minute total GPS time did not represent actual non-vehicle trips, a visual inspection was performed in ArcGIS of all 385 such segments. The same hypothesis has also been investigated with segments ranging from one to two minutes, some of which were observed to constitute real non-vehicle trips, and were therefore marked for inclusion in the final cleaned dataset.

A consideration is that the PEACH dataset used to train the model is applied to children living in a dense urban area and might not be generalizable to adults or people living in rural areas. Calculating on-foot exposures to the food environment might make a bigger difference in adults after excluding motorised vehicle journeys, as they spend more time in cars. Furthermore, the children in the PEACH study live in Bristol, a dense urban area, which means they are more likely to walk. This can indeed be observed by the fact that approximately 62% of the trips represent non-vehicle journeys.

Current studies in the field of public health have not attempted to decompose GPS tracks by systematically assessing the nature of activities practiced at the different places and the transportation modes for each trip⁸⁴. In the transportation field however, it has been reported³⁷⁸ that studies combine GPS tracking with precise mobility surveys that collect information on activities and transportation modes, though often only over 1 day^{317 379}. While

the method presented here differentiates between vehicle and non-vehicle exposures based on GPS data collected over 4 days, a survey was not conducted on the nature of activities at specific locations. Therefore, there was no way of knowing if non-vehicle exposures to the retail food environment meant that participants actually made use of those particular food outlets.

Conclusion:

This chapter presents a robust algorithm to clean GPS data that can be specifically applied to health studies making use of GPS in order to assess exposure to facilities in the environment. The method is particularly applicable to studies of the food environment, where only on-foot or slow cycling trips capture true exposures to retail food outlets. Extracting such exposures is important when attempting to better match them with actual food seeking behaviours of interest.

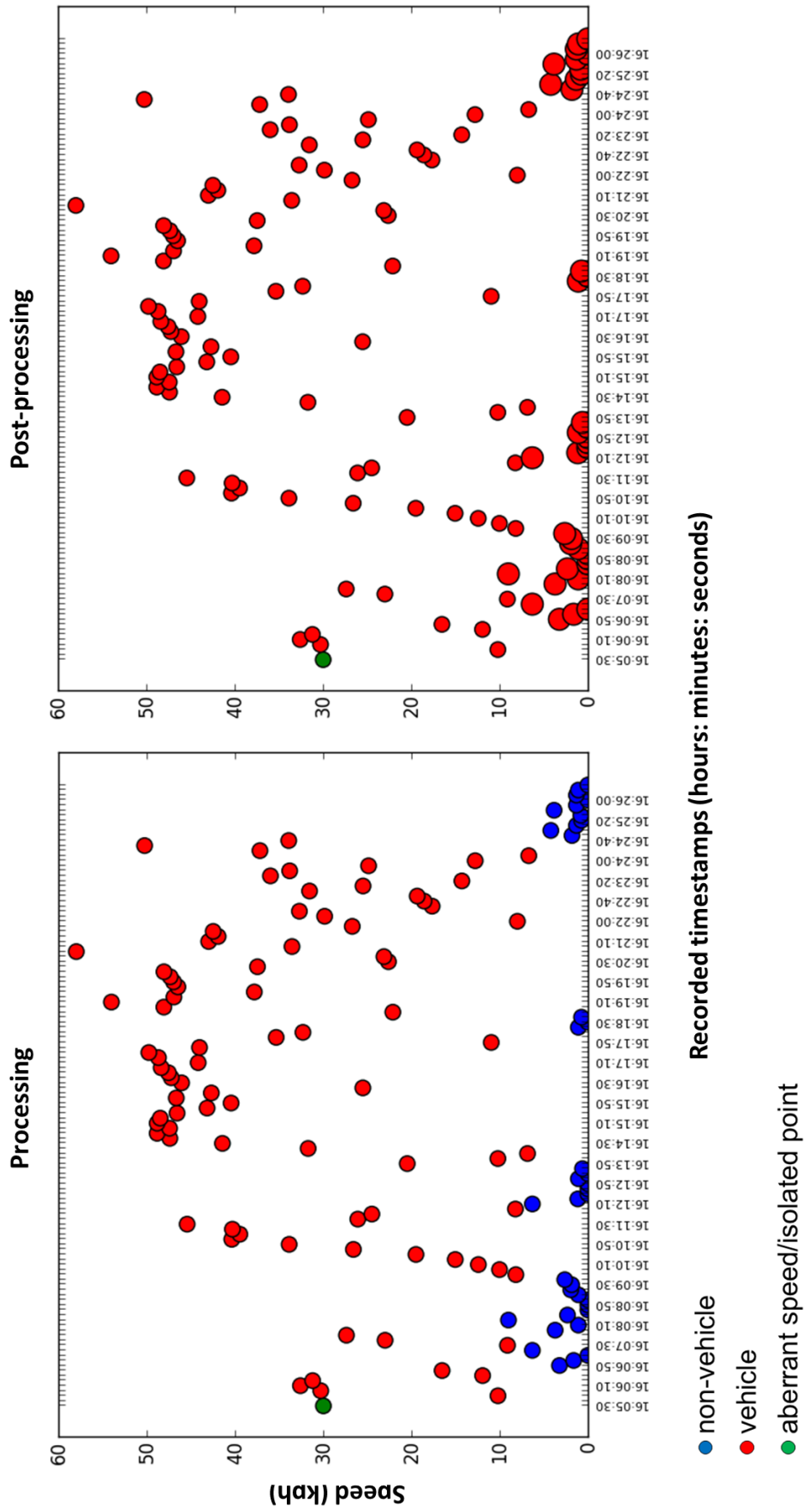


Figure 6.5. Example of a segment during and after processing

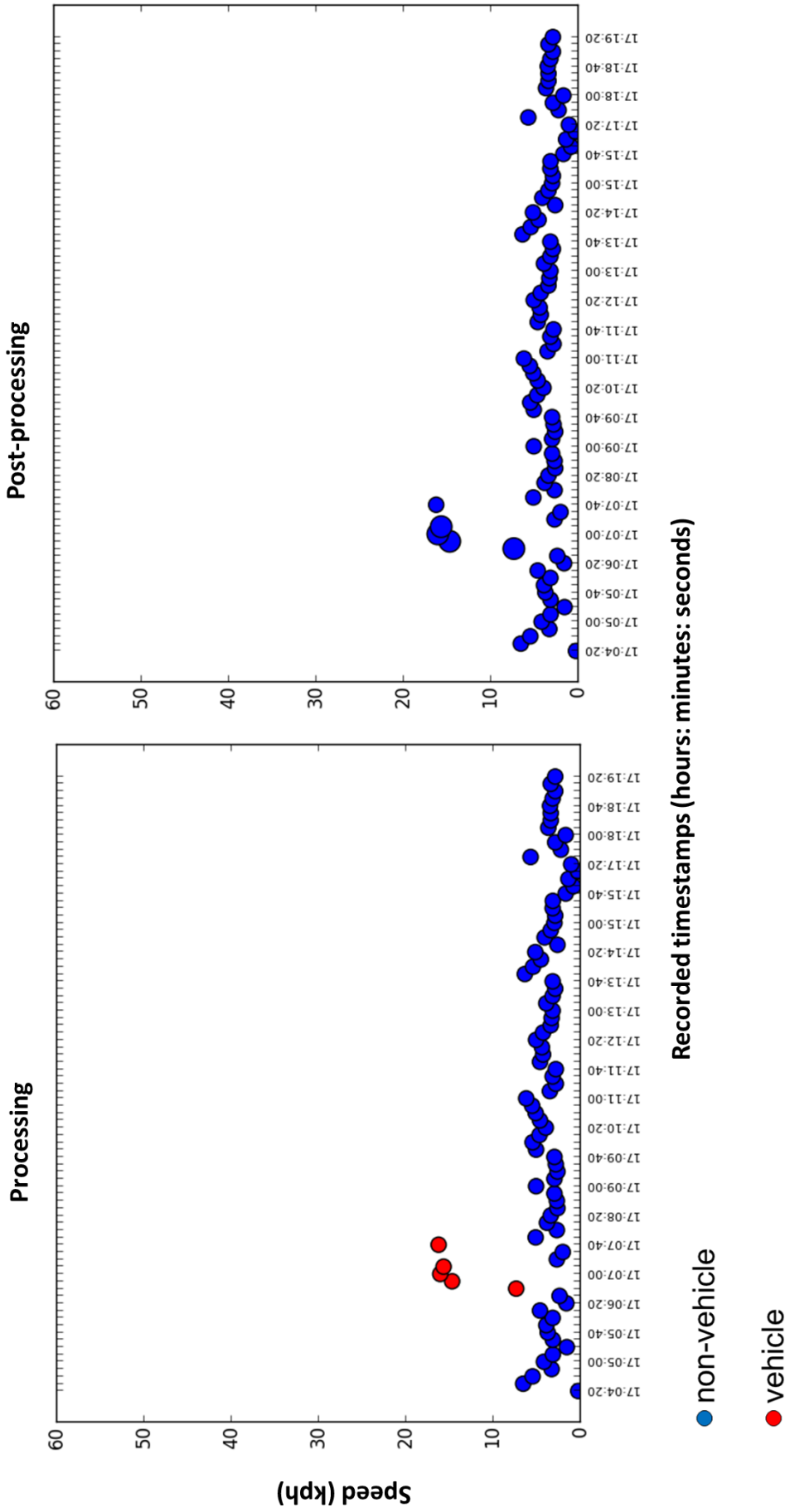


Figure 6.6. Example of a segment during and after

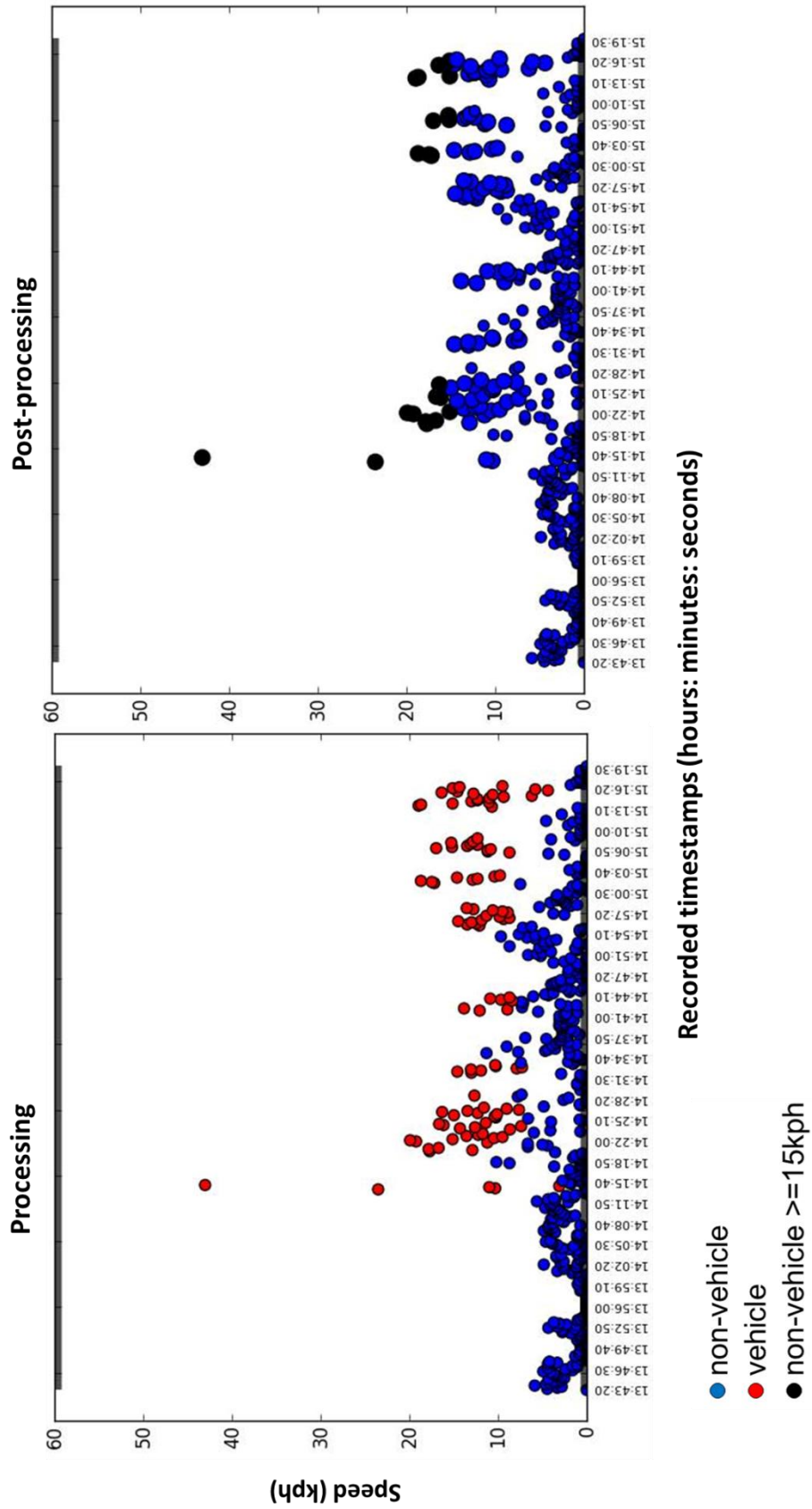


Figure 6.7. Example of a segment during and after processing

Chapter 7

Exposure to the food environment, food consumption and weight and in children aged 11-12 years: the PEACH-2 project

Abstract

Objective: Exposure to the retail food environment has become an increasingly important hypothesised determinant of dietary intake and weight. However, limited research focuses on personal exposures to food environments, with most evidence coming from associations with assumed neighbourhood exposure based on radii delineated around residential locations. Building on work done in chapters 3 and 4, where we did not have information on diet (chapter 3) or movement patterns of children (chapters 3 and 4), in this chapter the aim is to examine the associations between three dietary consumption outcomes, individual weight and both assumed and individual exposure to the food environment.

Methods: The chapter utilizes data for secondary school (11 to 12 yrs) children who participated in the PEACH Bristol based study. Children wore a GPS for 4 days, including one weekend day. They also completed a diet screener which records self-reported eating and lifestyle behaviours. Linear regression models were used to examine the association between diet, BMI and exposure to food outlets in the daily activity space, measured using GPS data, and in the school and home neighbourhoods. Interaction terms were also fitted for various hypothesised moderators.

Results: Few associations are found in this sample. Some significant trends were apparent between assumed exposure and diet and weight, but these were in the opposite direction of what was anticipated. There were also some significant interactions between assumed exposure to healthy and unhealthy food outlets and food preference and parental consumption of the relevant food groups, but the direction of this effect was not clear. Residential and school neighbourhood exposures were weakly correlated with activity spaces exposures, with correlation coefficients ranging from 0.007 to 0.100.

Conclusion: This study does not clearly support the hypothesis that more exposure to food outlets that sell particular types of food is necessarily associated with more consumption of those food items, an assumption which might over-simplify the interdependence between

individuals and their environments. It is recommended that policy makers take more substantive actions to address the rising problem of obesity.

Introduction

There is a growing interest in understanding how exposure to the food environment influences eating behaviour and weight-related health outcomes, particularly in young people^{24 76 82 236 329}. This concern is partly driven by the growing obesity epidemic witnessed in many countries, where increasing exposure to food is considered a contributing factor¹⁸. Yet although conceptual models posit a relationship between the retail food environment, diet and weight, there appears to be no clear empirically based picture of the existence or nature of any association, with reviews of the literature reporting equivocal findings^{45 82}. This might, at least in part, be associated with the wide variety of methodologies¹²⁷ used to measure food access for study participants, with no gold standard existing.

Most studies undertaken to date evaluate the relationship between assumed food environment exposure and diet or weight^{43 216 330-333}. In these, exposure to the food environment is assumed because actual food seeking behaviours are not measured. Rather, exposure is typically based on measures of proximity, with proximity to the home location being the most commonly employed metric. Only a few studies^{80 81} have looked at exposure to food environments based on the actual movement of people, measured using a global positioning system (GPS)²⁷⁶. Such movement patterns can be conceptualised as their daily activity space; a set of spatial locations visited by an individual over a given period, corresponding to the spatial footprint of their movement patterns.

To date, just one study⁴⁴ has investigated associations with diet and both neighbourhood assumed exposures and observed actual exposures in the activity space, whilst one⁸⁰ reports differences between neighbourhood and activity space based exposure estimates, without relating either to dietary outcomes. It may be however that the findings reported from these studies might be associated with whether exposures to the food environment are assumed or measured. For example, while one study found no associations between dietary intake and supermarket availability in the activity space⁴⁴, another reported that greater accessibility of supermarkets in the residential neighbourhood was associated with healthier dietary behaviours³³⁴. Further, Zenk et al. showed that fast food outlets in the activity space, but not the residential neighbourhood, were associated with dietary intakes⁴⁴.

Given that there is good evidence that most people travel outside their neighbourhoods to conduct their daily activities^{2 196 335} it is of concern that assumed exposures are typically based on some measure of distance around home. Indeed, amongst a sample of 131 participants of a variety of ages, Zenk et al⁴⁴ found that the environmental features of the residential neighbourhood were generally only weakly associated with those actually encountered in the daily activity space. This implies that the food environment of the residential neighbourhood may be a poor proxy for that which individuals are actually exposed to. Because people are mobile, it has been argued²⁹⁰ that multiple exposures should be accounted for to assess the relation between food environments and health outcomes and to better capture human behaviour.

The notion of ‘foodscape’³⁹⁻⁴² is increasingly being used within health promotion, public health nutrition and food studies as a tool to describe food environments and to assess the potential impact on food choice and food behaviour; it generally represents the multiplicity of sites where food is found and/or consumed. Geographic information systems (GIS) software and global positioning systems (GPS) have enabled a significant expansion of research on foodscape exposure and implications for dietary related behaviours. GIS based exposure measures commonly use store density using buffer (i.e. a zone around a map feature) distances or proximity to the nearest food store to operationalize food access, although finding appropriate and consistent criteria for defining geographic boundaries has proved challenging⁸².

Lately, researchers have started making use of GPS tracking, which can produce a more nuanced understanding of the role that the food environment plays in health and health related behaviours. However, its application comes largely from physical activity research^{284 286 287}, with very little from the food and diet area^{44 80 290}. The application of these technologies provides new possibilities to gain insight into the interactions between the presence of neighbourhood resources and their use for dietary behaviours, and combining GIS and GPS can provide an opportunity for future research to evaluate the complex relationship between the environment and location-based behaviours^{84 336}.

In Chapters 3 and 4 associations were examined between area level exposure to food and weight or diet. However in those studies information on the activity spaces of individuals was not available, and therefore it was necessary to assume exposures based on administrative census units (MSOAs) for Chapter 3 and home and school locations for Chapter 4. This study

expands the measurement of exposure to the foodscape by using data from the PEACH study (Personal and Environmental Associations with Children's Health), which provides an opportunity to look not only at food opportunities in the residential and school neighbourhoods, but also at the GPS recorded location of a cohort of children in Bristol, UK^{267 315 337}. In particular, PEACH provides the opportunity to examine exposures in the daily activity space that have been based on robustly cleaned GPS data with the help of a computational algorithm which we presented in the previous chapter. Building on the previous chapters, this study aims to evaluate if there is a difference in associations between dietary intakes or weight status in children with the use of assumed exposures to the food environment as compared to observed activity space.

Methods

Study population

PEACH is a longitudinal study undertaken in Bristol, UK which investigates how the environment can influence physical activity and dietary behaviours in children as they transition from primary to secondary school. The PEACH study's methods are described in more detail elsewhere³³⁸. In our analysis we included data for the years 2007/8 and 2008/9 for secondary school (Year 7) children who were 11 to 12 years old. In total, 953 participants from 29 secondary schools participated in the second phase of PEACH. The work presented here includes data for 688 children in their first year of secondary school who provided valid GPS data, which included those who had GPS recordings for any given period of time- the other 265 who were excluded from the present analysis had poor device wear compliance, or did not provide any GPS. Only children who lived or attended a school in the city of Bristol and up to 1 km outside its borders were included in the analysis.

Measures

Children provided a maximum of 4 days of GPS data, although not all children wore the GPS for the requested 4 days. Data collection took place during school term-time. Because children of this age would not be exposed to the environment around school during the school day, the periods of measurement were the morning commute to school (8am-9am), evening after school (3pm-10pm) and weekend (8am-10pm) periods. The GPS device used (Garmin Fortrex 201) recorded latitude-longitude coordinates at 10 second intervals and the precise date and time whenever there was sufficient satellite signal. Out of the 688 sample of interest,

626 children provided GPS data for the evening, 319 for the morning and 311 for the weekend. The compliance was better in the evening because some children forgot to switch on the GPS device in time to capture the before-school window, and the recording period was less influenced by a GPS cold start, which is a period after initial GPS switch-on during which time the unit is searching for the satellite signal and location is thus unavailable. The children were also asked to complete a diet screener (see Appendix 7.1), which recorded self-reported eating and lifestyle behaviours.

The variables generated for these analyses are described in Table 7.1. The outcome variables of interest were usual daily consumption of 'healthy food', 'unhealthy food', 'fast food or takeaways' as well as BMI. The food intake outcomes were derived from the diet screener. The recorded values in the screener were ordinal variables representing frequency of consumption of 15 different food/drink items per day or per week depending on food item. The food items of interest for this study were standardised into average frequency of portion consumption per day, allowing comparable outcome measures to be generated. The measure of 'healthy food' included fruit portions, vegetable portions and fruit juice; 'unhealthy food' included fizzy drinks, squash, sweets, biscuits, chocolate or crisps; and fast food included fast food or takeaways, as stated in the screener, and chips (fries). The development of these typologies was based on the evidence from the literature^{54 81 216 339}. A secondary outcome of interest was BMI (body mass index), available for each child. This was anthropometrically measured, based on height and weight measures collected by researchers using digital scales and a stadiometer (SECA) and standard methods (indoor clothing, shoes removed)³¹⁵.

Table 7.1. Descriptive statistics of sample, outcomes and explanatory variables

	Overall	Boys	Girls	<i>p-value for diff by sex</i>
N (%)	688	309 (44.9%)	379 (55.1%)	
Individual characteristics of sample:				
BMI, mean ± SD	19.31 ±	18.92 ± 3.45	19.64 ± 3.91	0.58
Age, mean ± SD	12.00 ±	12.00 ± 0.37	12.01 ± 0.39	0.63
IMD, mean ± SD	25.52 ±	25.03 ± 16.60	25.93 ± 16.61	0.21
Physical activity (counts per minute)	558.74 ±	614.94 ±	514.421 ± 168.35	<0.001
Ethnicity, % white:	87.4	89	84.9	0.08
Food preference, % strong preference				
- Fruit and vegetables	70.7	69.3	71.8	0.67
- Unhealthy food	70.9	74.4	68.3	0.16
- Takeaways	72.9	75.8	70.8	0.22
% of carers who regularly eat*:				
- Fruit and vegetables	84.2	80.0	87.3	0.08
- Unhealthy food	8.0	10.2	6.3	0.28
- Takeaways	15.8	19.1	13.4	0.10
Food intake outcome variables (daily portion consumption):				
Daily healthy food consumption, mean ± SD	6.48±2.65	6.50±2.63	6.45±2.66	0.89
Daily unhealthy food consumption, mean ± SD	2.91±1.17	2.88±1.20	2.94±1.15	0.47
Daily fast food consumption, mean ± SD	0.48±0.34	0.47±0.36	0.48±0.32	0.25
Primary <u>individual</u> food exposure variables (percentage of time spent within 50 meters of food outlets, out of overall time) where people can purchase:				
Healthy food				
% highest exposure (more than 0.20 %)	17.6	17.2	17.9	0.25
% middle exposure (less than 0.20 %)	17.0	14.6	19.0	
% no exposure	65.4	68.3	63.1	
Unhealthy food				
% highest exposure (more than 0.42 %)	27.8	25.6	29.6	0.51
% middle exposure (less than 0.42 %)	27.8	28.5	27.2	
% no exposure	44.5	46.0	43.3	
Fast food				
% highest exposure (more than 0.28 %)	23.8	23.6	24.0	0.59
% middle exposure (less than 0.28 %)	26.3	24.6	27.7	
% no exposure	49.9	51.8	48.3	
Primary <u>assumed</u> food exposure variables (density of food outlets within 800 meter buffers around the home):				
Healthy food				
% highest exposure	37.4	39.1	36.0	0.71
% middle exposure	37.2	36.1	38.2	
% no exposure	25.3	24.8	25.8	
Unhealthy food				
% highest exposure	47.0	47.6	46.5	0.30
% middle exposure	47.0	44.9	48.7	
% no exposure	6.0	7.5	4.8	

Fast food				
% highest exposure	45.0	43.9	45.9	0.88
% middle exposure	45.0	45.9	44.2	
% no exposure	10.0	10.2	9.9	
Primary <u>assumed</u> food exposure variables (density of food outlets within 800 meter buffers around the school):				
Healthy food				
% highest exposure	21.6	20.8	22.2	
% middle exposure	20.9	21.9	20.1	0.83
% no exposure	57.5	57.3	57.7	
Unhealthy food				
% highest exposure	36.9	35.0	38.4	0.60
% middle exposure	36.8	36.9	36.6	
% no exposure	26.3	28.1	24.9	
Fast food				
% highest exposure	23.1	22.7	23.4	0.87
% middle exposure	37.3	38.5	36.3	
% no exposure	39.6	38.8	40.2	
Percentage of time spent in the 800 meter home buffers, mean \pm SD	0.07 \pm 0.10	0.08 \pm 0.10	0.07 \pm 0.09	0.81
Percentage of time spent in the 800 meter school buffers, mean \pm SD	0.05 \pm 0.07	0.04 \pm 0.07	0.05 \pm 0.07	0.16

Note: Abbreviations: SD: standard deviation; BMI: body mass index; IMD: Index of Multiple Deprivation. The reported **p-value** is for sex differences (if $p > 0.05$, the same distribution across gender): **Mann-Whitney U** test for Food intake outcomes, age, IMD; **T-test** for BMI across categories of gender. **ChiSquare** test for Food exposure and covariates/moderator variables. **Food exposure** predictors (both individual and assumed) have been split in **3 categories** as follows: zero frequencies, below median, above median (median of sub-sample without any zero frequencies). *Data is for the 499 children out of 688 who provided information on these food preference questions

Measures of the food environment exposure were computed in a Geographical Information System (GIS) (ArcGIS 10.0 (ESRI Inc, Redlands, CA, USA)) using the UK Ordnance Survey Points of Interest (PoI) dataset²¹³, a dataset that includes the precise location of 21 categories of food outlets. So that the nature of any associations between the two exposure methods often utilised could be compared (typical GIS exposures vs novel GPS based exposures) two types of exposure measure were calculated: *individual (activity space) exposure* using the data collected from the GPS, and *assumed exposure in the home and school neighbourhood* based on boundaries generated around home and school locations using GIS. Additionally, in order to compare the GIS vs. GPS –derived environments, the percentage of activity (i.e., time) spent within the GIS (home and school) neighbourhoods were also calculated (Table 7.1.).

The individual food exposure measure was defined as percentage of the measurement period time spent outdoors and not in a vehicle in the vicinity (within 50 meters) of food outlets, by outlet type, for each child. For the purposes of analysis, patterns of exposure during all the time periods (morning, evening, weekend) measured in PEACH were combined. This was done because the amount of time spent in the vicinity of food outlets was generally small, particularly before school. The denominator for these percentages was the total period (1 hour in the morning, 7 hours in the evening, 14 hours in the weekend) rather than the period for which a location was recorded in the GPS as the devices used did not operate within a building. The percentage of time spent within the home and school neighbourhoods were calculated in a similar way (i.e., percentage of time spent outdoors and not in a motorised vehicle spent within 800 meters of the home/school network-based buffers, for each child).

For the purpose of this study, the location of all food outlets in the Points of Interest data were mapped and grouped into categories corresponding to the food consumption outcomes of interest. As with the outcome measures, these groupings were based on evidence in the literature^{54 217 308}, as well as fieldwork visits made by the authors to a sample of outlets falling within each category. These were ‘food outlets where people can purchase healthy food’ which was computed to include markets, grocers, organic, supermarket chains and independent supermarkets; ‘food outlets where people can purchase unhealthy food’ including bakeries, delicatessens, confectioners, convenience stores and newsagents; and ‘food outlets where people can purchase fast food’ (fast food outlets, takeaways, fast food delivery services that also have an eat in option, and fish and chip shops). For the purposes of analysis these measures were transformed into three-category variables: no exposure (no time spent), middle exposure (less time spent), and highest exposure (more time spent), with the less and more time spent categories being derived using a median split.

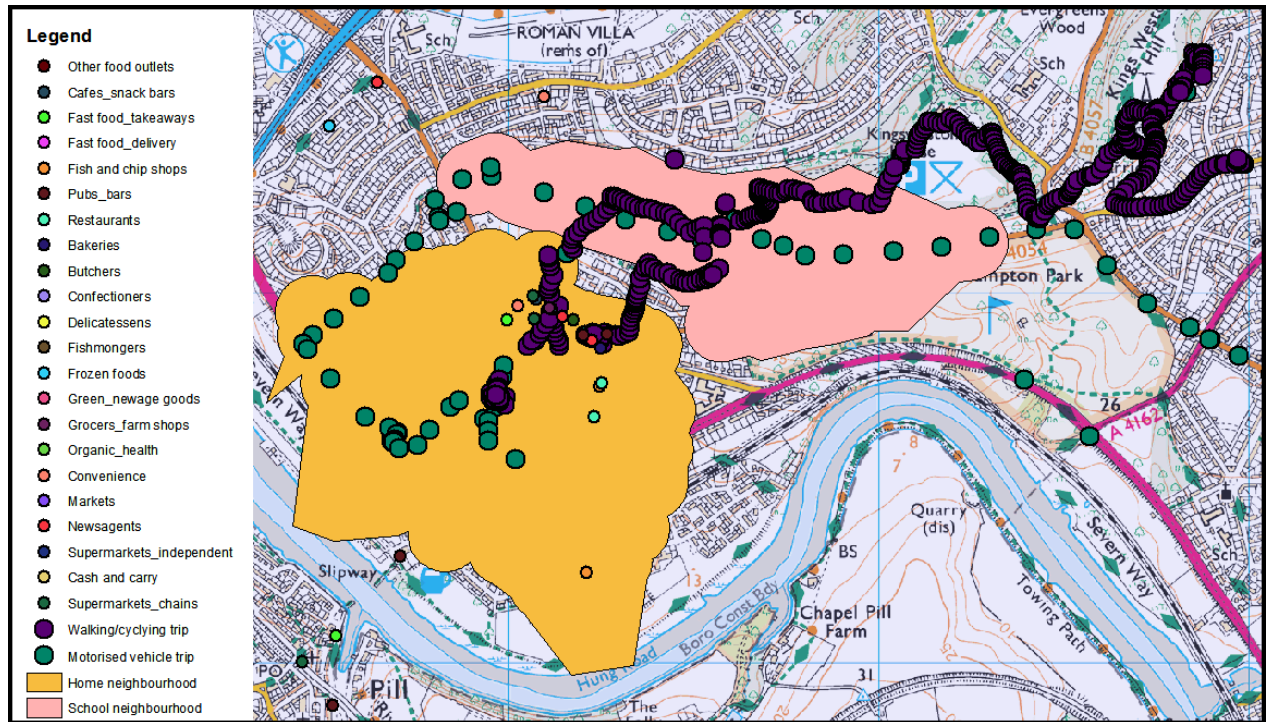
The assumed exposures to the food environment were calculated by buffering the home and school locations, identified using postcodes, in ArcGIS by 800 metres along the road network and counting the number of food outlets of each type that fall into these buffers. The 800 metre distance was chosen as this is equivalent to a 10 minute walk and has been commonly adopted in other studies^{2 43}. This was then divided per area in order to account for the fact that the buffers can vary substantially in area due to differences in the spatial structure of the road network. The assumed exposures are therefore expressed as number of outlets per km², based on previous practice in the literature⁴³. These were also transformed into three-category

variables derived using a median split: no exposure (no food outlets), middle exposure and highest exposure, with the middle and highest exposure being derived using a median split.

Examples of the GPS trips and home and school environments (anonymised) are shown in Figure 7.1. The motorised vehicle trips were not included in the analysis, as described in Chapter 6. In this example, this fictional participant spends 0.21% of their walking/slow cycling time near healthy food outlets, 0.79% near unhealthy food outlets, and no time near fast food outlet. There are 4.34 healthy food outlets per km², 4.34 unhealthy food outlets per km² and 3.26 fast food outlets per km² in this participant's home environment, but no food outlets in their school environment. Furthermore, 26% of the participant's GPS points fall inside the home neighbourhood, while 22% fall inside the school neighbourhood, so there is some overlap between the activity space and both the home and neighbourhood environments of this participant. These are equivalent to the participant spending 0.07% of their outdoor time inside the home neighbourhood, and 0.02% inside the school neighbourhood.

A number of covariates were also collected for use in the statistical analyses (Table 7.1). These were age, gender, ethnicity, physical activity (the latter was adjusted for only in models with BMI as the outcome) and area deprivation (English Index of Multiple Deprivation (IMD) 2007 score- which included all domains of the index)³⁴⁰, an area based measure of material deprivation, which was used as a proxy for social class, because individual data on parental education and household income was missing for half the sample.

Figure 7.1. Example of GPS trips (large purple dots: walking/slow cycling trips; large green dots: motorised vehicle trips) and home (blue 800 network buffers) and school (purple 800 network buffers) environments. The smaller multi-coloured dots represent the different food outlet types in the environment. © Crown Copyright/database right 2015. An Ordnance Survey/EDINA supplied service.



Statistical analysis

Percentage of time spent near food outlets and inside the home and school neighbourhoods were calculated using SPSS (version 21, IBM Corp, Armonk, NY, USA), STATA (version 13, StataCorp LP, Texas, USA) and Excel (2010). Associations between the food intake and weight outcomes and the three food exposure predictors were investigated in SPSS (version 21, IBM Corp, Armonk, NY, USA). In order to investigate how similar the activity space and assumed measures of food environment exposure were, we examined inter-method reliability using Pearson's correlation coefficients. Linear regression models were then fitted to examine the relationship between exposure to the food environment (both assumed and activity space) and the food consumption and BMI variables. These were examined unadjusted, as well as adjusted for the various covariates. Lowest category of exposure (no exposure) was considered the reference category in the regression models. The unadjusted and adjusted associations between the outcomes and measures of the food environment were represented using error-bar plots and tests for trend across the three food exposure categories.

Because the impact of any environmental exposures might be moderated by food preference of both the child and their carers, interaction effects for exposure to the food environment and food preference, as well as carer consumption, were tested for. Due to the fact that children measured in the earliest phase of PEACH data collection were not asked questions regarding food preference and frequency of consumption of carers in the diet screener, 189 of the 688 children were missing this information. Therefore, interaction effects could only be tested for the subsample of 499 children who provided this information.

Results

The sample was heterogeneous in terms of area level deprivation (IMD), but not ethnicity or affluence, with the majority of children coming from a white background (87.4%) and a middle or high income family (77.6%) (Table 7.1.). Girls had 0.3% missing data on food intake, and boys had 0.3 % missing data on age. There was 0.8% missing data for girls and 1.3% for boys on ethnicity, and 7.7% missing data for females and 10.7% for males on physical activity. There was however substantial missing data on parental education (48.2% for boys, 52.2% for girls) and household income (48.9% for boys, 50.9% for girls). Parents who did not report education or income were those coming from more deprived areas. Forty one of the children in the second year of data collection (2008/9) moved house, however only the fact that they had moved was recorded, not the new address. This has prevented us from calculating home postcode IMD scores, as well as home assumed food environment exposure measures for those children. Ninety five children attended schools outside the Bristol study area, and therefore school assumed exposure measures were not calculated for them. In order to avoid further loss of sample, values for the 41 participants missing information on IMD were imputed to the mean value (25.52), based on previous practice in the literature⁶⁵. As a result of the missing data, the final samples in the tested models were as follows: with diet as outcome, there were 679 for individual exposures, 641 for assumed home exposures, and 584 for assumed school exposures. For BMI as outcome, the final number of children included was 619 for individual exposures, 584 for assumed home exposures, and 536 for assumed school exposures.

Before any cleaning there were 366432 GPS locations provided by the children, which were reduced to 302047 after removing GPS points according to the cleaning algorithm (17.6% of original data removed). Compared to children excluded from the analysis due to not providing GPS data, included children were more likely to be male, live in a less deprived area and have lower BMI.

Bivariate correlations between the continuous measures of individual and assumed exposures to the food environment were generally weak in strength. For healthy food, the correlation between individual exposure and assumed home exposure was $r=0.100$ ($p<0.05$), and with assumed school exposure it was $r=0.007$ ($p=0.87$). For unhealthy food, the correlation between individual exposure and assumed home exposure was $r=0.042$ ($p=0.29$), and with assumed school exposure it was $r=-0.032$ ($p=0.44$). Finally, for fast food, the correlation between individual exposure and assumed home exposure was $r=0.022$ ($p=0.58$), and with assumed school exposure it was $r=-0.011$ ($p=0.80$).

Unadjusted trends in association between the exposure measures and reported food consumption and BMI are shown in Figures 7.2. and 7.3. respectively. Before adjustment, there was no significant trend in either food consumption or BMI over the individual food exposure categories. There were however some trends, albeit sometimes counterintuitive, for the associations with assumed food exposures; consumption of unhealthy food outlets decreased with increasing exposure to the relevant food outlets in the home and school environments. Similarly, consumption of fast food decreased with more exposure to fast food outlets in the home environment. No trend was clear for exposure in the school environment. For BMI the only statistically significant trend was counterintuitive; lower BMI was associated with higher assumed exposure to fast food in the home environment.

Figures 7.4. and 7.5. show associations after adjustment for covariates. Again, there was no significant trend in either of the outcomes across the individual food exposure categories. Similar counterintuitive but statistically significant trends were observed for the assumed exposure measures.

There was some evidence of effect modification by food preference and carer consumption in the assumed exposure models, but not in the individual exposure models. However, again trends were unclear (Figure 7.6.). For children reporting some preference for fruit and vegetables, more exposure to healthy food outlets around the home was associated with more consumption of fruit and vegetables, but no trend was clear for the strong preference group. Conversely, for children whose carers sometimes consume takeaway food, more exposure to fast food around the home was associated with less consumption of fast food or takeaways. There was also a statistically significant interaction between carer consumption of fruit and vegetables and density of food outlets around the school, but again trends over categories of food exposure were not clear.

Figure 7.2. Unadjusted associations between food exposure and food consumption (mean portions per day, error bars with 95% Confidence Intervals); test for linear trend across food exposure categories (* p<0.05; ** p<0.01)

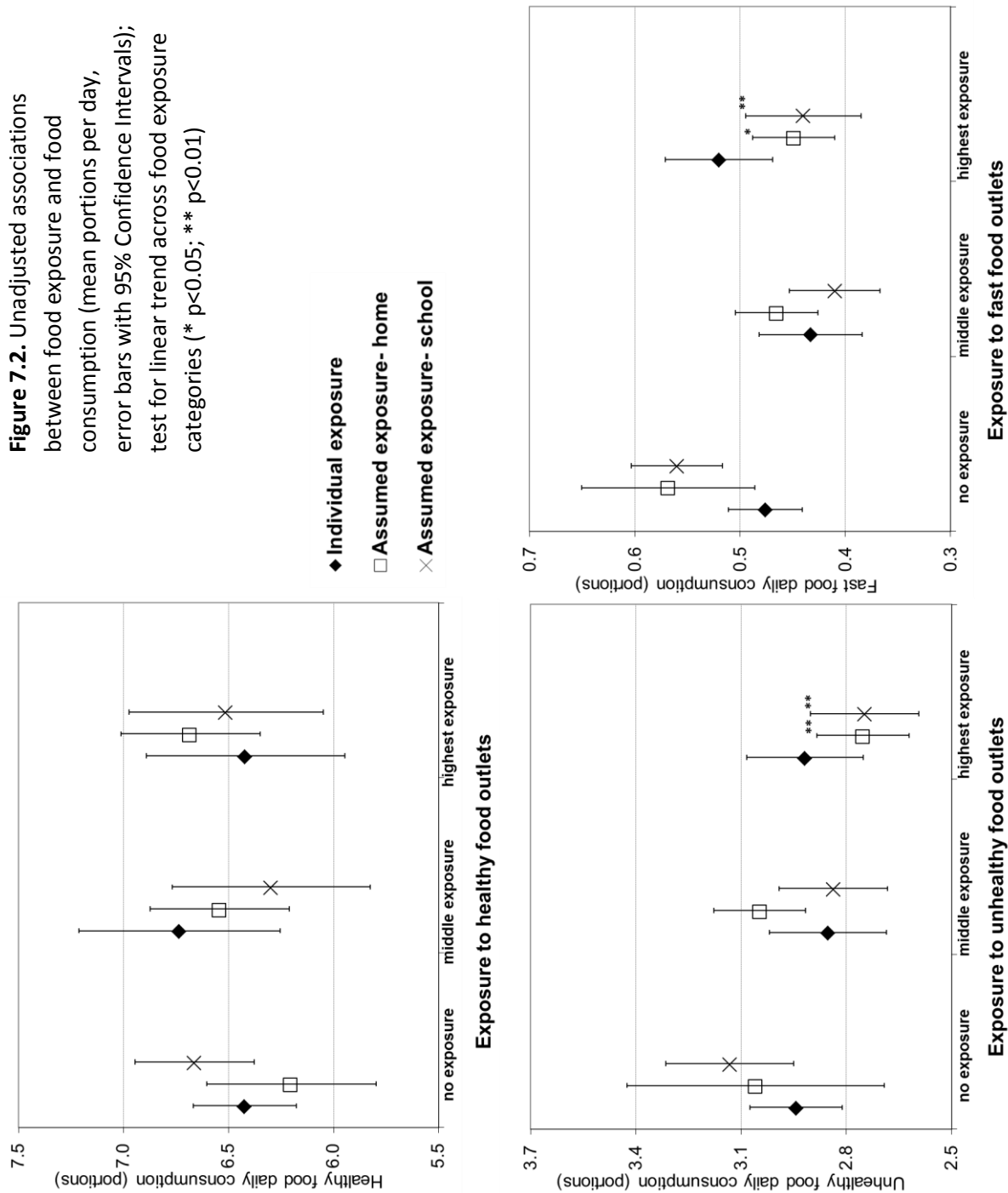


Figure 7.3. Unadjusted associations between food exposure and BMI in children (mean kg/m², error bars with 95% Confidence Intervals); test for linear trend across food exposure categories (* p<0.05)

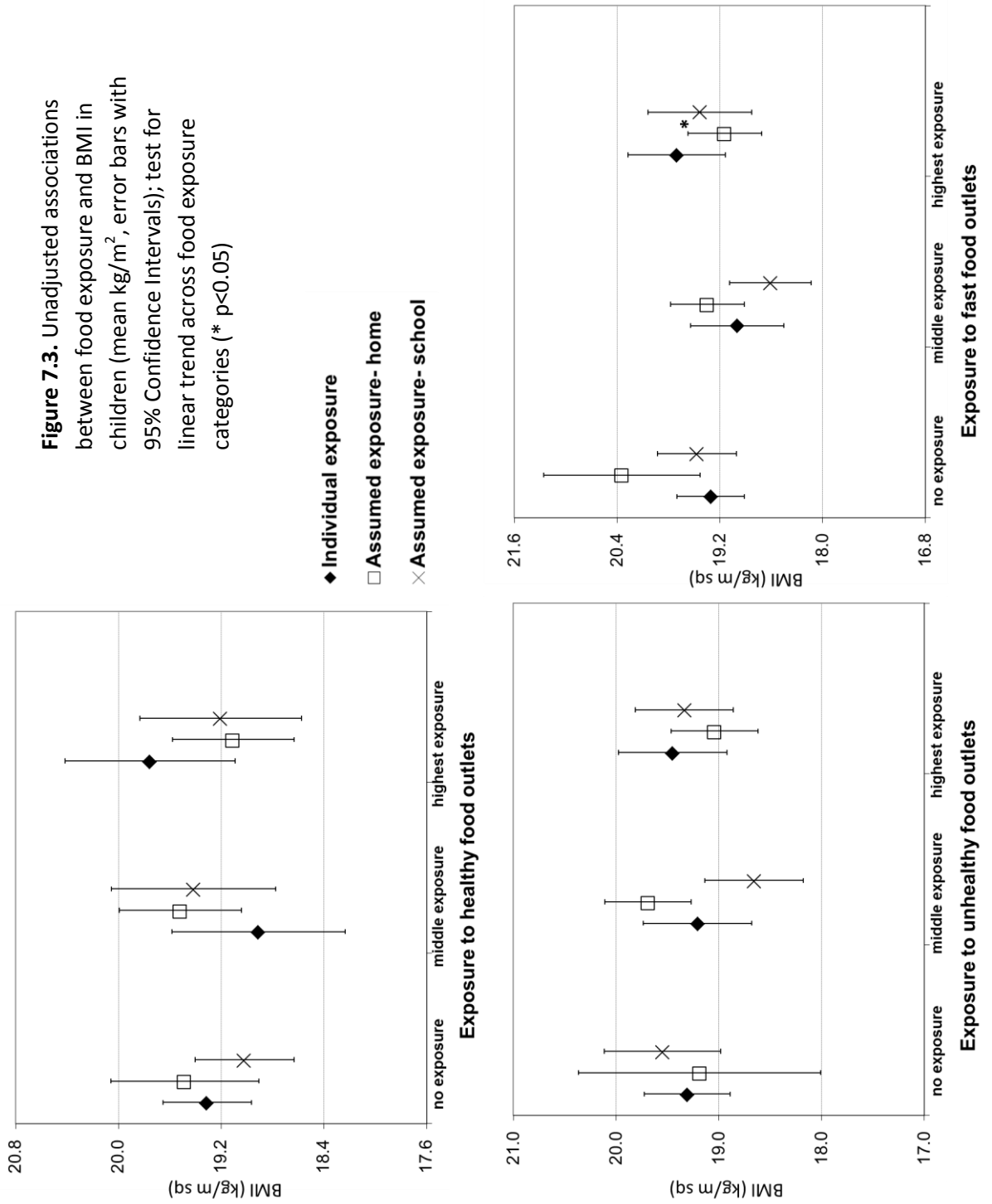


Figure 7.4. Associations between food consumption in children and exposure to the relevant food outlets, after adjustment for characteristics of the child and area (age, gender, ethnicity, deprivation); Error Bars with 95% Confidence Intervals; test for linear trend across food exposure categories (* p<0.05; ** p<0.01)

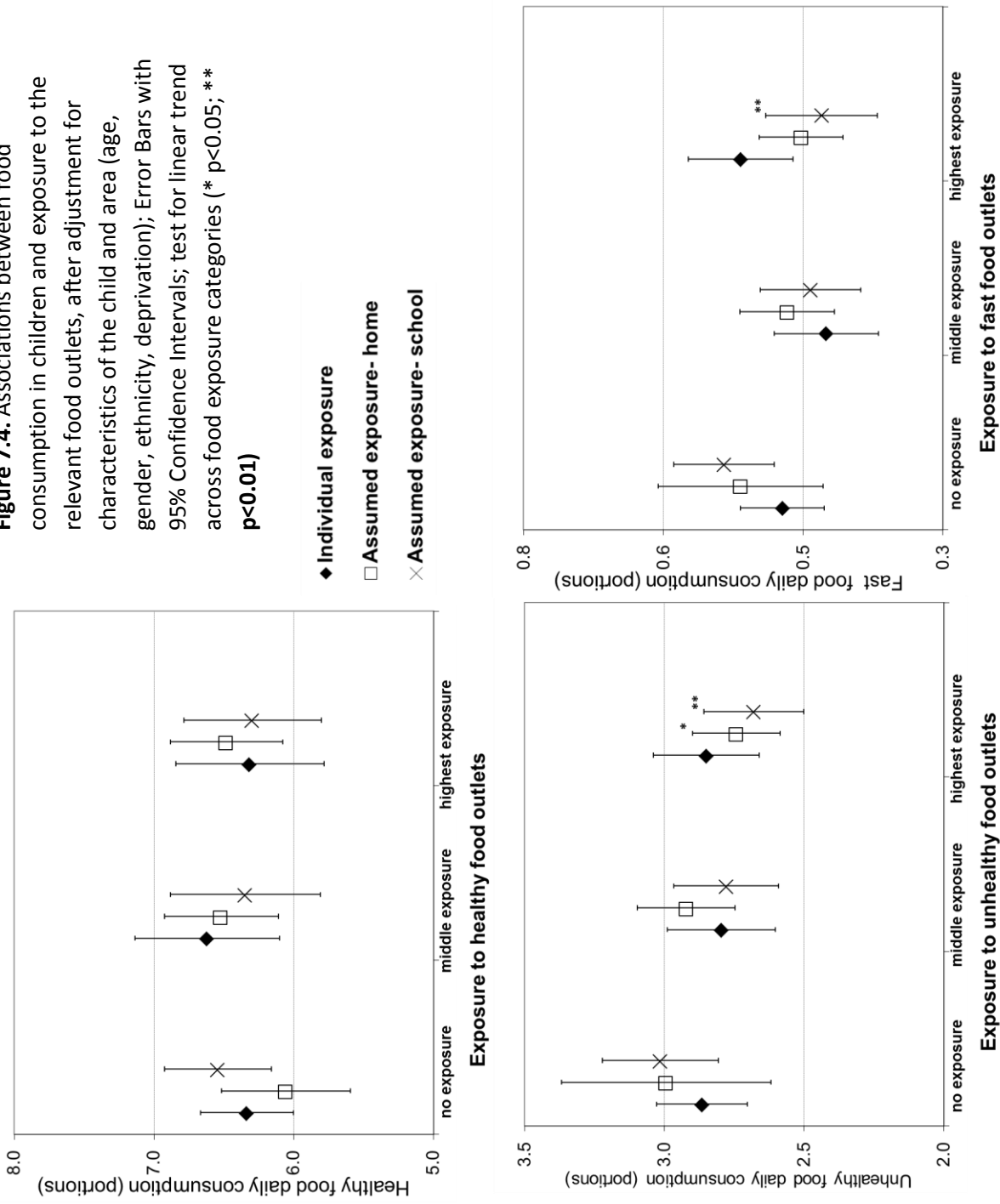
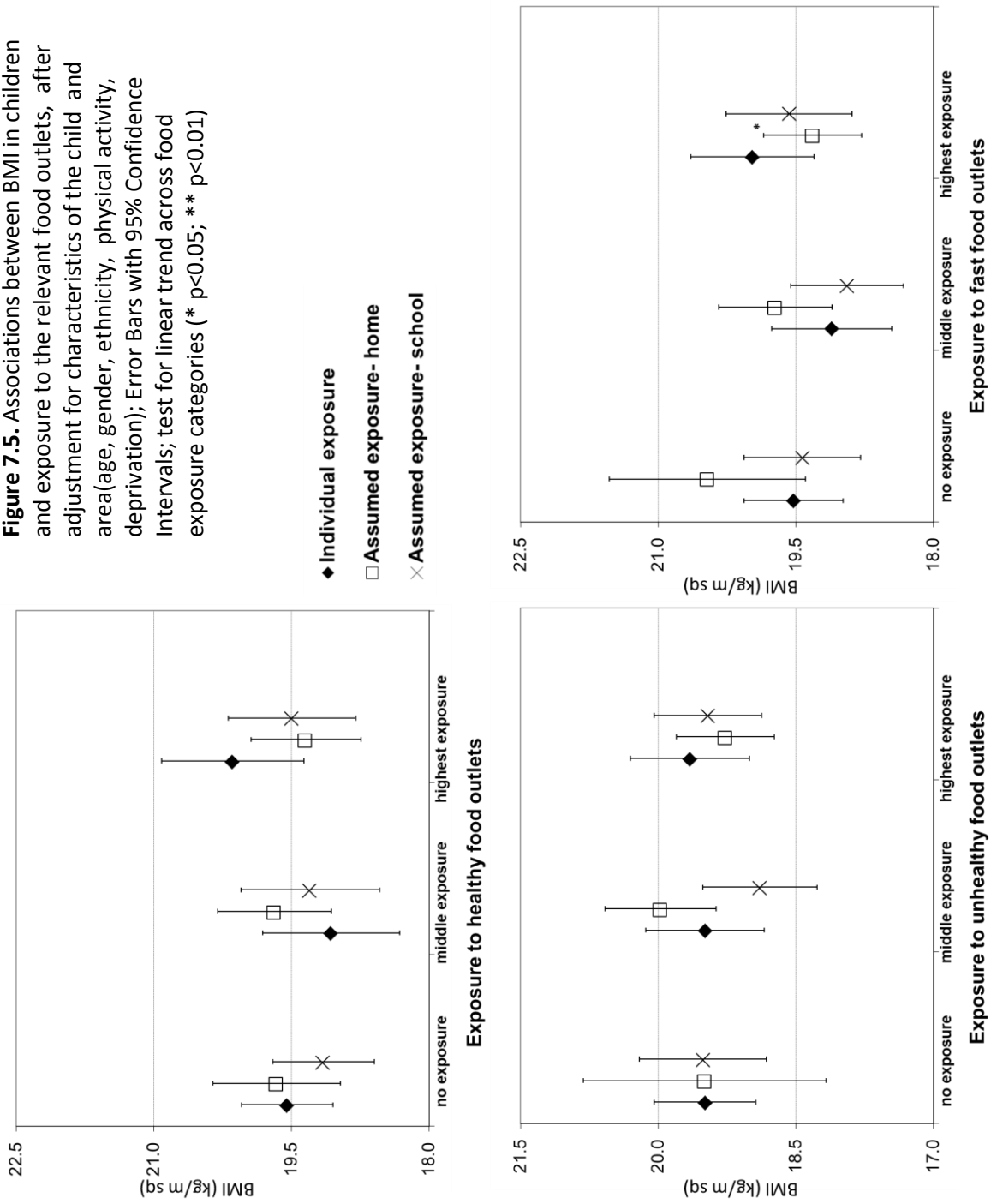


Figure 7.5. Associations between BMI in children and exposure to the relevant food outlets, after adjustment for characteristics of the child and area (age, gender, ethnicity, physical activity, deprivation); Error Bars with 95% Confidence Intervals; test for linear trend across food exposure categories (* $p < 0.05$; ** $p < 0.01$)



Discussion

This study explored whether there is evidence of an association between activity based and area based use of the food environment and dietary behaviours and weight in older children. In concordance with findings from a limited number of other studies^{44 80}, this study found that assumed exposures in the residential/school neighbourhood correlated weakly with measured exposures in the GPS-based activity space, which was supported by the fact that the study participants spent only 0.07% and 0.05% on average of their daily time outdoors near their homes, and schools respectively. Overall, this study does not clearly support the hypothesis that personal proximity to food outlets that sell particular types of food is necessarily associated with more consumption of those food items or with BMI, an assumption which might over-simplify the interdependence between individuals and their environments. Indeed where associations were detected, they tended to be in a counterintuitive direction. There was some evidence of an interaction between assumed exposure to food in the home and school neighbourhoods and food preferences of children and carer consumption, although the direction of this effect was not clear. More work is therefore needed to disentangle individuals' interactions with the food environment and weight-related outcomes.

Strengths and limitations

Study strengths include the use of a large well-characterised sample of individuals and the development, and subsequent comparison, of both assumed area based exposure measures and those recorded from a GPS. The measure of BMI used was also measured anthropometrically rather than being based on self-report. A data cleaning algorithm was also developed to identify times when children were outdoors and not travelling in a vehicle, thus refining the specificity of measurement of exposure to the food environment.

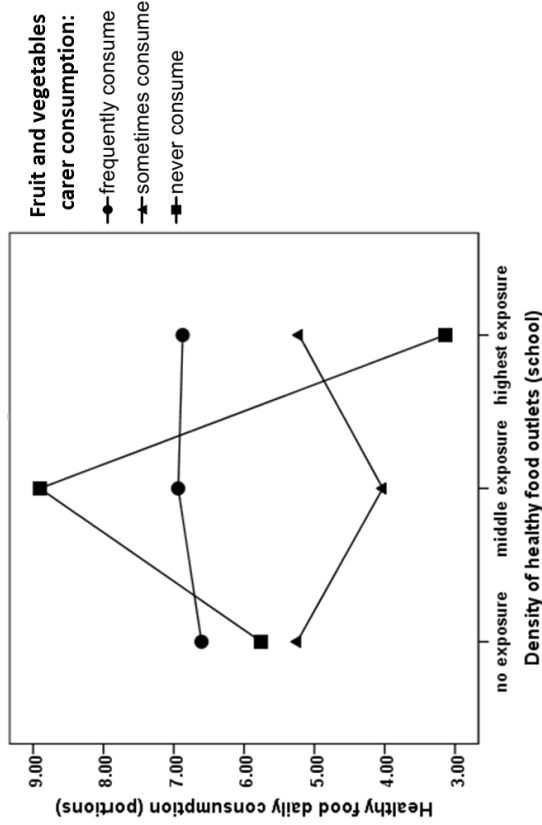
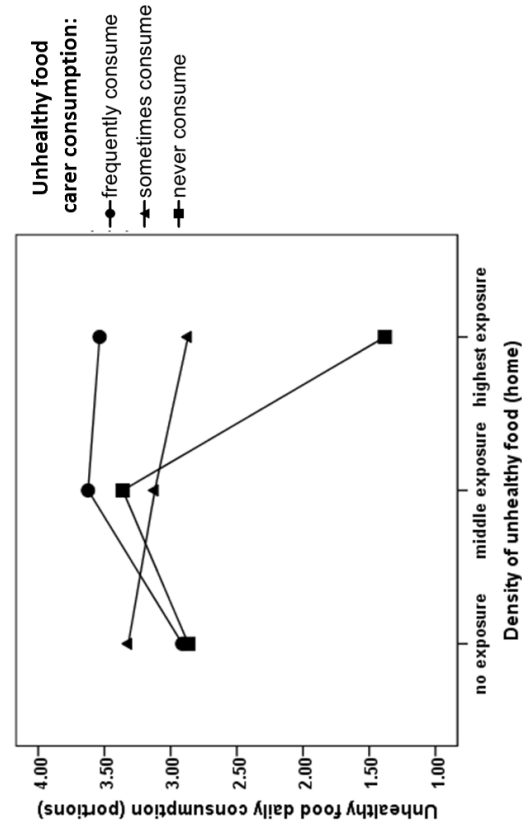
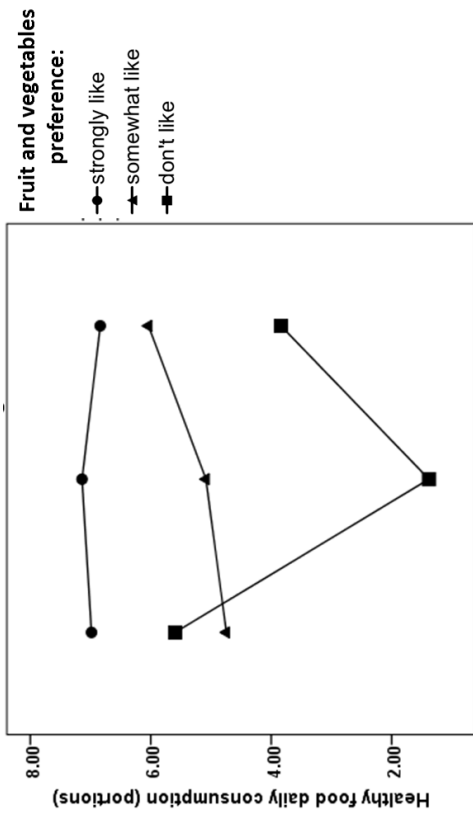
As with Chapters 3 and 4, sensitivity analysis was performed for all models by additionally controlling for exposure to the other remaining types of food outlets, in order to estimate the effect of each controlling for the other and account for food environment 'context', based on previous practice in the literature¹¹⁷ (results not presented here). However, just like with chapter 4, some associations were attenuated when doing that. This could mean that the effect of exposure to food on diet and weight might be to some extent associated with the availability of outlets of any type rather than solely down to one particular type of food outlet, such as those selling fast-food. This may be especially so in cities such as Bristol, where food

outlets tend to be concentrated in certain areas of the city. These potential effects cannot be clearly disentangled here due to the fact we only have a proxy measure of the actual use of outlets that is based on time spent in their vicinity.

This study has limitations and the findings should be interpreted within their context. One limitation is the considerable amount of missing data for SES, which meant that it was only possible to adjust for area level deprivation. A particular limitation associated with the use of GPS data is that whilst it is possible to tell if the wearer of a GPS unit has been in the vicinity of a food outlet, it is not possible to determine if they actually entered the outlet. Therefore it was assumed that any GPS points falling within 50m of an outlet constituted ‘exposure’. In order to test the sensitivity of the findings to this assumption, analyses were repeated using 3 additional different distances 10m (the more immediate food environment) and 100m and 200m (the wider food environment). However there was no substantial difference in findings, so only the results for the 50m assumption are presented here. A further consideration is the fact that many participants lived near to their schools (60% lived within 1 km), and hence many school and home neighbourhoods overlap. A consequence of this is that there will be some double-counting of the same food outlets when comparing the two measures.

Whilst the classification was based on common practice within the literature plus visits to actual food stores, a limitation of the nomenclature used, which is common to many studies using food store data, is the lack of assessment of the validity of the classification of food stores as healthy or unhealthy. Findings in the literature are equivocal regarding the classification of supermarkets as ‘healthy outlets’, as they also carry a large variety of unhealthy food; one study in the US³⁴¹ for example reported that in comparison to convenience stores supermarkets had a much greater display of energy-dense foods. Therefore, categorising supermarkets as ‘healthy’ may be misleading in certain contexts. Furthermore, the location of food outlets has not been validated, therefore it cannot be said with certainty that the food stores are actually there. Nevertheless, recent evidence suggests that the Points of Interest database we used provides an adequate representation of the food environment²¹⁵.

Figure 7.6. Statistically significant interactions between food exposure and food preference or carer consumption of food after adjustment for covariates (gender, ethnicity, age, deprivation); portions of food represent estimated marginal means



Another limitation is that while more nuanced measures of individual exposure than many other studies were adopted, no information on actual purchase or use of food was available and the measures of food intake were based on overall frequency of consumption rather than a time specific diet diary. Indeed, being in proximity to a food outlet will often not result in a purchase of food from it. Going forward, the novel approach of using GPS to determine food exposure creates the opportunity to explore different methods for measuring the relationship between the individual and their environment using techniques such as momentary assessment³⁴² of food purchase or consumption. One consideration is that, while it has been debated^{276 343} how many days of GPS tracking should be sufficient in order to capture regular food purchasing and consumption behaviour patterns^{17 45}, to date there is no gold standard to validate this against. Despite the objectivity and precision of GPS tracking data, a drawback is that environmental determinants of chronic health outcomes may not be representative when assessed over a short period; even if four or seven days are more informative than mobility data over one day, this period will be insufficient to capture elements such as the seasonality of mobility habits³⁷⁸. While classical surveys assess behaviour over longer periods compared to GPS tracking, they are nevertheless based on participant recall and therefore only provide declarative data. In the PEACH study, the GPS trackers only recorded for four days due to battery life: the older Garmin Foretrex device used at the time have lower battery life than newer GPS devices such as Qstarz. Nevertheless, seasonality was captured in this sample, as the different schools were measured across the year (from November and December 2007, January to December 2008 and January to July 2009), so each season was represented.

This study was based on the location of postcodes rather than actual building addresses, although in an urban area such as Bristol it is likely that any geographical disparities in location will be small. A potentially greater limitation is that, being an urban area with densely packed food outlets, low heterogeneity in exposures to the foodscape associated with ubiquity of outlets selling food in Bristol might limit power to detect associations. Finally, given the complex interdependence between individuals and their environments, it is possible that one of the reasons why some associations are found, albeit largely in a counterintuitive direction, at an area but not at an individual level is down to residual confounding related to characteristics of the area.

Points for future research

It has been argued that the failure to take into account spatial polygamy (an individual's interaction with multiple geographic places) is one of the main limitations of much of the literature on the neighbourhood environment and health⁸³. While GPS may be useful to advance environmental exposure assessment by accounting for daily mobility patterns, it can however lead to analytical biases related to selective daily mobility, which might preclude causal inference⁸⁴. Selective mobility refers to the fact that individuals who want to consume a particular type of food will seek out environments with higher concentration of that food type in order to obtain it. As a consequence in terms of the development of dietary interventions based on GPS measures of the foodscape is that the direction of causation linking a given exposure to a given health outcome or behaviour is unclear. By recognising that exposure measures that reflect actual behaviour can thus generate bias, it has been suggested that future research should investigate whether the actual use of resources mediates relationships between the potential access to resources around daily activity locations and weight-related behaviours⁴⁴.

Integrating GPS objective data with declarative data from electronic mobility surveys may help correct exposure measures and provide complementary information for an improved contextual understanding of exposure⁸³. While studies have tended to incorporate surveys on habitual food shopping and dietary behaviours^{80 81}, future work would benefit from a better developed survey tools for retail food purchasing data, choice of food venue or inside-venue food availability and quality. For example, availability of healthy food may differ substantially across the same type of stores located in different neighbourhoods^{344 345}.

An important factor when investigating exposure in children is that they often access food through their parents, who purchase it. Although the children in this sample were old enough to be independently mobile, it may be that the neighbourhood food environment influences what parents choose to purchase and feed their children, or that the family environment may be more important in influencing the food behaviours of children than the built environment. It is not always easy to separate the extent to which the influence of an adult is operating through the role of 'gatekeeper' or directly³⁶ and further work using GPS in paired samples of children and their parents may provide the opportunity to disentangle this. This has been done in studies looking at physical activity and would benefit work in the diet field³⁴⁶.

Conclusion

This study is one of the very few studies to take into account both assumed neighbourhood exposure and actual exposure, measured according to GPS tracking, in attempting to advance understanding the food environment and its association with diet and weight. We found few associations to suggest that exposure to the local retail food environment in children was associated with either food consumption patterns or BMI. Given the complex relationship between the individual and their environment, accurate and appropriate assessment of environmental exposures is needed in order to prioritize public health interventions and disentangle the most important determinants of health. In this case it may be that exposure to the food environments of parents are more important than those of children.

Chapter 8

General discussion

Introduction

This thesis has examined the associations between exposure to the food environment and diet and weight in children. The work undertaken attempts to advance understanding on these associations by exploring how different measures of exposure at varying scales might lead to divergent findings. There has been a large increase in the volume of research on the food environment over the past decade, which has led to recommendations by scientific panels and policy makers in favour of a healthier food environment as a strategy for dealing with the current obesity epidemic. Children have been a particularly important population group for targeting interventions, as improving behaviours early in life has long-term positive consequences later in life, and the food environment has a different importance in children than in adults. Children from lower SES households and communities are a group particularly vulnerable to the obesogenic environment, and this thesis also investigates the influence of social-class.

This final chapter draws on the findings from the previous chapters and considers strength of the evidence of the predictors studied on children's diet and weight. The overall implications of the research findings are discussed and recommendations for future research made.

Summary of principal findings

Chapter 2 presented a conceptual framework based on a system map which was developed as part of a scoping review of evidence on food-related determinants on diet and weight. The framework collated evidence of key determinants of weight and diet from different environments people are exposed to, such as the production environment, the retail food environment, the larger macro-economic environment, the socio-cultural settings in which individuals are embedded, the home environment- which is particularly relevant for children, and the consumer environment- which includes individual-level factors. A theme that emerged was that children and low social-class populations are particularly vulnerable to the obesogenic environment and policy makers should give special attention to these populations. It was also identified that the influence of the retail food environment to which people are exposed on health-outcomes is a growing area of research where more evidence is needed. A

limitation of the literature is that exposure to the food environment is operationalised in different ways, and efforts should be made to decrease heterogeneity in measures in order to compare results across studies. The subsequent chapters of the thesis focus on this aspect.

In Chapter 3, it was found that in a large sample of English children, the prevalence of elevated weight status was positively associated with the presence of fast food and other unhealthy food outlets in the neighbourhood, whilst negatively associated with food outlets selling healthy foods. Furthermore, a greater number of unhealthy food outlets were located in more deprived areas. Associations were clear for older children, but less so for younger children. The number of unhealthy food outlets only slightly explained the previous observed association between weight status and deprivation in older children.

Chapter 4 investigated similar associations as with Chapter 3, but in a sample of older children in Norfolk. The added value was that information on weight and socio-economic status was available at an individual level, and additionally there was information on individual diet (derived from a food diary). The results found to be statistically significant were consistent with some of the findings from Chapter 3, whereby increasing exposure to unhealthy food around the home was associated with higher BMI. Additionally, increasing exposure to fast food around the home and school was associated with higher intakes of fast food and more energy dense diets, while increasing exposure to healthy food around the home was associated with higher fibre intake in secondary school children. BMI, food intake and access to food were generally patterned by socio-economic status (parental education).

In Chapter 5, a systematic literature review was conducted to examine how Global Positioning Systems (GPS) are being used to quantify exposure to food environments and relate this to dietary and weight status outcomes. The application of GPS to examine interactions between people and the neighbourhood food environment has been little studied. Since 2008 just 18 studies have been published employing GPS in the food environment area. It was identified that GPS is used not just to identify actual location of people (and linking that to diet, weight, and related behaviours), but also to identify actual location of food outlets (as an audit tool to characterise the food environment). The studies were generally only of moderate quality, reflecting significant variations and challenges in the methods and techniques used. In contrast to many cross sectional comparisons, findings from GPS studies suggest that poorer dietary behaviours or weight status is not necessarily associated with more time spent near unhealthy food outlets. There are lessons to be learnt from the body of

physical activity research, where the application of GPS is more developed, as mentioned in the introduction in Chapter 5.

Chapter 6 presented an algorithm for identifying travel mode and trips and removing signal noise from raw GPS data. The aim was to extract GPS points that represented on-foot and slow-cycling modes of transport in order to better measure true exposure to the food environment in Chapter 7, as it was hypothesised that children travelling in motorised vehicles would not have to opportunity to access food outlets. The exposure measures to the food environment calculated before and after cleaning the raw GPS data applying the method developed in this chapter were strongly correlated ($p < 0.01$) although absolute levels of exposure were overestimated in the raw data. This suggested that the level of exposure to the food environment of children in this study was similar when calculated on the raw GPS data to that calculated on the processed GPS data. That might be explained by the fact that children spend less time in vehicles than adults, which is reflected by the fact that only about 18% of the raw GPS data represented motorised vehicles and noise due to location imprecision associated with a poor satellite signal.

In Chapter 7, there was little evidence to suggest that GPS-based personal proximity to food outlets during on-foot or slow-cycling trips was associated with diet (derived from a diet screener) or BMI in older children from an urban area (i.e., Bristol). This may in part be because Bristol is a densely packed urban area which meant that there is likely low heterogeneity in access to food. There was some evidence of an association between school and home neighbourhood GIS-based exposure and diet or BMI, but the statistically significant associations were counterintuitive. There was also evidence of an interaction between assumed neighbourhood exposures and both children's and parents' food preference, but the direction of effect was not clear. Importantly, the GPS-based and GIS-based measures of exposure were weakly correlated. More research is needed on activity spaces in studies with greater heterogeneity in environmental exposures.

Strengths and limitations

The work presented in this thesis has a number of strengths and weaknesses, explained in detail in the Discussion section of each chapter. One of the strengths of this thesis is that it used data from three large samples of children at different spatial scales. Another strength is that weight status was objectively measured in all three studies presented (NCMP, SPEEDY and PEACH), not self-reported. However, information on individual BMI was only available

for the SPEEDY and PEACH studies; in NCMP it was aggregated at an area level as prevalence of overweight and obesity, in order to protect identity of children taking place in the study. Furthermore, data on diet and actual locations of individuals were not available for all three studies; rather, each study built on from the previous one by incrementally adding such exposure related information. The analysis presented in this thesis therefore offered the opportunity to investigate if measuring the food environment and diet in different ways at different spatial scales makes a difference in terms of associations with diet and weight in children.

Search of the literature revealed that the work presented here is the first to explore both GIS assumed neighbourhood exposures and GPS-based activity space exposures to the food environment in children, for whom the environment may have a different importance than for adults. The work included two literature reviews, the first one being comprehensive but not systematic. The aim was not to quality assess studies like for Chapter 5, but to review the available general scientific evidence of different determinants of diet and weight status and to unpick the most important ones and those where there is currently a gap in the literature. One of these was exposure to the retail food environment, which was explored in the rest of the thesis. As the focus of the thesis narrowed down towards Chapter 7, where traditional measures of exposure to the food environment were compared to newer GPS-based measures, a systematic review of studies using GPS to measure the food environment was presented in Chapter 5 as a precursor to the work that followed. It was decided to make this review systematic to fully explore the available scientific evidence and to evaluate the quality of studies. The work presented in this thesis is one of the few studies to also explore mediation models in these relationships. Investigators should aim to move beyond simply exploring the correlates of health outcomes in isolation, but also explore ways in which these factors operate together. Knowledge on how the food environment, diet, weight and socio-economic status may influence each other through mediation mechanisms is limited.

There were a number of limitations in this thesis. All three studies included were cross-sectional, and therefore causality cannot be inferred from the results. Furthermore, under-representation of obese children in Chapters 3 (NCMP) and 4 (SPEEDY) is likely to have limited the range of the weight status outcome variable, potentially attenuating the strength of the associations observed. It is also likely that low heterogeneity is present in the environmental exposure in the sample of children in Chapters 4 (SPEEDY) and 7 (PEACH), which may have limited the ability to detect associations with weight and diet. While the

SPEEDY study (Chapter 4) was designed to maximise environmental heterogeneity, the schools and homes were all located in the same county, possibly reducing the variability of some exposures. For the PEACH study (Chapter 7), it is believed that heterogeneity in exposure is likely to be lower due to the fact that the whole sample was drawn from a single English city, and the comparatively short travel times to food outlets compared to less urban localities. Moreover, there was also low heterogeneity in ethnicity in Chapters 4 (SPEEDY) and 7 (PEACH), with a low proportion of non-white pupils. This may limit the generalizability of the findings to more ethnically diverse populations.

It must also be noted that while the methods used to assess the predictors and outcomes were generally robust, they were not without their limitations. A limitation of the exposure measures used was that information on actual use or purchase of food was not available in any of the studies. Regarding assessment of diet, although doing so adequately plays a significant role in research on health and nutrition³⁴⁷, all measurement tools are limited by specific errors. One of the limitations of the dietary intake assessment tool used in Chapter 4- a food diary- is that it was not validated. Unweighed food diaries are subject to a number of potential errors, such as children experiencing difficulty in estimating portion sizes²⁶⁴ and under-reporting, which may vary by food type and is a problem in self-reported dietary assessment. Other limitations of the food diary are that they do not take into consideration the long-term variety of consumption and possible changes in dietary habits (because they are expensive to administer in large samples)³⁴⁷, and it requires highly motivated individuals³⁰⁷. The diet screener used in Chapter 3 also has limitations^{307 348 349}, one of them being that it only provided information on habitual intake of key food groups. Furthermore, both the food diary and the diet screener in Chapter 4, respectively Chapter 7, were based on self-report.

Implications of results and recommendations for future work

As recommended by two previous systematic reviews^{33 82}, refining the measures used to capture dimensions of the food environment is vital. Nevertheless, there has been limited progress in understanding the spatial extent of health-related behaviours in order to select the most appropriate space in which to measure environmental influences. This thesis has aimed to advance understanding on this.

As emerged from the literature reviews undertaken in Chapters 2 and 5, there is inconsistency in findings across studies regarding evidence of the influence of the food environment on diet and weight, which may in part be because of variability in measuring exposure to the food

environment²²⁹, in dietary assessment^{350 351}, or in measuring obesity³⁵². Such differences in measures means there is little comparability across studies^{5 17 32}. This is consistent with findings from this thesis, where some of the expected associations are found in Chapters 3 and 4, but not in Chapter 7, as can be observed in Table 8.1., which presents the associations detected between the different exposure measures and the outcomes used in this thesis. Indeed using different spatial scales and attempting different ways of measuring diet and the food environment is unlikely to produce consistent findings. Table 8.1. presents associations in older children only, as in Chapter 3⁵⁴ associations between prevalence of food outlets in the area and weight status were stronger in older children as compared to their younger counterparts, and in Chapters 4 and 7 only associations with older children were subsequently investigated.

A question that may arise is therefore whether more refined measures such as food diaries and GPS are needed in order to disentangle relationships between exposure to the food environment and weight status and diet, or are conventional neighbourhood-based environmental exposures and diet screeners/FFQs sufficient? The answer to this question is not straightforward, as it is challenging to disentangle the importance of each of these factors in uncovering associations: in Chapter 7, the ability to detect associations could have been limited due to using a diet screener rather than a food diary, or due to the low heterogeneity in exposure to food in this urban sample. This chapter further attempts to consider some of the implications of such different measures in the light of the findings in this thesis, as well as highlight some potential areas for future research.

Chapter 3 supports the hypothesis that higher exposure to unhealthy food environments is conducive to weight gain; the opposite is true for exposure to food environments that offer a higher variety of food choices, including healthy ones, but this association remains significant after adjustment only for younger children (not presented in Table 8.1.). However, the ecological area-based associations found in the NCMP study (Chapter 3) do not track through to the individual ones in the SPEEDY (Chapter 4) and PEACH (Chapter 7) studies. Some associations are found in SPEEDY to suggest that exposure to unhealthy food might be conducive to weight gain, and that exposure to fast food might be conducive to higher intake of fast food, but not in PEACH.

Table 8.1. Associations between exposure to the food environment and weight and diet (key food groups) in this thesis in older children after adjustment

Exposure to the food environment	Weight status		Diet (daily consumption of food (mean grams): food diary)- SPEEDY			Diet (daily consumption of food (average frequency of portion):diet screener)- PEACH		
	Prevalence of overweight/obesity-NCMP	Individual BMI- SPEEDY	Individual BMI- BMI- PEACH	Consumption of healthy food	Consumption of unhealthy food	Consumption of fast food	Consumption of healthy food	Consumption of unhealthy food
Counts in census neighbourhoods								
Healthy (mixed) food outlets	No association	Not available	Not available	Not available	Not available	Not available	Not available	Not available
Unhealthy food outlets	Positive association	Not available	Not available	Not available	Not available	Not available	Not available	Not available
Fast food outlets	Positive association	Not available	Not available	Not available	Not available	Not available	Not available	Not available
Density in home neighbourhoods								
Healthy (mixed) food outlets	Not available	No association	No association	No association	N/A	N/A	No association	N/A
Unhealthy food outlets	Not available	Positive association	No association	N/A	No association	N/A	N/A	Negative association
Fast food outlets	Not available	No association	Negative association	N/A	Positive association	N/A	N/A	No association
Density in school neighbourhoods								
Healthy (mixed) food outlets	Not available	No association	No association	No association	N/A	N/A	No association	N/A
Unhealthy food outlets	Not available	No association	No association	N/A	No association	N/A	N/A	Negative association
Fast food outlets	Not available	No association	No association	N/A	Positive association	N/A	N/A	Negative association
Percentage of time spent within 50 meters of food outlets								
Healthy (mixed) food outlets	Not available	No association	No association	No association	Not available	Not available	No association	N/A
Unhealthy food outlets	Not available	No association	No association	Not available	Not available	Not available	No association	N/A
Fast food outlets	Not available	No association	No association	Not available	Not available	Not available	No association	N/A

Note 8.1.: N/A= not applicable

This observation might be in part due to heterogeneity in exposure to the food environment: while in NCMP, which was conducted across England, there was high environmental heterogeneity in the exposures, low heterogeneity in exposures to food might have limited power to detect associations in SPEEDY, which was conducted in a predominantly rural area and in PEACH, conducted in an urban area with densely packed food outlets. The work undertaken in Chapter 7 is believed to be the first study in the UK to examine associations between GPS-based exposures and health outcomes in children; as found in Chapter 5, all GPS studies to date investigating exposure to food have been conducted in the USA, where the contrasts in urban design and neighbourhood segregation may lead to a different importance of the food environment compared to the UK²³; not surprisingly therefore, these studies have detected some associations with activity spaces, although they were conducted in adults, for whom the food environment has a different importance than for children, who are generally less mobile.

In densely packed urban areas such as Bristol, it might be challenging to disentangle if the effect of exposure to food on diet and weight might be to some extent associated with the availability of outlets of any type rather than solely down to one particular type of food outlet. This has been termed as the ‘inner-city paradox’, and it has been shown in an American study³⁵³ that BMI is lower in areas with higher population density, more mixed land uses, more access to transit and more commercial space. This is consistent with findings from Chapter 7, where a higher density of fast food outlets in home neighbourhoods is associated with lower BMI (Table 8.1.). Further work utilising qualitative methods in heterogeneous samples of different ages and from diverse geographical spaces (rural, urban) may be required to gain a better understanding on defining environmental exposures.

Given the complex interdependence between individuals and their environments, it is possible that one of the reasons why some associations are found in this thesis at an area level, but not at an individual level, is down to residual confounding related to unmeasured or poorly measured characteristics of the area (such as deprivation) or the child (such as parental influences). Associations, direct or through mediation mechanisms, with deprivation or social class were considered in this thesis. Chapter 4 supports the evidence gleaned in Chapter 2 that points towards a social-class gradient in weight, diet and access to food, which makes the case for further investigating such associations in low social class groups. It is noteworthy that associations were strong in this ecological analysis. The evidence is consistent with

assumptions in the literature³⁵⁴ that the local environment may be more important to those of lower social class.

There was little evidence in this thesis that the food environment may substantially mediate the association between deprivation and weight status, or that diet may mediate the association between exposure to the food environment and weight status. Such mediation pathways should be further explored by taking into account factors such as the role of parents. It could be that children do not directly interact with their food environment as much, but they do so mostly through their parents who make choices for them. It may be that the food environment influences what parents choose to purchase and feed their children, therefore the family environment may be more important in influencing the food behaviours of children than the built environment. Future research could further disentangle this by using GPS to study food-related behaviours in paired samples of children and their parents. Additionally, objective GIS or GPS measures could be combined with perceived measures (i.e., how children perceive their environments), which may add an even deeper understanding into how they interact with their environment^{32 355}. An example of research on perceived neighbourhoods that has been conducted in adults would be the Veritas interactive mapping tool⁸³, whereby individuals are asked to draw the delimitations of their perceived residential neighbourhood.

As previously identified, some of the equivocal results in this thesis might also be due to the fact that exposure to the neighbourhood is measured in different ways, as reflected in the literature. While the neighbourhood definitions used in this thesis were drawn from previous evidence in the literature, it is acknowledged that neighbourhoods are hard to define and may not always reflect the area used or perceived as a neighbourhood by individuals. Traditionally researchers have assumed exposure to food outlets with the help of GIS (operationalised in different ways), but in reality behaviours may or may not occur within a predefined buffer, and very few studies^{44 80 81 127} have attempted to also examine behaviours outside such rigid neighbourhoods. To this end studies making use of GPS to investigate personal exposure have started to emerge.

Even though results remain inconclusive on which neighbourhood measure is most appropriate, studies using alternative buffers show that we can expand our understanding in this area. Few studies^{44 127} have compared alternative ways of measuring spatial exposures (based on GPS) with traditional methods (based on GIS). This is what was attempted in

Chapter 7, where it was found that home and school GIS-defined neighbourhoods were weakly correlated to the GPS-derived activity spaces of participants, which is consistent with findings from a previous study⁴⁴. This suggests that the food environment of the local neighbourhoods may be a poor proxy for that which individuals are exposed to while conducting their daily activities; it might be that both measures should hence be considered when making policy recommendations.

Both GIS and GPS methods have advantages and disadvantages, as detailed in Chapters 5 and 7. An advantage of GIS-based measures is that they are very useful in terms of describing the characteristics of the surroundings and the opportunities available, but they assume exposures in neighbourhoods where activities might not actually take place. This disadvantage of the GIS-based measures can be overcome with the use of GPS, which refine specificity of measurement of exposure to the food environment. A disadvantage of using GPS on the other hand is that it may increase residual confounding related to selective daily mobility bias (i.e., individuals with particular nutritional preferences seek out environments that cater for that), which might actually be a step backward in terms of assessing causal effects⁸⁴. This might in part explain the null results found in Chapter 7. Furthermore, it may not be feasible to apply GPS in large scale studies such as the one in Chapter 3 as it would be very costly and time consuming. Combining GIS and GPS may therefore provide an unprecedented opportunity to evaluate the complex relationship between the environment and location-based behaviours⁸⁴³³⁶, as it is very likely there are overlaps between environmental features of activity-spaces and those of residential neighbourhoods.

Because the use of GPS data in health research is relatively novel, there are several issues related to data collection, accuracy, behaviour classification and analysis¹²⁷ (discussed in Chapter 6) that need to be carefully considered. Such issues are related to managing the substantial quantities of data GPS produce or defining start and end points of trips, and these remain problematic. Such issues have been attempted to be at least in part addressed in Chapter 6, where the GPS data has been processed using a novel computational algorithm which was developed to remove signal noise in the GPS data and distinguish between motorised vehicle and on-foot or slow cycling trips. Studies using GPS data assume that exposures take place, but a lot of times people are in vehicles and those do not represent real exposures to the retail food environment. In the PEACH study however only 18% of the data (which included GPS drift and vehicles in journeys) has been removed, and therefore not surprisingly the exposure measures to the food environment before any processing were

strongly correlated to those after processing. It could be that associations with weight-related outcomes might differ in studies performed on adults or people living in rural areas, who spend more time in vehicles. It might also be that different scales should be tested against outcomes in the same study as more than one scale might have explanatory power.

As it is usually the case with automated processes, some degree of human intervention is still required in GPS data analysis. For example, a sub-sample of trips was visually inspected in Chapter 6 in order to investigate whether trips ranging from one to two minutes actually represented walking or slow-cycling trips, or if they were more likely to be caused by GPS drift. In the future, research may have the potential to use technological advancements such as positional augmentation using coordinates collected from a mobile phone or radio frequency identification tags that could provide solutions for GPS technical issues such as signal loss.

Some of the counterintuitive or null associations found in this thesis and detailed in Table 8.1. might in part also be due to the choice of categorisation of the food exposures. These were based on evidence in the literature, as researchers have generally labelled supermarkets a desirable feature of neighbourhoods⁶⁸, just as convenience stores are labelled detrimental^{51 57}. However, these have not been validated in any of the studies in this thesis and it might be simplistic to use store type alone as an indicator of food healthfulness. The expected associations with dietary health do not always hold, as it is often challenging to draw a categorical distinction between convenience stores and small grocery stores, and supermarkets hold both healthy and unhealthy food items on their shelves. While it has been shown^{341 356} that supermarkets do have much greater shelf space of fruits and vegetables than other store types, they also have a large number of displays of energy-dense snack foods in close proximity to cash registers³⁴¹. A distinction should therefore be made in future research between the community food environment versus the consumer food environment, which entails distinguishing the measurement of stores versus the measurement of foods⁸². Food store audits are a good way forward in that respect, but they can be costly and time consuming in large samples.

Another reason for the equivocal results in the thesis might be due to the measurement of the dietary outcomes. When measuring diet, some studies use diet screeners or food frequency questionnaires⁶¹, others used food diaries, 24 hour recalls³⁵⁷, or momentary assessment^{358 359}. In conducting studies of diet and disease risk, the use of methods of measuring diet with sufficient validity to detect important associations is essential³⁶⁰. The most common methods

used in the literature to date have been the FFQ or the diet screener (in a lot of studies it is unclear whether dietary intake is measured with an FFQ or a diet screener³⁶¹), followed by the food diary. Food diaries have revealed relationships not observed in the FFQ³⁶², and it has been shown that FFQs (or diet screeners) show weak associations with dietary biomarkers³⁴⁸. This may in part explain why some associations with diet are found in Chapter 4 (where a food diary was used), but not Chapter 7 (where a diet screener was used).

As detailed in the *Strengths and limitations* section, the food diary used in this thesis has not been validated, therefore being subject to potential errors such as under-reporting, which may have limited the potential to detect associations with diet in Chapter 4. Robust dietary assessment is however challenging and it can be costly to administer food diaries over long periods of time. In order to overcome such limitations, there is scope for future research to make use of tools such as the Youth/ Adolescent Questionnaire from the Harvard School of Public Health^{363 364}, which has been validated in children³³. Another reason why few associations with diet are found in Chapters 4 and 7 might be because dietary assessment was based on self-report, as it has almost always been the case in research to date. In order to attempt to reduce the influences of recall biases³⁶⁵, there is scope for future research to make use of tools such as the Ecological Momentary Assessment (EMA) via the use of smartphones or tablets, which can be very useful in measuring real-time dietary intake; despite this, there is a very limited number of studies making use of EMA, and virtually none in children; only one study³⁶⁶ was found in children, which assesses the relationship between eating context and fruit and vegetable consumption in UK children.

The sparse associations with BMI in Chapters 4 and 7 might also be due to the measurement of weight status. When measuring weight status, some studies use objectively measured BMI¹⁷⁴, while others use self-reported BMI⁴⁵; furthermore, some studies use measures such as fat mass index², waist circumference or body fat percentage⁴³ as a more reliable proxy for measuring adiposity. In this thesis weight status (BMI) was objectively measured for all three studies individually for each child. Although BMI is the gold standard for measuring obesity in public health research, other studies have found null associations between the food environment and BMI, as it has been suggested that BMI might be a problematic measure of adiposity in children^{367 368}. Future research might take into account measures such as the fat mass index, as it has been argued that it might be the acquisition of excess fat in the body rather than weight that constitutes a health risk².

This thesis provided an insight into the way children's interaction with their environment across space influences their diet and weight, when using different ways of measuring the food environment (i.e. conventional GIS-based neighbourhood measures and GPS-based refined measures) and diet (i.e. diet screeners or food diaries). Very few studies to date have used GPS, and this thesis suggests that although there are still methodological and technical challenges in their application, and they may not be possible to be applied at larger scales, future research can capitalize on the potential of GPS technology to explore how we define neighbourhoods. Several recommendations for directions in which future research may move have been made.

Overall conclusions

The complexity of the environment and the different research methods continue to present methodological challenges³³⁹ for researchers, a fact which is reflected in the equivocal findings across the literature and in this thesis. There is some evidence (Chapters 3 and 4) that exposure to the food environment in multiple locations relevant to individuals might act as a determinant of dietary intake and weight status. However, some of the associations found when measuring exposure to the food environment at an ecological level do not track through when measuring exposure at an individual level.

The case has been made for future research to work to decrease heterogeneity in measures of the built food environment by incorporating more uniform measures, which need to be developed and applied. GPS has been recently hailed as the way forward to refine exposures, as it has been deemed important for future research to explore a 'spatial polygamy' approach³⁶⁹ (i.e., accounting for the effects of multiple daily locations) and collect extra-residential exposures. Indeed that may be particularly relevant in adults, for whom residential neighbourhoods only partially reflect environmental features to which individuals are exposed, as they are more mobile. Children on the other hand are more likely to get attached to locations closer to their places of residence, as apparent in the associations found in Chapter 4. Therefore using neighbourhood-based measures in children may reveal important associations. Furthermore, applying GPS in large scale studies such as that in Chapter 3 may not be feasible, and it may be difficult to overcome the technical and methodological challenges in managing GPS data- the methodology developed in Chapter 6 represents a solution in overcoming that challenge.

As both methods are useful depending on context and scale, combining GIS and GPS may be a good way forward, and there is scope for future research to consider both residential space and activity space, as well as the connection between these spheres⁵. These could be coupled with behavioural surveys that reveal information on perceived neighbourhoods, as well as actual use or purchase of food. Further investigations are warranted that test multiple definitions of exposures, separately for adults than for children, on robust datasets conducted in settings with sufficient environmental heterogeneity. Additionally, as children might have access to food through their parents, understanding the role that the environment plays in influencing parental behaviours, both for themselves and for their children, may provide insight into the impact of the environment on children⁵.

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Appendix 5.1. Description of included studies-Category 1: mapping/assessing the food environment

Study	Study area, rural/urban status	Study area (size)	Objectives	GPS device type	Time period: primary data collection	Mapping/assessment	Primary data gathering approach * (number, name)	Food classification scheme used	Food locations (food outlets, food stores, food providers)	Environmental attributes (Identified through primary data collection) + Environmental analysis
(1.1.1) Field validation studies (various agreement statistics such as kappa, PPV (positive predictive values), sensitivity, Fisher's Exact test were reported)										
Liese (2010) ²⁹⁵ , US	8 counties in South Carolina (1 rural, 7 urban)	5,575 sq miles (8,920 sq km)	Assess the validity of 3 readily available, secondary data sources on food outlets	Trimble Juno ST GPS receiver, Trimble Navigation Ltd., Sunnyvale, California	Sept 2008 - July 2009	Geospatial accuracy of 2008 outlets - Euclidean distance between the geocoded outlet location and the GPS location recorded in the field; Percentage of outlets for which the geocoded position was less than 100 m from the GPS	3: State Department of Health (US); Info USA; Dun&Bradstreet	NAICS	Food stores: 5 (supermarket and grocery, convenience, dollar and variety, drug and pharmacy, specialty); Restaurants: 3 (full-service, franchised limited-service, non-franchised limited service)	2,208 food outlets (8 types identified as per Tables 1 and 2 of the paper) All distance analyses were conducted within ArcGIS software (version 9.3; ESRI) using 2008 street network data from the Topologically Integrated Geographic Encoding and Referencing System
Sharkey (2008) ²⁹⁶ , US	6-county rural region of Texas (101 rural neighbourhoods)	11,567 km sq	1) identifying and geocoding all food stores (FS) 2) understanding of potential spatial access to the rural food environment 3) examining the relationship between neighbourhood inequalities and network distance to the nearest FS.	camera based GPS - Bluetooth Wide Area Augmentation System-enabled portable GPS receiver	n.r.	208 FS- on-site measurement: identify and classify FS; "windshield survey" of the characteristics of each FS observed from the outside; Geographic position was measured in front of each FS after at least 4 satellite signals were detected	3: State Department of Agriculture (US); unidentified internet telephone directories; unidentified local/area telephone directories (US)	NAICS (not specified in paper)	213 food stores: location, potential spatial access (network distance from the neighbourhood population weighted centroid to the nearest FS); identified 5 types, analysed 4 types The population-weighted centroid for each CBG was calculated using the ArcGIS Desktop tool Mean Center (Version 9.2, Environmental Systems Research Institute).	
Fleischhacker (2012) ³⁰⁰ , US	7 State Designated Tribal Statistical Areas in North Carolina (NC) (4 urbanization levels: Urban, sub-urban, large town and small town/rural)	>1500 miles	Validate the retail food environment in American Indian communities and agreement of primary data with secondary data sources	Car GPS, Garmin model	February - June 2010	photographs of FS; classify FS	6: Reference USA; Dun&Bradstreet; County Health Department (US); State Department of Agriculture; Online Yellow Pages (US); Google Street View	NAICS, NEMS	Convenience stores, general merchandise, grocery stores, specialty markets/shops, restaurants, food bank	699 food outlets (6 types identified according to Table 2 of papers) ArcGIS 9.3.1 (Esri, Redlands, CA) used to: overlay ZIP Code and county boundaries with SDTSA boundaries; geocode the food sources identified by secondary data; convert GPS data into shapefiles; point distance tool to calculate the distance between all outlets identified in secondary data within 1600 meters of outlets identified in ground-truthed data

Study	Study area, rural/urban status	Study area (size)	Objectives	GPS device type	Time period: primary data collection	Mapping/assessment	Primary data gathering approach * (number :name)	Data sources examined	Food classification scheme used	Food locations (food outlets, food stores, food providers)	Environmental attributes (identified through primary data collection)+ Environmental analysis
(1.1.) Field validation studies (various agreement statistics such as kappa, PPV (positive predictive values), sensitivity, Fisher's Exact test were reported)	381= 274 urban census tracts across 9 counties the Chicago Metropolitan Statistical Area (MSA) + 46 suburban + 61 rural census tracts across 13 counties from a 50-mile buffer surrounding the MSA	26,507 total road miles	Validate food store and restaurant data from two commercial business lists conditional on classification of outlet type	n.r.	May-July 2009	Mapping/assessment: indoor audit to collect and entered each establishment to collect data on various outlet characteristics (e.g., number of cash registers)-not able to collect for all => 12 FS excluded	Ground- 2: Info USA; Dun&Bradstreet	2: Info USA; Dun&Bradstreet	NAICS, SIC	Convenience stores, supermarket, grocery of paper stores, specialty food stores, fast food restaurants, full-service restaurants, specialty restaurants	Food outlets (identified 7 types as per Table 1)
Toft (2011) ²⁹⁹ , Denmark	Capital Region of Denmark(urban)	n.r.	Validate the identification and location of fast-food restaurants according to a government list of inspected food stores and restaurants	n.r. (gathered primary data only for a portion of the larger study area)	May-June 2010	125 randomly selected 250_250m grid cells (out of overall 34,412)	Ground- Truthing	1: County Food Administration (Denmark)- the Smiley register, Spring 2010	Own, NACE	Fast food restaurants (focused on evening meals)	186 fast food restaurants For 95% of the restaurants, Universal Transverse Mercator (UTM) coordinates are given, making it possible to rather precisely map each restaurant. For restaurants without UTM coordinates, the address of the restaurant was used to geocode these.
Longacre (2011) ²⁹³ , US	32 geographically dispersed towns from two rural states in Northern New England (11 rural); 7 small town; 8 mid-sized town; and 6 urban)	1,237.6 square miles	Evaluate the efficacy of public directories vs. rigorous onsitefield verification to characterize the community food environment	n.r. (Not specified in the paper that they use GPS; it has been confirmed by author they use handheld GPS devices)	n.r.	in-store observations were conducted to verify outlet classification	On-site verification	2: Yahoo! Yellow Pages (Yahoo! Inc; Sunnyvale, CA); Google Earth (Google Inc; Mountain View, CA)	NAICS (modified version)	General store, convenience store, supermarket/grocery, specialty food, big box grocery, farm/produce stand, fast food restaurant, full-service restaurant	1340 total unique food outlets after overlap with secondary data sources (8 types- assessed in 2007; 960 identified through field observations) ArcGIS 9.1 (ESRI, 2004, Redlands,CA) was employed to create an aerial photo map of each town that identified town boundaries, street networks and inventoried food outlet locations derived from the public directories. Field verification was conducted within 1 month of public directory data collection by two-person coding teams who confirmed the presence and location of food outlets

Study	Study area, rural/urban status	Study area (size)	Objectives	GPS device type	Time period: primary data collection	Mapping/assessment	Primary data gathering approach * (number/name)	Data sources examined	Food classification scheme used	Food locations (food outlets, food stores, food providers)	Environmental attributes (identified through primary data collection) + Environmental analysis
(1.1.1) Field validation studies	(various agreement statistics such as kappa, PPV (positive predictive values), sensitivity, Fisher's Exact test were reported)										
Hosler (2010) ²⁹¹ , US	Six ZIP code areas in Albany NY, urban community	n.r.	Identify retail food stores from administrative lists in an urban community in order to evaluate the food environment	n.r.	2009	in-store audit	On-site verification of Agriculture (US)-Department of Health authorized Women, Infant and Children (WIC) retailers (US); State Department of Taxation and Finance (US); State Liquor Authority (US); State Authorized Lottery Ticket Retailers (US); US Department of Agriculture authorized Supplemental Nutrition Assistance Program (SNAP) retailers	6-State Department of Agriculture (US)-Inspected Food Stores (IFS), Farmers' markets (FM), inspected gasoline retailers (IGR); State Department of Health authorized Women, Infant and Children (WIC) retailers (US); State Department of Taxation and Finance (US); State Liquor Authority (US); State Authorized Lottery Ticket Retailers (US); US Department of Agriculture authorized Supplemental Nutrition Assistance Program (SNAP) retailers	A more generally-inclusive categorisation: 1) Food stores (retail establishment); 2) licensed cigarette retailers; 3) off-premises liquor licenses; 4) gasoline retailers; 5) farmers' markets	166 stores total (4 from on-site), 43 disqualified=>123 included in study (over 5 types identified as per administrative lists, Table 1 of paper) GIS software was used to remove stores located outside the study area	
Seliske (2012) ²⁹⁸ , Canada	34 schools located in 22 cities and towns across southern Ontario, Canada, urban (25 schools) + non-urban (9 schools)	n.r.	Validate information provided by two GIS databases, comparing the positional accuracy of food service places within a 1 km circular buffer surrounding schools	Garmin Dakota 10 handheld GPS device (Garmin International Inc., Olathe, KS, USA)	June-August 2010		On-site verification of Yellow Pages (Canada) targeted observations on	2: InfoCanada; Online Yellow Pages (Canada)	NAICS	A more generally-inclusive categorisation- Food service places: full service, limited service, convenience	794-595 food service plates identified in the field (3 types identified as per Table 1 of paper) A 1 km circular buffer was created around each school using ArcGIS (ESRI, version 9.3, Redlands, CA, USA) and no buffers overlapped. The location of various types of food service places was obtained from two databases and geocoded within a 1 km circular buffer surrounding each school. Their locations were then confirmed by conducting a field validation.
McGuirt (2011) ²⁹⁷ , US	10 communities in a rural eastern North Carolina county (Pitt county): 6 rural and 4 urban towns	651.8 square miles	Describe approach to conducting a community audit to enumerate resources, to assess community characteristics, and to inform revisions to a community guide on nutrition and PA resources	Vehicular GPS (n.r.)	2010	windshield tour observations	On-site verification of targeted observations on	2: ReferenceUSA; State Department of Agriculture (US)	Own (fast food outlets classified based on national/regional chain name recognition)	supermarkets, grocery stores, fast food and convenience stores, farmers' markets, produce stands	80 (38 additional public resources on top of 42 from resource guide) such as: walking trails; community parks, free/ low-cost gyms, food outlets (6 types of food outlets identified); types of resources; fast food outlets density (per capita); used ArcGIS 9.3 mapping software (ESRI, Redlands, California) to assign geographic codes to fast-food restaurant and convenience store locations; conducted a road-network analysis by using ArcGIS Network Analyst and Spatial Analyst (ESRI, Redlands, California) to measure 1-mile road-network buffers from the fast-food and convenience stores.

Study	Study area, rural/urban status	Study area (size)	Objectives	GPS device type	Time period: primary data collection	Mapping/assessment	Primary data gathering approach * (number, name)	Food classification scheme used	Food locations (food outlets, food stores, food providers)	Environmental attributes (identified through primary data collection) + Environmental analysis
Gustafson (2012) ²⁷ , US	14 counties out of 54 in the Appalachian region; rural	n.r.	1) Validate one commercially available data source with direct field observations of food retailers; 2) Examine the association between modified neighbourhood deprivation and the modified retail food environment score (mRFEI)	n.r. (Not specified in the paper that they use r 2011 GPS; it has been confirmed by author they use car GPS)	September - November r 2011	US Department of Agriculture (USDA) Food Security Assessment Toolkit; Food Store Survey Instrument market basket	On-site verification Department of Agriculture (US); targeted observations	NAICS	Grocery store, supermarket, convenience store, gas station with food mart, fast food and fast-casual restaurants, pizza parlors, dollar stores, farmers' markets	Neighbourhood deprivation: mRFEI= indicator of access to retailers selling healthy foods such as low-fat foods and fruits and vegetables relative to retailers selling more energy dense foods); 9 types of food stores identified (as per Table 2 of paper); the paper does not specify whether they use a GIS software, but it was confirmed by main author that ArcGIS is used to geocode food outlets.
[1.2.] Other food mapping studies										
O'Connell (2011) ³⁰ , US	22 American Indian reservations (tribes) in Washington state	n.r.	Characterize the nutrition environment of American Indian reservations in Washington State	n.r. (Handheld GPS)	April - May 2009	US Department of Agriculture (USDA) Food Security Assessment Toolkit; Food Store Survey Instrument market basket	1: Reference USA	NAICS	Convenience, grocery, supermarket	Data collected from 47 out of 50 stores identified (25 convenience, 16 grocery, and 9 supermarkets); type, number, location, proportion, weighted mean density, availability and cost of the Thrifty Food Plan market basket (68 individual, 8 food group items) by food store type; shortest straight-line distance from the tribe's headquarters to food outlet; telephone survey. The nearest off-reservation supermarket was identified using the ReferenceUSA database and Geographic Information Systems mapping, or by using the handheld global positioning system device, for each of the 17 tribes lacking a supermarket on their reservation.
Gasevic (2011) ³⁰ , Canada	42 Prospective Urban Rural Epidemiology (PURE) study recruitment areas/ 'communities', both rural and urban. Audited: 36500 segments; 882 segments in one high-income Vancouver community and 750 in another, low-income community.	n.r.	Assessment of the 'obesogenic' built environment	Garmin models Legend H and HCx, Garmin Ltd, Salem, Oregon	n.r.	visual record: photographs of neighbourhood features; Maps of each community from: Googlemaps and DMTI Spatial Inc.; 2 audit tools: (1) objective-modified paper version of the Irvine-Minnesota inventory (IMI)-pilot scan; (2) PA and Nutrition Features audit tool where environmental features were recorded using a GPS;	0: No secondary databases used (direct assessment of the environment (going to the actual environment and recording presence/absence of built environment features) using 2 audit tools	NAICS (2007)	Supermarkets/grocery stores, convenience/general stores, meat/fish/seafood/market stores, fruit and vegetable/market stores, baked goods stores, confectionery/nut stores, beer/wine/liquor stores, specialty food stores, full-service restaurants, limited-service restaurants (cafes/fast food/pizza/buffets); drinking places	Urban: Segments (the distance between two intersections) within a 500m buffer area around ISA (Forward Sortation Area borders); Rural: 1000m buffer Border; 125 built environment items such as facilities: centres, green space, different types of food stores (identified 9 types in Table 1, provided in the paper). Before conducting the environmental audits, detailed maps of each community were obtained from Googlemaps and DMTI Spatial Inc. (displayed using ArcGIS 9 geographic information system software, Esri, Redlands, Calif, USA) for modified IMI and GIS/GIS methods, respectively

Study	Study area, rural/urban status	Study area (size)	Objectives	GPS device type	Time period: primary data collection	Mapping/assessment	Primary data gathering approach * (number: name)	Data sources examined (number: name)	Food classification scheme used	Food locations (food outlets, food stores, food providers)	Environmental attributes (identified through primary data collection) + Environmental analysis
(1.2.) Other food mapping studies											
Lopez (2010) ³⁰² , US	rural/urban status: a Latino and surrounding neighborhoods in a city located in East Central New York, on the Mohawk River	n.r.	Assess availability, affordability, and accessibility of food items in a low-income Latino neighbourhood compared to a non-Latino one	n.r.	June-July 2004	in-store survey tool (32 stores): availability of nutritionally important foods (as per dietary guidelines)	Ground-truthing	3: the New York State Department of Agriculture and Markets; farmers' markets List; online Yellow Pages	NAICS, existing literature	Supermarket, grocery store, farm produce store, gas station/convenience, other (drug store, dollar discount store, meat shop)	35 food stores: location, disability access measures, spatial distribution- store density per 1000 residents, physical distances; 5 types identified as per Table 1 of the paper. GIS mapping techniques were applied to depict neighbourhood boundaries and store locations, and to measure physical distances between residential neighbourhoods and food stores.
Sharkey(2009) ³⁰⁴ , US	197 census block group (CBG) area of Hidalgo County	772 sq miles	Determine the extent to which neighborhood needs are associated with spatial access (distance to nearest & number) to food stores and fast food restaurants in neighbourhoods of Colonias	Bluetooth Wide Area Augmentatio n System (WAAS)-enabled GPS receiver and the latest World Geodetic System 1984 (WGS 84) datum	n.r.	direct observation and on-site GPS	Ground-truthing	1 **: the 2006-2007 Colonias Food Environment Project (CFEP)	NAICS (modified version)	Supercentre, supermarket, grocery store, dollar store, mass merchandisers, pharmacy, fast food restaurants	315 food stores and 204 fast food restaurants (8 types identified as per Table 1 of paper); 2 spatial access criteria: (1) proximity= shortest network between each FS&FF and the population-weighted centre of each CBG; (2) coverage= number of each type of FS&FF within a network distance of 1, 3, and 5 miles of each population-weighted CBG center.

n.r. = not reported; n.e.= not examined; n.a.= not applicable; PA= physical activity; FFO= food frequency questionnaire

commercial sources (secondary database): Info USA; Reference USA; Dun&Bradstreet (USA)

government sources (secondary database): County Health Departments (US); County Food Administration (Denmark); State Department of Agriculture (US); the New York State Department of Agriculture and Markets; State Department of Health authorized Women, Infant and Children (WIC) retailers (US); State Department of Taxation and Finance (US); State Department of Health (US); State Liquor Authority (US); State Authorized Lottery Ticket Retailers (US); US Department of Agriculture authorized Supplemental Nutrition Assistance Program (SNAP) retailers;

online (secondary database): Yellow Pages (US); telephone directories; Yahoo! Yellow Pages (US); Yellow Pages (Canada)

telephone books (secondary database): telephone directories

omnidirectional sources (secondary database): Google Earth (US)

other sources (secondary database): Farmer's markets lists

* (Fleischacker et al., 2013) typology (targeted observation on-site verification with/without systematic canvass, ground-truthing)

** primary database collected for the study: the 2006-2007 Colonias Food Environment Project (CFEP)

Appendix 5.2. Description of included studies-Category 2: use of/exposure to the food environment

Study	Subjects	Objectives	Dietary measures	Anthropometric measure	Other covariates	GPS device	Time period of GPS wear	Activity space calculation	GPS Data loss (DL) + problems (P) + solutions (S) used	Secondary data source used	Food classification scheme used	Food locations/outlets, food stores, food providers	Environmental analysis/attributes
(Christian, 2012) ⁸⁰ , US	N:121 (representing about 4.9% of eligible adults in the target area); N:101 participants with complete three-day GPS tracks Age: 18-65 Gender: 56.4% female (out of 101)	(1) How do individuals' activity-based measures of food accessibility compare to neighbourhood based measures? (2) How do these activity-based measures relate to individual characteristics, including weight? (3) Are activity-based measures associated with diet and food purchasing?	Survey on diet (FFQ) and food purchase (frequency)	BMI, self-reported, categorical (underweight/normal for BMI < 25, overweight for BMI ≥ 25, obese for BMI ≥ 30)	Age, gender, race, household income, education, employment, marital status	Ostarz BT-1000XT Travel Recorder	3 weekdays	ArcGIS 10: Euclidean buffer of 0.50 miles (2640 feet) around participants' three-day GPS track line.	DL: approx. 17% lost from participants with not enough GPS data P: unknown routes between destinations, presumably due to reception issues S: data were deemed inadequate and excluded from the analysis	Lexington-Fayette County Health Department	Own	Food stores: 4 (supermarkets; convenience stores; FV markets; limited service restaurants)	counts within daily activity buffer; proportion of healthy to unhealthy (RFEI score)
(Gustafson et al., 2013) ⁸¹ , US	N:121 Age: 18+ Gender: (153 responded, 121 not eligible)	Determine the association between six various dietary indicators and 1) food venue availability; 2) food venue choice and frequency; and 3) availability of healthy food within food venue	Survey on food shopping behaviours and dietary outcomes	BMI, self-reported	Age, gender, race, marital status, education, household income, employment, automobile ownership	Ostarz BT-1000XT Travel Recorder	3 days (2 weekdays, 1 weekend)	Euclidean buffer of 0.50 miles (2640 feet) around participants' three-day GPS track line.	2 people out of the 121 not eligible did not agree to wear GPS for 3 days	InfoUSA	NAICS, Own	Food stores: around 8 (healthy: produce stands, farmer's markets, supermarkets/grocery store; less healthy: supercenters, convenience stores, gas stations, fast food restaurants; speciality stores)	counts of each venue type within activity's space buffer; proportion of healthy to unhealthy (RFEI score); audits using Nutrition Environment Measurement Survey-Store Rudd (NEMS-S), n=22

Study	Subjects	Objectives	Anthropo metric measure	Other covariates	GPS device	Time period of GPS wear	Activity space calculation	GPS Data loss (DL) + problems (P) + solutions (S)	Secondary data source used	Food classification scheme used	Food locations (food outlets, food stores, food providers)	Environmental analysis/attributes
(Huang et al., 2012) ³⁰⁵ , US	N: 35 Age: 50+ (with mobility disability) Gender: 74.3% female	Examine: 1) where participants accessed food outside the home, 2) how they travelled to these food destinations, and 3) facilitators and barriers to food access using qualitative interviews	n.e. (information on type of food outlets accessed)	Age, sex, race/ethnicity, household income, driving status, neighbourhood walkability score, type of assisted device, reside in low income, desert, living in facilities that provide meals	Qstarz BT-Q1000XT	3 days, weekdays, 1 weekend	n.r.	n.r.	None, self-reported interview	Own	Food locations accessed: 13, as per Figure 1 of paper (grocery store, full-service restaurant, other, coffee shop, fast food restaurant, food bank, senior centre, warehouse store, farmers market, convenience store, corner store, drug store, shopping mall)	self reported barriers and facilitators and types of foods accessed; self-reported used transportation mode; neighbourhood walkability; food desert locator; self-reported PA locations used
(Zenk et al., 2011) ⁴⁴ , US	N: 131 N: 120 who wore GPS Age: 3 categories (<45, 45-65, >64) Gender: 75% female	Examine associations between individual and area characteristics of the environment and activity spaces, and weight related behaviour (diet, PA)	FFQ (7 days recall) (n=116- complete data)	Age, gender, race/ethnicity, and four indicators of socioeconomic position (SEP): education, labour force participation, annual household income, and auto ownership.	Foretrex (Garmin, Olathe, KS)	7 days	ArcGIS 9.2: 2 standard deviation ellipse; 2 daily path area (buffering all GPS points at 0.5 mile and dissolving these separate features into a single space)	D.L.: 11 people out of 131 P: GPS data collection errors by staff (n=3); did not wear GPS or suspicious data (n=8) S: excluded	Fast Food : county departments of agriculture, city of Detroit; supermarkets: Michigan department of agriculture	Own, based on previous literature	Food outlets: fast food outlets, supermarket residential neighbourhood (0.5 mile street-network buffer around the census block centroid); park land use, fast food outlets density and supermarket availability in residential neighbourhood and activity space	

Food classification scheme used: North America Industry Classification System (NAICS); Nutrition Environment Measures Survey (NEMS); Standard Industrial Classification (SIC); European Business Codes/ Nomenclature des Activités Economiques (NACE); Irvine-Minnesota Inventory (IMI); Lexington-Fayette County Health Department; own (developed its own definition for classifying food outlets, based on existing literature, hypothesis, chain-name recognition etc.

Appendix 6.1.: Python source code

Pre-processing sub-routines:

Build database:

```
import sqlite3
import csv
import sys

conn = sqlite3.connect("gps.db")
c = conn.cursor()

cr = csv.reader(open(sys.argv[1], "rb"))
header = cr.next()

columns = " text, ".join(header) + " float"
columns = "OBJECTID text, ID text, PUPILID text , DATETIME datetime,
TIMETXT2 text, DT text, DATETXT text, DAY text, X int, Y int, INTAKE text,
TOD text, TIMEDIFF text, TIMESEC text, DISTM float, KPHACTUAL float,
KPHNORM float, STATE text, SEG int"
statement = "create table gps (%s)"%columns
try:
    c.execute(statement)
except Exception, e:
    print str(e)

for line in cr:
    line.append("-1")
    line.append("null")
    statement = "insert into gps values ('%s')"%','.join(line)
    c.execute(statement)

c.execute('create index "index1" on "gps" ("PUPILID")')
c.execute('create index "index2" on "gps" ("X")')
c.execute('create index "index3" on "gps" ("Y")')
c.execute('create index "index4" on "gps" ("OBJECTID")')
conn.commit()
```

Mark aberrant speeds:

```
import csv
import sys
import os
```

```
import math
import sqlite3

conn = sqlite3.connect("andreea.db")
cursor = conn.cursor()

data = cursor.execute("SELECT DISTINCT pupilid from gps;")
pupil_ids = []
for el in data:
    pupil_ids.append(el[0])

all_outlier_times = []

def select(statement):
    data = cursor.execute(statement)
    res = []
    for el in data:
        res.append(el)
    return res

def update(statement):
    cursor.execute(statement)
    conn.commit()

data = cursor.execute("SELECT OBJECTID from gps where state = -1 and
KPHACTUAL > 100")
l = [el for el in data]
for el in l:

    print el
    update("UPDATE gps SET STATE = 11 where objectid = '%s'"%(el[0]))
    conn.commit()

Mark isolated points:
import csv
import sys
import os
import math
import sqlite3

conn = sqlite3.connect("andreea.db")
cursor = conn.cursor()
```

```

data = cursor.execute("SELECT DISTINCT pupilid from gps;")
pupil_ids = []
for el in data:
    pupil_ids.append(el[0])

all_outlier_times = []

def select(statement):
    data = cursor.execute(statement)
    res = []
    for el in data:
        res.append(el)
    return res

def update(statement):
    cursor.execute(statement)
    conn.commit()

pupils = select("SELECT DISTINCT pupilid from gps;")

for pupil in pupils:
    print pupil[0]
    points = select("SELECT distinct X, Y from gps where pupilid =
'%s'"%pupil[0])
    for point in points:
        found = False
        for point2 in points:
            if point != point2:
                if math.sqrt((point[0] - point2[0]) ** 2 +
(point[1] - point2[1]) ** 2) < 500:
                    #print point
                    found = True
                    break
        if found == False:
            print point
            update("UPDATE gps set STATE = 10 WHERE pupilid = %s and
X = %s and Y = %s"%(pupil[0], point[0], point[1]))

```

Pre-processing:

```

import os
import sqlite3
import csv
import sys

```

```

os.system("python build_database.py ALL_RAW_GPS.csv.norm")
os.system("python build_database_poi.py POI_Food_inBristolStudyArea.csv")
os.system("python mark_abernat_speeds.py")
os.system("python mark_isolated_points.py")
'''
data = []
cr = csv.reader(open(sys.argv[1], "rb"))
header = cr.next()
for line in cr:
    data.append(float(line[-1]))

X = preprocessing.scale(data)

cr = csv.reader(open(sys.argv[1], "rb"))
header = cr.next()

g = open(sys.argv[1] + ".norm", "wb")
header.append("KPHNORM")
g.write(",".join(header) + "\n")

for i, line in enumerate(cr):
    if i % 100 == 0:
        print "Processed %s of %s"%(i, len(X))
    line.append(str(X[i]))
    g.write(",".join(line) + "\n")
g.close()
'''

```

Processing:

```

from sklearn import hmm
import numpy as np
import csv
import sys
import os
import math
import sqlite3
import datetime
import pylab as pl
import random
from matplotlib.finance import quotes_historical_yahoo
from matplotlib.dates import YearLocator, MonthLocator, DateFormatter
from sklearn.hmm import GaussianHMM

conn = sqlite3.connect("andreea.db")
cursor = conn.cursor()

def select(statement):
    data = cursor.execute(statement)
    res = []
    for el in data:
        res.append(el)
    return res

def update(statement):
    cursor.execute(statement)
    conn.commit()

pupils = select("SELECT DISTINCT pupilid from gps;")
pupils2 = list(pupils)

```



```

random.shuffle(pupils2)

selected_pupils = str(tuple(map(int, zip(*pupils2)[0][0:50])))

#data = cursor.execute("SELECT DISTINCT pupilid from gps;")
statement = "SELECT OBJECTID, KPHACTUAL, DATETIME FROM gps WHERE pupilid
in %s and state < 10 order by pupilid, datetime"%(selected_pupils)
print statement
data = select(statement)
X = np.reshape(np.array([el[1] for el in data]), (-1, 1))

transmat = np.array([[0.999, 0.001],
                     [0.001, 0.999]])
n_components = 2
model = hmm.GaussianHMM(n_components, "full")#, transmat=transmat)

model.fit([X])

print "means and vars of each hidden state"
for i in xrange(n_components):
    print "%dth hidden state" % i
    print "mean = ", model.means_[i]
    print "var = ", np.diag(model.covars_[i])
    print ""

print "Transition matrix"
print model.transmat_
print ""

limit = 0

for pupil in pupils:
    limit += 1
    print pupil[0]
    data = select("SELECT OBJECTID, KPHACTUAL FROM gps WHERE pupilid = '%s'
and state < 10 order by datetime"%pupil[0])
    if len(data) < 6:
        for i in range(len(data)):
            update("UPDATE gps SET state = '%s' where objectid = '%s'"%(13,
data[i][0]))#ignore those that are of length less than 10
            continue
    X = np.reshape(np.array([el[1] for el in data]), (-1, 1))

Z = model.predict(X)

for i in range(len(data)):

    if model.means_[0] < model.means_[1]:
        if Z[i] == 0:
            state = "walk"
        else:
            state = "car"
    else:
        if Z[i] == 0:
            state = "car"
        else:
            state = "walk"

```

```
        update("UPDATE gps SET state = '%s' where objectid = '%s'"%(Z[i],
data[i][0]))
```

Post-processing:

```
import sqlite3
import time
import datetime
import matplotlib.pyplot as plt
from matplotlib.dates import date2num

conn = sqlite3.connect("andreea.db")
cursor = conn.cursor()

seg_id = 0

def select(statement):
    data = cursor.execute(statement)
    res = []
    for el in data:
        res.append(el)
    return res

def update(statement):
    cursor.execute(statement)
    conn.commit()

def text2time(text):
    return time.mktime(datetime.datetime.strptime(text,
"%d/%m/%Y %H:%M:%S").timetuple())

def updatePoints(points):
    sg=-1
    for i in range(len(points)):
        sg=points[i][6]
        if(int(points[i][5])<10):
```

```

        update("UPDATE gps set STATE = %s, seg = %d WHERE
objectid = '%s'"%(points[i][3], points[i][6], points[i][0]))#if not
abberant point, update state with corrected state
        else: update("UPDATE gps set STATE = %s, seg = %d WHERE
objectid = '%s'"%(points[i][5], points[i][6], points[i][0]))#if abberant
point update state with previous abberant state

        update("UPDATE gps SET state=16 WHERE seg=%f AND kphactual>15 AND
state=0"%sg)

def removeIsolatedPoints(points):
    changes = False
    for i in range(1, len(points) - 1):
        if points[i][3] != points[i - 1][3] and points[i - 1][3] ==
points[i + 1][3] and int(points[i][3])<10 and int(points[i-
1][3])<10:#abberant points ignored
            points[i][5] = points[i][3]
            points[i][3] = points[i - 1][3]
            changes = True
        if points[0][3] != points[1][3] and int(points[0][3]) < 10 and
int(points[1][3])<10:
            points[0][5] = points[0][3]
            points[0][3] = points[1][3]
            changes = True
        if points[-1][3] != points[-2][3] and int(points[-1][3]) < 10 and
int(points[-2][3]<10):
            points[-1][5] = points[-1][3]
            points[-1][3] = points[-2][3]
            changes = True
    return changes

def lessThan20Rule(points):
    count = 0
    for point in points:
        if float(point[1])>15:#
            count += 1
    if count * 100 < len(points) * 5 or count < 5:
        for point in points:
            if(int(point[3])>=10 or int(point[5])>=10):continue
            point[5] = point[3]

```

```
        point[3] = '0'
    return True
return False

def lessThan5Lth(points):
    if len(points) < 6:
        for point in points:
            point[5] = point[3]
            point[3] = '14'
        return True
    return False

def changePoints(points, start, end, state):
    for i in range (start, end):
        if(int(points[i][3])>=10 or int(points[i][5])>=10):continue
        points[i][5] = points[i][3]
        points[i][3] = str(state)

def car_slow_down(points):
    majo = 1
    mino = 0
    start = 0
    tstart = text2time(points[0][2])
    state = None
    for (i, point) in enumerate(points):
        if state == None and (int(point[3]) == 0 or int(point[3]) ==
1):
            state = int(point[3])
        if int(point[3]) == majo:
            if state == mino:
                cur_time = text2time(point[2])
                if abs(cur_time - tstart) <= 2 * 60:
                    changePoints(points, start, i, majo)
                state = majo
        elif int(point[3]) == mino:
            if state == majo:
                start = i
                tstart = text2time(point[2])
                state = mino
```

```

    cur_time = text2time(points[-1][2])
    if abs(cur_time - tstart) <= 2 * 60:
        changePoints(points, start, len(points), majo)

def split_into_segments(pupilid):
    global seg_id
    points = select("SELECT objectid, kphactual, datetime, state, pupilid
from gps where pupilid = '%s' order by datetime;"%pupilid)#no abberants are
of interest,currently resuming from where it last failed
    if(len(points)==0):return []
    last_time = text2time(points[0][2])
    tpoints = []
    all_segments = []
    seg_id += 1

    for point in points:

        cur_time = text2time(point[2])
        if abs(cur_time - last_time) > 5 * 60:
            all_segments.append(tpoints)
            seg_id += 1
            tpoints = [list(point) + [point[3], seg_id]]
        else:
            tpoints.append(list(point) + [point[3], seg_id])
        last_time = cur_time
    all_segments.append(tpoints)
    return all_segments

def processSegment(segment):
    plotPoints(segment, "1")
    if lessThan5Lth(segment):
        updatePoints(segment)
    else:
        removeIsolatedPoints(segment)
        if not lessThan20Rule(segment):
            car_slow_down(segment)

    updatePoints(segment)
    plotPoints(segment, "2")

```

```
def plotPoints(points, obs = ""):
    plt.subplots_adjust(bottom = .50)
    zips = list(zip(*points))
    zips[2] = list(zips[2])
    fig = plt.figure()

    if len(points) > 200:
        for i in range(len(zips[2])):
            if i % 10 != 0:
                zips[2][i] = ""

    elif len(points) > 100:
        for i in range(len(zips[2])):
            if i % 5 != 0:
                zips[2][i] = ""

    plt.xticks(range(len(zips[2])), zips[2])
    locs, labels = plt.xticks()
    plt.setp(labels, rotation=90)
    colors = []
    ss = []
    for el in points:
        if el[3] != el[5]:
            ss.append(100)
        else:
            ss.append(50)
        if el[3] == '0':
            color = "b"
        elif el[3] == '1':
            color = "r"
        elif el[3] == '16':
            color = 'k'
        elif int(el[3]) < 0:
            color = "y"
        else:
            color = "g"
        colors.append(color)
```

```
plt.scatter(range(len(zips[2])), zips[1], marker = 'o', c = colors, s
= ss)
plt.grid(b='on')
plt.ylim((0,100))
sum = 0
for el in zips[1]:
    sum += float(el)
fig.suptitle("%s - %s"%(points[0][4], points[0][6] ))
fig.savefig("plots/%s - %s %s.png"%(points[0][4], points[0][6], obs))
plt.close('all')
```

```
pupils = select("SELECT DISTINCT pupilid from gps;")
for pupil in pupils:
    pupilid = pupil[0]
    print pupilid
    segments = split_into_segments(pupilid)
    for segment in segments:
        processSegment(segment)
```

Appendix 7.1. Diet screener (only variables used in the analysis are presented below)

Q.76 How many portions of fruit do you usually eat in a day?

(A portion of fruit is, for example, an apple, a handful of grapes, a glass of pure fruit juice)

- ₁ 5 or more portions per day
- ₂ 4 portions per day
- ₃ 3 portions per day
- ₄ 2 portions per day
- ₅ 1 portion per day
- ₆ I eat fruit some days but not everyday
- ₇ I never eat fruit

Q.77 How many portions of vegetables (not including potatoes/crisps/chips!) do you usually eat in a day?

(A portion of vegetables is roughly a handful of any vegetables)

- ₁ 5 or more portions per day
- ₂ 4 portions per day
- ₃ 3 portions per day
- ₄ 2 portions per day
- ₅ 1 portion per day
- ₆ I eat vegetables some days but not everyday
- ₇ I never eat vegetables

Q.81 How often do you usually drink the following:

	Nearly every day	3-4 times a week	1-2 times a week	Once a month	Never or hardly ever
Milk (pq151_T1/_T2)	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
Water (pq152_T1/_T2)	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
Fizzy drink (pq153_T1/_T2)	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅

Fruit juice (pq154_T1/_T2)	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
Squash (pq155_T1/_T2)	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅

Q.82 How often do you usually eat the following:

	Nearly every day	3-4 times a week	1-2 times a week	Once a month	Never or hardly ever
Sweets (pq156_T1/_T2)	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
Biscuits (pq157_T1/_T2)	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
Chocolate (pq158_T1/_T2)	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
Crisps (pq159_T1/_T2)	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
Fruit (pq160_T1/_T2)	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅
Chips (pq161_T1/_T2)	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄	<input type="checkbox"/> ₅

Q.85 How often do you go out to eat fast food or have them at home as a takeaway. Here we mean things like McDonalds, KFC, Burger King, Fish and Chips, Pizza (pq169_T1/_T2)

- ₁ Nearly every day
- ₂ 4-5 days a week
- ₃ 3-4 days a week
- ₄ 1-2 days a week
- ₅ Less than once a week
- ₆ Once a month
- ₇ Never or hardly ever

Q.113 Which of the following do you like to eat?

	Really like	Like a bit	Don't like much	Really don't like
Fruit	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄
Vegetables	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄
Sweet snacks (eg chocolate, sweets)	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄
Cakes & biscuits	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄

Q.114 Which of the following do you like to eat?

	Really like	Like a bit	Don't like much	Really don't like
Salty/savoury snacks (eg chips, pizza, crisps, sausage rolls)	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄
Fizzy drinks	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄

Take-aways	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄
------------	---------------------------------------	---------------------------------------	---------------------------------------	---------------------------------------

Q.115 How often does your mum, dad or the person who looks after you eat the following?

	Never	Some times	Often	Always
Fruit	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄
Vegetables	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄
Sweet snacks (eg chocolate, sweets)	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄
Cakes & biscuits	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄

Q.116 How often does your mum, dad or the person who looks after you eat the following?

	Never	Some times	Often	Always
Salty/savoury snacks (eg chips, pizza, crisps, sausage rolls)	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄
Fizzy drinks	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄
Take-aways	<input type="checkbox"/> ₁	<input type="checkbox"/> ₂	<input type="checkbox"/> ₃	<input type="checkbox"/> ₄

APPENDIX A: Glossary of technical terms

Term	Operational Definition
1. Activity space**	Set of spatial locations visited by an individual over a given period, corresponding to her/his exhaustive spatial footprint; the regular activity space is the subset of locations regularly visited over that period
2. Buffer	A buffer in GIS is a zone around a map feature measured in units of distance or time. A buffer is useful for proximity analysis. A buffer is an area defined by the bounding region determined by a set of points at a specified maximum distance from all nodes along segments of an object.
3. Daily mobility**	Everyday movement of individuals over space between activity locations
4. Epoch	A specific instant in time. GPS carrier phase measurements are made at a given frequency (e.g. every 10 seconds) or epoch rate
5. Selective daily mobility**	Selective daily mobility refers to the fact that people who visit particular activity places during their daily lives have particular characteristics (e.g., socio-demographic, psychological, or cognitive characteristics; behavioural habits) that also influence their health status
6. Agreement*	The percentage of the primary retail food outlet data that matched the secondary retail food outlet data.
7. Cohen's Kappa Coefficient*	The agreement between primary and secondary retail food outlet data sources that takes into account the agreement occurring by chance.
8. Fisher's Exact test*	Test for statistically significant differences in the agreement statistics, evaluate accuracy
9. Geographic Information Systems (GIS)	A computer system designed to capture, store, manipulate, analyze, manage, and present all types of geographical data
10. Global Positioning Systems (GPS)	A satellite-based global navigation system that provides an accurate location of any point on the Earth's surface, i.e., the latitude and longitude of a retail food outlet or a person.
11. Ground-Truthed*	Primary data on retail food outlet type and location, gathered by trained observers not guided in the field by a list and/or map of retail food outlets identified through secondary data sources. A systematic canvass of the targeted study area is conducted, with or without the use of GPS or other remote sensing technologies.
12. Obesogenic environment	The sum of influences that the surroundings, opportunities, or conditions of life have on promoting obesity in individuals or populations ^{32 370} .
13. Omnidirectional sources (Observations)*	Uses omnidirectional imagery (i.e., sources that simultaneous collect images in multiple directions from a single location producing a panoramic view such as Google Street View) to visually tour a targeted study area, not guided by a list of predetermined

	retail food outlets in the study area from primary or secondary data sources.
14. On-Site Verification*	Primary data on retail food outlet type and location, gathered by trained observers guided in the field by a list and/or map of food outlets identified through secondary data sources that could occur with or without a systematic canvass of the targeted study area and with or without the use of GPS or other remote sensing technologies.
15. Positive Predictive Value*	The proportion of the retail food outlets listed by the secondary retail food outlet data sources that were observed during primary data collection.
16. Primary Retail Food Data*	Data collected through direct field observations by the team conducting the research to characterize the local retail food environment. Primary data is considered the gold standard to characterize retail food environments given that secondary retail food outlet data sources have been found to under- and over-estimate food access, when compared to primary data.
17. Retail Food Outlet*	Retail or commercial outlet in the business of selling food to the public. Does not include household availability or institutional food service such as child care centers, schools, hospitals, correctional facilities, or municipal.
18. Secondary Retail Food Data*	Data collected by someone else. For example, government sources, such as local food inspection registries; commercial sources, such as InfoUSA and Dun and Bradstreet; online directories, such as Yellow Pages; and omnidirectional sources, such as Google Street View and Google Earth. These sources have been shown to under- and over- count the number of retail food outlets in comparison to primary data.
19. Sensitivity*	The ratio of the number of retail food outlets ascertained via primary data that matched retail food outlets ascertained via secondary data source(s), to the number of retail food outlets ascertained via primary data that matched retail outlets ascertained via secondary data source(s) plus the number of retail food outlets ascertained via primary data that did not match retail food outlets ascertained via secondary data source(s).
20. Systematic Canvass*	Thorough and detailed primary data examination of a defined geographical setting using defined geographical parameters. Evidence of a systematic canvass includes a detailed description or discussion of study maps marking areas to include and exclude during primary data collection and were not limited to the areas where secondary data sources indicated the presence of a retail food outlet. Ground-truthed studies by definition include systematic canvasses, while on-site verification studies could occur with or without a systematic canvass.
21. Targeted Observational Field Data*	Primary data gathered by trained observers that targets a specific study area such as a study participant's residential block or selected street block segments. These observations do not

	systematically canvass beyond the targeted field areas. These observations may or may not use GPS or other remote sensing technologies. These studies do not include a list of predetermined resources in the study area to target the field observations, but the observational area is limited or guided by a participant's residential address or based on study selection criteria such as high-walkability block segments in New York City.
22. Validity *	Criterion-related validity, defined as the accuracy with which secondary data sources identified the type and location of retail food outlets, using primary data to represent the gold standard.

* Fleischhacker et al³⁷¹ ; ** Chaix et al⁸³