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Exploring cross-sectional associations between unhealthy food outlet exposure and BMI z-score in elementary school children in London, Canada

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A thesis submitted in partial fulfillment of the requirements for the Master of Science degree in Epidemiology and Biostatistics

EXPLORING CROSS-SECTIONAL ASSOCIATIONS BETWEEN UNHEALTHY FOOD OUTLET EXPOSURE AND BMI Z-SCORE IN ELEMENTARY SCHOOL CHILDREN IN LONDON, CANADA

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Abstract

The food environment has been implicated in the continuing epidemic of childhood obesity in Canada. The purpose of this thesis is to examine associations between the food environment, childhood weight, and unhealthy diets using data collected by the Spatial Temporal Environmental and Activity Monitoring (STEAM) project conducted among children (N=852) aged 9 to 14 years in Southwestern Ontario between 2010 and 2013. Global Positioning System (GPS) monitors and Geographic Information Systems (GIS) were used to determine the time children spent within 100m of an unhealthy food outlet on weekdays. Structural equation modeling was used to assess the effect of exposure to fast food and variety stores on children's weight, mediated by unhealthy dietary intake, stratified by sex. There were no significant associations between food outlet exposure and weight for males or females, nor was unhealthy diet a significant mediator of this relationship. Future work and public health implications are discussed.

Keywords

Child, body mass, unhealthy dietary intake, food environment, activity space, Global Positioning System (GPS), Geographic Information System (GIS), Southwestern Ontario, structural equation modeling

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List of Abbreviations

EST	Ecological Systems Theory
BMI	Body Mass Index
FMI	Fat Mass Index
SES	Socioeconomic Status
MRI	Magnetic Resonance Imaging
DEXA	Dual-energy X-ray Absorptiometry
HDL	High Density Lipoprotein
LDL	Low Density Lipoprotein
STEAM	Spatial Temporal Environmental Analysis and Monitoring
CIHR	Canadian Institutes of Health Research
SSHRC	Social Sciences and Humanities Research Council
HRFC	Heart and Stroke Foundation of Canada
SWO	Southwestern Ontario
GPS	Global Positioning System
WHO	World Health Organization
CFGHE	Canada's Food Guide for Healthy Eating
DA	Dissemination Area
HNSY	Healthy Neighbourhoods Survey for Youth
HNSP	Healthy Neighbourhoods Survey for Parents

SEM	Structural Equation Model
CDC	Centers for Disease Control and Prevention
MAR	Missing at Random
RMSEA	Root Mean Square Error of Approximation
GOF	Goodness of Fit
SRMR	Standardized Root Mean Square Residual
CFI	Comparative Fit Index
AIC	Akaike Information Criterion
FFO	Fast Food Outlet
SSB	Sugar-Sweetened Beverage
F/V	Fruits and Vegetables

Chapter 1

1 Background and Introduction

1.1 Childhood Obesity Rates

The rapid rise in obesity among children and youth in Canada has made obesity one of the most concerning health trends currently faced by public health and allied health professionals (1). Currently, nearly one third (31.5%), or about 1.6 million Canadians aged 5-17 are classified as overweight (19.8%) or obese (11.7%) (2). Prevalence of overweight and obesity has been rising steadily at a rate of about 1% each year since 1981 (1, 3). These numbers are comparable to those in the US, where obesity rates have tripled among children aged 6-11 years and nearly quadrupled among youth ages 12-17 years over the last three decades (4). In Canada, youth between the ages of 12 and 17 years old appear to be at the greatest risk; the prevalence of overweight and obesity rose from 14% in 1979 to 29% in 2004 (1). For both boys and girls, the prevalence of obesity increases steadily with age, but is consistently higher among boys (1). Globally, prevalence rates are estimated to be about 10%; lower than those seen in North America (5).

1.2 Burden of Childhood Obesity

1.2.1 Health Outcomes

Childhood obesity is an important problem for several reasons; those pertaining to children's immediate and future health and wellness being among the most pressing. Obesity is associated with type 2 diabetes, hyperinsulinaemia, poor glucose tolerance, sleep apnoea, asthma, and psychosocial disorders such as depression and social exclusion in children and youth (6-8). Type 2 diabetes, once restricted almost exclusively to adults, increased tenfold between 1982 and 1994, paralleling the rise in childhood obesity (9). Children who are overweight or obese also have a greater likelihood of presenting with multiple risk factors for chronic diseases such as type 2 diabetes and heart disease before they reach adulthood (7). The wide range of physical and emotional health problems associated with excess weight in childhood frequently carry over, and often become exacerbated, into adulthood (7). In addition, it has been estimated that about 1 in

10 premature deaths among Canadian adults between the ages of 20 and 64 years can be directly attributed to obesity (10).

1.2.2 Financial Burden of Obesity

There is also large financial burden associated with the rising prevalence of obesity in Canada (11). In 2006 it was estimated that the direct costs of adult and childhood obesity accounted for $6 billion, or 4.1% of the total health care costs in Canada (12). The cost of being obese was estimated to account for about 66% of healthcare spending on weight related health outcomes, while overweight was accountable for the remaining 34% (12). This is notably less than that spent on obesity related healthcare costs in the United States, which were estimated in 2002 to be as high as $78.5 billion, while still only accounting for 9.1% of all health care spending (13). Both of these estimates included only the direct costs of obesity (ex. drugs, physician visits, hospital care) and omitted indirect costs such as lost work time due to illness or disability, or premature death (14, 15). As such, the true cost of obesity is likely to be much higher. Indeed, the indirect costs of obesity in 2006 were estimated to be an additional $5 billion (12). In Canada, the indirect costs of all diseases for which obesity and overweight are risk factors was estimated to be a staggering $52.6 billion (12). Of this, approximately 9.5% of this cost is attributable to overweight (3.4%) and obesity (6.1%) (12). Many obesity related health care costs accrue later in life, making the financial burden associated specifically with childhood obesity difficult to calculate. However, given that excess weight in childhood is strongly associated with a higher risk for more severe co-morbidities in adulthood, childhood obesity is still considered to be an important contributor to the overall cost of the disease (1, 5).

1.3 Childhood and Pre-Adolescence

Successful interventions to reduce and prevent excessive weight gain in childhood are critical in order to both improve long term health outcomes and reduce health care costs in Canada. Childhood and adolescence represents a particularly opportune time frame for successful interventions to have great impact because excess weight in childhood is a strong predictor of continued excess weight or additional weight gain in adulthood (16, 17). As many as a third of children aged 5-12 years, and half of adolescents aged 13-18 years who are overweight or obese will remain so as adults (5). Without intervention, the prevalence of obesity is likely to continue to rise as the current generation of children and youth enter adulthood (10). Thus, there remains a great need for public health interventions that successfully reduce the prevalence of childhood obesity.

The prevention and control of childhood obesity warrants special attention because children are particularly vulnerable to obesity promoting environments, termed obesogenic environments, compared to adults (18). Children are not mature and are less able to appreciate the consequences of their behaviours (19). Obesity and its associated co-morbidities are subject to discounting because there are no immediate effects associated with obesity promoting behaviours (19). For example, becoming ill from a risky behaviour such as eating expired food will happen within hours. This timeline makes it possible to draw a direct association between the behaviour and undesirable outcome, and modify future choices to avoid a similar outcome. By contrast, obesity often takes years to develop and negative health effects may take even longer to present (7). Children are also a primary target for, and strongly influenced by, marketing by food companies (20). Children do not have adequate nutritional knowledge to make informed decisions regarding their diet and are unable to recognize advertising to promote unhealthy foods (20). Advertisements for food are pervasive in children's lives, and have been found to strongly influence children's food preferences, requests and consumptions (20). These preferences may persist later into life, contributing to unhealthy dietary habits that are a risk factor for obesity (7). Current public health strategies attempt to increase children's knowledge of nutrition and obesity, but do little to protect them from an environment which overwhelmingly contradicts the messages regarding healthy behaviours from public health professionals (21).

1.4 Rationale and Objective

With the recognition of the urgent need for programs to reduce the prevalence of obesity, there has been a large amount of effort directed at identifying and understanding the risk factors for weight gain in childhood (22-25). Obesity has traditionally been viewed as a problem of the individual, thus the bulk of research focused on individual level risk factors such as genetic predispositions and personal health behaviours (26). Following this, a large number of interventions and strategies to promote weight loss and healthy weight maintenance have been designed and implemented with the goal of educating youth and encouraging them to adopt health promoting behaviours (17, 21, 27, 28). However, while individual level factors are useful to explain individual risk for and between-person variability in weight gain, they are unable to adequately account for population level trends or inform public health strategies designed to have an effect on large groups of people (10, 22, 29). Unsurprisingly then, these strategies have proven to be unsuccessful at achieving effective and sustainable weight loss at a population level (21, 24, 27, 28, 30).

A number of authors have since called for a broad based public health approach that moves beyond the individual to recognize the contribution of the higher level factors responsible for promoting child obesity in the Canadian population (22, 31, 32). Changes in society and the physical environment over the last few decades, discussed in more detail later, promote a sedentary lifestyle and have changed the way we interact with and experience our environments (32-34). The rise in obesity in the last thirty years loosely corresponds with this time period, providing a rationale for examining more closely the influence of environmental factors in weight gain. When compared to individuals' decisions and health behaviours, these higher level factors have the potential to influence the behaviours of large groups of people simultaneously (32, 34).

Earlier strategies largely ignored the possible role of the environment in the obesity epidemic (32). This was an important oversight because treatments for obesity are unlikely to be successful if they address only the individual without considering the individual's environmental context (5, 22). Interventions for other health outcomes serve as an exemplar for how individual efforts to alter behaviour must be supported by the larger environment to achieve results that persist beyond the end of the intervention program (5, 35). For example, public health education strategies to reduce smoking became more widely successful once the role of the environment was considered and steps taken to remove or reduce environments supportive of smoking (35). For obesity, interventions targeting individuals in schools or the community will need to be matched by changes in the social and cultural contexts so that benefits can be sustained and enhanced.

In order for public health professionals to incorporate environmental factors into obesity reduction strategies, high quality evidence is necessary to guide the design and decision making process. Since the importance of contextual factors was first recognized in the late 1990's there has been steady growth of research into the role of environmental and contextual factors in weight gain (35). However, most of this research has focused on adults and physical activity; there remains a paucity of research examining the influence of the built environment on children's diets (36-39). A systematic review of the built environment and obesity noted that 16 of the 20 articles on this topic assessed only physical activity (38). Given that obesity is the result of an energy imbalance between both energy intake and expenditure, the contribution of the food environment to diet will be equally as important as the influence of the built environment on activity levels in environmental research aimed at reducing childhood weight gain.

Additionally, independent research on how children interact with their environment is necessary because children are more vulnerable to their environments than adults (36, 37). Children of different ages and cultures interact with their environments differently (25). For example, young children's diets are likely limited by their parent's food choices (40). Older children, aged about 9-15 years, have more independence and mobility such that their diets may be affected by the food environment that is accessible by foot or bicycle (40). Certain characteristics of the built environment may have an important impact on this age group as adolescents exert their independence and begin to explore their environment independently or with their peers (38).

Of the twenty studies identified in a literature search that have explored the associations between the food environment, diet and childhood obesity, five took place in a Canadian context (41-45). Majority of these studies have taken place in the United States; however several researchers in Australia have also assessed this relationship. Thus, there remains a need for research that examines the influence of the built environment on diets in children, especially in a Canadian context.

The primary objective of this thesis is to examine the association between exposure to fast food outlets and variety stores and body mass in older children aged 9 to 14 years old living in a mid-sized Canadian city. The literature to date on this association has been largely inconclusive, possibly as a result of inconsistencies in methods used to define and assess environmental exposure and measure body mass (23, 25). This thesis will contribute to the literature by improving upon existing methodologies by using objectively measured height and weight to calculate BMI, and a novel method of assessing food exposure which bypasses the need to define and estimate a static environment.

The remainder of this thesis will be laid out in the following order: an overview of the theoretical models describing the associations between the built environment and health behaviours leading to obesity, previous research on environmental food accessibility and diet, proposed plan of study, methods, results and discussion. First, the theoretical model implicating features of the built and social environments in the development of health outcomes will be reviewed, with a focus on the food environment and obesity related health behaviours. This theory proposes that there is a bidirectional relationship between individuals and their environment, so the possible mechanisms for both these directions of effect will be discussed. A literature review will follow, summarizing cross-sectional environmental health research examining the association between food environment and body mass in children. Emphasis is placed on the different techniques used to assess the food environment in this section. Chapter 2 concludes with a summary of limitations in the literature, an outline of the objectives for this study and specific hypotheses. Next, methods will be discussed, including the data source, variables used and the analytic plan for each specific objective. Finally, results will be presented, followed by a discussion of findings in the context of the existing literature and suggestions for future research.

Chapter 2

2 Literature Review

The goal of this literature review is to describe the existing evidence describing the relationship between the food environment and body mass in children. First, the overarching model framework for this relationship will be described, followed by a discussion of potential mechanisms for the effect of the environment on individuals and vice versa. Second, the results of the literature review will be presented in the context of the theoretical framework just described. This will be followed by a review of the limitations in the literature and finally an outline of the individual objectives of this study.

2.1 Theoretical Models Describing the Association between the Food Environment and Childhood Obesity

2.1.1 Ecological Systems Theory

The following literature review will first outline the current theoretical model accounting for the association between the food environment and the development of childhood obesity. As discussed briefly in the introduction, obesity is increasingly understood as the result of a combination of many factors, not only at the individual level, but also at the level of the environment. Environmental level factors can then be further broken down into subgroups and hierarchical levels of factors that have a similar effect on weight gain in children (39, 46). Ecological Systems Theory (EST) has been developed to integrate these levels of context into a comprehensive model that describes the multifactorial etiology of childhood weight gain (22). EST asserts that individual changes or developments cannot be explained without consideration of the context in which an individual is present, also termed their ecological niche (22). A person’s ecological niche includes not only their personal contexts, but also the higher level factors of the environment that context is part of (22). For example, a person’s neighbourhood may include various food outlets, but their societal environment and government policies may influence the types of food sold or hours of operation, both of which also influence individual behaviours (47). In this way, EST provides a framework for investigating and assessing the many layers of context embedded in one another, and the dynamic bi-directional interactions between contexts with respect to any individual health outcome or development (22).

Ecological Systems Theory was adapted to provide a theoretical framework for understanding obesity as a normal physiological response to an abnormal environment while integrating emerging risk factors for obesity in the late 1990's (35). This early version identified three main influences on body weight, mediated by energy intake and expenditure: Biology, Behaviour and Environment (35). Under this framework, weight maintenance is determined by the net effect of the interactions between these groups of influential factors (22, 35). More recent versions have expanded upon this model to incorporate and describe the bi-directional relationships between various aspects of the environment and individuals, including the roles of media and cultural messages, social structures and policies, physical structures and availability (48).

The following section will provide an overview of the pathways describing how physical structures and food availability are mediated by energy balance to contribute to healthy weight maintenance. There will first be a focus on the influence of the environment on individuals, and second, a focus on the influence of individuals on their environments. Energy balance is determined by both energy intake and expenditure; however, the role of energy intake is less well understood with respect to childhood obesity (33). Thus, the food environment and dietary intake will be the primary focus of this literature review and thesis.

2.1.2 Influence of Changes in the Food Environment on Dietary Patterns

Social and physical environments have undergone radical changes in the past several decades and the outcomes of these changes are not entirely positive (32, 33). Changes in community design, lifestyle and resource availability have provided the foundation for creating "obesogenic" environments (33). An obesogenic environment has been defined as "the sum of influences that the surroundings, opportunities, or conditions of life have on promoting obesity in individuals or populations" (49).

Additionally, several trends around eating have been identified that, in conjunction with changes in the physical environment and food availability, are likely contributing to increased energy intake (33, 50). Navigating the physical environment is a constant, complicated process; as such, many eating behaviour decisions occur automatically in response to environmental cues (33, 48). Obesogenic environments provide stimuli and support eating decisions by individuals' that lead to passive overconsumption and sedentary behaviour on a regular basis (48). The following section will discuss five key ways in which the physical and social environments have changed in the last several decades to promote eating behaviours leading to excess energy intake in children and youth. These factors provide a critical link between the environment and human behaviours (33).

2.1.2.1 Nutrition Transition and Increased Food Supply

An important driver of the obesity epidemic is the nutrition transition and increased energy supply (33, 51). The nutrition transition refers to the replacement of diets traditionally high in complex carbohydrates and fiber with sugars, animal products and fat, in combination with a sedentary lifestyle (51). This shift has been facilitated in part by the increasing availability and dropping costs of producing edible oils and sugars (52). Additionally, recent improvements in tool and crop varieties have led to dramatic increases in yields of corn, cereals, wheat and other staples (33). These foods can be produced cheaply in great quantities, making them more accessible such that people are able to afford to consume food purchased outside the home more than ever before (33).

2.1.2.2 Increased Density of Unhealthy Food Retailers

Recent decades have also seen a substantial increase in the number of locations providing access to food, such as convenience stores, fast food restaurants and other retailers (29). Between 1986 and 1996 in the United States, there was a 78% increase in the number of commercial food outlets, and an 85% increase in the number of fast food retailers (33). Many non-food stores also offer snacks and beverages for sale; a study found that 41% of non-food retail stores (Ex. electronic stores, salons) offered at least one type of snack food item (53). An analysis of typical fast foods found them to be twice as energy dense as is recommended for a healthful diet, as well as being higher in total energy, total fat, saturated fat, cholesterol and sodium and lower in dietary fibre and calcium (52, 54). During the same time period, the number of grocery food stores decreased by about 15%. Changes in food availability affects where people purchase their food; in the 1990s nearly 90% of all food purchases took place at traditional grocery stores compared to just 69% of food purchases twenty years later (32, 55).

2.1.2.3 Frequency of Eating Foods Prepared Away from Home

Foods prepared away from home are becoming an increasingly common source for meals and snacks in North America (56). In two decades, total calories obtained from food prepared away from home increased from 18% to 32% (57). In a similar time period, children's consumption of fast food alone has increased 300% (58). Between 1996 and 2006, the proportion of money for food spent on food prepared away from home increased from 24% to 42%; other sources have estimated this number to be as high as 53% in 2010 (33). Among children and youth, fast food outlets have become as common a source for food acquired away from home as school cafeterias, mostly at the expense of home prepared food (57). Among a sample of Canadian children, those who were obese ate out more frequently than did those who were considered healthy weight (59). This trend has negative implications for nutritional health and weight because meals consisting of foods prepared outside the home often contain more calories, fat and saturated fat than those prepared at home (57). These meals and snacks also contain on average less dietary fibre, iron and calcium; nutrients which are considered indicative of a healthful diet (57).

2.1.2.4 Increased Frequency and Changing Composition of Snacks

Frequent snacking throughout the day has also become a widespread North American habit that may be contributing to the rise in child obesity (52, 60). In the United States, the frequency and contribution of snacks to overall dietary intake has increased in the past three decades (61, 62). Among children and adolescents, the average frequency of snacking increased by one per day, and the energy consumed at a single snack increased by 168 kcal between 1977 and 2004 (62, 63). During the same time period, the types of foods typically consumed as snacks has also changed to include more energy dense, nutrient poor foods and beverages (62, 63). The contribution of sweetened beverages and high fat, salty snacks to snacking kilocalories doubled from 1977 to 2003-5, increasing average daily energy intake from snacks (50, 60, 62, 63). This is problematic for healthy weight maintenance because snacks of this type are poor triggers for satiety (5). Despite contributing more calories, snacks of this type have little to no impact on how much is consumed at the next meal time, potentially leading to a higher overall caloric intake (5).

2.1.2.5 Increasing Portion Sizes

The fifth systematic change to the food environment that may be contributing to weight gain is the increase in portion sizes offered at food establishments and stores (29, 33, 64). A study that measured portion sizes of food served for immediate consumption at popular outlets and restaurants in the United States found that, with the exception of sliced white bread, all commonly available serving sizes exceeded USDA and FDA standard portions (65). This trend has negative implications for weight maintenance because there is evidence that most people are incapable of accurately regulating their food intake at a single meal based on their caloric and nutrient requirements (5). This trend has also been identified not only in fast food outlets and restaurants, but also for meals sold in grocery stores and newer cookbooks (65). Larger portion sizes both contain more calories and encourage people to eat more in a single sitting (64, 66). Young children are the exception to this finding; however, by the time a child is only 5 years old, this innate ability to regulate food intake begins to be overridden by environmental and social factors (66, 67). Over the course of the day, neither children nor adults typically compensate for excess energy consumed, leading to a caloric surplus (66).

2.1.2.6 Summary

In summary, the built environment may play a role in promoting childhood obesity through a number of different pathways. Food availability increased as a result of improvements in production and also greater numbers of stores selling food. Types of food available for consumption are higher in fat and sugar than they once were. Trends in food consumption that have gained traction in North American society serve to further facilitate over-consuming foods that are nutrient poor and energy dense. These include frequent snacking, consuming food prepared away from home and increased portion sizes. These factors link environmental food availability to dietary behaviours in support of the theory that energy intake mediates weight gain in the context of the environment.

2.1.3 Influence of Individuals on their Environments

A central tenet of EST is the bi-directionality of relationships between levels of context and individuals; it is possible for both individuals and environments to exert influence on each other (22, 48). The previous section highlighted the pathways by which the environment may influence children's behaviours and health outcomes. In contrast, the coming section will examine and critique the alternate hypothesis that health outcomes are the result of the influence children have on their environments.

There are two main ways individuals can influence their environment (46). Direct self-selection occurs when individuals who are intrinsically motivated to follow a particular behaviour intentionally choose an environment with attributes that support their personal behaviours and preferences (68). Indirect selection arises because environments differ in non-random ways, and individuals choose to spend time in certain environments based in part on these non-random factors, indirectly influencing the types of features they are exposed to (69).

2.1.3.1 Direct Self-Selection

Individuals who are intrinsically motivated (or not) with respect to one or more health behaviours are likely to choose environments with amenities that are consistent with their pre-existing beliefs and values (46, 68). Environmental self-selection occurs on a daily basis as children move through their day and is referred to as daily mobility bias (68, 70). Associations between the food environment and weight may reflect these internal preferences rather than occur as a result of the environment. For example, it is possible a preference for fast food motivates individuals to seek out environments with a higher density of food retailers selling prepared foods (71). If unaccounted for, environmental self-selection may lead to spurious correlations overestimating the influence of the built environment on behaviours and health outcomes (68).

There is some evidence indicating daily self-selection may exist in children. A recent study of English school children found that routes taken on the way home from school were longer than those taken on the way to school, and this resulted in greater food exposure in the afternoon (72). They suggest this finding may reflect some degree of food preference in the afternoon compared to the morning (72). However, other work has failed to find evidence for daily mobility selection in kids (73). This may be a reflection of the fact that many children are driven or bused to school and therefore have little influence over the environments they travel through on a daily basis, regardless of personal preferences (73). Thus, the influence of individuals on their environments may be less of a concern in children due to their limited ability to interact with their environment according to their preferences (73).

2.1.3.2 Indirect Self-Selection

Indirect self-selection may result in spurious associations between the built environment and health outcomes when the neighbourhood reflects individual characteristics that are independently linked to that same health outcome (74). This arises because individuals are not randomly distributed between neighbourhoods; rather, they are more likely to spend time in neighbourhoods that are comprised of demographically similar individuals (46). If neighbourhoods affect health, the stratification of demographically similar individuals into certain neighbourhoods creates problems in assessing the independent effect of environmental exposure on health (74). For example, a low income family is likely to live in a lower income neighbourhood (46). This neighbourhood is more likely to have a higher concentration of unhealthy food retailers (75). Additionally, socio-economic status (SES) is independently predictive of weight (76). Part of the effect of living in this neighbourhood then is likely to be clouded by individual characteristics that influenced the likelihood of living in that neighbourhood in the first place (74). If this association is not accounted for, it can lead to spurious associations between environmental exposure and health outcomes that overestimate the effect of the environment (69).

These measured or unmeasured endogenous variables also play a role in people's daily mobility patterns in a similar fashion to direct daily mobility bias described above (68, 70). To the end that individuals make decisions to travel to and utilize a particular resource based on these factors, their resulting exposure to factors within the built environment and consequent outcomes are likely to differ from other individuals in non-random ways (68). As with direct self-selection, indirect self-selection is unlikely to have a strong influence on children due to their limited ability to select their own environments.

2.1.3.3 Summary

Overall, it is evident that behaviours and health outcomes may manifest as result of individuals' predispositions and preferences regarding their diets, rather than as a side effect of their environments. This can occur by individuals either directly or indirectly selecting their daily environments. This relationship is important to consider since ignoring it may limit the researcher's ability to accurately assess whether additional or fewer food retailers will further improve the ability of the child to engage in health promoting behaviours (46). However, the ability of children's behaviour preferences to affect their environments may be limited due to their semi-restricted independence and mobility (73).

2.2 Cross-sectional Research Examining the Association between the Food Environment and Childhood Obesity

With this understanding of the theoretical model of the association between the environment and childhood obesity, existing research that has examined this association will be considered next. Given that the influence of children on their environment is unlikely to be important based on existing research and in theory, the literature review will focus on work that has examined the influence of the environment on health outcomes in children (72, 73). The goals of this section are to highlight the main findings and qualities of the studies that have investigated this research question, emphasize the methodological and analytical challenges of environmental research that may contribute to inconsistent findings between studies, and to identify the important limitations in the existing research.

Several exclusion criteria were applied when searching the literature in order to ensure that the findings from this review are applicable to the research question. First, since childhood and adolescence is a period of rapid changes in autonomy, studies were only included if the age group of the sample was comparable to that of the sample used for this thesis project (9-14 years). Children or adolescents outside of this age group are likely to experience their environments differently due to age specific differences in independence and resources (77). Second, exclusively ecological level studies were excluded since the primary outcome of interest is childhood obesity associated with individual exposure. Third, in order to draw comparisons between studies and to the current thesis project, only studies that examined either diet or body mass as outcomes were included. Fourth, among studies that examined the association between the food environment and child weight, only findings pertaining to unhealthy food outlets are described to be consistent with the present study. Studies that also examined associations between healthier food outlets, such as grocery stores and supermarkets are included in a summary table in Appendix C.

There is a wide degree of variation in the way that studies have measured body mass and the food environment. As such, there will be a section prior to the literature review summarizing the methods and techniques that have been employed to assess children's body mass and attempted to capture food exposure in the environment. This section will provide the background and context for the subsequent literature review.

This section will be laid out in the following order: 1. Measures of body mass and environmental food availability and accessibility; 2. Cross-sectional research using objective measures of the environment; 3. Cross-sectional research using subjective measures of the environment; and 4. Key limitations between and within studies. Research that used objective measures of the environment will be further grouped into measures of availability, accessibility, and the use of daily mobility paths. Accessibility will be considered first, followed by availability, divided into the two main methods used to measure availability. Since a secondary objective of this study is to examine unhealthy food intake as a mediator between the environment and childhood obesity, research examining this association will also be presented, prior to discussing study limitations.

2.2.1 Assessing Childhood Overweight and Obesity

Body mass index (BMI) is a measure of weight adjusted for height that has become a widely used and practical method for assessing body fat in clinical settings and large scale epidemiological studies (78, 79). This method is somewhat less accurate at assessing body fat than other methods such as hydrodensitrometry, magnetic resonance imaging (MRI), computed tomography or dual energy x-ray absorptiometry (DEXA), but it has the benefits of being safe, straightforward to calculate, and inexpensive (80). As an indicator for health outcomes, BMI has been well validated in adults as a measure of fatness and is predictive of adverse health outcomes (78, 81). In children and adolescents, BMI has also been found to correlate strongly with total body fat and percentage body as measured more accurately using DEXA (80). Adverse health outcomes in children are more difficult to assess since they often present in adulthood; however, several studies have found that BMI is predictive of serum insulin levels, total cholesterol and high density lipoprotein (HDL) and low density lipoprotein (LDL) cholesterol, and diastolic and systolic blood pressure in youth aged 5 to 18 years old (82, 83).

Childhood and adolescence is a period of rapid growth and development, and this presents challenges to using BMI to assess body fatness (78, 84). Unlike adults, as children grow their healthy body composition changes substantially (85). For example, the median BMI at birth is 13 kg/m^2, this rises to 17 kg/m^2 by one year before falling to 15 kg/m^2 at age 6 (84). Additionally, males and females differ in their growth curve trajectories, particularly during puberty (84). In order to make comparisons between children of different ages and sex, it is necessary to standardize BMI for age and sex (78, 79). BMI z-scores, or standard deviation scores, are a measure of weight adjusted for age and sex, based on an external reference population that accommodate for age and sex differences (79). This scale is optimal for assessing adiposity for cross sectional research (84).

2.2.2 Assessing the Built Environment and Food Exposure

Accurately assessing features of the built environment in a way that is theoretically meaningful with respect to health outcomes is an ongoing challenge in environmental health research (86, 87). Variation in measurement techniques contributes to incompatibility across studies, making it difficult to draw valid conclusions regarding the effect of exposure to food retailers on childhood obesity (87). The following section will discuss first the methods that have been used to assess features of the built environment, and second, methods used to define the geographic space where people are exposed to their environments. This will provide the base for a review of the literature studying the association between environmental food exposure and child obesity.

2.2.2.1 Determining Food Exposure

The community nutrition environment, as described by Glanz *et al.* includes the number, type, location and accessibility of food retailers in the environment (88, 89). Objectively assessing the influence of these features on individuals' food choices and development of obesity requires accurately identifying and measuring the spatial accessibility of food outlets (90). Ideally, features of the built environment are assessed directly by trained researchers (27). This requires in person audits of buildings and businesses to acquire a complete and current picture of the environment (27). Other indirect and intermediate options are available that are less resource intensive to utilize, but suffer the possibility of being outdated or inaccurate (27). For example, indirect environmental measures include information garnered from census data collection, which may be outdated and fail to accurately reflect the environment at the time of the study. Intermediate tools include the use of phone books, marketing databases, or aerial photography to identify features and their locations in the built environment (27). These tools may also be outdated, and can be problematic if they rely on self-report or if the actual building use and operation status cannot be confirmed from the secondary resource (27). In comparison, in person assessment of the environment avoids these issues and ensures for accurate measurement of the built environment.

There are two main approaches used to aggregate information on the presence and location of food outlets into a comprehensive, objective measure of food outlet exposure (90). The first, accessibility, quantifies the distance to the nearest food outlet from a set location, often the subject's home, by measuring distance or travel times (90). Locations under a 1500m distance or 15 minute walking distance are typically considered accessible (91). Measuring distance, either as a Euclidean distance or along a road network is most common; 15 of 20 studies that used proximity as a measure of food accessibility used one of those two techniques (90).

The second approach to assessing food exposure is availability, often assessed by density (90). Food outlet density assesses the availability of food outlets within a predefined area using a buffer method, kernel density approach or spatial clustering (90). Kernel density allows researchers to estimate "the intensity of referenced points across a surface, by calculating the overall number of cases situated within a given search radius from a target point", weighted by the distance to the food outlet from the geographic center of the area (92). Spatial clustering assesses evidence for clustering of food outlets, for example around schools, beyond what is reasonably expected due to random distribution (93). Buffer methods are the most common method of assessing density; 18 of 21 studies identified in a systematic review used buffers to calculate food outlet density (90). This method requires defining a zone with a specified distance or shape around a given location within which to determine food accessibility (90).

2.2.2.2 Defining Boundaries for Geographic Space

Defining food exposure by availability as described above requires defining a geographic buffer zone (90). This buffer zone is often located around homes or schools and attempts to capture the space that is most likely to be considered the surrounding 'neighbourhood'. However, despite this goal being nearly unanimous across studies, the methods used to delineate neighbourhoods have varied greatly and there is often little empirical justification for the boundaries used (86). The following section will discuss the main methods that have been used to define neighbourhoods with the goal of capturing environmental exposure, with a focus on more recent methodologies utilizing GIS and GPS technology to describe neighbourhoods centered on individuals.

Early studies focused primarily on residential neighbourhoods and pre-defined administrative geographic areas such as census tracts, postal codes or voting precincts (27, 86, 90). While convenient for data collection, the use of these boundaries largely ignored the theoretical underpinnings relating place to unique individual environmental interaction and resulting health behaviours (86). Additionally, these geographic boundaries were static and treated individuals living near the edge of their geographic area the same as those living near the middle (86).

Technological advancements and the integration of Geographic Information Systems (GIS) technology into environmental health research has helped to facilitate the development of an ego-centric definition of neighbourhood (86). These neighbourhood boundaries are centered on an anchor point that is unique to each individual and may be a better reflection of the actual lived environment (86, 94). However, there is a wide degree of discrepancy in the shape and size of buffers used to delineate neighbourhoods; no clear indicator exists for a best practice method (23). In most cases, researchers have justified buffer sizes based on what is thought to be a reasonable walking distance which has led to a remarkably wide range of distances (23, 25, 90). A recent systematic review found that papers used buffers ranging in size from 160 m to 4.8 km to delineate the area within walking distance for children around schools (23). There is some inconsistency in the location chosen to anchor the buffer as well; however, studies of children mostly use either the home, school, or both as an anchor point (23, 25).

The two main types of buffers are circular or straight-line, and network or street buffers (23, 27, 95). Both are based around a central anchor point, but circular buffers define a circle shaped geographic space based on a straight line radius from the anchor. Circular buffers may inaccurately capture environmental exposure because they ignore the design of the environment or land use within the buffer zone (86). For example, an 800m circular buffer includes all the space and food outlets within an 800m radius of home, but some of this space may be inaccessible due to poor street connectivity, leading to an overestimation of environment exposure compared to what is actually accessible.

In contrast, network buffers are created by following road and path networks for a given distance, and then outlining the non-uniform area that includes all the space accessible by road or path within that distance. Network buffers may provide a closer approximation of the lived experience of the environment by following streets and paths, thereby ensuring that only the environment that is actually accessible is include in the neighbourhood buffer (95). Two other buffers types have also been developed that are similar in design to network buffers (43, 95). The first are called sausage buffers and are anchored on a central point but include only features of the environment along the street/path network that are located within 50m to 150m of the road (95). The goal of this type of buffer is to approximate the aspects of the environment that people see, smell and hear as they travel along streets, rather than defining a unit shape (95). The second is a walkshed, designed for delineating children's environments around school (43). The school walkshed was defined as the territory within a school's catchment area that includes only those students living within walking distance (43).

While the development of these buffers represents important advancements for the assessment of the environment, they are still limited in their ability to capture only the residential or local environment (86). Some researchers have argued that this "local trap" ignores the non-residential environment, and contexts outside the local environment where people spend part of their day (86). As a result, the use of activity spaces has been developed to attempt to account for people's patterns of movement over the course of the day both within and outside their residential spaces (86).

Activity spaces provide a more flexible, individual centered method that is able to capture the heterogeneity between individuals in terms of their daily habits (86). Activity space has been defined as the "subset of all locations within which an individual has direct contact as a result of his or her day to day activities" (96). Methods are currently being developed to measure individuals' activity spaces, such as wearable GPS units (86).The use of this method to assess individual environmental exposure, rather than defining a neighbourhood, may help to better understand which types, characteristics and spatial scale of environment matters with respect to a particular health outcome (86).

Finally, subjective measures can also be used as a means to assess the built environment. Including subjective measures, such as perceptions of food availability or accessibility may more precisely identify which features of the environment are most salient or influential to different people. This has the potential to allow researchers to more accurately describe relationships between environmental influences and health outcomes by partially accounting for individual beliefs and values (97). Assessing the environment in terms of how it is perceived by children may be important in translating external environmental influences into individual behaviours.

2.2.3 Associations between food exposure and childhood weight using objective measures of the environment

The literature search identified sixteen articles that studied the relationship between environmental food exposure and body mass in children aged 10 to 14 years on average, using objective measures of the environment (41-44, 73, 98-108). Of these, eight studies assessed the environment using measures of accessibility, and fifteen used measures of availability. Findings from these studies will be summarized in the following section. An additional three studies were identified that studied this association using subjective measures of the environment (45, 109, 110). These will be summarized at the end of this section.

2.2.3.1 Studies assessing food exposure by accessibility

The literature assessing the relationship between childhood obesity and the food environment using measures of proximity is highly inconsistent. There are several variations in the way that researchers assess participant’s proximity to food outlets which will be noted for each study in the following section. Studies that found a positive association between features of the built environment using measures of proximity will be covered first, followed by studies that failed to find an association, or that found a significant association in the opposite direction to that hypothesized.

First, a study in California of over half a million children whose average age was 14 years old, assessed the distance to the nearest fast food outlet or other restaurant type from children’s schools (100). They found that for each additional 400m to the nearest restaurant, children's BMI percentile was expected to decrease by about 0.03 (100).

Second, a study of another large sample (n=21, 008) of children in Massachusetts also found associations between proximity measures of food outlets and the odds of being overweight or obese (102). They found the distance to the nearest fast food restaurant was inversely associated with BMI (102). In a subset of this sample (n=6680), there was evidence of income disparities in the association between the built environment and weight (101). Among high income quartile towns only, the odds of overweight and the odds of obesity were reduced with increasing distance to the nearest fast food outlet (101). This association remained significant only for the odds of being overweight after adjustment for neighbourhood level covariates (101).

Next, Jilcott *et al.* assessed proximity of youth aged about 12.9 years old to the nearest food outlet from home, in kilometers (103). They assessed several different types of unhealthy food outlets, including fast food outlets, sit-down restaurants, pizza outlets, and convenience stores (103). Using these indicators, they found that for children belonging to minority groups, BMI percentile increased with decreasing distance to the nearest convenience store (103). This finding approached significance for African American youth, and was not significant for white children (103). No other types of food outlets were associated with BMI percentile.

The fourth study to report a positive association between children's proximity to built environment food outlets and weight was a community based sample of 10 year old children in New Jersey (104). They found that the odds of being overweight or obese were reduced for each additional mile in distance participants lived from the nearest convenience store (104). Proximity to the nearest food outlet was assessed in miles along the road network (104).

As with Jilcott *et al.*, many of the studies mentioned above that did report associations in the expected direction between food outlet proximity and child weight also assessed other measures that were not significant. For example, Davis *et al.* studied over half a million youth and while they did find an association between students' BMI percentile and the distance to the nearest restaurant, they found no association with the nearest fast food outlet (100). Likewise, Ohri-Vachaspati *et al.* assessed proximity to both fast food outlets and convenience stores, but did not find an association between proximity to fast food outlets and the odds of overweight or obesity in their sample (104).

Additionally, several studies did not detect a relationship between food outlet proximity and child obesity (44, 98, 105). A study of a sample of children aged 8 to 9 and 13 to 15 years old from 19 schools in Melbourne, Australia, found no significant relationships between BMI z-score and distance in kilometers to the nearest fast food outlet from school (105). The association approached significance for boys aged 8 to 9 years old (105).

Carroll-Scott *et al.* also found no evidence of a relationship between fast food outlets or convenience stores and BMI in a sample of children aged about 10.9 years in the United States (98). Rather than measuring proximity as a continuous measure of distance, they grouped children into two groups: those that lived within 800m of a food retailer, and those that did not (98).

Finally, a Canadian study of over 1000 youth aged 11 years in Toronto assessed the distance to the nearest fast food outlets, as well as other unhealthy food stores from children's homes (44). They found no evidence of an association between the odds of overweight or obesity and the proximity of these food retailers to children's residence (44).

2.2.3.2 Studies assessing food exposure by availability

Food retailer density is the technique commonly used to assess the availability of food outlets in the environment. Studies that aim to assess the relationship between the density of food retailers and weight status often delineate a spatial area beyond which is considered too far to be readily accessible by a child (90). Circular and network buffers are most commonly used to do this (90). The following findings from literature assessing the built environment using a measure of density will be divided into those that defined neighbourhoods using circular or network buffers, or daily mobility paths.

2.2.3.2.1 Circular buffers to define neighbourhoods

As with measures of proximity, assessing the density of food retailers within a circular buffer has yielded inconsistent associations with overweight and obesity among children and youth (23). A large study (n=966) of children aged 12 years in a mid-sized Canadian city led by Gilliland *et al.*

found a modest, but significant positive association between children's BMI z-scores and the presence of either a convenience store or a fast food outlet within a 1 km or 500m circular buffer around homes (43). This positive association held for the presence of a convenience store within a 1 km circular buffer of schools as well (43).

A large study of 939 Korean children, on average 12.1 years old, also found a positive association between the density of fast food outlets and the odds of obesity among girls only, after adjustment for individual, school and neighbourhood covariates (106). This group assessed density as a continuous count of food outlets located within a 500m buffer centered on children's homes (106). However, the same study also found an inverse relationship when snacking outlets were considered. Increasing density of snacking outlets was associated with reduced odds of being overweight or obese among boys and girls (106).

In a group of youth (n=744), aged on average 12.9 years, in North Carolina, United States, researchers assessed the relationship between BMI percentile and the density of eight different types of healthy and unhealthy food retailers in 400m, 800m, and 1600m circular buffers (103). They found that the only food exposure variable significantly associated with BMI percentile was the density of fast food and pizza outlets in an 800m buffer (103).

These findings are corroborated by a similarly large study (n=702) of children aged about 10 years old from New Jersey, United States (104). This group found that the odds of being overweight or obese were greater when a convenience store was located within a 400m circular buffer of home, and increased by 11% for each additional convenience store within that buffer (104). Odds of overweight or obesity were increased by 90% when fast food density was assessed as the presence of at least one outlet versus none within the buffer. 800m and 1.5km buffer sizes were also assessed; however there were no associations for these distances (104).

A separate, very large (n=21, 008) American study of children aged 5 to 12 years, found an income dependent positive association between the density of fast food outlets and the odds of overweight, indicating the income level of the neighbourhood may interact with fast food outlet density to affect child weight gain (102). Researchers used a 400m circular buffer and a continuous measure of fast food outlet density to assess exposure (102). Fast food outlet density within a 400m circular buffer around home was significantly associated with overweight and obesity both before and after adjustment for neighbourhood covariates, but only for children residing in low income quartile neighbourhoods (102).

These positive findings are challenged by a number of other studies that failed to find a significant association between food outlets and children weight, or found an association in the opposite direction of that predicted (41, 42, 99, 105). For instance, a large (n=7281) nationally representative sample of Canadian youth aged about 13 years found that the presence of at least one food outlet of various types (fast food, coffee shop, or sandwich shop) was significantly predictive of a reduced odds of overweight or obesity (41). They used a large 1000m circular buffer around children's home to assess the presence or lack thereof of food outlets (41).

Furthermore, another Canadian study of 1264 elementary school children in grade 7 failed to find any significant associations between the odds of being overweight and the density of six different types of environmental food retailers (42). Density was assessed here as a continuous variable within a 1000m circular buffer around schools (42).

Contradictory findings have also been found in Australian children and youth (105). Among youth aged 13 to 15 years old, the presence of at least one fast food outlet within a 2km radius from home was negatively associated with BMI z-score, among both boys and girls separately (105). Among girls only, the odds of being overweight or obese were reduced by 81% if there was at least one fast food outlet located within the 2km buffer compared to none, and an additional 14% with each additional outlet (105).

A study in France had similar findings; among low income students, those with below average density of general food outlets and fast foods outlets within a 1 km circular buffer had greater odds of being overweight or obese compared to similar students with better access to those stores (99). This association was significant for general food stores, and approached significance for fast food outlets. Bakeries were also considered. Of note, this group also found evidence for an income effect, similar to Oreskovic *et al.,* although the effect here was in the opposite direction to that in the American study (102).

In summary, five studies examining the relationship between the built environment and child obesity found a positive association between a measure of unhealthy food outlet density and child weight (43, 102-104, 106). However, a similar number (n=4) either failed to detect any significant relationship, or found a significant association in the direction opposite of that predicted by theory (41, 42, 99, 105). Even among the studies that did report positive findings, they often assessed several different buffer sizes or food outlet types, yet reported only one or two noteworthy associations.

2.2.3.2.2 Network Buffers to Define Neighbourhoods

The use of network buffers has also been unable to clarify the association between the food environment and childhood obesity. Four studies found positive associations between food outlet density and child weight (43, 100, 103, 107). A very large study (n=529, 367) of youth in California aged about 14 years old, mentioned previously when discussing proximity measures, used a continuous measure of food outlet density and 800m network buffers to assess food exposure. They found the odds of being overweight or obese were increased by 6% and 4% for each additional fast food outlet or other restaurant, respectively (100). Additionally, BMI percentile was also positively associated with the densities of both of these food outlet types (100).

The study of youth from North Carolina, mentioned in the previous sections, also assessed the density of four different types of unhealthy food outlets in 400m, 800, and 1600m network buffers (103). In doing so, they identified a single significant positive association between density of fast food outlets and BMI percentile (103). None of the associations between the densities of sit-down restaurants, dollar stores, or pizza outlets in 400 or 1600m buffers were associated with BMI percentile (103).

Gilliland *et al.* utilized 500m and 1000m network buffers around children's homes and schools to simultaneously assess the influence of both of these environments on children's BMI z-scores (43). The average age of children in this study was about 12 years. They also developed a novel school walkshed measure to delineate neighborhood boundaries around school for food exposure and this measure was assessed in addition to network buffers in their multilevel models (43). Using this method, they found a positive association between BMI z-score and the presence of fast food outlets in the school walkshed (43). None of the variables in the home environment or school environment network buffers were predictive of BMI z-score (43). When compared to the circular and network buffers also evaluated in this study, the school walkshed was the only one that retained a significant association between any type of food outlet and BMI z-score after adjusting for covariates (43).

One study considered the dominant mode of travel children used to commute to school: active or inactive (107). Network buffers within 6km were used to assess the density of healthy and unhealthy food outlets according to tertiles of best to least access, since there were no facilities located within the 800m buffer considered initially for many students (107). There were no associations with unhealthy food outlets in the home environment. In the school environment, for both inactive and active female travelers, being in the tertile with the best access to unhealthy food outlets was predictive of higher fat mass index (FMI) (107). There were no significant associations between food access variables and FMI for boys in either the home, school or route environments (107).

In contrast, two studies did not find a relationship between measures of food density in a network buffer and child weight (44, 108). First, a large sample (n=1669) of students aged 10.2 years in the United Kingdom failed to detect any significant associations between the density, measured as a binary variable, of three types of food outlets (BMI healthy, intermediate and unhealthy) and weight status (108). Outlet density in this study was assessed using an 800m network buffer (108).

A large Canadian study (n=1035) of elementary school children aged on average about 11 years old defined neighbourhood exposure using 1000m network buffers and considered the influence of fast food stores, less healthy food stores and several healthy food store types on weight status (44). Researchers found there were no significant associations between the density, measured continuously, of unhealthy food outlets and the odds of overweight or obesity among this group of children (44).

2.2.3.3 Daily Mobility Paths

It has been suggested that the environments children are exposed to on their daily mobility paths should be considered in order to gain a more accurate picture of how children experience their environment (23, 86). Daily mobility paths, or activity spaces, describe the free living experience of an individual as they move through their environment on a daily basis, either traveling to work or school, or for leisure (86). This recommendation comes in light of the recognition that, among adults, environmental health research has centered on residential or workplace neighbourhoods, yet many daily activities take place outside of residential activity spaces (70, 111). A study of children in a mid-sized Canadian city found this to be true among older children as well (112). This finding offers support for the transition of environmental health research towards considering exposure to factors within children's activity spaces beyond their immediate neighbourhoods.

As mentioned above, there is evidence that children are interacting with environments beyond the commonly assessed 400m or 800m neighbourhood buffers. A pilot study that used GPS monitors to assess location and duration of activities for 100 children found that 37.5% of time was spent outside their neighbourhood, defined as an 800m network buffer (113). This fraction was slightly higher for boys, and rural children (113). More recently, Loebach *et al.* found that, among children aged 9-13 years, approximately one quarter of leisure time (e.g., time not in school) is spent in environments beyond that within walking distance from home (112). The remaining three quarters of leisure time was spent within the neighbourhood activity space, although about half of this time was actually spent indoors at home. So, of the time children spend outside on a daily basis, almost half may be in environments not traditionally considered within walking distance (112). Indeed, the average distance traveled by children in their neighbourhood activity space was nearly 1000m, with about a fifth of children traveling over 1600m (112).

Exposure to environmental factors outside of traditional neighbourhood buffers may be an important influence on children, yet very few studies to date that have attempted to account for this exposure (73, 107). The two studies that assessed environmental exposure to food outlets and weight will be summarized below. While few, these two papers highlight important methodological differences arising from advancing technology.

The first study to assess the association between food outlets and body weight, measured as fat mass index (FMI), among a large group (n=1995) of children aged on average 10.3 years took place in the United Kingdom (107). This group assessed children's exposure to food outlets on their travel routes to and from school, in addition to assessing school and home neighbourhoods (107). Of note, travel paths of children were not actually measured, but modelled on the route that was the shortest distance. Food outlets that were located within 100m of this route were included in the child's exposure to environmental factors, and classified into tertiles of low to high exposure (107). There were no significant associations between both healthy or unhealthy food outlets and fat mass index (FMI) located along routes to school among boys or girls, or by mode of travel (107).

The second study to assess route exposure included a much smaller sample of children (n=94) aged 5 to 11 years old in a community in North Carolina, United States (73). They assigned participants GPS devices to ascertain the actual paths traveled by children outside of school. Consistent with Harrison *et al.*, and the sausage buffers used by Forsyth et al, this group buffered the activity paths at 100m to estimate environmental exposure (73). Exposure to takeaway food outlets and all food outlets was considered in tertiles of least to greatest exposure; however, there were no significant associations between exposure measures and BMI z-score in this sample of children (73).

A key difference between these two studies that both assessed children's environmental exposure along activity paths is the methods used to estimate the path taken by children. Harrison *et al*. predicted a Euclidean path between home and school, while Burgoine *et al*. used a combination of GPS and GIS software to measure children's actual routes taken, in addition to predicting a shortest distance route (73, 107). The type of method used to estimate children's routes may be important in determining exposure because there is evidence that the actual route taken according to GPS measures was longer on average than the predicted Euclidean path (72, 73). Neither of these studies identified a significant association between environmental food exposure and weight outcomes (73, 107). Both studies only considered the routes to and from school, yet there may be traveling occurring later or at other times in the day that may be contributing to children's food environment exposure.

While the assessment of daily activity space exposure is not yet widely used, it has the potential to improve objective environmental measures (86). Measurement of environmental exposure as an individual aggregation may be more accurate in relation to behaviour because it reflects the actual patterns of use of the environment in daily mobility trajectories (68). Compared to the circular and network buffer methods described previously, activity space path buffers are descriptive of what the individual actually did and where they went, rather than where they could or should have gone, and captures all of the activity destinations (111).

2.2.3.4 Subjective Measures of the Environment

Subjective measures are an alternative to objectively measuring the built environment. These may include survey responses regarding the participant's perceptions of how safe their neighbourhood is, how many food outlets are within walking distance or how affordable food is in their neighbourhood (45, 109, 110, 114, 115). Subjective measures may be able to account for factors not captured using objective measures in order to ascertain which features of the environment an individual uses (114). For example, children's eating patterns and use of environmental resources are strongly influenced by their family and peer networks, as well as the social norms and media (97). Assessing the environment in terms of how it is perceived by children may be important in translating external environmental influences into individual behaviours.

Very few studies have assessed the relationship between the environment, children's diets and obesity using subjective measures. The vast majority of research examining neighbourhood perceptions has focused on various aspects of the built environment and physical activity, and has mostly focused on adults. A search of the literature found only three articles using perception of access to food stores to assess the relationship between the built environment and childhood obesity (45, 109, 110). Since these studies assessed adults' perceptions of their child's food environment instead of children's, these papers will only be summarized briefly to highlight the use of this method.

Overall, all three studies assessed access to neighbourhood shops; however their findings are mixed. Two studies found no association between subjective measures of food accessibility and weight status (109, 110) and one found a positive association (45). Methods of measuring the food environment are as varied as with objective measures; each study used a different assessment method. One study used parental perceptions of shops within walking distance (109), another used a parent survey rating shop access on a scale (45), and the third surveyed children about the perceived walking time to the nearest shop (110). There were also differences in the way food outlets were classified and body mass was assessed, and in the country where the study took place. As with objective measures, these differences may be contributing the poor reproducibility between studies.

Findings among studies using environmental perceptions of the neighbourhood resources with respect to weight have been largely inconsistent (109, 115, 116). As a result, one study suggested that a combination of both objective and subjective measures of the environment may be the most effective way to assess the relationship between the built environment and behavioural outcomes (114). This study assessed the environment objectively and using participants' perceptions of how the environment influences physical activity, and found independent associations with both types of measures (114). However, the inclusion of both perceptions and objective environmental measures in statistical models improved the model fit and associations with physical activity, indicating both measures may be necessary to account for associations with environmental exposure (114). Of note, there was poor agreement between objective and subjective measures, indicating substituting one for the other may not be an appropriate approach (114).

2.2.4 Cross-sectional associations between food exposure and dietary outcomes

A literature search identified six publications that examined the association between the food environment and dietary outcomes using objective measures (108, 117-121) and one that used subjective measures (110). All except one article assessed both accessibility and availability (108), and one modelled mobility paths to assess food exposure (119). These articles will be summarized below using the same structure as the previous literature reviewing body mass outcomes.

2.2.4.1 Studies assessing food exposure by accessibility

The five articles that measured accessibility reported differing associations. A study of elementary school students conducted in a mid-sized Canadian city found several positive associations between food exposure and diet quality (122). They measured the distance from students' homes and schools to the nearest convenience store and fast food outlet along the shortest road or path network (122). Students were grouped into those who lived or went to school within 1 km of the nearest retailer, and those whose homes and schools were further than 1 km. Dietary quality was assessed using the 2005 Healthy Eating Index, created using responses from the Block Kids 2004 Food Frequency Questionnaire (122). Using these measures, researchers found that students who lived within 1 km of a convenience store, or attended a school within 1 km of either a convenience store or a fast food outlet had a lower diet quality than those students who were not within 1 km of these outlets (122). Proximity of fast food outlets was not associated with diet quality in the residential neighbourhood (122).

Another Canadian study assessed this relationship, but failed to find any significant associations. They assessed 512 children aged on average 9.6 years from Quebec, all of whom had at least one obese biological parent (121). Children did three dietary recalls and these food reports were converted into four dietary outcome variables: fruit and vegetable intake, sugar sweetened beverage intake, eating takeout food at least once a week, and eating or snacking out at least once a week. Proximity was measured as the road network distance between four different types of healthy and unhealthy food outlets and children’s homes and schools and categorized into tertiles (121). Proximity of food outlets of any type was found to be not predictive of any of the dietary outcomes assessed (121).

A study of 204 Boy Scouts in Texas found several significant relationships between diet and food availability using the Euclidean distance to assess proximity to food outlets around the home (120). Diet was assessed as the frequency of consumption of either fruit or juice, low fat vegetables or high fat vegetables (e.g., coleslaw, fries), according to the Cullen Food Frequency Questionnaire. They found that increasing distance to the nearest small food store was modestly, but significantly predictive of higher fruit and juice consumption, and low and high fat vegetables (120). There was also an inverse association between high fat vegetable and fruit/juice consumption and fast food outlet proximity: smaller distances to fast food stores were predictive of higher intakes of these foods (120).

An Australian study found that food environmental variables influenced both intakes of fruit and vegetables and unhealthy foods in children (117, 119). Proximity of five different types of healthy and unhealthy food outlets was measured as the shortest street distance from home.

Parent surveys were utilized to measure children's intakes of fruit and vegetables, dichotomized according to Australian Food Guide recommendations, and intake of takeaway or fast foods, dichotomized at once or more each week (117, 119). The odds of consuming at least 3 servings of vegetables each day were significantly increased with increasing distance to the nearest supermarket and fast food outlet (117). Intake of takeaway or fast food was not significantly related to the proximity of any of the food retailers assessed (119).

2.2.4.2 Studies assessing food exposure by availability

2.2.4.2.1 Circular buffers to calculate density

Of the six articles that assessed availability, only two of them used a circular buffer to define the neighbourhood zone (120, 122). He *et al*., outlined above, also assessed the density of food retailers using 1 km circular buffers around both students' homes and schools (122). Density was categorized into tertiles of exposure: zero, one to two, or more than three food outlets located within the buffer zone (122). Dietary quality was found to be significantly associated only with the density of fast food outlets around schools; having more than three food outlets within 1 km was predictive of a lower Healthy Eating Index score (122). No associations were found in the home environment or for convenience store density (122).

One other study assessed the density of food outlets within a circular buffer and some index of dietary quality and did not find evidence of a significant relationship (120).

2.2.4.2.2 Network buffers to calculate density

The remaining four studies assessed density within a network buffer zone. The study of children in the United Kingdom by Jennings *et al.*, weight outcome findings presented above, also assessed dietary quality in relation to food outlet availability (108). Food outlets were grouped into BMI healthy, intermediate or unhealthy and accessibility of each was assessed by the presence or lack of within an 800m network buffer centered on children's homes. Study participants completed a four day food diary with parental assistance and this was used to estimate intakes for nine different food categories (e.g., savoury snacks, fizzy drinks, red meat). It was determined that children with BMI unhealthy food outlets located in their neighbourhood consumed more fizzy and non-carbonated fruit drinks than kids without outlets of that type (108).

Children with BMI healthy outlets located in their neighbourhoods consumed fewer fizz drinks than children with no BMI healthy outlets nearby (108). There were no differences for other food categories.

The Australian study described above in the section on proximity measures also assessed food outlet density in an 800m buffer zone (117, 119). Using both a binary and continuous measure of density, several associations were identified between the food environment and children's diets. The presence of at least one convenience store or fast food outlet within the 800m network buffer was significantly associated with lower odds of consuming at least 2 servings of fruit and 3 servings of vegetables each day, respectively (117). Furthermore, for the presence of each additional convenience store, the odds of consuming at least 2 servings of fruit and 3 servings of vegetables dropped by 16% each (117). Each additional fast food outlet was associated with an 18% reduction in the odds of meeting the 2 servings a day of fruit recommendation (117). The odds of consuming takeout or fast food once or more each week were slightly but significantly lower for each additional food outlet selling this type of food, opposite of the expected direction of effect (119).

The study from Quebec also assessed 1 km network buffers and dietary outcomes (121). Density was calculated using the kernel density function and categorized into tertiles of lowest to highest exposure (121). In the residential environment, higher densities of fast food restaurants were significantly associated with greater odds of eating or snacking out at least once a week (121). The density of convenience stores in the residential neighbourhood was also predictive of reduced odds of snacking out, but the difference was only significant for neighbourhoods with the lowest densities compared to those with the highest (121). In the school environment, none of the environmental food variables were associated with dietary outcomes (121).

2.2.4.3 Daily Mobility Paths

The only study to assess the effect of environmental food exposure beyond the neighbourhood buffer zone on children's dietary intake was by Timperio *et al.* (119). They modelled the route to school for children as the shortest road network distance between home and school, and determined the number of food outlets located within 50m of this route. Diet was measured as the consumption of takeaway or fast foods at least once a week or less. While over two thirds of children had access to at least one food outlet on the modelled route to school, food outlet exposure along the route was not predictive of takeaway food consumption in this sample (119).

2.2.4.4 Subjective Measures of the Environment

The only study identified to assess the associations between dietary quality and the food environment in children using perceptions to assess the food environment took place in a study of Puerto Rican school children (n=114) (110). Dietary quality was assessed by dietitians using a 2 day dietary recall transformed into a healthy eating index according to the USDA guidelines (110). This score from 0-100 was split into three categories corresponding to either "poor", "good" or "needs improvement" (110). The environment was assessed using a validated survey that asked participants to estimate the distance in time to the nearest healthy and unhealthy food outlet (110). Researchers found that there was a significant trend for the perception of shorter distances to the nearest unhealthy food outlet among those whose diets were "poor", and "needs improvement". No children in the study scored "good" for dietary quality (110).

2.3 Limitations of the Current Literature

In addition to the differences between studies highlighted above, there are several other key between and within-study limitations that warrant attention. The main between-study limitations are: inconsistent measures and methods of assessing childhood obesity, differences in classifying food retailers, and discrepancies in buffer size and type. Key within-study limitations are: the prevalence of cross-sectional literature, focus on the school and residential neighbourhood, and the lack of validity of food outlet databases. These limitations will be explained in detail below.

2.3.1 Between Study Limitations

2.3.1.1 Inconsistent Neighbourhood Buffer Size

As is evident from the literature review above, there is little consistency between studies on which buffer size is most appropriate to reflect neighbourhood space used by children. Both circular and network buffers are used frequently, and the size of the buffers ranged from 400m to 2000m. Despite the variation in buffer size, most authors provided justification for choosing the distance they did. The most commonly cited rationale was that the distance was considered accessible by foot or active transport (41, 44, 98, 100, 107, 108, 120, 122). Other reasons included “2-km buffer displayed the strongest level of significance in […] regressions,” (123), “A 2 km buffer was chosen […] on the basis that for fast foods, convenience is a major factor and thus proximity is likely to be important,” (105), “A distance of 1 km was selected as it has been used in previous work on food access and is a common measure of accessibility,” (44). However, several studies failed to clearly provide a rationale for their choice of neighbourhood buffer distance (42, 99, 103, 106, 117, 119) or assessed several different sizes on the grounds that there is no established distance (43, 104). The wide degree of variation is an important limitation because it prevents the pooling or direct comparison of results across studies (23, 124). This makes drawing firm conclusions regarding the influence of the environment on child obesity difficult.

2.3.1.2 Inconsistent Classification of Food Outlets

Last, the classification of different types of food outlets represents another major between-study limitation in the current research. Currently, there is no validated classification system for food retailers, or evidence for which types of retailers may be the most important to focus on (23). For example, Cetateanu *et al.* classified food outlets as one of “healthy”, “unhealthy” or mixed”, and each category contained several types of food retailers (125). This classification is similar to that used by Harrison *et al.* and Jennings *et al.* (107, 108). However, a number of studies considered food outlets types individually, defining five to eight different types of food outlets and examined the relationship between each of them to child weight or dietary quality (41, 42, 103, 104, 106, 117, 119-121, 126). Other studies made only a distinction between fast food outlets and other retailers (43, 100, 105, 122) or simply referred to food retailers vaguely as shops (45). Lastly, one study created a composite food index variable by summing over similar food outlet types (126). Interestingly, they found this was the best predictor of census tract BMI z-score compared to specific types of food outlets (126). Including a variety of different food outlet types other than just fast food outlets has been recommended in light of the initial focus on fast food outlets by earlier studies (90). While this may have the benefit of providing a more complete picture of the food environment – child weight relationship, it inhibits between study comparisons and emphasizes the importance of establishing a validated method of classifying food retailers (23).

2.3.2 Within Study Limitations

2.3.2.1 Lack of Longitudinal Studies

One of the main limitations of the research to date is that all the studies assessing the association between childhood obesity and environmental food exposure in children aged between 9 to 14 years old are cross sectional. Indeed, even when the scope is increased to include all children and adolescents under the age of 18, cross sectional studies dominate the literature. For example, a systematic review in 2007 assessing home and neighbourhood environmental correlates of obesity related dietary behaviours in children and adolescents aged 3 to 18 years old found that only three of fifty-five studies were longitudinal (31). Another, more recent systematic review assessing obesity related outcomes in children 18 years or less and objectively measured food retailer environments around schools found that only two of the thirty papers identified were longitudinal studies (23). As per the guidelines established by Bradford-Hill, establishing temporality is necessary to infer causation (127). Cross-sectional research does not allow researchers to determine which of the exposure or outcome occurred first, only whether there is an association between them. Emphasis on undertaking longitudinal studies has been recommended to strengthen the existing research and to assess if there is a causal association between how changes in the physical and social environments affect the development of childhood obesity (23, 31).

2.3.2.2 Systematic Focus on Residential/School Neighbourhoods

The systematic focus of children's environmental health research on the residential or school neighbourhood is another important limitation to the existing literature (68). Evidence is emerging that indicates children spend substantial amounts of their free time outside of these immediate neighbourhoods (112, 113). Only two studies were identified among children that attempted to measure the relationship between food exposure according by daily mobility patterns and childhood obesity (72, 73) and one that assessed dietary quality (119). By not including exposure to food outlets outside the residential or school neighbourhood, research may be missing an important component of children's interactions with food retailers that could be influencing their dietary habits and the development of obesity.

2.3.2.3 Use of Databases to Determine Food Exposure

Another important limitation concerns the validity of the data used to calculate food outlet density and proximity. Williams *et al.* noted that the most common approach to determining the presence of food retailers in the environment is using indirect sources of food outlet data, such as directories or large databases (23). This is consistent with the methods used by papers summarized in the above literature review; only three studies stated they used ground-truthing to ensure the validity of their food retailer database (43, 103, 122). The remaining studies used one, or a combination of resources such as the internet, phone book yellow pages, company websites, commercially purchased data, or United States Census data to create a food source database (41, 42, 44, 73, 98-100, 104-108, 117, 120, 121, 125, 126, 128). This may be concerning since these databases are often imperfect or outdated (129). There were only two cases where authors cited recent work validating the quality their database source (108, 125). This limitation raises questions about the validity of data accuracy and comprehensiveness and may have implications for the findings of many studies.

2.3.2.4 Self-Selection and Mobility Bias

The ability of individuals to self-select their environment may lead to spurious correlations overestimating the influence of the built environment on behaviours and health outcomes (68). Despite this potentially important source of bias, few studies have assessed the role of self-selection as part of the study design, or discussed it in interpreting findings (71, 73). The study by Burgoine *et al.* was the only one to consider mobility bias among children by comparing actual GPS routes to modelled GIS routes (73). They found no difference in predicted BMI z-score between GPS actual and GIS modelled approaches to estimating environmental exposure, indicating mobility bias was non-evident in this sample (73). The other study took place in a sample of adults, and did not assess mobility bias, but considered it in interpretation of their findings (71). Zenk *et al.* found an association between food outlet densities in the daily path area and saturated fat intake, and suggested that a limitation of their study is the inability to assess whether saturated fat intake is increased as a result of a high density of fast food outlets, or because individuals who want to consume fast food seek out areas with more fast food outlets in order to obtain it (71). They recommended that future research investigate whether or not actual patronage of food outlets mediates the relationship between access to environmental resources and health outcomes as an indicator of personal preference (71).

2.3.3 Summary of Literature Review

In summary, there are a number of methodological and analytical discrepancies in the current body of literature assessing the relationship between the food environment and childhood obesity. Despite a growing body of literature focusing on this topic, the wide degree of variation in methodology limits reproducibility among studies, making interpretation of the existing findings challenging. Within studies, these limitations include the use of non-validated databases for food outlet location, failure to consider non-residential or school neighbourhood environments, failure to assess longitudinal changes in the environment and weight status, and ignoring the potential for mobility bias to confound associations. Between studies, comparability is limited largely because of the lack of a standard for classifying food outlets and the absence of an acceptable definition of how neighbourhoods should be defined for children. As a result, it is difficult to draw conclusions about the nature of the relationships between childhood obesity, diet and the local food environment. With these limitations in mind, the following section will provide a rationale for this study and outline the objectives and hypotheses.

2.4 Plan of Study, Objectives and Hypotheses

The overall purpose of this study is to assess the cross-sectional association between exposure to fast food outlets and variety stores and body mass in older children in a mid-sized Canadian city. As can be inferred from the above literature review, a number of studies have examined this research question in similar populations. However, there are a number of limitations associated with previous studies and this study was conducted to use strong methodological and analytical techniques to contribute to improving the level of consistency between studies. Given the lack of evidence justifying the use of a neighbourhood buffer zone to assess food availability and accessibility, this study will explore this association using a novel combination of GPS and GIS to measure the food environment encountered during children's leisure time as they move freely through the environment.

Due to the inconsistent findings in the literature regarding the association between the food environment and childhood obesity, the objectives of this study are exploratory in nature. They will be assessed in the following order: 1. To assess the cross-sectional relationship between fast food outlet and variety store exposure and BMI z-score in older elementary school children; 2. If there is an association, to assess whether this relationship is mediated by the frequency of unhealthy food consumption; 3. To examine whether this relationship can be partially explained by differences in socioeconomic status between children; 4. To assess if the association between BMI z-score and the food environment varies by the type of food outlet; and 5. To examine whether any of these associations differ by sex.

The above objectives will be examined in an exploratory manner; however, there are several hypotheses with respect to the associations being examined. For objective one, we expect that greater exposure to food outlets will be associated with higher BMI z-scores among both males and females. This prediction is based on theoretical evidence linking community level features of the built environment with child weight status (22, 39). This finding would be consistent with evidence from similar populations (43, 44, 103, 126). We expect this association to be stronger for girls based on previous research (106, 107).

For objective two, we expect that unhealthy food intake will mediate part of the association between food outlet exposure and body mass. This is based on research indicating exposure to unhealthy food outlets is associated with less healthful diets (23, 25) and work indicating unhealthy diets are strongly linked to weight gain (130). As with the first objective, this is predicted based on theoretical evidence that the influence of the environment on weight is mediated by dietary intake (22, 39). By extension, we also expect there to be a positive association between exposure to fast food outlets, variety stores and body mass when considered separately. Evidence indicating boys have a greater preference for foods that are high in fat and sugar, meats and processed meats – foods that are available at fast food and variety stores (131). Thus, for both objectives two and four, we expect that there will be stronger associations for boys.

With respect to the third objective, we expect that the inclusion of socioeconomic status variables will attenuate the association between the food environment and BMI z-score. This is based on strong evidence that child BMI decreases with increasing neighbourhood income (76). There is also evidence that lower income neighbourhoods are more likely to have more unhealthy food outlets compared to higher income neighbourhoods (75). Thus, these variables will likely account for some of the variability in both levels of food exposure and also body mass, reducing the association between these two measures.

Chapter 3

3 Methods

The first part of this chapter will cover the tools and techniques used for data collection as well as describe the Spatial Temporal Environment and Activity Monitoring (STEAM) project that provided the data for this thesis. In the following sections, the definitions and measures used for key constructs will be described, as well as the analytic procedures used to assess the objectives of this thesis.

3.1 Data

3.1.1 Data Source

This study uses data collected by the STEAM research project (funding provided by CIHR, SSHRC, and the HSFC; PI: Gilliland). The STEAM project was a multi-year study conducted among elementary school children in Southwestern Ontario (SWO) in 2010, 2011, 2012, and 2013. Grade 6 and 7 students were the target age group, but students in grades 5 and 8 were also included since many schools have split grade classrooms. There were two periods of data collections for each student: 7 days in the spring and 7 days in the fall. Students participating in the project were assigned accelerometers and GPS monitors for the seven day study period each season to collect data on their daily activity levels and travel patterns. Detailed surveys were completed by students, along with a parent survey, for each data collection period. New schools were recruited for the study each year, resulting in a total of 34 schools and 852 children who participated in the spring period of data collection.

A particular strength of the STEAM project is that researcher visited the schools each day during the data collection period. This allowed the team to develop positive relationships with the students, which helped to ensure higher quality data from the GPS monitors and activity diaries. Additionally, researchers were able to remind students to complete their diaries and check the monitors to ensure they were charged and working each day. Daily contact with students demonstrated that their feedback and involvement was valued. While resource intensive, these efforts helped ensure higher compliancy and data quality than is typically seen in other similar studies where equipment is dropped off and picked up a week later (132). Due to the level of commitment from researchers, data was collected from one school at a time for each week of data collection. Thus, data collection lasted several months for the research team each spring and fall, but each student was only involved for seven days at a time.

The STEAM project was developed in response to recent research suggesting the physical environment plays a role in some children's health issues by enabling or inhibiting certain behaviours. The main objective of STEAM was to assess how the physical environment, both natural and man-made, impacts physical activity and eating behaviours among elementary school children. It used a combination of innovative tools and study design to investigate how environments are actually experienced and used by children on a daily basis.

STEAM collected data on children in elementary schools from grades 5, 6, 7, and 8. This age group may represent a critical period in the development of habits and environmental interaction, since adolescence is associated with increased mobility and independence (38, 77, 133). Research has suggested that during this period, adolescents begin to develop relationships and bonds to locations outside their home neighbourhoods (134). The influence of the built environment may be a stronger influence on developing habits and preferences as youth begin to explore more of their environment independently (38). This age group has also been associated with a reduction in dietary quality, and increase in "unhealthy" food consumption (131).

3.1.2 Recruitment Procedures

Ethics approval for STEAM was granted by the Non-Medical Ethics board of Western University (see Appendix D) before approaching elementary schools. Upon approval, four public school boards (Thames Valley District School Board, London District Catholic School Board, Conseil Viamonde and Conseil Providence) and one private school (Montessori Academy of London) were approached and gave permission for their schools to participate in the STEAM project. Additional ethics approval was obtained from each participating school board prior to contacting schools directly. Principals from selected schools were sent a letter detailing the STEAM project and requesting permission to work with their students. Once principals approved the project, students in grades 6 and 7 were given a presentation explaining the project and then asked to participate. Interested students took home a letter with information on the STEAM project and a letter of consent to be signed by their parents or primary caregiver. Students participating in the project had a signed parental consent form and an additional assent form signed on the first day of the study confirming their interest in participating. This additional form was only completed by students who had returned their signed parental consent form.

3.1.3 Data Collection and Tools

Data collection for the STEAM project took place over seven consecutive days (five week days and two weekend days) for two phases each year, once in the spring and a follow up in the fall. The STEAM project used a number of innovative tools and protocols to collect data; the Healthy Neighbourhood Survey for Parents/Youth (HNSY or HNSP; see Appendix E), Global Positioning System monitors, and Geographic Information Systems are pertinent to the relationships being examined in this study and will be described in more detail.

For both the spring and fall phase of data collection, participants completed the HNSY, a 14 item (172 questions) comprehensive survey to provide information on demographics, active and sedentary behaviours, consumption of certain foods, environmental perceptions and mobility behaviours and health related quality of life. Parents were also sent a 12 item (148 questions) optional parent survey to supplement the youth survey with information about parent background and work life and perceptions about the environment with respect to their child's activities.

As stated previously, researchers were onsite in schools during each day of the study period. Anthropometric measurements were taken by STEAM researchers on the first day of each phase of data collection using standard procedures (e.g., light indoor clothing, shoes removed) with a tape measure and digital scale. On the following days, researchers checked the GPS monitors and collected measurements for students who were absent on the initial measurement day.

Third, GPS monitors were used to gather data on the travel patterns of children in order to determine exposure to features of the environment. Each child was equipped with a portable Global Positioning System (GPS) (Visiontac VGPS-900) on the first day of data collection which was worn for all 7 consecutive days during each phase of data collection. Participants were instructed to wear the GPS units attached to a collapsible lanyard worn around the neck during all waking hours except for bathing or swimming. GPS devices are able to accurately and objectively measure the participant's location as they freely experience their environment (71, 135, 136). Time and date, spatial location, sped, altitude and trip distance are continuously recorded in one second intervals by the GPS monitors. Data was downloaded daily by researchers and students returned equipment on the final day of data collections. At the end of the study period, the GPS data was uploaded into ArcGIS 10.1 for inspection and data cleaning.

GPS tracking is a widely used and accurate approach of measuring real-time location and presents novel opportunities to integrate geography into place-based health research (134, 135). Recently, work by Shearer *et al.* demonstrated that GPS loggers may provide a more accurate description of food exposure compared to a home based approach in a population of adolescents (137). Objective techniques used previously to measure environmental food exposure included the use of circular or street network buffer zones delineating the environment deemed accessible within a short walk or drive (138). However, these methods assume youth spend most of their time within these buffer zones. This assumption may overestimate the effect of the neighbourhood around the home or school "anchor point" and fails to capture environmental exposure outside these buffers (23, 68, 137). GPS monitors overcome these limitations by allowing researchers to map an individual's outdoor location through multiple contexts, making them an extremely useful tool for understanding how environmental contexts can influence health and well-being (134, 136).

Finally, a previously validated database from the Middlesex London Health Unit was used to identify all fast food and convenience stores open for business during the study period in the city of London and Middlesex County. The geographic locations of food outlets were geocoded to the correct building using addresses from a master database provided by the City of London. Validity of these databases was checked by "ground-truthing". Trained research assistants performed on site environmental audits of food retailer locations around six schools to confirm that all locations were still open for business and no new retailers had opened. Additional verification procedures involved using streetscape photographs available in Google StreetView to visually compare contents of our food retailer database against information revealed in photographs of streetscapes within 1.6km around participating schools; however, site visits and telephone calls to understand any discrepancies revealed that the MLHU database was more accurate, as it was more up-to-date than Google StreetView. As suggested in the earlier review of the literature, ground-truthing and other forms of validation are important to ensure data accuracy, since municipal databases may be inaccurate or outdated (27).

The categories of food outlets considered for this study included “fast food outlets” (including fast food chains and pizza take-outs) and “variety stores” (equivalent to convenience stores, or party stores in the US) (139). Fast food outlets were defined as restaurants where food is ordered at a counter and paid for in advance. Variety stores were defined as small food stores with a floor area of less than 1000m. These definitions were based on the Health Inspector Database categories and were manually revised as needed to better reflect reality (139).

3.2 Measures

This thesis uses data collected from the four spring season cycles of the STEAM project (2010, 2011, 2012, 2013) from 24 urban and suburban schools within the city of London and Middlesex County, Ontario. This section will describe how individual level variables were defined and which STEAM tool they were derived from.

3.2.1 Body Mass

BMI was calculated from researcher measured height and weight, as well as self-reported height and weight. Researcher measured values were used preferentially, since self-reported height and weight values have been found to provide biased estimates of BMI (140).

Body mass was assessed using Body Mass Index z-score (BMI z-score), which allows for age and sex specific standardization, unlike BMI. BMI z-score is derived from age- and sex- adjusted standard deviations from the mean, based on a standard reference population, creating a relative scale that is comparable between children and youth (79, 84). For this study, BMI z-score was calculated based on the 2007 World Health Organization (WHO). This calculation is shown in the following equation:

$$BMI\ z - score = \frac{x_i - \bar{x}_{ref}}{\sigma_{ref}} \tag{1.1}$$

Where x_i is the observed BMI for the i^{th} child, $\bar{x}_{ref}$ is the average BMI of the reference population, and σ_{ref} is the standard deviation of the reference population. For example, a 15 year old boy with a BMI of 20 kg/m^2 has a BMI z-score of about 0.0, which corresponds to the 50^{th} percentile (79).

BMI z-score was chosen to assess body mass in children for several reasons. First, the normal range for BMI varies widely as children grow, making standardization for age and sex necessary for meaningful comparisons between children (79). For example, a 5 year old boy with a BMI of 20 kg/m2 is likely overweight, while a 15 year old boy with the same BMI is more likely to be lean (79).

Second, the use of BMI z-score allows body mass to be analyzed as a continuous measure. This is likely a better method for research in children and youth since no clear rationale based on health risk exists for defining overweight and obesity cut-points in children (78, 84). Dose response curves linking obesity to health outcomes are approximately linear, such that there is no apparent cut point (78). Suggested cut offs for children are therefore somewhat arbitrary, since it is not clear that the health consequences in adults associated with BMI cut offs hold for BMI in children, yet they remain the baseline for defining cut points (84). The use of BMI z-score as a continuous measure avoids the need to assign cut off values.

Finally, it has been suggested that BMI z-scores are well suited for statistical analysis in cross sectional studies (79, 141). While less intuitive to interpret, z-score can be easily converted back to BMI for interpretation of results (79).

3.2.2 Environmental Food Outlet Exposure

Children’s exposure to food outlets was assessed as the length of time in seconds that a child spent within 100m of either a fast food outlet or variety store. Researchers analyzed GPS location points collected for each child and the geocoded locations of fast food and variety stores in London in a geographic information system (GIS) to determine when the child was within 100m of an outlet. Among the studies examining environmental food exposure that have integrated the use of GPS units, all have assessed exposure as a count of outlet density (71, 73, 137). We felt time was a more accurate exposure measure since it may be better able to capture the difference between walking and driving past a store.

Distances of 50m, 100m, and 150m were also considered for defining proximity to outlets since it was felt these distances included most outlets that would be seen traveling along the road or sidewalk. However, 50m was thought to be too small based on the fact that large advertisements targeted towards drivers can also be seen by pedestrians further than 50 m away, and outlets located in malls or strip malls are typically located over 50m from the road. Thus, these individuals would be considered 'exposed' to these signs and outlets. Furthermore, 100m was found to have the highest correlations with BMI z-score and will be used for subsequent analyses. Exposure time was calculated in seconds from the time stamped location data recorded by each participant's GPS unit while the participant was in proximity to an outlet.

Studies using GPS devices to measure children's location-time data outdoors have focused primarily on physical activity, so there is little guidance from the literature to date on best practices to assess food exposure (71, 132, 142, 143). Research assessing park and green space use by children for physical activity collapsed location data to thirty second or one minute intervals (132, 142, 143). For the purpose of food exposure, it was felt that thirty or sixty second intervals would be too long to adequately capture the time children spent in proximity to a food outlet, especially if the child was traveling by bus or private vehicle. For this reason, exposure time was left in seconds.

Since GPS time points are used in this study to determine the main exposure variable, study participants completely missing GPS data were excluded from the analysis. A number of other participants did not submit complete GPS data for the full five days of the study. In order to avoid reductions in sample size, a daily average exposure time was calculated for each student by dividing their total exposure time in seconds by the number of days they had recorded GPS points. Common reasons for missing GPS data include loss of GPS signal, wearer compliance with keeping batteries charged and turning the units on each day, or equipment faults (135, 142, 143). At the time of this study, usable GPS data was available for just over half of the students who participated in the STEAM project.

Exposure times to all food outlets, fast food outlets and variety stores were transformed into tertiles of exposure since these variables were not normally distributed. There are no indicators from previous work regarding theoretically meaningful cut points for food exposure time in adults or children, so exposure times were split into categories at 0-1 minutes, 1-5 minutes, and greater than 5 minutes based on a visual inspection of the data.

3.2.3 Unhealthy Food Consumption

Unhealthy food intake is a Likert type scale derived from the food frequency questions in the Healthy Neighbourhoods Survey for Youth. The survey question used was: “How often do you eat the following food items?” Respondents indicated how frequently on a scale from one to five (e.g., never, rarely, sometimes, frequently, always) they ate foods from various categories. Unhealthy food intake responses were summed to a frequency score between 0 and 24, where a score of 0 indicates consuming all of the food items ‘never’, and a score of 24 indicates consuming all of them ‘always’. This measure was left as an ordinal variable because there was no clear rationale for dichotomizing it. Canada’s Food Guide for Healthy Eating recommends limiting intake of unhealthy foods, but makes no clear indication as to what a limited intake of unhealthy food corresponds to on a daily or weekly basis (144).

The six food categories used for this measure included 100% fruit juice, candies/chocolate bars, bakery goods (e.g., cookies, muffins), chips (e.g., potato, corn or tortilla), regular pop with sugar, and juice drinks (e.g., Snapple, Sunny Delight). Foods that are high in sugar and/or fat have been found to contribute to an energy dense diet, which in turn is associated with weight gain and obesity (24, 145). These food items were chosen based on their high sugar and/or fat content, in addition to being readily available from many fast food outlets or variety stores.

There is some disagreement in the literature on whether or not diet or sugar free beverages contribute to weight gain (146, 147). Several previous studies have included diet beverages as part of an unhealthy dietary measure; however, we chose not to include this category for several reasons. First, there remains no clear causal association between calorie free sweeteners used in diet beverages, and in some cases these beverages have been found to be inversely associated with weight gain in youth (145, 147, 148). Second, while it has been suggested that some non-nutritive sweeteners may have detrimental effects on various aspects of metabolic health, our primary outcome was BMI and it was felt that since these beverages are calorie free, they were unlikely to contribute to weight gain (146, 147).

By contrast, 100% fruit juices are considered by many to contribute to a healthy diet and are included in the ‘Fruit and Vegetable’ food group by Canada’s Food Guide (144). However, the natural sugars present in 100% fruit juices should still be considered with respect to diet and weight maintenance (149). The most recent guidelines from the WHO on sugar intakes for children recommended reducing the intake of free sugars to less than 10% of total daily intake, including those from 100% fruit juices (149). Research has found that children and youth derive up to 15% of their total energy intake from a combination of sugar sweetened beverages and 100% fruit juice (150). Thus, this food category was included in the unhealthy food consumption variable due to the high sugar content.

3.2.4 Age

The variable for age was derived from a combination of sources including researcher report, the Healthy Neighbourhoods Survey for Youth, and the Healthy Neighbourhoods Survey for Parents. When researchers were in schools measuring participants’ height and weight, they asked children directly how old they were and their birthday. This value was used preferentially for child age. In some situations where there was no value reported, missing values for age were supplemented first with child reported age, and if still necessary, with parent reported child age. Child age was measured in years. In the situation where a child was reported as being a fraction of a year old, this value was rounded down to the age at the child’s most recent birthday (e.g., 11.5 years old becomes 11 years old).

3.2.5 Sex

Sex was assessed on the Healthy Neighbourhoods Survey for Youth by the following question: Please Circle: Male or Female. In the few situations where no sex was reported, answers were obtained first from the HNSY, or from the HNSP, which asked children and parents to report their child’s sex, respectively.

3.2.6 Survey Year

Year of survey was included as a control variable for use in statistical analyses, described in more detail in later sections. The date was recorded by researchers during the study and was also included in the HNSY (e.g., What is today's date? ____month ____ day ____year). Researcher recorded date was used preferentially for this variable. In cases where no date was available, the year was determined from the date the child completed the HNSY.

3.2.7 Highest Level of Parent Education

Parents' educational attainment was derived from the Health Neighbourhoods Survey for Parents, provided. The specific survey question of interest was: "What is your current level of education?" and there was an option to answer for both parents separately. Answer options were: less than high school, high school, college or university, or graduate or professional school. In order to reduce missing data, the highest level of education reported by either parent was used. This was done based on research indicating both maternal and paternal educational attainment is associated with health outcomes in children (151). Highest level of education attainment was dichotomized into two categories, those with more than a high school education, and those with a high school education or less. Classifying parental educational attainment in two categories instead of four allowed for a larger sample size in each group.

3.2.8 Median Family Income

Due to a large proportion of data missing due to non-response or 'prefer not to say' in response to the survey item on family income on the Healthy Neighbourhoods Survey for Parents, median family income of the family's home neighbourhood as determined by Statistics Canada was used instead (152). This data was collected at the level of Dissemination Area (DA) since this is the smallest aggregated geographic unit for which Statistics Canada releases relevant socioeconomic data from the Census of Canada (153). Furthermore, we used data from previous Census (2006) rather than the recently-released 2011 Census (2011), which has been deemed unreliable for certain variables due to procedural changes (i.e., long-form Census no longer being mandatory) (154). DA median family income data was linked to each child in STEAM based on their home postal code.

3.3 Overview of Structural Equation Modeling

3.3.1 Modeling Strategy

The purpose of this thesis is to examine the associations between environmental food exposure, unhealthy food consumption, and body mass in children. Structural Equation Modeling (SEM) is the method used to assess this research question in this study. The following section provides a brief explanation of SEM and justification for why this modeling technique is well suited for this research question.

In SEM, (also called pathway analysis, simultaneous equation, structural relations, or covariance structure) there are two important aspects (155). The first is that the causal processes under study are represented by a series of structural, or regression, equations; and the second is that these equations can be modeled pictorially to allow for a clear conceptualization of the theoretical model (155). SEM allows for the simultaneous analysis of each structural equation to examine how well the proposed structural model fits the data (155). This process is explained in more detail below.

In SEM, a structural model is constructed based on theoretical relationships between unmeasured, or latent, constructs (155). Latent constructs are estimated using one or more measurable proxy variable that is related to the latent construct (155). These relationships are represented mathematically by a series of highly restricted regression equations, creating a causal model with a certain structural form and unknown parameters (155). Regression equations in the context of a structural model are referred to as structural equations and their parameters are structural parameters (155). This series of equations consists of predictor variables, their variances and covariances, if variables are correlated, and the error term (155). Structural equations are fit simultaneously to the data in order to estimate the model parameters in terms of the hypothesized latent variables (155). Model parameters are assessed to determine the goodness of fit of the model; if the fit is poor then the theoretical model is rejected as a possible causal structure (155). Causal models may include a single structural equation, but often consist of multiple equations.

Graphically, there are several conventions when drawing a structural equation model. Measured variables are drawn in rectangles and latent constructs are in ellipses (156). Single headed arrows indicate the influence of one variable on another, and double headed arrows indicate correlations between pairs of variables (156). As an example, the causal model proposed for this thesis is shown in Figure 1. Error terms are not included in this diagram because, for the purpose if this thesis, constructs were assumed to have been measured without error.

There are several reasons why SEM is an appropriate approach to examine this research question. First, compared to traditionally multivariate methods, SEM is well suited to confirmatory hypothesis testing (156). In contrast to typical exploratory multivariate methods, SEM requires that the theoretical model be specified a priori. Thus, SEM is useful for evaluating proposed theories, rather than being used as a method to help inform the design of new theories.

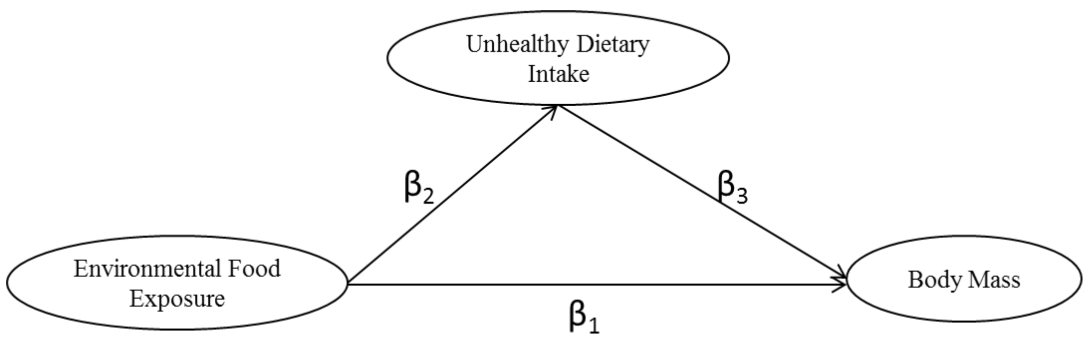

Figure 1: Proposed causal model of the influence of the food environment and unhealthy food consumption on children's BMI z-score, depicted using structural equation model conventions.

Second, SEM allows for the inclusion of unmeasured, or latent, constructs (156). SEM facilitates the inclusion of these variables in a structural equation by allowing the researcher to operationally define the unobserved variable by linking it to one or more observed variables (156). Given the data available from the STEAM project, we were unable to assess dietary quality as a latent construct. We therefore used a linear score derived from food frequency survey items as has been suggested in place of latent variables (157). While there are statistical limitations to this approach, derived variables are considered an acceptable and practical alternative when it is not possible to use latent variables (155).

Finally, SEM is capable of estimating direct, indirect, and total effects among constructs simultaneously (156). Currently, there are no readily available alternatives that offer these features for modeling multivariate equations (156).

In summary, it is clear that SEM is an appropriate statistical method for evaluating the proposed research question for this study. These characteristics make SEM well suited for examining research questions where experimental research would be unethical but the methods for examining observational data are not yet well developed (155).

3.4 Other Model Considerations

3.4.1 Data Screening

All variables were examined for data outliers and implausible values. BMI was checked using the following steps. Children with BMI scores below or above the Centers for Disease and Control 2000 5th and 95th percentiles, respectively, were flagged for closer examination in order to identify biologically implausible values (158). Four values for girls and four values for boys were identified using this method, and of these, two were determined to be incorrect and recoded to missing. The corresponding BMI z-score was also deleted when BMI was considered to be incorrect. BMI z-score was approximately normally distributed.

Unhealthy food consumption was checked to ensure all values fell within the plausible index range. One score was outside this range, and it was determined this was due to an error in data entry. This error was corrected manually.

Food exposure was screened for outlying data points. Several outlying data points were identified for all food outlets (females: n=23, males: n=21), fast food outlets (females n=32, males: n=28), and variety stores (females n=37, males: n=24). It was decided after expert consultation that these data points were likely indicative of the few individuals living in areas of very high food outlet density, rather than due to error in GPS recording or data entry. Thus, no changes were made to these data. All food outlet exposure variables were highly positively skewed (All Food Outlets: skew = 4.18, kurtosis = 26.92; Fast Food Outlets: skew = 9.46, kurtosis = 113.45; Variety Stores: skew = 11.82, kurtosis = 182.31) so this variable was categorized into tertiles as described previously.

Missing values for all variables except for food exposure were imputed using multiple imputations in Stata 13. These methods are described in more detail in the following section.

3.4.2 Missing Data

The missing data in this study was due to survey non-response. These missing data were assumed to be missing at random (MAR). Data that is MAR is not associated with unobserved data, but may be associated with observed data (159). Deletion of these data may lead to biased results, thus the following steps were used to fill in missing values. Where possible, missing data were supplemented with information obtained from the Healthy Neighbourhoods Survey for Parents or Youth. For example, child age was obtained by researchers on-site, as well as in both the parent and youth surveys. Recorded age was used preferentially, followed by child reported age, and finally parent reported age where values were still missing. Similar processes were conducted for sex and parent education.

Missing values that remained after this process were imputed using Multiple Imputation in Stata. Stata's multiple imputation commands, designed for survey non-response, are capable of effectively handling missing data (160). Missing data is handled in a way that results in valid statistical inference for results by generating *n* complete datasets using a flexible, simulation based statistical technique (159). Regression equations are used to fill in missing data using existing values in the dataset. The method used is determined by the type variable being imputed (e.g., logit, ologit). Stata's manual on multiple imputation recommends the use of at least 20 imputations when there is a low proportion of data missing to reduce sampling error due to imputations, but suggests more than this is preferable when parameters are estimated using robust standard errors (159). Thus, 50 imputations were used for analyses and this number provided stable results. For more information on Multiple Imputation in Stata 13, see Stata Multiple-Imputation Reference Manual, Release 13 (159).

Diagnostics were run on imputed data using the command *midiagplots* to compare the distribution of observed, imputed and completed values (161). Continuous variables were checked graphically, and proportions of categorical variables were checked using tables (Appendix B). All analyses were run with and without imputation for missing data and similar results were found (Appendix C).

3.4.3 Model Fit

There are a number of fit indices available to assess model fit for structural equation modeling (162). Absolute fit indices provide a measure of how well the model fits compared to no model at all and includes such indices as the chi-squared test, root mean square error of approximation (RMSEA), goodness of fit (GIF), or the standardized root mean square residual (SRMR) (162). These tests assess the fit of the model in various ways. For example the SRMR is the square root of the difference between the residuals of the sample covariance matrix and the hypothesized causal model (162). Good models obtain values of less than 0.5 (162). Model fit can also be assessed using the comparative fit index (CFI), and model parsimony using the Akaike Information Criterion (AIC). It has been recommended that model fit be assessed using a combination of fit indices; ideally the chi-squared test, RMSEA, CFI and SRMR (163). These indices are recommended since they are the most robust problems of small sample size and the number of parameters to estimated (163).

Unfortunately, post-estimation goodness of fit tests are not available in Stata for multiply imputed data (159). This is because the pooling step required multiple imputations to produce an overall estimate of the model renders concepts like the likelihood and deviance non-interpretable (159). Furthermore, Stata supplies the post-estimation subcommand *estat gof* which is available for use after *sem* but not *gsem*. Our analysis required the use of *gsem*, therefore post-estimation calculations for the SRMR, RMSEA and chi-squared test were not available.

3.4.4 Robust Standard Errors

Due to the sampling strategy used in the STEAM project, children are clustered within schools. This feature of the data means that children who attend the same school may be more similar on some measures than children attending different schools. In this situation, the assumption that observations are statistically independent is violated (164). This assumption is required for the accurate calculation of the standard error of parameter estimates in statistical models, required for significance testing (164). If the clustered nature of the data is not taken into account, standard error estimates are likely to be underestimated, increasing the possibility of detecting a significant association when none exists (165).

Robust standard errors are one recommended method for analyzing clustered data (164). This technique results in valid statistical inferences under the relaxed assumption that errors are not independent of one another but rather correlated within clusters (166). The use of robust standard errors results in similar point estimates of parameters, but inflates the standard error estimates, making statistical analysis more conservative (165).

3.4.5 Power/Sample Size Calculations

The literature suggests a sample size of about 200 subjects for latent variable structural equation models (167, 168). Samples of this size have been found to provide robust parameters estimates using maximum likelihood estimation as long as the data approximately follows the normal distribution (168). As sample size approaches 100 subjects, the maximum likelihood estimator begins to break down (167). Furthermore, similar to the way that the ratio of number of variables to the number of subjects guides sample size decisions in multiple regression, the ratio of the number of parameters estimated to the number of subjects is tied to sample size selection for SEM (169). This is because in SEM, both predictor and error parameters are estimated for the relations between variables simultaneously compared to just variable coefficients in regression (169).

Our study is limited to a finite sample size of girls (n=294) and boys (n=180). Given that there are few parameters being estimated in the causal model and the sample size of each group is near to, or exceeds the suggested size of 200, our sample size is adequate for the proposed analysis method.

3.5 Statistical Analyses

The following section provides an outline of the analytic plan used to assess each objective, as well as descriptive statistics for the sample. Preliminary and descriptive statistics will be covered first, followed by each objective in sequential order.

3.5.1 Preliminary Analyses

Descriptive statistics were performed to determine the characteristics of the study sample. All preliminary analyses were performed separately for males and females, to be consistent with Objective 5. Furthermore, results were presented both for students with and without exposure data in order to examine differences between the two groups. For the main outcome of interest, body mass, means and standard deviations for BMI and BMI z-score were calculated for all groups. For the continuous variables, median family income, unhealthy food consumption, and age, means and standard deviations are reported. For parental education, frequency and percentages are reported. Frequencies and percentages are also reported for tertiles of exposure to all food outlets, fast food outlets, and variety stores for children with food exposure data available.

Prior to analyses, the relationship between tertiles of food exposure and unhealthy eating score, and tertiles of food exposure and BMI z-score in males and females was assessed for linearity and non-linearity. This was done by visual inspection using Microsoft Excel (2013).

3.5.2 Analysis for Objective 1

The first objective was to assess the association between exposure to all food outlets and BMI z-score. Child age and survey year were controlled for. This was done using linear regression to regress BMI z-score on the variable for food exposure, indicated in the figure below (Figure 2). The model is summarized by regression equation 1.2 below. Linear regressions were run separately for females and males.

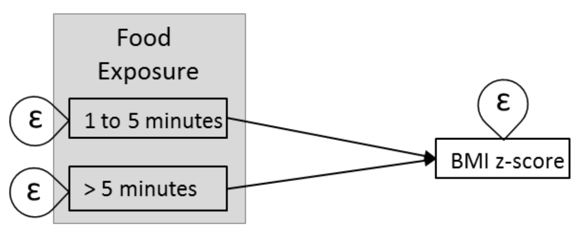

Figure 2: Linear regression model for Objective 1. Association between food exposure to any food outlet and BMI z-score. The category of lowest exposure time (<1 minute) was the reference category, not shown.

$$E(zBMI|x_i) = \beta_0 + \beta_1 x_{FOexp_{1i}} + \beta_2 x_{FOexp_{2i}} + \beta_3 x_{age_i} + \beta_4 x_{year_i} + \varepsilon_i \quad (1.2)$$

3.5.3 Analysis for Objective 2

The second objective was to assess the direct and indirect effect, through unhealthy food intake, of food exposure on BMI z-score. This was done by adding the variables for unhealthy food consumption, and unhealthy food consumption (Figure 3). The structural equation model is depicted mathematically by regression equations 1.3-1.4 below. The direct effect of food exposure was assessed by regressing BMI z-score on food exposure.

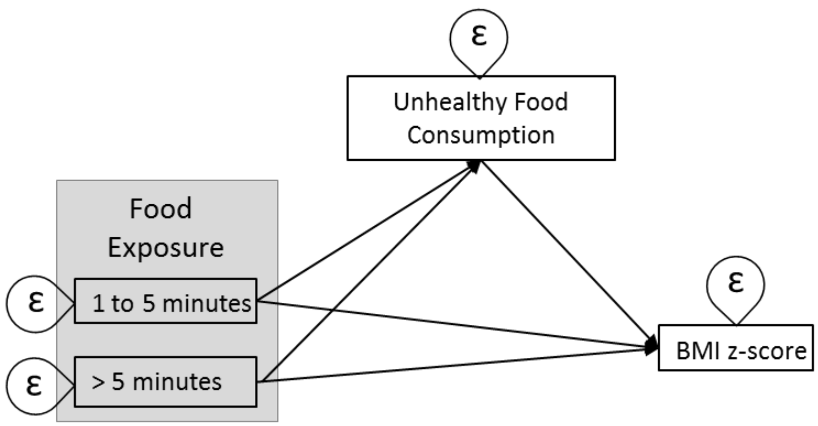

Figure 3: Structural equation model for Objective 2. Association between food exposure to any food outlet and BMI z-score, mediated by unhealthy food consumption. The category of lowest exposure time (<1 minute) was the reference category, not shown.

$$E(UHFC|x_i) = \beta_0 + \beta_1 x_{FOexp_{1i}} + \beta_2 x_{FOexp_{2i}} + \beta_3 x_{age_i} + \beta_4 x_{year_i} + \varepsilon_i \tag{1.3}$$

$$E(zBMI|x_i) = \beta_0 + \beta_1 x_{FOexp_{1i}} + \beta_2 x_{FOexp_{2i}} + \beta_3 x_{UHFC_i} + \beta_4 x_{age_i} + \beta_5 x_{year_i} + \varepsilon_i \tag{1.4}$$

The indirect effect of food exposure on BMI z-score, through unhealthy food intake, was assessed in two steps. The first step consisted of two regressions equations, unhealthy food consumption regressed on food exposure; and BMI z-score regressed on unhealthy food consumption. The use of *gsem* to calculate robust standard errors for clustered data, and *mi estimate* for multiply imputed data prohibited testing for indirect effects using Stata's command *estat teffects*. Thus, the second step was manually calculating the indirect effect, shown in equation 1.5 below. Significance was assessed manually using the Sobel test for indirect effects (170, 171). Figure 4 illustrates the model for the Sobel test, where a and b represent each component of the indirect effect and *c* represents the parameter estimate for the direct effect (170). The equation for the calculation of the Sobel test for indirect effects is shown in equation 1.6 below.

$$Indirect\ Effect = a * b \tag{1.5}$$

$$t = \frac{(ab)}{\sqrt{(a^2\sigma_b^2 + b^2\sigma_a^2)}} \tag{1.6}$$

The denominator is the pooled standard error, in which σ_b^2 is the variance of the estimate b and σ_a^2 is the variance of the estimate a. This test statistic was calculated separately for females and males.

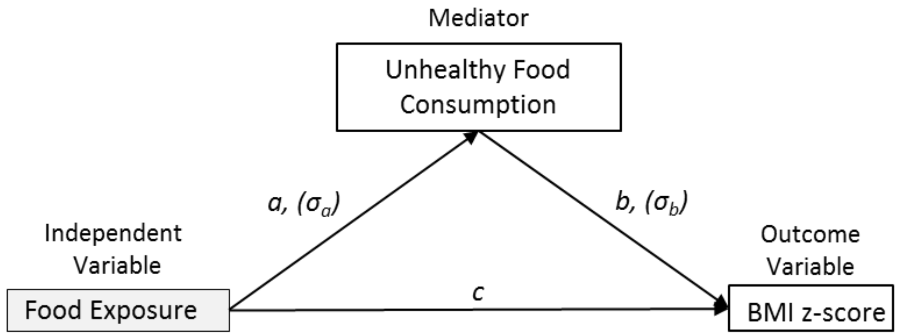

Figure 4: Parameters of the Sobel test for indirect effects.

3.5.4 Analysis for Objective 3

The third objective was to assess whether or not the associations from the previous objective can be partially explained by the socioeconomic status variables median family income and parental education. These variables are independently associated with both environmental food exposure and are also predictive of child BMI and diet quality, making them potential confounders of this association (Figure 5) (75, 76, 172).

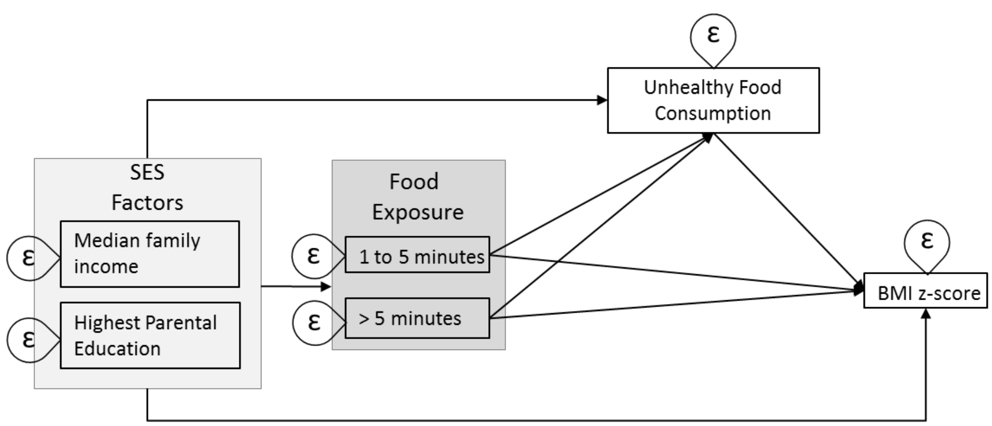

Figure 5: Structural equation model for Objective 3. Association between food exposure to any food outlet and BMI z-score, mediated by unhealthy food intake and adjusting for SES factors. The category of lowest exposure time (<1 minute) was the reference category.

The regression equations for this structural equation model are summarized below in equations 1.7-1.9. This model differs from the previous one in several ways. First, the variables for unhealthy food consumption and BMI z-score are now regressed on family income and parental education. Second, food exposure is also regressed on these variables. The structural equation model for Objective 3 was assessed separately for females and males.

$$E(i.FOexp|x_i) = \beta_0 + \beta_1 x_{mfi_i} + \beta_2 i.x_{peduc_i} + \beta_3 x_{age_i} + \beta_4 x_{year_i} + \varepsilon_i \tag{1.7}$$

$$E(UHFC|x_i) = \beta_0 + \beta_1 x_{FOexp_{1i}} + \beta_2 x_{FOexp_{2i}} + \beta_3 x_{mfi_i} + \beta_4 i.x_{peduc_i} + \beta_5 x_{age_i} + \beta_6 x_{year_i} + \varepsilon_i \tag{1.8}$$

$$E(zBMI|x_i) = \beta_0 + \beta_1 x_{FOexp_{1i}} + \beta_2 x_{FOexp_{2i}} + \beta_3 x_{UHFC_i} + \beta_4 x_{mfi_i} + \beta_5 i.x_{peduc_i} + \beta_6 x_{age_i} + \beta_7 x_{year_i} + \varepsilon_i \tag{1.9}$$

3.5.5 Analysis for Objective 4

The fourth objective was to assess whether or not the previous associations between food outlet exposure and BMI z-score differ by the type of food outlet children are exposed to. This was done using the same approach as for Objective 1, run separately for exposure to fast food outlets and variety stores (Figure 6). Since all study participants who had data available for previous analyses also had separate data for food outlet exposure by type, this analysis was conducted without compromising sample size. The regression equations for this model are the same as equations 1.2, substituting *FOexp* for *FFexp* or *VSexp* for the association between fast food outlet and variety store exposure on BMI z-score, respectively. Objective 4 was assessed separately for females and males.

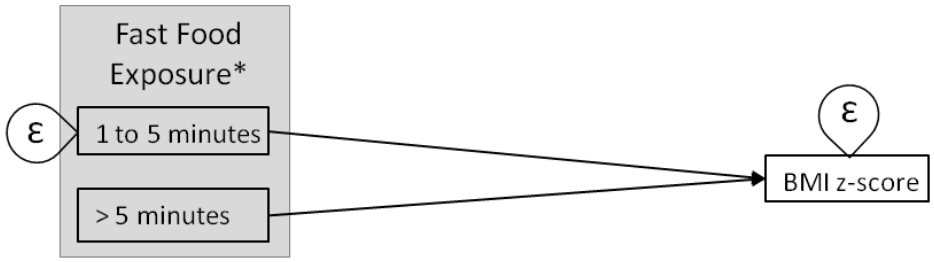

Figure 6: Structural equation model for Objective 4. Association between food outlet exposure, by type of food outlet, and BMI z-score. The category of lowest exposure time (<1 minute) was the reference category. *Same model for exposure to variety stores, not shown.

3.5.6 Analysis for Objective 5

The fifth objective was to assess whether the relationship between the food environment and childhood weight is different for boys and girls. In order to assess this final objective, models from Objectives 1 through 4 were re-run including a variable for sex and an interaction term between the variables for sex and environmental food exposure. The interaction term was assessed using the post-estimation command *testparm* in Stata (164). This command is not supported with multiply imputed datasets, so these models were run using non-imputed data with list-wise deletion of missing variables (159). A sensitivity analysis is included in Appendix B to demonstrate that parameter estimates are similar when SEMs are run with or without imputed data. Since there are no latent constructs in any of the SEMs, parameter estimates for males and females were allowed to vary between models (166).

Equations are shown below for Objective 1 (1.10), and Objective 2 (1.11a, 1.11b). The equations for Objective 3 were similar to those for Objective 2, except that variables for median family income and parent education attainment were included. Equations for Objective 4 were the same as in (1.10) with the exception of including fast food exposure or variety store exposure, rather than total food outlet exposure. The interaction term was included to test the hypothesis that the effect of environmental food exposure is moderated by sex. Models were estimated with females as the reference category.

$$E(zbmi|x_i) = \beta_0 + \beta_1 x_{FOexp_{1i}} + \beta_2 x_{FOexp_{2i}} + \beta_3 x_{sex_i} + +\beta_4 x_{age_i} + \beta_5 x_{year_i} + \beta_6 x_{sex_i} * x_{FOexp_{1i}} + \beta_7 x_{sex_i} * x_{FOexp_{2i}} + \varepsilon_i$$

(1.10)

$$E(zbmi|x_i) = \beta_0 + \beta_1 x_{FOexp_{1i}} + \beta_2 x_{FOexp_{2i}} + \beta_3 x_{sex_i} + \beta_4 x_{UHFC_i} + \beta_5 x_{age_i} + \beta_6 x_{year_i} + \beta_7 x_{sex_i} * x_{FOexp_{1i}} + \beta_{80} x_{sex_i} * x_{FOexp_{2i}} + \varepsilon_i$$

(1.11 a)

$$E(UHFC|x_i) = \beta_0 + \beta_1 x_{FOexp_{1i}} + \beta_2 x_{FOexp_{2i}} + \beta_3 x_{sex_i} + \beta_4 x_{age_i} + \beta_5 x_{year_i} + \varepsilon_i$$

(1.11 b)

Chapter 4

4 Results

This section will begin with an overview of the characteristics of the sample used for this study. Our sample was selected to be representative of children in London and Middlesex County, Southwestern Ontario. Following this, results will be presented from each of the specified objectives: 1. Association between the food environment and body mass (Section 4.2); 2. Direct and indirect effects of environmental food exposure on body mass through unhealthy food consumption, adjusted and unadjusted for SES factors (Section 4.3); and 3. The association of the food environment on body mass by type of food outlet (Section 4.4). As part of Objective 5, sex differences will be highlighted in each section. For all analyses, the level of $\alpha = 0.05$ was used to assess statistical significance.

4.1 Sample Characteristics

The sample of children living in London and Middlesex County in Southwestern Ontario who participated in the STEAM project between 2010 and 2013 consisted of 827 children, 350 of whom were male (46%) and 448 of whom were females (54%). 353 of these children were excluded from analyses due to a lack of environmental food exposure data, leaving a sample size of 474. Of these children, 294 were female (62%) and 180 were male (38%). To avoid reducing the sample further, missing data on other variables was imputed using multiple imputation, as described in Chapter 3. Processed exposure data was not available for a large proportion of children and these children are excluded from the analysis. Characteristics of the sample will be provided for both children with and without exposure data in order to assess for differences between these two groups. Differences were assessed using a t-test or chi squared test for means or proportions, respectively. Fisher's exact test was used for small sample sizes, where necessary.

Table 1 provides characteristics of the female children who participated in the STEAM project. There were 448 girls in the study; 294 of them (66%) with exposure data and 152 (34%) missing exposure data. For all variables assessed, there were no significant differences between the average values or proportions in each group of children. Females were on average about 11 years old (with exposure data: 11.35 years, no exposure data: 11.38 years, $p = 0.779$). Among girls with exposure data, the majority were considered to be at a healthy weight (65.83%), followed by overweight (18.71%) and obese (10.43%) and very few were underweight (5.04%). Proportions were similar for girls without exposure data, with a slightly higher, but statistically non-significant proportion of girls who were overweight (Healthy weight = 66.40%, Overweight = 21.60%, Obese = 10.40%, Underweight = 1.60%, $p = 0.565$). The average BMI was between 19 and 20 kg/m^2 for both groups. Additionally, parent educational attainment was most commonly college or university, followed by post-graduate or professional training, less than high school and finally having a high school diploma for both groups of girls. Median family income was about $71, 800 for girls with exposure data and $71, 300 for girls without exposure data, but this difference was not significant.

There were similar findings for boys in that none of the variables assessed were significantly different for boys with or without data on environmental food exposure. These findings are summarized in Table 2. There were 350 boys in the sample, 180 of whom had exposure data (51%), and 170 who did not (49%). Boys were about the same age as girls, about 11 years old (with exposure data: 11.34 years, no exposure data: 11.27 years, $p = 0.512$). Weight distribution was similar between both groups of boys, with most boys falling into the healthy weight category, followed by overweight, obese and underweight (with exposure data: healthy weight = 64.33%, overweight = 21.64%, obese = 12.28%, underweight = 1.75%; no exposure data: healthy weight = 61.34%, overweight = 19.33%, obese = 18.94%, underweight = 0.84%, $p = 0.579$). Of note, there were a non-significant higher proportion of obese boys in the group with no exposure data. The average BMI in both groups was between 19 and 20 kg/m^2. As with females, parent education was most commonly college or university degree, followed by graduate or professional degrees, then less than high school and high school diploma. Median family income appeared slightly lower for boys without exposure data, but this difference was also not significant ($p = 0.152$).

For both females and males with and without exposure data, unhealthy food consumption scores were all similar. The average score for all these groups was about 11, which corresponds roughly to answering ‘rarely’ or ‘sometimes’ consuming the foods included in the Healthy Neighbourhoods Survey for Children.

Tables 3 and 4 summarize the changes in average BMI z-score for both females and males by tertile of food exposure for all food outlets, fast food outlets and variety stores. For every category of food exposure, males' average BMI z-score increased non-significantly (Figure 7). Females' BMI z-score increases with increasing exposure to all food outlets and fast food outlets, but not variety stores (Figure 8).

4.2 Objective 1: Cross-sectional association between food exposure and BMI z-score

Structural equation models with robust standard errors to model the cross-sectional association between environmental food exposure in female and male children aged 9 to 14 years and BMI z-score. Study participants were excluded from the analysis if they were missing data on food exposure (females: n=154; males: n=170). Missing values for age and BMI z-score were imputed (age, n=1; BMI z-score: n=27).

Results are summarized below in Table 5. There were no significant associations between environment exposure to fast food outlets and variety stores combined and BMI z-score in either males or females (females: tertile 2: β_1 = 0.073, S. E. = 0.185, p = 0.698; tertile 3: β_1 = 0.275, S. E. = 0.293, p = 0.358; males: tertile 2: β_1 = 0.0.193, S. E. = 0.268, p = 0.478; tertile 3: β_1 = 0.405, S. E. = 0.163, p = 0.163). For both males and females, food exposure parameter estimates increased approximately linearly by tertile.

4.3 Objectives 2 and 3: Unadjusted and Adjusted Effects of Food Outlet Exposure on BMI z-score, Mediated by Unhealthy Food Consumption

Results for the unadjusted and adjusted estimates of the direct and indirect effects of food exposure on BMI z-score are summarized in Tables 6 and 7. There were no significant effects of food outlet exposure on unhealthy food consumption (females: tertile 2: β = 0.449, S.E. = 0.478, p = 0.347; tertile 3: β = -0.001, S. E. = 0.551, p = 0.999; males: tertile 2: β = 0.446, S. E. = 0.644, p = 0.489; tertile 3: β = 0.354, S. E. = 0.835, p = 0.523) or food outlet exposure on BMI z-score (females: tertile 2: β = 0.078, S. E. = 0.186, p = 0.675; tertile 3: β = 0.275, S. E. = 0.289, p = 0.343; males: tertile 2: β = 0.207, S. E. = 0.262, p = 0.428; tertile 3: β = 0.422, S. E. = 0.284, p = 0.137), for both females and males. As with results from Objective 1, parameter estimates were slightly larger for males compared to females, despite being insignificant. There was a non-significant negative effect of unhealthy food consumption on BMI z-score in females (β = -0.011) and males (β = -0.031), indicating more frequent consumption of unhealthy foods was associated with lower BMI z-scores for both sexes.

When SES factors were included in the SEMs, parameter estimates for all effects remained insignificant (Tables 7 and 8). For males, the addition of SES variables median family income and parental education to the model slightly increased the parameter estimate of the effect of food exposure on BMI z-score (tertile 2: β = 0.234, S. E. = 0.265, p = 0.377; tertile 3: β = 0.430, S. E. = 0.273, p = 0.114). In females, parameter estimates also increased slightly (tertile 2: β = 0.110, S. E. = 0.182, p = 0.544; tertile 3: β = 0.290, S. E. = 0.289, p = 0.317). There were similar results for the effect of food exposure on unhealthy eating score, and the direction of effect became positive for females in the highest category of food exposure compared to when SES variables were not included in the model (females: tertile 2: β = 0.516, S. E. = 0.493, p = 0.295; tertile 3: β = 0.063, S. E. = 0.502, p = 0.899; males: tertile 2: β = 0.490, S. E. = 0.620, p = 0.429; tertile 3: β = 0.558, S. E. = 0.756, p = 0.460). The direct effect of unhealthy food consumption on BMI z-score decreased to -0.020 (p = 0.237) in females and -0.047 (p = 0.135) in males.

Median family income was significantly predictive of BMI z-score for both females and males (females: p = 0.010; males: p = 0.001) but highest parental education was not (females: p = 0.411; males: p = 0.951).

A summary of the total, direct and indirect effects for females and males are presented in Table 8 and Figures 9 and 10. The total and direct effects of food exposure on BMI z-score in females were 0.073 and 0.078 for Tertile 2 and 0.275 and 0.275 for Tertile 3, respectively. The total and direct effects of food exposure on BMI z-score in males were 0.193 and 0.207 for Tertile 2 and 0.405 and 0.422 for Tertile 3, respectively. For both females and males, indirect effects were very small, and inverse. Results from the Sobel test for indirect effects, shown in Table 9, indicated that the indirect effect of food outlet exposure through unhealthy food consumption was insignificant for both females and males (females: tertile 2: p = 0.574, tertile 3: p = 0.573; males: tertile 2: p = 0.566, tertile 3: p =0.579).

4.4 Objective 4: Association Between the Food Environment and BMI z-score, by Food Outlet Type

Objective 4 was assessed using SEMs to estimate the effect of food outlets on BMI z-score by food outlet type. Thus, models were estimated separately for females and males, and also separately for exposure to fast food outlets and variety stores. Results from four models are presented by sex in Tables 10 and 11. Unhealthy dietary intake was not included as a mediator in these models based on the insignificance of this pathway in Objective 2.

For females, there was a significant effect of exposure to fast food outlets on BMI z-score. BMI z-score was significantly greater for girls who were exposed to fast food outlets for 5 minutes or more on average each day compared to girls with less than a minute of exposure daily ($\beta = 0.491$, S. E. = 0.239, $p = 0.040$). The difference between the first and second tertile of exposure was not significant ($\beta = 0.176$, S. E. = 0.192, $p = 0.359$). The effect of variety store exposure on BMI z-score was not significant.

In males, there were no significant effects of fast food exposure on BMI z-score. However, variety store exposure was significantly associated with BMI z-score. Boys who had more than 5 minute of daily exposure on average to variety stores had higher BMI z-scores than boys who had, on average, less than one minute of daily exposure to variety stores ($\beta = 1.129$, S. E. = 419, $p = 0.007$). There was no significant difference in BMI z-score between the first and second tertile of variety store exposure ($\beta = 0.226$ S. E. = 0.260, $p = 0.386$).

4.5 Objective 5: Differences between Females and Males

The final objective of this study was to assess whether the associations between the food environment and body mass in children varied by sex. For all models except the third objective, sex was not statistically significantly associated with BMI z-score (Objective 1: $p = 0.199$; Objective 2: $p = 0.133$; Objective 3: $p = 0.044$; Objective 4, FF: $p = 0.077$; Objective 4, VS: $p = 0.352$ (Table 12).

Parameter estimates were generated for each SEM for males with either 1 to 5 minutes or more than 5 minutes of exposure to the food environment. For most SEMs, the interaction term was positively, but not significantly, associated with BMI z-score (Table 12). The only model where this was not the case was the fourth objective modeling fast food outlet exposure. This relationship was not significant for any of the SEMs, indicating that sex does not moderate the effect of the food environment on body mass in elementary school children. This was the case despite the finding that exposure to variety stores was statistically significant for males and exposure to fast food outlets was statistically significant for females, with respect to BMI z-score.

Table 1: Sample characteristics and selected demographics for female students.

Girls (n= 448)

	With Exposure Data (n=294)		Missing Exposure Data (n=154)		
Variable	Value	N	Value	N	p-value
Age - Year (S.D)	11.35 (0.97)	294	11.38 (1.05)	152	0.7785
BMI - kg/m^2 (S.D)	19.32 (4.16)	276	19.73 (4.50)	125	0.3792
Weight Status (%)					
Underweight	5.04%	14	1.60%	2	0.565
Healthy Weight	65.83%	183	66.40%	83	
Overweight	18.71%	52	21.60%	27	
Obese	10.43%	29	10.40%	13	
Unhealthy Diet Score - Score (S.D.)	11.27 (3.91)	278	10.90 (3.70)	149	0.3427
Parent Education (%)					
Less than High School	9.91%	21	10.00%	12	0.146
High School	4.25%	9	4.17%	5	
College/University	62.26%	132	72.50%	87	
Graduate/Professional	23.58%	50	13.33%	16	
Median Family Income - $ (S.D.)	71,797 (25,103)	265	71,302 (23,695)	107	0.8612

Table 2: Sample characteristics and selected demographics for male students.

Boys (n= 350)

	With Exposure Data (n=180)		Missing Exposure Data (n=170)		
Variable	Value	N	Value	N	p-value
Age - Year (S.D)	11.34 (0.88)	179	11.27 (0.83)	164	0.5121
BMI - kg/m^2 (S.D)	19.36 (3.97)	171	19.91 (4.63)	119	0.2845
Weight Status (%)					
Underweight	1.75%	3	0.84%	1	0.579
Healthy Weight	64.33%	110	61.34%	73	
Overweight	21.64%	37	19.33%	23	
Obese	12.28%	21	18.49%	22	
Unhealthy Diet Score - Score (S.D.)	11.47 (3.67)	175.00	11.27 (3.38)	154	0.617
Parent Education (%)					
Less than High School	7.25%	10	9.84%	12	0.709
High School	2.17%	3	2.46%	3	
College/University	70.29%	97	72.13%	88	
Graduate/Professional	20.29%	28	15.57%	19	
Median Family Income - $ (S.D.)	73,564 (29,416)	151	68,535 (25,571)	109	0.152

Table 3: Average BMI z-score by tertile of environmental food exposure.

Girls (n=294)

	All Food Outlets		Fast Food Outlets		Variety Stores	
Minutes of Exposure	BMI z-score (S. D.)		BMI z-score (S. D.)	n	BMI z-score (S. D.)	n
0-1 minutes	0.210 (1.510)	118	0.143 (1.452)	140	0.255 (1.383)	188
1-5 minutes	0.255 (1.217)	123	0.302 (1.236)	95	0.321 (1.349)	68
5+ minutes	0.517 (1.301)	35	0.626 (1.261)	41	0.224 (1.208)	20

Table 4: Average BMI z-score by tertile of environmental food exposure.

Boys (n=180)

	All Food Outlets		Fast Food Outlets		Variety Stores	
Minutes of Exposure	BMI z-score (S. D.)	n	BMI z-score (S. D.)	n	BMI z-score (S. D.)	n
0-1 minutes	0.441 (1.423)	96	0.441 (1.411)	109	0.406 (1.386)	129
1-5 minutes	0.528 (1.333)	57	0.470 (1.234)	42	0.536 (1.240)	32
5+ minutes	0.641 (1.223)	18	0.806 (1.418)	20	1.446 (1.257)	10

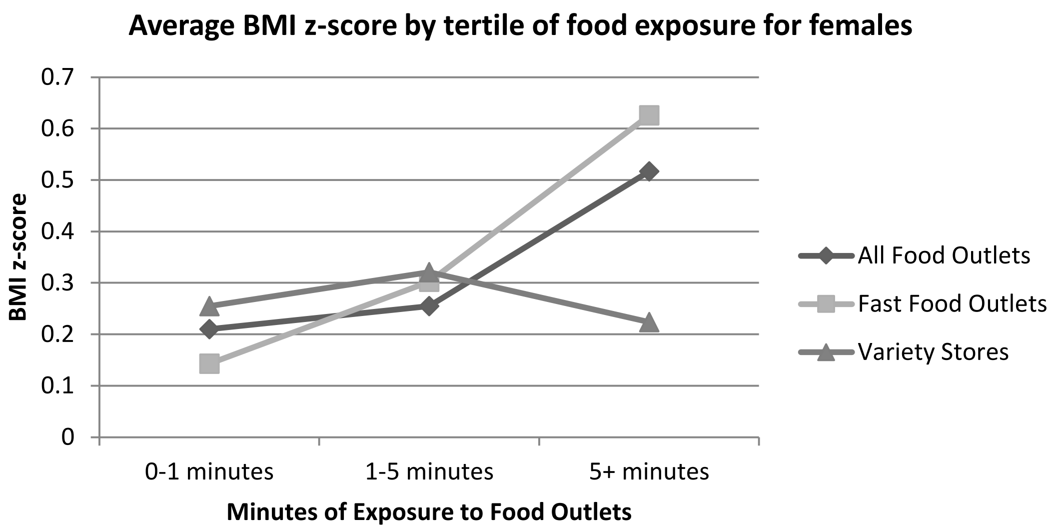

Figure 7: Average BMI z-score by tertile of food exposure for all food outlets, fast food outlets, and variety stores among females.

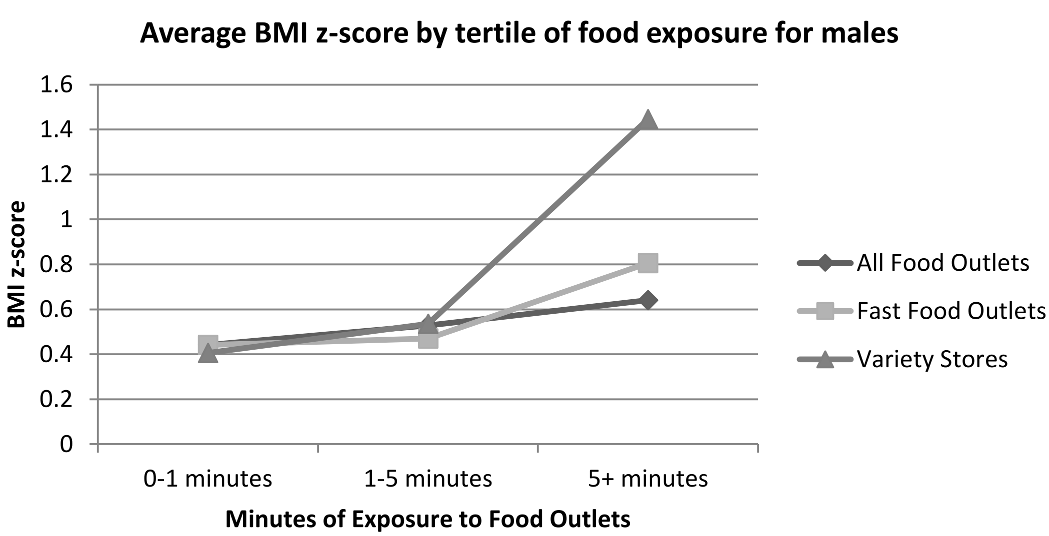

Figure 8: Average BMI z-score by tertile of food exposure for all food outlets, fast food outlets, and variety stores among males.

Table 5: Linear regression model of the effect of environmental food exposure on BMI z-score, by sex.

	Females (n=294)		Males (n=180)	
Regression Weights	Estimate (S.E.)	95% Confidence Intervals	Estimate (S.E.)	95% Confidence Intervals
Minutes of Exposure				
<1 minute	*ref*	*ref*	*ref*	*ref*
1-5 minutes	0.073 (0.185)	-0.213 to 0.458	0.193 (0.268)	-0.364 to 0.750
>5 minutes	0.275 (0.293)	-0.335 to 0.885	0.405 (0.279)	-0.180 to 0.990

Table 6: SEM of the effect of environmental food exposure on BMI z-score mediated by unhealthy food consumption, for females. Model 2: Unadjusted. Model 3: Adjusted for SES factors.

Females (n=294)	Model 2		Model 3	
Regression Weights	Estimate (S.E.)	95% Confidence Interval	Estimate (S.E.)	95% Confidence Interval
Food Outlet Exposure				
Tertile 1 ON x_{UHFC}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{UHFC}	0.449 (0.478)	-0.488 to 1.386	0.516 (0.493)	-0.450 to 1.482
Tertile 3 ON x_{UHFC}	-0.001 (0.551)	-1.081 to 1.079	0.063 (0.502)	-0.921 to 1.048
Tertile 1 ON x_{zBMI}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{zBMI}	0.078 (0.186)	-0.286 to 0.442	0.110 (0.182)	-0.246 to 0.467
Tertile 3 ON x_{zBMI}	0.275 (0.289)	-0.293 to 0.842	0.290 (0.289)	-0.277 to 0.857
UHFC ON zBMI	-0.011 (0.016)	-0.043 to 0.020	-0.020 (0.017)	-0.054 to 0.013
Residual Variances				
zBMI	1.64 (0.347)	1.470 to 2.307	1.771 (0.194)	1.429 to 2.194
UHFC	13.94 (1.393)	11.461 to 16.955	13.649 (1.235)	11.430 to 16.298

Table 7: SEM of the effect of environmental food exposure on BMI z-score mediated by unhealthy food consumption, for males. Model 2: Unadjusted. Model 3: Adjusted for SES factors.

Males (n=180)	Model 2		Model 3	
Regression Weights	Estimate (S.E.)	95% Confidence Interval	Estimate (S.E.)	95% Confidence Interval
Food Outlet Exposure				
Tertile 1 ON x_{UHFC}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{UHFC}	0.446 (0.644)	-0.817 to 1.709	0.490 (0.620)	-0.725 to 1.705
Tertile 3 ON x_{UHFC}	0.534 (0.835)	-1.103 to 2.170	0.558 (0.756)	-0.923 to 2.040
Tertile 1 ON x_{zBMI}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{zBMI}	0.207 (0.262)	-0.305 to 0.720	0.234 (0.265)	-0.286 to 0.754
Tertile 3 ON x_{zBMI}	0.422 (0.284)	-0.135 to 0.979	0.430 (0.273)	-0.104 to 0.965
UHFC ON zBMI	-0.031 (0.028)	-0.086 to 0.024	-0.047 (0.031)	-0.108 to 0.015
Residual Variances				
zBMI	1.763 (0.228)	1.368 to 2.273	1.579 (.0181)	1.262 to 1.977
UHFC	12.393 (1.249)	10.172 to 15.099	12.116 (1.154)	10.053 to 14.602

Table 8: Estimates for the total, direct and indirect effect of food exposure on BMI z-score through unhealthy dietary intake.

	Females (n=294)		Males (n=180)	
Food Exposure	Tertile 2	Tertile 3	Tertile 2	Tertile 3
Total Effect	0.073	0.275	0.193	0.405
Direct Effect	0.078	0.275	0.207	0.422
Indirect Effect	-0.005	0.000	-0.014	-0.017

Table 9: Results of the Sobel Test for the indirect effect of food exposure on BMI z-score through unhealthy dietary intake.

	Females (n=294)		Males (n=180)	
All Food Outlets	Test Statistic	p-value	Test Statistic	p-value
Tertile 1	*ref*	*ref*	*ref*	*ref*
Tertile 2	-0.562	0.574	-0.588	0.556
Tertile 3	-0.564	0.573	-0.555	0.579

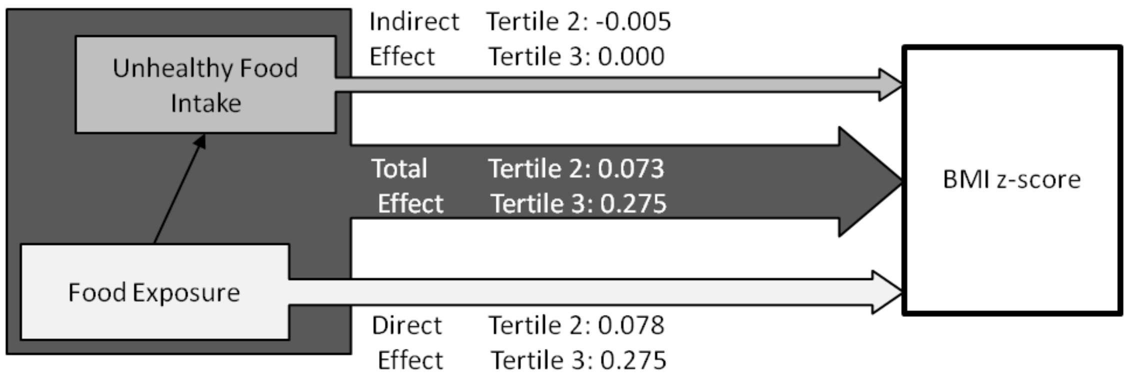

Figure 9: Total, Direct, and Indirect effect of environmental food exposure through unhealthy food intake on BMI z-score in females.

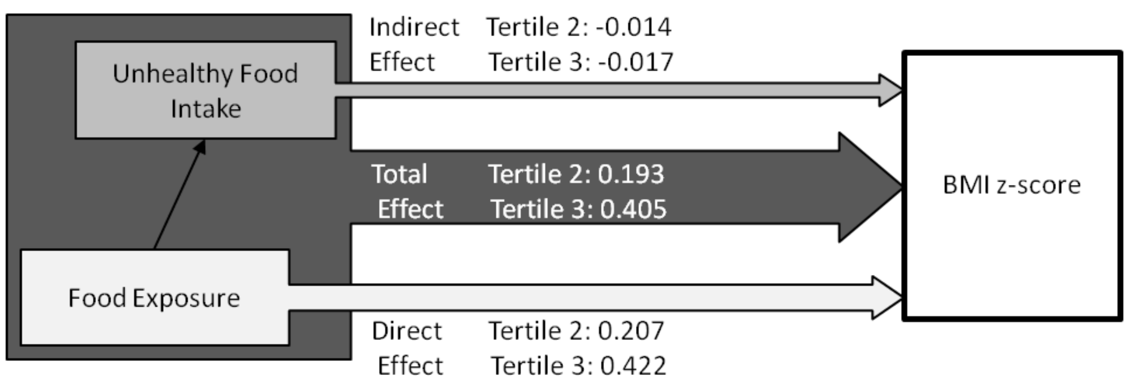

Figure 10: Total, Direct, and Indirect effect of environmental food exposure through unhealthy food intake on BMI z-score in males.

Table 10: SEM of the effect of environmental food exposure on BMI z-score for females, by type of food outlet.

Females (n=294)

	Fast Food Outlets		Variety Stores	
Regression Weights	Est. (S.E.)	95% Confidence Interval	Est. (S.E.)	95% Confidence Interval
Food Outlet Exposure				
Tertile 1 ON x_{zBMI}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{zBMI}	0.173 (0.192)	-0.200 to 0.553	0.065 (0.254)	-0.432 to 0.563
Tertile 3 ON x_{zBMI}	0.491 (0.239)*	0.022 to 0.960	-0.041 (0.310)	-0.649 to 0.567

Table 11: SEM of the effect of environmental food exposure on BMI z-score for males, by type of food outlet.

Males (n=180)

	Fast Food Outlets		Variety Stores	
Regression Weights	Est. (S.E.)	95% Confidence Interval	Est. (S.E.)	95% Confidence Interval
Food Outlet Exposure				
Tertile 1 ON x_{zBMI}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{zBMI}	0.117 (0.062)	-0.251 to 0.485	0.226 (0.260)	-0.285 to 0.736
Tertile 3 ON x_{zBMI}	0.468 (0.322)	-0.162 to 1.098	1.129 (0.419)*	0.308 to 1.949

Table 12: SEMs for Objectives 1, 2, 3 and 4 assessing sex as a moderator. Wald test for significance (α=0.05).

	Model 1 (n=446)		Model 2 (n=453)		Model 3 (n=298)	
	Est. (S.E.)	95% C. I.	Est. (S.E.)	95% C. I.	Est. (S.E.)	95% C. I.
Sex (Ref: Female)	0.222 (0.173)	-0.117 to 0.561)	0.259 (0.172)	-0.079 to 0.596	0.430 (0.213)*	0.012 to 0.848
Sex*FO_Exp$_{<1}$	*ref*	*ref*	*ref*	*ref*	*ref*	*ref*
Sex*FO_Exp$_{1-5}$	0.088 (0.2750	-0.450 to 0.626)	0.060 (0.282)	-0.493 to 0.613	-0.251 (0.262)	-0.764 to 0.262
Sex*FO_Exp$_{5+}$	-0.072 (0.368)	-0.794 to 0.650	0.041 (0.371)	-0.685 to 0.768	0.284 (0.406)	-0.511 to 1.080
	Value	p-value	Value	p-value	Value	p-value
χ^2	0.18	0.916	0.05	0.977	1.23	0.54

	Model 4 (Fast Food Stores, n=446)		Model 4 (Variety Stores, n=446)	
	Est. (S.E.)	95% C. I.	Est. (S.E.)	95% C. I.
Sex (Ref: Female)	0.296 (0.167)	-0.032 to 0.624	0.152 (0.164)	-0.168 to 0.473
Sex*FO_Exp$_{<1}$	*ref*	*ref*	*ref*	*ref*
Sex*FO_Exp$_{1-5}$	-0.089 (0.213)	-0.507 to 0.328	0.089 (0.372)	-0.641 to 0.818
Sex*FO_Exp$_{5+}$	-0.103 (0.402)	-0.892 to 0.685	1.089 (0.525)	0.059 to 2.119
	Value	p-value	Value	p-value
χ^2	0.2	0.903	4.51	0.105

Chapter 5

5 Discussion

This chapter begins with an overview of the main findings from this study. These will be followed by a discussion of the results in the context of the existing literature, with respect to each of the aforementioned research objectives. This will be followed by a discussion of strengths and weaknesses of the current study, recommendations for future research and finally implications for public health.

5.1 Summary of Main Findings

The overall goal of this project was to examine the cross-sectional association between environmental exposure to food outlets and body mass in elementary school aged children. As part of this goal, five objectives were developed: first, to assess the association between food outlet exposure and body mass; second, to examine whether this relationship is mediated by unhealthy dietary intake; third, to assess whether socioeconomic factors explain some of the association between food exposure and body mass; fourth, to assess whether this relationship differs by the type of food outlet; and fifth, to assess whether any of these associations differ by sex.

With respect to the first objective assessing the cross-sectional relationship between environmental exposure to both fast food and variety stores and body mass, the results were non-significant. Graphically, there appeared to be a positive relationship between BMI z-score and exposure to unhealthy food outlets, but for both females and males this relationship was not statistically significant.

The results from the assessment of the second objective examining whether unhealthy food intake mediates the relationship between food exposure and BMI z-score indicated that this variable is not a significant mediator of this relationship. For both males and females, the indirect effect of food exposure through unhealthy food intake accounted for a very small proportion of the total effect, and was in the direction opposite of that hypothesized. These results were non-significant, for each category of food exposure.

The results from the assessment of the third objective indicate that median family income and parental educational attainment do not explain the previous associations. The inclusion of these variables increased parameter estimates for the effect of food exposure on BMI z-score, rather than the decrease that would be expected if these variables were accounting for part of the association between environmental food exposure and BMI z-score. Findings were non-significant for both males and females, although parameter estimates for males were again slightly larger than for females.

For the fourth objective, the association between environmental food exposure and body size, outcomes were assessed by category of food outlet type. For females, there was a significant positive relationship between exposure to fast food outlets and BMI z-score. For males, there was a significant positive relationship between exposure to variety stores and BMI z-score. For both of these relationships, children in the category with the highest level of exposure were statistically significantly more likely to have a higher BMI z-score than children in the category with the lowest level of exposure.

Finally, findings from the assessment of the fifth objective indicated that differences between males and females for the previous objectives were not statistically significant. Sex was not predicative of BMI z-score in any of the structural equation models assessed. There was also no evidence that sex moderated the effect of the food environment on body mass. This finding indicates that our hypothesis that the effect of the food environment on body weight would be greater in males should be rejected.

Overall, most of the findings from this study were not statistically significant. The following section suggests several reasons for this with respect to each objective. There were also a number of limitations of our study that may have hindered our ability to detect an association between the food environment, unhealthy diet, and body mass.

5.2 Objective 1: Cross-sectional association between food exposure and BMI z-score

The directions of effect in the results from objective one were in the expected direction, albeit non-significant. As stated in the hypothesis, we expected that females and males who spent more time exposed to food outlets would have a higher body mass.

As discussed previously, few studies have assessed the relationship between body mass in children and exposure to the food environment experienced by children traveling through their environments. These studies both measured food outlet exposure using a count of the food outlets encountered by children, and similar to this study, neither of them detected a significant association between food exposure and body mass (73, 107). Thus, our results are in agreement with similar studies conducted previously in other countries, despite evidence of a positive effect of the environment on body mass when other methods of assessing the food environmental are implemented (23, 25).

There are several possible reasons for why these findings were non-significant. These include the type of food outlets included in this study, age of the children, and mode of transportation. First, our measure of environmental food exposure may not have been comprehensive enough to fully capture the influence of the food environment on children's body mass. Our measure included only fast food outlets and variety stores, whereas other studies have included up to four different types of unhealthy food outlets in an overall index (126). These indexes included other outlets such as bakeries, food stands, sit-down restaurants, or other snacking outlets that were considered unhealthy (99, 106, 125, 126). While children are unlikely patrons of sit down restaurants or bakeries on their commute to school, the presence of these outlets and others is a form of advertising that may influence health behaviour choices regarding dietary intake at other times in the day (20). Children will ask their parents for certain brands or types of foods that they have been exposed to through advertising (20). It is possible that restaurants children are exposed to on the way to school lead them to request these foods from their parents, for example at dinnertime. This level of exposure effect would not have been captured in our study.

Additionally, it is possible that the mode of transportation children take to and from school may have influenced our results in ways that were not accounted for. Harrison *et al.* found that the effect of both healthy and unhealthy food outlets on fat mass index in female children was stronger among those who walked or cycled to school (107). Children who walk or cycle to school may have more independence than those traveling by vehicle and therefore more susceptible to exposure to food outlets they encounter on the way to and from school. We made the assumption that differences in transportation type would be partially accounted for in this analysis since environmental food exposure was assessed in seconds. For instance, children traveling by vehicle would have less exposure time than a child who walked to school due to the faster speed of travel. However, this assumption may not adequately distinguish between children who take a bus to school or are driven. Driving may be more similar to walking or cycling in that it allows the possibility of stopping (e.g., at a drive-through) en route, unlike public transportation or school buses. Thus, it may be important to more explicitly account for differences between children who use different modes of transportation to and from school in future analyses.

5.3 Objective 2: Unadjusted Effects of Food Outlet Exposure on BMI z-score, Mediated by Unhealthy Food Consumption

For objective 2, it was expected that unhealthy dietary intake would mediate the association between environmental food exposure and body mass in children. However, there was no evidence of a significant indirect effect of food exposure through children's diets, measured by frequency of unhealthy food intake.

To establish mediation, variation in the independent variable should be predictive of variation in the mediator, and variation in the mediator should be predictive of variation in the outcome (173). The results of the SEM used to analyze objective 2 indicated that environmental food exposure was not predictive of unhealthy dietary intake, nor was unhealthy dietary intake associated with body mass.

Previous studies have not explicitly assessed the role of dietary intake as a mediator, but have identified associations between body mass and unhealthy food intake (117, 119, 120, 122) or the food environment (43, 100-104, 106, 107). A diet where unhealthy foods are consumed frequently is associated with weight gain because the high energy density of these foods often leads to overconsumption and an energy surplus (54). Environmental availability of unhealthy foods has also been found to be associated with less healthy diets (108, 121, 122), although this association is inconsistent (117, 119, 120).

Given these findings, there appears to be theoretical evidence for a pathway by which the food environment influences body mass through the consumption of unhealthy food. There were several shortcomings associated with the measure we used to assess unhealthy dietary intake that may have limited our model's ability to detect this relationship. First, we were unable to assess the consumption frequency of some foods typically available at fast food outlets or variety stores due to the limited scope of the HNSY. For example, previous studies have found that boys indicate a preference for meat and processed meat products, which are often available at fast food restaurants in the form of high fat meal options, but we were not able to include these types of unhealthy foods in our score (131).

Second, we were unable to distinguish whether the unhealthy foods children reported consuming on the HNSY were acquired from a fast food outlet or variety store, or another source such as home or school cafeterias. The inability to distinguish between unhealthy foods acquired from food outlets or other sources may have clouded the association between the food environment and unhealthy dietary intake. Other measures may more accurately mediate the association between food outlets and body mass, such as actual patronage or foods purchased and consumed from these outlets (71). We were unable to account for these activities in our analyses due to the unavailability of this data at the time of this project.

Additionally, it is possible that the age of children in our sample may have reduced the potential for the food environment to influence child weight through unhealthy dietary intake. Elementary school children aged between 9 and 13 years old are less independent than teenagers and their diets are more likely to be heavily influenced by what their parents or school provide for them (151). Of note, it has been estimated that American children spend nearly $30 billion of their own money on foods, suggesting future studies should still consider the possibility that food outlets affect children's diets and weights through food purchased by children from these sites (20).

5.4 Objective 3: Adjusted Effects of Food Outlet Exposure on BMI z-score, Mediated by Unhealthy Food Consumption

The results for objective 3 were inconsistent with our hypothesis, and unsurprising given the non-significant unadjusted associations between constructs. We predicted that the inclusion of two SES factors would partially explain some of the variability in child body mass, reducing the effect of environmental food exposure. Instead, every environmental food exposure parameter estimate increased with the inclusion of these variables. Due to the limitations associated with using multiply imputed data in Stata, we were unable to assess whether or not the inclusion of these variables significantly improved the fit of the model.

Based on the available evidence, it is likely that family income and parental educational attainment are associated with body mass (174). It may be possible that these socioeconomic factors had little influence on our models because there was no strong unadjusted association between the food environment, unhealthy diet and body mass.

A number of studies have found that family income is a good predictor of body mass in children, and there appears to be evidence of a dose-response relationship from low to high income families (172, 174, 175). Income is also positively associated with healthier diets high in foods such as low fat milk, polyunsaturated fats and various nutrients and minerals (176). Higher parental educational attainment is has also been associated with making healthier food choices (177) and lower body mass (178).

5.5 Objective 4: Association Between the Food Environment and BMI z-score, by Food Outlet Type

With respect to objective 4, we expected that there would be an association between body mass and fast food outlets or variety stores, respectively, for both males and females. Exposure to variety stores was more predictive of higher body mass in males than females, and this association was significant for males. The opposite was true for fast food outlets. There was a stronger association between greater exposure time to fast food outlets and higher body mass in girls than boys, and this association was only significant for girls.

The finding that exposure to fast food outlets is associated with greater body mass in girls is in agreement with two other studies (106, 107). Both of these studies found that there was a statistically significant association between the density of fast food outlets and body mass, but only among females (106, 107). None of the studies reviewed in the literature review reported a positive significant association between the food environment and body mass among males alone.

Gender based differences in food preferences may offer some explanation for the current findings. As discussed previously, males report greater preferences for animal products, such as barbequed meats, beef, pork or ethnic foods compared to girls (131, 179). Girls indicate greater preferences for fruits and vegetables, and starches and sweets (179). One study observed a sharp drop in preference for starches, sweet and fast foods among middle school aged boys (179). Some fast food restaurants offer 'healthier alternatives', as well as sweet treats or starchy foods like french fries which may appeal to girls. This explanation does little to explain why variety store exposure was associated with body mass in males, although some variety stores may offer food appealing to boys such as hot dogs or pizza.

Gender differences have been noted in studies examining other features of the built environment and health outcomes (180, 181). The presence of pedestrian friendly stores is associated with physical activity in boys (180). Researchers suggested this may indicate boys are more likely to walk to these types of shops, which could include variety stores located near the route taken to or from school (180).

5.6 Objective 5: Differences between Females and Males

For objective 5, we hypothesized that the effect of the food environment on body mass would be greater for males than females. This was predicted based on evidence indicating that males have greater food preference for foods typically available at fast food outlets and variety stores (131, 179) and that males in this age group have higher BMIs than females (1). However, for all objectives assessed in this study, there was no statistical difference between males or females.

For all SEMs, being male was non-significantly associated with higher BMI z-score. The direction of this finding is consistent with reports that among Canadian children, levels of obesity are higher among boys (1). Furthermore, studies in adults have found that women eat more healthfully than men, and this behaviour is driven by factors such as attaching greater importance to consuming a healthy diet and weight control (182). Research indicates girls as young as five years are self-aware of their physical appearance and may exhibit similar behaviours such as dieting and watching intake of certain foods perceived to be unhealthy (22, 183). This suggests girls may be exerting more self-control in response to their food environment than boys explaining the smaller, albeit non-significant, effect sizes in girls.

None of the studies reviewed in the literature objectively assessed whether sex modified the association between the food environment and body mass, but four reported inconsistent differential findings by sex (42, 105-107). These studies took place in different countries and reported both positive (106, 107), inverse (105) and non-significant (42) associations between unhealthy food exposure and body mass in children.

5.7 Strengths

This study had several strengths that improved upon the limitations identified in the existing literature. The previous limitations included inconsistency in defining children's neighbourhood environments, the use of non-validated food retail databases to determine food outlet exposure, and the use of subjective measures to assess children's body mass.

A major limitation common to studies examining the relationship between the food environment and health outcomes is the inconsistency in buffer sizes and shapes when objectively assessing the environment. Our study used GPS technology to measure children's activity space on their way to and from school in order to determine how many fast food and variety stores children were actually exposed to and how much time children were actually exposed to such stores. This method avoids the need to create buffer zones, for which there currently exists no agreed upon best size and shape (86). The use of a buffer zone based on a predefined distance in all directions around a home or school may also lead to the inclusion of outlets and areas that are deemed accessible, but where a child may actually spend very little time during their typical travel patterns (91, 184). GPS monitors allows for the identification and measurement of environments children are actually exposed to, rather than accessible environments. Furthermore, this method avoids the fallacy of ignoring food outlets that children are exposed to beyond their defined home and school neighbourhoods by recording the child's location at all points on the route to and from school.

A second strength of this study is that it used a validated and ground-truthed dataset of fast food outlets and variety stores. This resource intensive method is important because, for a county-wide study such as this one, it is important to ensure that children's exposure to food outlets is being accurately assessed. Some databases may be outdated or inaccurate, leading to error in the measurement variable which may compromise the results of the study (129).

Another strength of our study is that body mass was assessed using researcher measured height and weight to calculate age adjusted BMI and BMI z-scores. There is evidence indicating that BMI can be calculated more accurately when height and weight are measured objectively, rather than when self-reported values are used (140). BMI tends to be biased downwards when participants are asked to report their height and weight (140).

We used BMI z-score to assess body mass and this was left as a continuous variable. This may be more meaningful in children than classifying children by weight status since BMI cutoffs in children are less meaningful with respect to adverse health outcomes than in adults (78, 84).

5.8 Limitations and Suggestions for Future Research

One of the major limitations in the literature is the paucity of longitudinal studies assessing the influence of the food environment on children's diets and weight. Unfortunately, this is also a limitation of this study, as we were only able to assess the cross-sectional association between fast food and variety store exposure and body mass in our sample. This limits our ability to draw causal inferences about the effect of the food environment on body mass. The development of obesity is a slow process, thus there is a need for long term studies that follow children over the course of several years in order to assess changes in body mass over time in response to static and changing environments.

Environmental research that focuses on activity spaces is subject to the possibility of self-selection bias. The presence of this influence may lead to spurious associations between the environment and health outcomes that may overstate the influence of environmental factors. One previous study in children failed to find evidence of selection bias (73). It has also been suggested that the potential for this bias in populations with less independence and mobility, such as children, is minimal (73). Nonetheless, there remains the possibility of self-selection bias among older children and future studies should consider assessing children's food preferences in order to examine the possibility of selection bias.

The third objective of this study was to assess whether or not part of the effect of the built environment on body mass is mediated by diet, namely unhealthy food consumption. However, our ability to accurately assess this measure was limited by the questions regarding diet that were included in the HNSY. We were unable to objectively assess children's diets, and the self-reported scale we used was limited to six categories of foods. As a result, we were unable to include a number or other foods and snacks (e.g., hamburgers, tacos, fries, and baked goods) that are often sold at fast food outlets or convenience stores. Furthermore, our unhealthy dietary intake scale was developed using self-reported food frequency intake questions. Self-reported food intake has been found to underestimate actual intake (185). For these reasons, our measure of unhealthy diet may represent an inaccurate estimate of children's actual intake of unhealthy food. Actual food consumption is difficult to measure objectively, thus various methods for attaining self-reported intakes may be a reasonable proxy for diet in children (186). Studies interested in clarifying the role of diet as a mediator of the relationship between the food environment and body mass or other nutrition related health outcomes should use a more thorough tool to assess children's dietary quality.

Another limitation of the current study was that we did not include a variable for various factors that may have confounded the relationship between the food environment and body mass in children. Possibly the most important of these potential confounders is physical activity. Physical activity level has an important role in body mass and is likely to have contributed to differences in body mass between children. Furthermore, there is evidence that physical activity level is associated with the built environment (187). It was determined that including a measure of children's levels of physical activity was beyond the scope of this project, therefore physical activity levels were not included in this analysis. However, given the novel use of GPS monitoring of children's activity spaces, the main objective of our study was to explore the association between the food environment and body mass. Future research assessing the evidence for a causal relationship between these factors should consider the role of physical activity and other potential confounders of this relationship.

Future studies examining similar research questions linking the food environment and children's health outcomes should continue to build upon the limitations in this study and the existing literature. Specifically, this field of research would benefit from additional longitudinal studies to allow for more rigorous assessment of this potentially causal relationship.

5.9 Implications and Conclusion

Our study found limited evidence that there is an effect of the food environment on 9 to 14 year old children's intake of unhealthy foods and their weight. The only significant relationships identified in this study were the effect of exposure to fast food outlets on girls' body mass and variety store exposure on boys' body mass. However, this study, in combination with the existing body of literature published on this topic, will hopefully contribute to the evidence base necessary to guide decision making regarding policy and the development of communities that encourage healthy behaviours in children.

Childhood obesity in Canada is an important healthcare issue and one that continues to demand the immediate attention of healthcare providers and public health officials alike. Reducing childhood overweight and obesity will have the positive downstream effects of reducing people's risk for various metabolic and mental health problems, as well as reducing the financial burden to the healthcare system. Actions to implement healthy nutrition and lifestyle programs by public health officials and community partners are well underway. These programs are effective at educating children and youth about the importance of following a healthy diet low in unhealthy foods, but have been unsuccessful at improving adherence to healthy dietary guidelines (188). However, without supportive environments in place, it will remain challenging for children and youth to put their knowledge of healthy lifestyles into practice. A multi-faceted approach combining individual behaviour strategies with community and environmental structural changes is needed in order to effectively slow and eventually reverse the trend towards excess body weight. Evidence, such as that presented by this study, will help to identify modifiable features of the food environment that can be targeted through municipal land use and development policies in order to reduce opportunities for unhealthy behaviours, and promote health enhancing decisions by individuals instead. This information may inform decisions regarding school board policies with respect to the locations of new schools, and guide parents' choices around the route their child takes to school.

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Appendices

Appendix A: Diagnostics for imputed data.

Table 13: Imputed and non-imputed values for parental education.

Parent Educational Attainment (m=3)			
	Observed	Imputed	Combined
High School or less	0.123	0.153	0.131
More than High School	0.877	0.847	0.869
Number of Imputed Values			124
Total			474

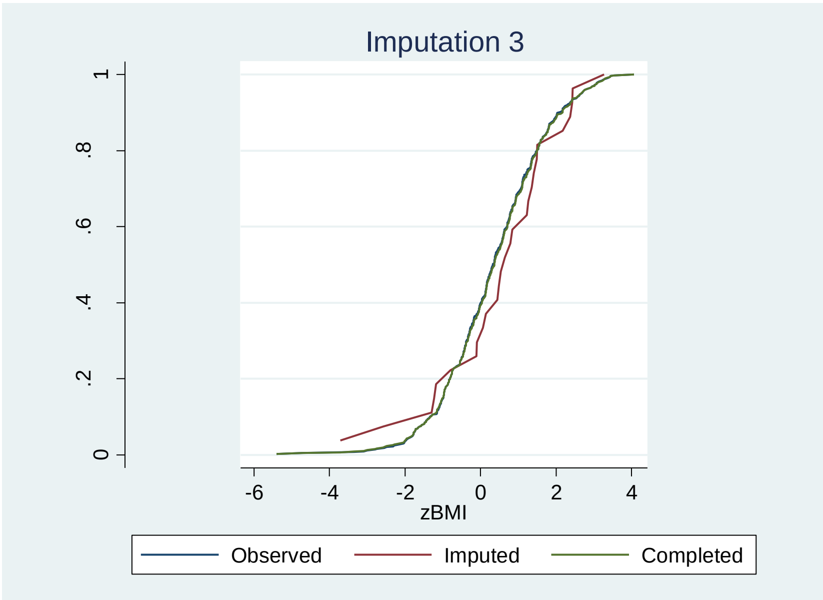

Figure 11: Imputed and non-imputed values for zBMI score.

zBMI (m=3); Number of Imputed Values: 27; Total: 474

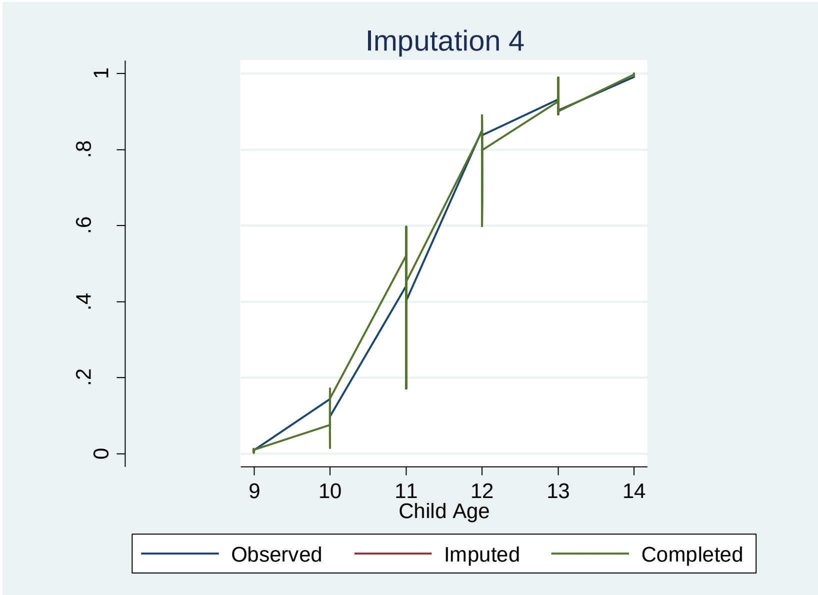

Figure 13: Imputed and non-imputed values for child age score.

Child Age (m=4); Number of Imputed Values: 1; Total: 474

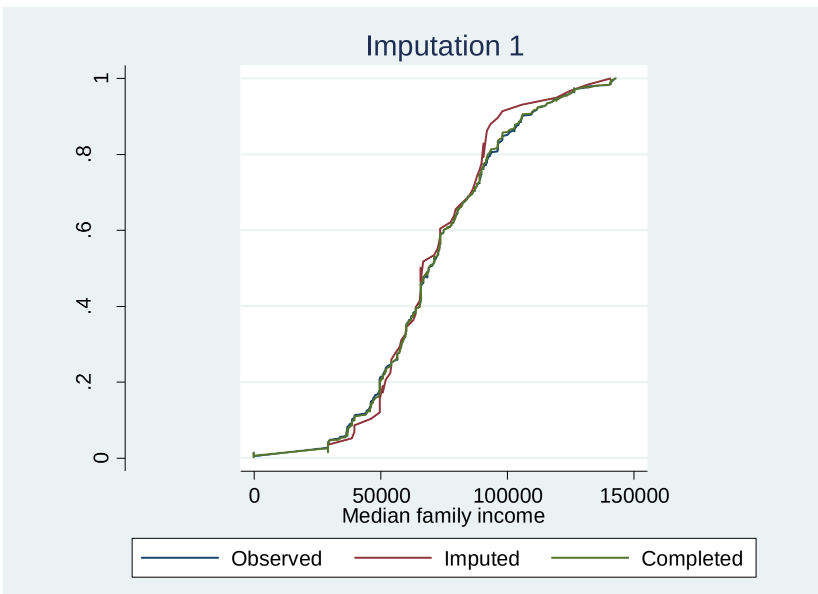

Figure 12: Imputed and non-imputed values for median family income.

Median Family Income (m=1); Number of Imputed Values: 58; Total: 474

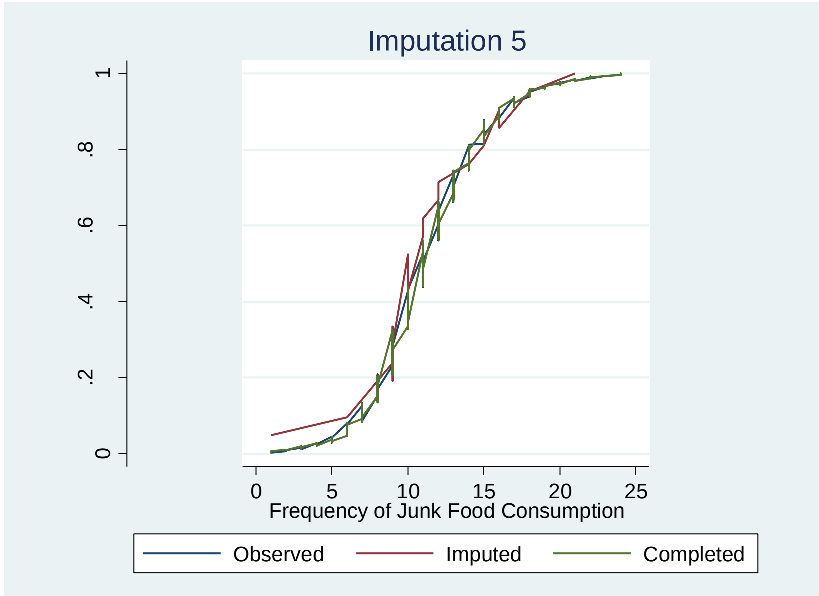

Figure 14: Imputed and non-imputed values for frequency of junk food consumption. UnHEI (m=3); Number of Imputed Values: 21; Total: 474

Appendix B: SEM parameter estimates with and without imputation for missing values. SEMs without imputation run using listwise deletion.

Table 14: Parameter estimates for Objective 1, females and males.

Females	Imputed Values (n=294)		Non-Imputed Values (n=276)	
Regression Weights	Est. (S.E.)	95% Confidence Intervals	Est. (S.E.)	95% Confidence Intervals
Minutes of Exposure				
0-1 minutes	*ref*	*ref*	*ref*	*ref*
1-5 minutes	0.073 (0.185)	-0.213 to 0.458	0.055 (0.186)	-0.330 to 0.439
5+ minutes	0.275 (0.293)	-0.335 to 0.885	0.311 (0.289)	-0.287 to 0.909

Males	Imputed Values (n=180)		Non-Imputed Values (n=170)	
Regression Weights	Est. (S.E.)	95% Confidence Intervals	Est. (S.E.)	95% Confidence Intervals
Minutes of Exposure				
0-1 minutes	*ref*	*ref*	*ref*	*ref*
1-5 minutes	0.193 (0.268)	-0.364 to 0.750	0.221 (0.270)	-0.337 to 0.780
5+ minutes	0.405 (0.279)	-0.180 to 0.990	0.362 (0.253)	-0.161 to 0.886

Table 15: Parameter estimates for Objective 2, females and males.

Females	Imputed Values (n=294)		Non-Imputed Values (n=278)	
Regression Weights	Est. (S.E.)	95% Confidence Interval	Est. (S.E.)	95% Confidence Interval
Food Outlet Exposure				
Tertile 1 ON x_{UHFC}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{UHFC}	0.449 (0.478)	-0.488 to 1.386	0.477 (0.479)	-0.461 to 1.415
Tertile 3 ON x_{UHFC}	-0.001 (0.551)	-1.081 to 1.079	-0.012 (0.539)	-1.069 to 1.044
Tertile 1 ON x_{zBMI}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{zBMI}	0.078 (0.186)	-0.286 to 0.442	0.477 (0.479)	-0.284 to 0.478
Tertile 3 ON x_{zBMI}	0.275 (0.289)	-0.293 to 0.842	0.226 (0.301)	-0.363 to 0.815
UHFC ON zBMI	-0.011 (0.016)	-0.043 to 0.020	-0.011 (0.015)	-0.040 to 0.018
Residual Variances				
zBMI	1.64 (0.347)	1.470 to 2.307	1.822 (0.225)	1.430 to 2.322
UHFC	13.94 (1.393)	11.461 to 16.955	14.001 (1.434)	11.462 to 17.122

Males	Imputed Values (n=180)		Non-Imputed Values (n=175)	
Regression Weights	Est. (S.E.)	95% Confidence Interval	Est. (S.E.)	95% Confidence Interval
Food Outlet Exposure				
Tertile 1 ON x_{UHFC}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{UHFC}	0.446 (0.644)	-0.817 to 1.709	0.462 (0.647)	-0.807 to 1.730
Tertile 3 ON x_{UHFC}	0.534 (0.835)	-1.103 to 2.170	0.580 (0.855)	-1.096 to 2.256
Tertile 1 ON x_{zBMI}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{zBMI}	0.207 (0.262)	-0.305 to 0.720	0.246 (0.264)	-0.271 to 0.763
Tertile 3 ON x_{zBMI}	0.422 (0.284)	-0.135 to 0.979	0.375 (0.268)	-0.151 to 0.901
UHFC ON zBMI	-0.031 (0.028)	-0.086 to 0.024	-0.030 (0.028)	-0.085 to 0.025
Residual Variances				
zBMI	1.763 (0.228)	1.368 to 2.273	1.778 (0.233)	1.375 to 2.298
UHFC	12.393 (1.249)	10.172 to 15.099	12.401 (1.241)	10.197 to 15.092

Table 16: Parameter estimates for Objective 3, females and males.

Females	Imputed Values (n=294)		Non-Imputed Values (n=189)	
Regression Weights	Est. (S.E.)	95% Confidence Interval	Est. (S.E.)	95% Confidence Interval
Food Outlet Exposure				
Tertile 1 ON x_{UHFC}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{UHFC}	0.516 (0.493)	-0.450 to 1.482	0.549 (0.501)	-0.432 to 1.530
Tertile 3 ON x_{UHFC}	0.063 (0.502)	-0.921 to 1.048	0.280 (0.734)	-1.159 to 1.718
Tertile 1 ON x_{zBMI}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{zBMI}	0.110 (0.182)	-0.246 to 0.467	0.147 (0.201)	-0.247 to 0.540
Tertile 3 ON x_{zBMI}	0.290 (0.289)	-0.277 to 0.857	0.209 (0.250)	-0.281 to 0.698
UHFC ON zBMI	-0.020 (0.017)	-0.054 to 0.013	-0.026 (-0.017)	-0.059 to 0.007
Family Income on zBMI	-9.42×10^{-6} (3.63×10^{-6})	-1.65×10^{-5} to 2.30×10^{-6}	-1.29×10^{-5} (3.68×10^{-6})	-2.02×10^{-5} to -5.74×10^{-6}
P. Education on zBMI	-0.268 (0.326)	-0.908 to 0.371	0.008 (0.370)	-0.717 to 0.734

Residual Variances				
zBMI	1.771 (0.194)	1.429 to 2.194	1.833 (0.268)	1.376 to 2.442
UHFC	13.649 (1.235)	11.430 to 16.298	12.764 (1.173)	10.659 to 15.283

Table 16: Parameter estimates for Objective 3, females and males *(continued).*

Males	Imputed Values (n=180)		Non-Imputed Values (n=109)	
Regression Weights	Est. (S.E.)	95% Confidence Interval	Est. (S.E.)	95% Confidence Interval
Food Outlet Exposure				
Tertile 1 ON x_{UHFC}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{UHFC}	0.490 (0.620)	-0.725 to 1.705	0.270 (0.656)	-1.015 to 1.555
Tertile 3 ON x_{UHFC}	0.558 (0.756)	-0.923 to 2.040	1.167 (1.005)	-0.903 to 3.137
Tertile 1 ON x_{zBMI}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{zBMI}	0.234 (0.265)	-0.286 to 0.754	0.008 (0.224)	-0.432 to 0.448
Tertile 3 ON x_{zBMI}	0.430 (0.273)	-0.104 to 0.965	0.621 (0.323)	-0.013 to 2.255
UHFC ON zBMI	-0.047 (0.031)	-0.108 to 0.015	-0.023 (0.035)	-0.091 to 0.045
Family Income on zBMI	-1.46×10^{-5} (4.41×10^{-6})	-2.33×10^{-5} to -6.00×10^{-6}	-1.55×10^{-5} (5.21×10^{-6})	-2.57×10^{-5} to -5.25×10^{-6}
P. Education on zBMI	-0.025 (0.413)	-0.839 to 0.788	0.318 (0.422)	-0.510 to 1.145
Residual Variances				
zBMI	1.579 (.0181)	1.262 to 1.977	1.429 (0.229)	1.043 to 1.958
UHFC	12.116 (1.154)	10.053 to 14.602	11.006 (1.129)	9.001 to 13.457

Table 17: Parameter estimates of Objective 4, females and males.

Females	Imputed Values (n=294)		Non-Imputed Values (n=276)	
Regression Weights	Est. (S.E.)	95% Confidence Interval	Est. (S.E.)	95% Confidence Interval
Fast Food Outlets				
Tertile 1 ON x_{zBMI}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{zBMI}	0.173 (0.192)	-0.200 to 0.553	0.172 (0.191)	0.202 to 0.545
Tertile 3 ON x_{zBMI}	0.491 (0.239)*	0.022 to 0.960	0.485 (0.241)*	0.013 to 0.956
Variety Stores				
Tertile 1 ON x_{zBMI}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{zBMI}	0.065 (0.254)	-0.432 to 0.563	0.070 (0.263)	-0.445 to 0.585
Tertile 3 ON x_{zBMI}	-0.041 (0.310)	-0.649 to 0.567	-0.029 (0.333)	-0.681 to 0.623

Males	Imputed Values (n=180)		Non-Imputed Values (n=180)	
Regression Weights	Est. (S.E.)	95% Confidence Interval	Est. (S.E.)	95% Confidence Interval
Fast Food Outlets				
Tertile 1 ON x_{zBMI}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{zBMI}	0.117 (0.062)	-0.251 to 0.485	0.139 (0.193)	-0.238 to 0.517
Tertile 3 ON x_{zBMI}	0.468 (0.322)	-0.162 to 1.098	0.435 (0.320)	-0.191 to 1.062
Variety Stores				
Tertile 1 ON x_{zBMI}	*ref*	*ref*	*ref*	*ref*
Tertile 2 ON x_{zBMI}	0.226 (0.260)	-0.285 to 0.736	0.230 (0.62)	-0.282 to 0.741)
Tertile 3 ON x_{zBMI}	1.129 (0.419)*	0.308 to 1.949	1.152 (0.427)*	0.314 to 1.989

Appendix C: Supplementary literature review tables.

Table 18: Studies examining the cross-sectional association between the food environment and childhood weight.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Objective Measures								
Larsen, Cook, Stone *et al.* 2014	Community based sample part of Project BEAT including 17 schools from neighbourhoods with diverse built environments and income levels. Conducted in 2010-2011. Toronto Ontario *N* = 1035 *Mean Age (y)* = 11 *Sex* = Both	*Binary* Researcher measured HW, used this to calculate BMI. Underweight/normal or overweight/obese was classified according to age and sex specific international cut points	*Buffer Type:* Network *Buffer Distance:* 1000m *Food Outlet Types:* Fast food outlets, healthy stores, less healthy stores, and supermarkets Density (continuous, weighted count) Proximity (continuous) around home	Gender, age, median household income	*Logistic Regression:* OR and 95% CI. One model for the effect of each food outlet type on likelihood of overweight/obesity	None presented	*Supermarket Proximity* OR=1.477 (1.060 to 2.059) *Healthy Store Density* OR: 0.904 (0.847 to 0.964)	There were no significant associations between the distance to or density of fast food or unhealthy stores and overweight/obesity. Distance to the nearest supermarket was positively associated with the odds of being overweight or obese. Density of healthy food stores was inversely related to the odds of being overweight or obese.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Gilliland, Rangel, Healy *et al.* 2012	Community based sample of students in grades 6-8 in London, Canada (2010-2011) *N*= 966 *Mean Age (y)*= 12 years *Sex*=Both	*Continuous* Measured height and weight, calculated BMI z-scores using WHO growth curves.	*Buffer Type*: Circular, Network, School walkshed *Buffer distance:* 500m, 1000m *Food Outlet Types:* Convenience stores, Fast Food restaurants Proximity (dichotomized at 500m network buffer for homes, and school walkshed boundary for schools)	Level 1: Presence of fast food outlets, convenience stores, recreation opportunities within 500m Level 2: Presence of fast food outlets, convenience stores, recreation opportunities within school walkshed.	*Multilevel Structural Equations:* β estimates and standard error to simultaneously assess home and school level effects on BMI z-score.	Level 1 Presence of convenience stores 1000m Circular Buffer: 0.044 (0.02) 500m Network Buffer: 0.219 (0.10) Presence of FFO 500m Circular Buffer: 0.204 (0.09) Level 2 Presence of FFO Walkshed: 0.095 (0.03) Presence of Convenience Stores 1000m Circular Buffer: 0.048 (0.02) Walkshed: 0.057 (0.02)	Presence of FFO: 0.073 (0.034) All other neighbourhood predictors: NS	The presence of fast food outlets within with school walkshed was the only statistically significant predictor of BMI z-score in the multivariate multilevel model

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Jilcott, Wade, McGuirt *et al.* 2011	Community sample of youth from Pitt County, North Carolina (2007-2008) *N*= 744 *Mean Age (y)*= 12.9 years *Sex*=Both	*Continuous* BMI percentiles based on CDC growth charts reference dataBMI from electronic medical records	*Buffer Type:* Circular and Network *Buffer Distances:* 400m, 800m, 1600m, 8.0km *Food Outlet Types:* FFO, sit-down restaurants, pizza restaurants, chain supermarkets, grocery stores, supercenters, dollar stores, produce stands/markets Density (continuous) Proximity (continuous, in km)	Rural/urban residence, race, insurance status	*Generalized Linear Regression:* β estimates and standard error for BMI percentile regressed on food accessibility variablesConsidered interactions between independent variables	*Density of Markets/Produce Stands* 400m Circular: -0.07 (p=0.0423) 800m Circular: -0.11 (p=0.0036) 800m Network: -0.08 (p=0.0308) 1600m Network: -0.10 (p=0.0086) *Density of FFO and Pizza Restaurants* 800m Circular: 0.07 (p=0.0442) 800m Network: 0.11 (p=0.0032) *Proximity Markets/Produce Stands*: 0.07 (p=0.0585) *Convenience Stores:* -0.07 (p=0.0725)	*Convenience store Proximity (95% CI)* African American: -0.010 (-0.020 to 0.000) Other:-0.033 (-0.051 to -0.015) *Market proximity (95% CI)* Other: 0.020 (0.008 to 0.032)	For children of "Other" minority groups, smaller distances to the nearest market/produce stand were associated with lower BMI. This finding approached significance for African American adolescents, and was not significant for "White" children. For African American and adolescents of "Other" minority groups, smaller distances to the nearest convenience store was associated with a higher BMI. This finding was not statistically significant for "White" children

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Burns, Goff, Karamian 2011	Community sample of students from Kindergarten to grade 12 in Massachusetts (2005-2006). Predominantly low SES, minority groups *N* = 10 513 *Mean Age (y)* = 9.41 years *Sex* = Both	*Continuous* Mean BMI z-score for census tracts.BMI z-scores standardized for age and gender based on CDC growth charts reference dataSchool nurse took weight and height measurements.	*Buffer Type*: Circular *Buffer Distances:* 400m *Food Outlet Types:* FFOs, sit-down restaurants, convenience store/bodega, supermarkets/produce stores. Density (continuous, count)	Proportion by race/ethnicity, gender, enrollment in free/reduced price NSLP, mode of transportation to schoolMean age, median household income, mean parent education.	*OLS Linear Regression:* β estimates and standard error to assess the effect of the local food environment, by food outlet type, on mean BMI of census tract.	*Fast Food Outlets:* 0.537 (p=0.001) *Sit-down restaurants:* 0.529 (p=0.001) *Convenience stores/bodegas:* 0.535 (p=0.001)	*Convenience stores/bodegas:* β=0.482 (p=0.004) *Fast Food Outlets:* β=0.458 (p=0.002) *Sit-down restaurants:* β=0.450 (p=0.003) *Composite Food Index:* β=0.559 (p=0.001)controlled for an additional composite *High Risk* variable (income, education, race/ethnicity, enrollment in reduced price NSLP)	Convenience stores/bodegas, Fast food outlets, and sit-down restaurants were all found to be significantly associated with census tract BMI z-score.Composite food access was the best predictor of census tract BMI z-score

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Casey, Chaix, Weber *et al.* 2012	Representative community sample of students selected from 88 middle schools located in Eastern France. *N*= 3327 *Mean Age (y)* = 12 years *Sex* = Both	*Binary* Measured height and weight. Overweight defined according to the IOTF age and gender cut-offs.	*Buffer Type:* Circular *Buffer Distance:* 1000m *Food Outlet Types:* Bakeries, General Food Retail and FFO Density (Categorical; absence, below median, above median)	*Level 1:* gender, age, SES *Level 2:* urbanisation, tax income, educational level and county	*Multilevel Logistic Regression:* Odds Ratios and 95% CIs for the effect of each type of food outlet on weight status, random effect defined at school level. Included 4 measured dietary behaviours	Among Lower Income Students: *General Food Retail*: OR=1.86 (1.20 to 2.86) *Fast Food:* OR=1.35 (1.00 to 1.81)	NS	Among lower SES students, the likelihood of being overweight was inversely associated with spatial accessibility to general food retailers. This relationship was significant for the lowest level of accessibility only. Low spatial accessibility to fast food outlets was inversely associated with overweight, approached significance. No other food accessibility measures were significant.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Cetateanu and Jones 2013	Nationally representative cross-sectional sample of students in England from the National Child Measurement Program (NCMP)Used data from 2007/08, 2008/09 and 2009/10. *N*= not clear, approximately 1 501 600 *Mean Age (y)* = 10-11 years *Sex* = Both	*Categorical* BMI from NCMP *Binary* Used for MSOA specific analysis. Overweight (BMI greater than or equal to 85% percentile) and Obese (BMI greater than or equal to 95% percentile) based on UK90 BMI reference data.	*Buffer Type:* MSOA *Buffer Distance:* N/A *Food Outlet Types:* Fast food outlets, Other unhealthy outlets, and mixed food outlets. Density (categorical quartiles, by type)	Percentage: area domestic gardens, green space, population under 7 years, population 10-14 years, mixed ethnicity, professional occupation among adults IDACI scores.	*ANOVA:* unadjusted associations of the food environment and weight status outcomes. *Linear Regression:* β estimates and 95% CI for the relationship between weight status and food outlet availability.	Positive trend for weight status with increasing density of Fast Food Outlets and Other Unhealthy Outlets:<0.01	*Fast Food Outlets (reference is lowest quartile)* Q2: β=0.695 (0.415 to 0.975) Q3: β=0.880 (0.559 to 1.160) Q4: β=0.846 (0.541 to 1.152) *Other Unhealthy Outlets (reference is lowest quartile)* Q2: β=0.372 (0.0092 to 0653) Q3: β=0.628 (0.346 to 0.910) Q4: β=0.721 (0.413 to 1.029)	There was a statistically significant positive trend for overweight and obese and the density of both fast food and other unhealthy food outlets both before and after adjustment for covariates.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Harrison, Jones, van Sluijs *et al.* 2011	Community based sample from 92 schools in Norfolk, UK. Data was from the Sport, Physical activity and Eating behaviours, Environmental Determinants in Young people (SPEEDY study), conducted in 2007. *N* = 1995 Mean Age (y) = 10.25 years *Sex* = Analysed separately	*Continuous* Fat Mass Index [FMI = FM(kg)/height((m)^2]	*Buffer Type:* Network *Buffer Distance:* 800m *Food Outlet Types:* Healthy and Unhealthy Categorical (Lowest, Middle, and Best Access tertiles)	Age, parent's highest education	*Multilevel linear regression:* β estimates and 95% CI for effect of unhealthy and healthy FO measures on FMI. FMI was log transformed. Random effect term at school level. Stratified by environment (home/school/route)	*Girls – Home* Active Travel, Healthy FO: Middle Access β=-0.138 (-0.223 to -0.0.52) Best Access β= -0.149 (-0.246 to -0.052) Inactive travel, Healthy FO: Middle Access β=-0.109 (-0.191 to -0.026) *Girls – School* Active Travel, Unhealthy FO: Best access β=0.133 (0..023 to 0.243) Inactive travel, Unhealthy FO: Best Access β=0.124 (0.014 to 0.234) *Boys* NS	NS	For girls in the home environment, better access to healthy food outlets is associated with lower FMI among active travellers, while better access to unhealthy outlets is associated with higher FMI along all children. In the school environment, active travellers with more access to unhealthy food outlets had a higher FMI. There were no significant associations between food access variables and FMI for boys in either the home, school or route environments.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Ohri-Vachaspati, Llyod, DeLia *et al.* 2013	Community based sample from four New Jersey, conducted in 2009-2010. *N* = 702 *Mean Age (y)* = 10 years *Sex*= Both	*Binary* Parent-measured height and weight used to calculate BMI percentile. Overweight/obese defined as BMI at or above 85% percentile using the 2000 CDC sex- and age- specific CDC Growth charts as reference data.	*Buffer Type:* Circular *Buffer Distance:* 400m, 800m, 1.5km *Food Outlet Types:* supermarkets, small grocery stores, specialty stores, convenience stores, FFOs Proximity - Continuous (Distance to nearest outlet) Density - Binary (presence v. absence) and Continuous (counts of FO)	Age, gender, race/ethnicity, mother's education, parent's self-measured BMI, household poverty status, parental nativity, household language status, median income and racial composition in neighbourhood block group.	*Logistic Regression:* OR and 95% CI, assess bivariate and multivariate association between geospatial food variables and weight status.	OR and 95% CI *Convenience Stores:* *Presence in 800m:* OR=3.54 (1.14 to 10.98) *Presence in 400m:* OR=1.99 (1.15 to 3.45) *400m Buffer Density:* OR=1.09 (1.00 to 1.20)	OR and 95% CI *Convenience Stores:* *Presence in 400m:* OR=1.90 (1.04 to 3.45) *400m Buffer Density:* OR=1.11 (1.00 to 1.22)	After adjustment for covariates, the presence of a convenience store within 400m of home was associated with a greater likelihood of being overweight or obese. Higher density of convenience stores within a 400m circular buffer was associated with an 11% increase in the odds of overweight/obese.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Park, Choi, Wang *et al.* 2013	Community based sample from 15 schools in Seoul, South Korea. Conducted in 2011 *N*= 939 *Mean Age (y)* = 12.1 years *Sex* = Both	*Binary* Height and weight collected from school check-ups used to calculate BMI. Overweight/obese defined as BMI at or above the 85% percentile according to the 2007 Korean National Growth Charts.	*Buffer Type:* Circular *Buffer Distance:* 500m *Food Outlet Types:* Healthy FO, restaurants, Snacking outlets, FFO/bakery shops Density - Continuous (counts of FO)	*Individual Level:* Age, sex, family affluence scale, mother's employment status, weekday screen time *School:* School size, proportion enrollment in free/reduced price lunch *Neighbourhood:* % population with a college degree, % social safety net program participants	*Generalized Estimating Equations:* OR and 95% CI for association between weight status and neighbourhood nutrition environment. Adjusted analyses stratified by gender.	Not presented	*Snacking Outlets* OR=0.83 (0.72 to 0.96) *FFO* OR=0.83 (0.72 to 0.96) *FFO (girls, adjusted for all covariates)* OR=1.03 (1.01 to 1.05)	Students in neighbourhoods with a greater density of snacking or fast food outlets had a lower odds of being overweight/obese after adjustment for individual level covariates. Among girls only, higher density of FFO was associated with a 3% increase in odds of overweight/obese after adjustment for individual, school and neighbourhood level factors.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Carroll-Scott, Gilstad-Hayden, Rosenthal *et al.* 2013	Community based sample of gr. 5 and 6 students from schools in New Haven, Connecticut. Conducted in 2009. Population has higher than average poverty levels, minority population and chronic disease, compared to rest of the state. *N*= 1048 *Mean Age (y)* = 10.9 years *Sex* = Both	*Continuous* Height and weight measured by trained researchers to calculate BMI.	*Buffer Type:* Census Tract *Buffer Distance*: N/A *Food Outlet Type:* Grocery stores, convenience stores Density - continuous (count within census tract) Proximity - dichotomous (at cut points)	*Level 1:* Gender, race/ethnicity, lunch program eligibility. *Level 2*: Proportion black and Latino population, concentrated affluence, concentrated disadvantage, school clustering.	*Multilevel Linear Regression:* β estimates and standard error for effect of neighbourhood variables on BMI. Random effect at school level.	Not presented	*Proximity* Grocery Stores: 1.484 (0.493) *Density* NS	Living further than 800m from the nearest grocery store was significantly associated with higher BMI after adjustment for individual and neighbourhood level covariates.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Jennings, Welch, Jones *et al.* 2011	Community based sample from 92 schools in Norfolk, UK. Data was from the Sport, Physical activity and Eating behaviours, Environmental Determinants in Young people (SPEEDY study), conducted in 2007. *N*= 1669 *Mean Age (y)* = 10.2 years *Sex* = Both	*Categorical* Height and weight measured by trained researchers. Calculated BMI z-scores standardized to the 1990 British Growth Reference data. Overweight and obese defined according to gender and age dependent cut points.	*Buffer Type:* Network *Buffer Distance:*800m *Food Outlet Types:* BMI Healthy, BMI Unhealthy and BMI Intermediate Density - Binary (presence v. no)	*Level 1:* Gender, parental education, physical activity, under-reporting of food intake. *Level 2:* Other FO categories, index multiple deprivation, population density, land-use mix, density of commercial buildings and bus stops.	*Multilevel Linear Regression:* β estimates for the association between overweight and obese and each class of food outlets.	Not presented	NS	No significant associations between weight status and the availability of BMI Healthy, Unhealthy or Intermediate food outlets.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Leatherdale, Pouliou, Church *et al.* 2010	Convenience sample of grades 5-8 students from 30 elementary schools in Ontario, Canada as part of the PLAY-ON study. Conducted in 2007-2008. *N*= 1264 *Mean Age* = grade 7 *Sex* = Analysed separately	*Binary* Self-reported height and weight to calculate age and sex adjusted BMI using CDC as reference. Underweight (5th percentile), normal weight (6-84th percentile), overweight (85-94th percentile) and obese (95th percentile). Combined overweight and obese for analyses.	*Buffer Type:* Circular *Buffer Distance:* 1000m *Food Outlet Types:* gas stations, FFO, variety stores, bakeries, grocery stores, recreation facilities. Proximity (continuous, count) Density (continuous, count)	Physical activity, sedentary activity, ethnicity, number of active friends, self weight perception	*Multilevel Logistic Regression:* Odds Ratios and 95% CIs for the association of student and school level factor with overweight.	NS	NS	There were significant differences in the odds of being overweight between schools, but there were no significant associations between overweight and the food environment around schools.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Oreskovic, Kuhlthau, Romm *et al.* 2009	Community sample of youth receiving care from Partners HealthCare in eastern Massachusetts. Slightly higher Hispanic population compared to rest of the state. *N* = 21 008 *Mean Age (y)* = 5-12 years *Sex* = Both	*Binary* Height and weight from clinical database to calculate age and sex adjusted BMI percentiles. Overweight (85th percentile) and Obese (95th percentile).	*Buffer Type:* Circular *Buffer Distance:* 400m *Food Outlet Types:* Fast Food Outlets Density (continuous, count) Proximity (continuous)	Gender, race, town clustering, census tract, household income, educational attainment by census block.	*Multilevel Logistic Regression:* Odds Ratios and 95% CIsfor the effect of fast food restaurant Proximity and density on the odds of being overweight or obese. Stratified the analysis by income quartile (HIQ vs LIQ) and age group (2 to 5, 5 to 12, 12 to 18 years).	Ages 5-12 years, HIQ *Proximity, Overweight* OR = 0.86 (0.78 to 0.98) *Proximity, Obese* OR = 0.87 (0.76 to 0.99) Ages 5-12 years, LIQ *Density, Obese* OR = 1.11 (1.01 to 1.21)	Ages 5-12 years, HIQ *Proximity, Overweight* OR = 0.88 (0.80 to 0.98) Ages 5-12 years, LIQ *Density, Overweight* OR = 1.09 (1.06 to 1.11) *Density, Obese* OR = 1.09 (1.04 to 1.15) *Proximity, Obese* OR = 0.86 (0.78 to 0.95)	Among HIQ towns, greater distance to the nearest fast food restaurant was associated with a lower odds of overweight and obesity, though only the overweight association remained significant after adjustment. Among LIQ, fast food restaurant density was significantly associated with a greater odds of obesity, both unadjusted and adjusted, but only with overweight in the adjusted model. All statistically significant effects were small.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Oreskovic, Winickoff, Kuhlthau *et al.* 2009	Community sample of youth receiving care from Partners HealthCare in eastern Massachusetts. Slightly higher Hispanic population compared to rest of the state. *N* = 21 008 *Mean Age (y)* = 9.3 years *Sex* = Both	*Binary* Height and weight from clinical database to calculate age and sex adjusted BMI percentiles. Overweight (85th percentile) and obese (95th percentile).	*Buffer Type:* Circular *Buffer Distance:* 400m around home *Food Outlet Types:* Fast Food Outlets Density (continuous, count and binary, presence within buffer) Proximity (continuous, km)	Age, gender, race/ethnicity, family income	*Bivariate Associations and Multilevel Logistic Regression:* Adjusted OR and 95% CI for effect of environmental variables on the odds of being overweight or obese.	*Normal weight v. Overweight* *Proximity* OR = 0.84 (0.82 to 0.87) *Density, presence* OR = 1.29 (1.21 to 1.37) *Normal weight v. Obese* *Proximity* OR = 0.80 (0.77 to 0.83) *Density, presence* OR = 1.35 (1.26 to 1.45)	NS	Children who are overweight or obese lived significantly closer to fast food outlets than normal weight children. The presence of a fast food outlet within a 400m buffer around the home was significantly associated with greater odds of both overweight and obesity. This relationship lost significance in the adjusted models.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Crawford, Timperio, Salmon *et al.* 2008	Community sample of elementary school students selected from 19 state schools in Melbourne, Australia in 2004. Data were collected as part of the Children Living in Active Neighbourhoods (CLAN) study. *N* = 409 *Mean Age (y)* = 8-9, 13-15 *Sex* = Analyzed separately	*Continuous* Height and weight measured by researchers, used to calculate BMI. Overweight/ obesity defined using international sex- and age- specific cut-points. BMI z-scores calculated using US reference data.	*Buffer Type:* Circular *Buffer Distance:* 2 km *Food Outlet Types:* FFOs Density (binary - presence of FFO in 2km and continuous - count) Proximity (continuous, distance)	physical activity, school clustering	*Linear and Logistic Regression:* β estimates, Odds Ratios and 95% CIs for influence of environmental measures on weight status and BMI z-score	Not presented	*Density, binary* 13-15 yrs, Boys β= -0.49 (-0.95 to -0.03) 13-15 yrs, Girls β= -0.35 (-0.69 to -0.02) *Density, continuous* 13-15 yrs, Girls OR=0.86 (0.74 to 0.99) *Density, binary* 13-15 yrs, Girls OR=0.19 (0.09 to 0.41)	Among youth aged 13-15 years old, the presence of at least one fast food outlet within a 2km radius was negatively associated with BMI z-score. Among girls aged 13-15 years, the odds of being overweight or obese were 14% lower with each additional fast food outlet located within 2 km, and were 81% lower if there was at least one fast food outlet within the 2 km radius.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Seliske, Pickett, Boyce *et al.* 2009	Regionally representative sample of Canadian students in grades 6-10 from 178 schools. Data were part of the Health Behaviour in School Aged-Children (HBSC) survey in 2005/2006 *N* = 7281 *Mean Age (y)* = 13.6 years *Sex* = Both	*Binary* Self-reported height and weight to calculate age and sex adjusted BMI. Overweight/Obese defined according to International Obesity Taskforce recommendations.	*Buffer Type:* Circular *Buffer Distance:* 1 km *Food Outlet Types*: Total number, Restaurants, FFO, sandwich shops, coffee shops, convenience stores Density, Binary (Presence of FFO in 1km)	Area level SES, age, sex, physical activity, family affluence (construct), individual level SES	*Multilevel Logistic Regression:* Odds ratios and 95% CIs for effect of food outlet types on overweight/obesity.	*Restaurants* OR= 0.81 (0.69 to 0.94) *Fast Food Outlets* OR= 0.70 (0.58 to 0.81) *Sandwich Shops* OR= 0.65 (0.56 to 0.76) *Coffee Shops* OR= 0.68 (0.59 to 0.78) *Convenience Stores* OR= 0.79 (0.69 to 0.92) *Total Food Retailers* OR= 0.69 (0.06 to 0.79)	*Fast Food Outlets* OR= 0.83 (0.70 to 0.98) *Sandwich Shops* OR= 0.78 (0.64 to 0.93) *Coffee Shops* OR= 0.81 (0.68 to 0.96) *Total Food Retailers* OR= 0.70 (0.61 to 0.81)	Before adjustment for covariates, all types of food outlets were inversely related to the odds of being overweight or obese. After adjustment, this inverse relationship remained statistically significant for fast food retailers, sandwich/sub shops, coffee shops and for the total retailer number within 1km. Findings were opposite to the hypothesized direction of association.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Davis, Carpenter 2009	District representative sample of school kids in California, USA.Data were part of the 2002-2005 California Healthy Kids Survey (CHKS) *N* = 529 367 *Mean Age (y)* = 14 years *Sex* = *B*oth	*Binary and Continuous* Self-reported height and weight, used to calculate BMI. BMI age and gender specific percentiles based on CDC.	*Buffer Type*: Network *Buffer Distance:* Half mile (800m) *Food Outlet Types:* FFO, Other restaurants Density (Continuous, count) Proximity (Continuous)	Gender, age, race/ethnicity, physical activity level, school location type	*OLS Linear Regression*: β estimates and standard error to assess the effect of the local food environment, by food outlet type, on BMI. *Logistic Regression:* Adjusted ORs and 95% confidence intervals. Controlled for clustering by school	Not presented	*FFO within 0.5miles* Overweight/Obese: OR=1.06 (1.01 to 1.10) BMI: β = 0.1 (0.03 to 0.16) *Other Restaurant w/in 0.5 miles* Overweight/Obese: OR=1.04 (1.02 to 1.08) BMI: β = 0.8 (0.01 to 0.14) *Proximity* β = -0.03 (-0.05 to -0.01)	Significant positive relationship between BMI and FFO within 0.25 miles and between 0.25 to 0.5miles, but not over 0.05 miles.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Burgoine, Jones, Brouwer *et al.* 2015	Community representative sample of children selected from schools. Data were part of the Mebane on the Move study, conducted in North Carolina, US in 2011. *N* = 94 *Mean Age* = 8 years *Sex* = Both	*Continuous* Age specific BMI z-scores, derived from researcher measured heights and weights and calculated using the US CDC growth charts.	*Buffer Type:* Network, Activity Space *Buffer Distance:* 800m around home and school, 100m around GPS path *Food Outlet Types:* Unhealthy food outlets Combined proximity/density (Categorical, inverse distance weighted sum of distances to all food outlets) Density (Categorical, for GPS routes only)	Sex, parental educational attainment	*Linear Regression:* Adjusted and unadjusted BMI z-score by tertile of environmental food exposure for each environment.	*Home buffer* Tertile 1: 0.606 Tertile 2: 0.710 Tertile 3: 1.157	NS	Mean BMI z-score for the tertile with the most nearby food outlets was significantly higher than mean BMI z-score in the lowest tertile. Adjusted associations between BMI z-score and environmental food exposure were non-significant for home and school buffers, as well as activity space routes.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Subjective Measures								
Veugelers, Sithole *et al.* 2008	Representative community sample of students selected from 282 schools in Nova Scotia, Canada. Data were part of the 2003 Children's Lifestyle and School Performance Study (CLASS). *N* = 4298 *Mean Age (y)* = 10-11 years *Sex* = Both	*Binary* Researcher measured height and weight to calculate BMI. Overweight and obesity defined using international cut offs for children and youth.	*Buffer Type:* N/A *Buffer distance:* N/A *FO Types:* Shops Non-objective measure of access - parent survey of neighbourhood perception to shops (5 point scale: Poor to Excellent)	Gender, parental educational attainment and household income Controlled for clustering within neighbourhoods	*Multivariate multilevel Logistic Regression:* ORs for association of neighbourhood factors and children's weight status. Stratified by rural and urban schools	Not shown	*Combined Rural/Urban* *Overweight* OR=0.74 (0.60 to 0.91) *Obese* OR=0.67 (0.48 to 0.94) *Urban* *Overweight* OR=0.75 (0.57 to 0.99) OR=0.68 (0.52 to 0.90)	Significant differences between kids in neighbourhoods in the top third of access to shops and kids in the bottom third. Significant differences between normal weight and overweight for kids in middle and top third of best access, compared to bottom third.
Timperio, Salmon, *et al.* 2005	Representative community sample from 19 state primary schools in Melbourne, Australia. *N* = 919 families *Mean age (y)* = 11 years *Sex:* Both	*Binary* Measured height and weight to calculate BMI International age and sex specific cut points used to define overweight and obesity	Parent Survey "Are there shops within walking distance for child" > Yes/No	Sex, # of family cars, SES (family and area level)	*Logistic Regression*: ORs and 95% confidence intervals for effect of environmental features and overweight/obesity and obesity alone. Controlled for clustering by school.	*Perception of shops within walking distance* *Overweight/Obese* OR = 1.0 (0.7 to 1.7) *Obese* OR = 1.7 (0.6 to 4.8)`	Not performed since unadjusted analyses were insignificant	No statistical significance for perceived accessibility of shops.

Author(s), Year	Sample Characteristics	Body Mass Measure	Environmental Measure	Covariates	Analysis Type	Unadjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Torres, Serrano, Perez *et al.* 2014	Students sampled from 4 schools with an above average prevalence of obesity in San Juan, Puerto Rico during the 2012/2013 school year. *N* = 114 *Mean Age* = 12 years *Sex* = Both	*Binary* Measure height and weight to calculate age and sex adjusted BMI percentiles using the US CDC growth charts. Categorized as either normal weight or overweight/obese	*Continuous* *Food Outlet Types:* FFO, street vendors PE data was collected using a modified *Active Where?* Survey Questions: Distance to healthy and unhealthy food outlets from home, frequency of visits to unhealthy outlets from school	N/A	*Spearman's Correlation test:* Compare associations between food environment variables and total HEI scores.	*Home, Unhealthy Food Availability* Normal weight = 13.0 minutes Overweight = 10.0 minutes	N/A	There was a significant difference in perceived median distance to nearest unhealthy food outlets between normal weight children and overweight/obese children.

Table 19: Studies examining the cross-sectional association between the food environment and dietary intake.

Author(s), Year	Sample Characteristics	Dietary Intake	Environmental Measure	Covariates	Analysis Type	Adjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Objective Measures								
Jennings, Welch, Jones *et al.* 2011	Community based sample from 92 schools in Norfolk, UK. Data was from the Sport, Physical activity and Eating behaviours, Environmental Determinants in Young people (SPEEDY study), conducted in 2007. *N* = 1669 *Mean Age (y)* = 10.2 *Sex* = Both	*Continuous* Mean intakes for 9 food categories estimated from a 4 day food diary completed by children with parental assistance.	*Buffer Type:* Network *Buffer Distance:*800m *Food Outlet Types:* BMI Healthy, BMI Unhealthy and BMI Intermediate Density - Binary (presence v. no)	*Level 1:* Gender, parental education, physical activity, under-reporting of food intake. *Level 2:* Other FO categories, index multiple deprivation, population density, land-use mix, density of commercial buildings and bus stops.	Percentage differences in mean intake across 9 food groups between children with and without availability of different food outlet types.	Not presented numerically	N/A	Children living in neighbourhoods with BMI unhealthy food outlets had significantly higher intakes of fizzy drinks and noncarbonated fruit drinks compared to children whose neighbourhoods had no BMI unhealthy food outlets.

Author(s), Year	Sample Characteristics	Dietary Intake	Environmental Measure	Covariates	Analysis Type	Adjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
He, Tucker, Irwin *et al.* 2012	Community representative sample of students at 21 elementary schools in London, Ontario Canada. Data collected from 2006 to 2007. *N* = 810 *Mean Age* = 13 years *Sex* = Both	*Continuous* Overall diet quality measured using a modified Block Kids 2004 Food Frequency Questionnaire	*Buffer Type:* Circular *Buffer distance:* 1km around home postal code and school *FO Types:* FFO, convenience stores and supermarkets Density (continuous, count) Proximity (binary, cut off at 1km)	Grade, gender, neighbourhood distress tertile	*Generalized Linear Models:*β estimates for the effect of home and school food environments on Healthy eating index Controlled for clustering by school	Not presented	*Home* *Proximity to Convenience Store* β = 1.80 (0.79) *School* *Proximity to Convenience Store* β = 2.00 (1.00) *Fast Food Outlet* β = 2.6 (0.98)	Close proximity to convenience stores around homes, and convenience stores and fast food outlets around schools was associated with poorer diet quality score.
Timperio, Ball, Roberts et al. 2008	Community representative sample of students from 24 elementary schools in Melbourne and Geelong, Australia. Survey data collected in 2002 and 2003. *N* = 463 *Mean Age* = 11 years *Sex* = Both	*Binary* Parent surveys for how often children ate takeaway or fast food, dichotomized at less than or at least once per week	*Buffer Type:* Network *Buffer distance:* 800m around home *FO Types:* FFO, cafes, restaurants, takeaway stores, and convenience stores. Proximity (Continuous, shortest distance) Density (Continuous and binary, count/presence within buffer)	Neighbourhood SES	*Logistic Regression:* OR for effect of each measure of food environment on consumption of takeaway or fast food, adjusted and unadjusted. Controlled for clustering by school.	*Density - Continuous* OR = 0.98 (0.96 to 0.995)	*Density - Continuous* OR = 0.98 (0.96 to 0.999)	Only significant association was negative. **E**ach additional FO within 800m of home was associated with a 2% lower odds of consuming fast food at least once/week Two other measures of availability were not significant.

Author(s), Year	Sample Characteristics	Dietary Intake	Environmental Measure	Covariates	Analysis Type	Adjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Timperio, Ball, Roberts *et al.* 2008	Community representative sample of students from 24 elementary schools in Melbourne and Geelong, Australia. Survey data collected in 2002 and 2003. *N* = 461 *Mean Age* = 11 years *Sex* = Both	*Binary* Parent surveys for how often children ate fruits or vegetables, dichotomized at twice or more/day for fruit and three times or more/day for vegetables	*Buffer Type:* Network *Buffer distance:* 800m around home *FO Types:* greengrocers, supermarkets, convenience stores, fast food outlets, restaurants, cafes, takeaway outlets Proximity (Continuous, shortest distance in km) Density (Continuous and binary, count/presence within buffer)	None	*Logistic Regression:* OR for effect of each measure of food environment on consumption of fruit twice or more each day, and vegetables three times or more each day. Controlled for clustering by school	*Supermarkets Proximity - Vegetables* OR = 1.27 (1.07 to 1.51) *Convenience Stores Density, binary - Vegetables* OR = 0.75 (0.57 to 0.99) *Density, cont. - Fruit* OR = 0.84 (0.73 to 0.98) *Density, cont. - Vegetables* OR = 0.84 (0.74 to 0.95)	N/A	Children were 16% less likely to consume the recommended servings of fruits and vegetables each day for each additional convenience store within 800m, and 25% less likely to consume three or more servings of vegetables daily if there was at least one convenience store within 800m. Shorter distance was associated with greater odds of consuming vegetables at least three times daily.

Author(s), Year	Sample Characteristics	Dietary Intake	Environmental Measure	Covariates	Analysis Type	Adjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Jago, Baranowski, Baranowski *et al.* 2007	Sample was a subsample of Boy Scouts from the greater Houston area, Texas, United States. *N* = 204 *Mean Age* = 12.8 years *Sex* = Males	*Continuous* Fruit, juice and high/low vegetable consumption were assessed using Cullen FFQ	*Buffer Type:* Circular *Buffer distance:* 1609m around homes *FO Types:* Supermarket, small food store, convenience stores, restaurants, cafeteria, fast food restaurant Proximity (continuous, shortest distance) Density (Continuous, count within buffer)	BMI percentile, age, ethnicity, parental education, social desirability,	*Linear Regression:* β estimates for effect of food environment variables on fruit and vegetable intake. Assessed main and mediation effects, with food preferences assessed as a mediator. Controlled for clustering by Boy Scout Troop.	Not presented	*Fruit and Juice* *Proximity to Small Food Store* β = 0.00 *Proximity to Fast Food* β = -0.00 *Low Fat Vegetables* *Distance to Small Food Store* β = 0.001 *High Fat Vegetables* *Proximity to Small Food Store* β = 0.003 *Proximity to Fast Food* β = -0.001	Distance to small food stores was significantly associated with greater intake of fruit/juice, low fat and high fat vegetables. Less distance to fast food restaurants was associated with higher intake of high fat vegetables. None of the variables for food density were significant.

Author(s), Year	Sample Characteristics	Dietary Intake	Environmental Measure	Covariates	Analysis Type	Adjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Van Hulst, Barnett, Gauvin *et al.* 2012	Data were collected as part of the Quebec Adipose and Lifestyle Intervention in Youth (QUALITY) study between 2005 and 2008. Participants were recruited from schools and had at least one obese biological parent. *N* = 512 *Mean Age* = 9.6 years *Sex* = Both	*Binary* Three dietary recalls conducted by trained dietitians. Servings of fruit and vegetables, daily mean intake of soft drinks, weekly intake of take-out food.	*Buffer Type:* Network *Buffer distance:* 1 km around home and schools *FO Types:* supermarkets, convenience stores, fast food restaurants, specialty food stores Proximity (Categorical, shortest road distance) Density (Categorical, average density)	Age, sex, parental education, household income, residential population density, and residential deprivation	*Logistic Regression:* OR estimates for effect of residential food environment variables on dietary outcomes *Multivariable Generalized Estimating Equations:* OR estimates for school neighbourhood food environment and dietary outcomes. Controlled for clustering by school.	Not presented.	*Residential Density* *Eating/Snacking Out* *FFO* OR_{low} = 0.52 (0.30 to 0.91) OR_{middle} = 0.60 (0.36 to 0.99) *Convenience Stores* OR_{low} = 0.44 (0.25 to 0.80)	Children living in neighbourhoods that had the lowest and intermediate densities of fast food outlets were less likely to snack or eat out once or more each week. The lowest density of convenience stores was associated with a 56% lower likelihood of snacking or eating out weekly. Proximity measures and school neighbourhood environments were not statistically significant.

Author(s), Year	Sample Characteristics	Dietary Intake	Environmental Measure	Covariates	Analysis Type	Adjusted β Estimates (SE) or Other Reported Statistics	Adjusted β Estimates (SE) or Other Reported Statistics	Observed Relationship
Subjective Measures								
Torres, Serrano, Perez *et al.* 2014	Students sampled from 4 schools with an above average prevalence of obesity in San Juan, Puerto Rico during the 2012/2013 school year. *N* = 114 *Mean Age* = 12 years *Sex* = Both	*Categorical* 24 dietary recalls to calculate the Healthy Eating Index (HEI) - 2010	*Continuous* PE data was collected using a modified *Active Where?* Survey Questions: Distance to healthy and unhealthy food outlets from home, frequency of visits to unhealthy outlets from school	N/A	*Mann-Whitney U test:* Compare median HEI scores by food environment variables *Spearman's Correlation test:* Compare associations between food environment variables and total HEI scores	Not significant	N/A	Non-significant trend for higher perceived availability of healthy foods and less accessibility of unhealthy food outlets around the homes of children whose diets scored 'Needs Improvement'. Total HEI scores did not vary significantly across food environment variables

Appendix D: Ethics Approval for Use of Human Participants

re-issued

Use of Human Participants - Ethics Approval Notice

Research Western

Principal Investigator: Dr. Jason Gilliland
Review Number: 17918S
Review Level: Delegated
Approved Local Adult Participants: 1200
Approved Local Minor Participants: 1200
Protocol Title: Identifying casual effects on the built environment on physical activity, diet, and obesity among children.
Department & Institution: Social Science\Geography, University of Western Ontario
Sponsor: Canadian Institutes of Health Research
Heart and Stroke Foundation of Canada

Ethics Approval Date: June 08, 2011 **Expiry Date:** August 31, 2014

Documents Reviewed & Approved & Documents Received for Information:

Document Name	Comments	Version Date
Other	Revised Healthy Neighbourhood Survey for Parents.	
Other	Revised Health Neighbourhoods Survey for Youth	
Other	Revised Activity and Travel Diary for School Days and Weekend Days.	

This is to notify you that The University of Western Ontario Research Ethics Board for Non-Medical Research Involving Human Subjects (NMREB) which is organized and operates according to the Tri-Council Policy Statement: Ethical Conduct of Research Involving Humans and the applicable laws and regulations of Ontario has granted approval to the above referenced revision(s) or amendment(s) on the approval date noted above.

This approval shall remain valid until the expiry date noted above assuming timely and acceptable responses to the NMREB's periodic requests for surveillance and monitoring information.

Members of the NMREB who are named as investigators in research studies, or declare a conflict of interest, do not participate in discussions related to, nor vote on, such studies when they are presented to the NMREB.

The Chair of the NMREB is Dr. Riley Hinson. The NMREB is registered with the U.S. Department of Health & Human Services under the IRB registration number IRB 00000941.

Appendix E: Healthy Neighbourhoods Survey for Youth

15. I might get bullied or teased along the way	●	○	○	○
16. There is nowhere to safely leave a bike at school	○	○	○	●
17. Other reasons? ________	○	○	○	○

18. Do you often stop somewhere on the way to school? ○ Yes ● No

18a. If yes, where do you usually stop? (ex. Variety store, friend's house)

____

E. The Types of Food You Eat

1. In a typical day, about how many servings of fruit do you eat?

Example – 1 serving is equal to:

- A piece of fresh fruit, like an apple
- A small bowl of fruit salad
- A small glass of real fruit juice, like orange or apple juice (Do not count fruit punch, lemonade, Gatorade, Sunny Delight or fruit drink)

None (0) **1** **2** **3** **4 or more**

2. In a typical day, about how many servings of vegetables do you eat?

Example – 1 serving is equal to:

- A carrot or other fresh vegetable (Do not count French fries, potato chips)
- A small bowl of green salad
- A small bowl of fresh or cooked vegetables

None (0) **1** **2** **3** **4 or more**

How often do you eat the following food items? Please circle one answer for each type of food.

	Never	Rarely	Sometimes	Frequently	Always
3. 100% fruit juice	○	○	●	○	○
4. Fruit-flavoured drinks (like Fruitopia, Gatorade, Snapple)	○	●	○	○	○
5. milk	○	○	○	○	●
6. regular pop with sugar	○	●	○	○	○
7. diet or sugar free pop	○	○	○	●	○

		Never	Rarely	Sometimes	Frequently	Always
8	unsweetened breakfast cereal (like Cheerios, Rice Krispies)	●	○	○	○	○
9	sweetened breakfast cereal (like Frootloops, Frosted Flakes)	○	●	○	○	○
10	chocolate bars or other candies	○	○	○	●	○
11	Cakes, brownies, cookies	○	○	●	○	○
12	Potato or corn chips	○	○	●	○	○
13	Vitamins	○	○	○	●	○
14	Ice cream	○	○	○	●	○
15	French fries	○	●	○	○	○

F. Eating during the School Day

1. Are you allowed to leave the school grounds at lunch time? ○ Yes ● No
2. During a normal school week, how many days per week do you go home to eat lunch?
   Number of days per week: 0 (1) 2 3 4 5
3. How many days do you typically bring a lunch from home?
   Number of days per week: 0 1 2 3 (4) 5
4. During a normal school week, how many days per week do you get lunch off school grounds at a fast food restaurant?
   Number of days per week: 0 (1) 2 3 4 5
5. During a normal school week, how many days per week do you get lunch off school grounds at a convenience/variety store?
   Number of days per week: (0) 1 2 3 4 5
6. How many days do you typically get breakfast at school?
   Number of days per week: (0) 1 2 3 4 5

Curriculum Vitae

Name:	Krista Cook
Post-secondary Education and Degrees:	Queen's University Kingston, Ontario, Canada 2008-2012 B.Sc.(Honours) Life Sciences, Specialization
	The University of Western Ontario London, Ontario, Canada 2013-2015 M.Sc. Epidemiology and Biostatistics
Honours and Awards:	Ontario Graduate Scholarship 2014-2015
	Children's Health Research Institute, London Health Sciences Quality of Life Initiative Grant 2014
	2nd place Canadian Society for Epidemiology (CSEB) Poster Competition Mississauga, Ontario, Canada
Related Work Experience	Teaching Assistant (Introduction to Health Economics, Health Economics II) The University of Western Ontario 2014-2015

Poster Presentations:

Cook, K., Gilliland, J., O'Connor, C., Wilk, P. Exploring associations between food outlet exposure and BMI z-score in elementary school children using Global Positioning Systems (GPS). Poster presented at the 2015 Association of Public Health Epidemiologists in Ontario (APHEO) Conference, London ON, June 14-16 2015

Cook, K., Gilliland, J., O'Connor, C., Wilk, P. Exploring associations between food outlet exposure and BMI z-score in elementary school children using Global Positioning Systems (GPS). Poster presented at the 2015 Canadian Society for Epidemiology and Biostatistics (CSEB) Conference, Mississauga ON, June 1-4 2015