The Compositional Effects of Time Spent in Sleep, Sedentary Behaviour and Physical Activity on Obesity in Children

By

Robert Talarico

A thesis submitted to the Department of Public Health Sciences in conformity with the requirements for the degree Master of Science

Queen’s University

Kingston, Ontario, Canada

(August, 2017)

Copyright ©Robert Talarico, 2017
Abstract

Purpose

Physical activity, sedentary behaviour (SB) and sleep have traditionally been studied as independent behaviours and not as co-dependent behaviours that are compositional in nature. This study used compositional data analyses to investigate the co-dependent relationships between time spent in movement behaviours (sleep, SB, light intensity physical activity (LIPA), and moderate-to-vigorous physical activity MVPA) and obesity among children.

Methods

434 children aged 10-13 years were studied. Participants wore an Actical accelerometer for 7 days to determine time spent in SB, LIPA, and MVPA. Time spent sleeping was determined from the accelerometer and a log. The outcomes of interest were the body mass index, waist circumference, and fat mass index. Compositional data analysis was used to examine associations. This involved transforming the movement behaviours using an isometric log ratio transformation, using regression to model the associations, and back-transforming the regression coefficients to estimate how displacing time from one movement behaviour with another influenced the obesity measures.

Results

The composition of movement behaviours was associated with all three obesity measures (p<0.001). Relative to the other movement behaviours, time spent in MVPA was negatively associated with the obesity measures (p<0.01), time spent in LIPA was positively associated with the obesity measures (p<0.05), while time spent in SB and sleep were not associated with the obesity measures. The most meaningful time displacements were for MVPA, and these displacements were larger at lower MVPA levels. For example, reallocating 10 minutes of MVPA to 10 minutes of LIPA was associated with a 2.7% (95% CI: 2.4, 2.8), 2.0% (95% CI: 1.8, 2.1), and 1.5% (95% CI: 1.4,1.6) increase in BMI z-score at the 25th, mean, and 75th MVPA percentiles, respectively.
Conclusion

The composition of movement behaviours across the day was associated with the obesity measures. The displacement of time from MVPA to LIPA were associated with the most significant changes in the obesity measures.
Co-Authorship

This thesis is the work of Robert Talarico under the supervision of Dr. Ian Janssen.

The data used in this thesis are from the Active Play Study, for which Ms. Chao Xue was the coordinator and Dr. Janssen was the primary investigator. The conceptualization of this thesis was a collaborative effort between Robert Talarico and Dr. Janssen. Robert Talarico performed the literature review, SAS dataset management, manipulations and merges, relevant analyses, interpretation of results, and writing of the chapters. Dr. Janssen provided ongoing feedback and guidance, and assisted in editing the thesis.
Acknowledgments

First and foremost, I would like to thank my supervisor Dr. Ian Janssen for his guidance and support. It was his knowledge and expertise that guided me and allowed me to thrive in an epidemiological and biostatistical setting. Thank you for your continual mentorship, which challenged me to grow as a researcher and ensure this thesis was completed to the best of my abilities.

I would also like to thank the Active Play team for their support and their countless hours spent cleaning data. It was a great experience being a part of such a strong team that functioned so well despite many hardships and setbacks and I think we all grew to become better researchers together. Also, thank you to my parents, Sam and Anna Talarico, who have always supported my endeavors and whom I will always look to for guidance and strive to make you guys proud.

Lastly, thank you to Dr. Ian Janssen, the Heart and Stroke Foundation and Queen’s University for their financial support which funded this thesis.
# Table of Contents

Abstract ........................................................................................................................................................................ ii

Co-Authorship................................................................................................................................................................ iii

Acknowledgments.......................................................................................................................................................... v

Chapter 1 Introduction .................................................................................................................................................. 1

1.1 Overview............................................................................................................................................................... 1

1.2 Objectives and Hypotheses..................................................................................................................................... 3

1.3 Scientific and Public Health Significance............................................................................................................... 4

1.4 Thesis Organization................................................................................................................................................. 4

1.5 References............................................................................................................................................................. 6

Chapter 2 Literature Review....................................................................................................................................... 8

2.1 Introduction............................................................................................................................................................ 8

2.2 Key Terms and Concepts....................................................................................................................................... 8

2.3 Importance of Obesity as a Health Measure in Children and Adolescents....................................................... 9

2.4 Associations Between Individual Movement Behaviours and Obesity............................................................. 11

2.5 Stability of Movement Behaviours and Obesity Over Time............................................................................. 19

2.6 Multiple Movement Behaviours and Obesity..................................................................................................... 21

2.7 Study Rationale.................................................................................................................................................... 29

2.8 References.......................................................................................................................................................... 30
Chapter 1

Introduction

1.1 Overview

Overweight and obesity in children and adolescents is a serious and continued public health concern. It is well established that obesity in children and adolescents is associated with a host of cardio-metabolic abnormalities and psycho-social problems.[1,2] Also, a child’s weight status tracks into adulthood.[3] In other words, children or adolescents who are categorized as overweight or obese are much more likely to become an adult with overweight/obese than young people with a healthy weight. Furthermore, evidence shows that adolescents with obesity have an increased risk of cardiovascular disease and all-cause mortality in adulthood independent of adult obesity status.[4] According to the Canadian Health Measures Survey, close to one third (31.5%) of 5-to 17-year-old Canadians have a body mass index (BMI) in the overweight or obese range.[5] The good news is that pediatric overweight/obesity can be prevented through a healthy lifestyle.

Movement is an important determinant of obesity. A child’s day is made up of sequences of four movement behaviours including periods of sleep, sedentary behaviour (SB) (e.g., watching television), light intensity physical activity (LIPA) (e.g., incidental tasks of daily living), and moderate-to-vigorous physical activity (MVPA) (e.g., playing sports). Research has demonstrated that the amount of time spent in each of these movement behaviours is related to obesity and other health measures within children and adolescents.[6–10]

While the vast majority of the literature has focused on the health effects of a single movement behaviour in isolation, in recent years there has been an interest in studying multiple movement behaviours in combination.[11,12] The approach typically used in these multiple movement behaviour
studies was to include two or more movement behaviours as exposure variables in the same regression model.[11,13] For instance, several studies have shown that excessive television viewing is associated with obesity and a myriad of other health indicators after adjusting for MVPA as a confounder using common regression approaches such as linear or logistic regression.[14] This approach is problematic for reasons outlined in the following two paragraphs.

First, movement behaviours are not truly independent behaviours and should therefore not be treated as such in statistical analysis. Rather, movement behaviours are co-dependant with one another as a change in the time spent in any given movement behaviour must influence the time spent in at least one other movement behaviour. For example, to increase MVPA by 10 minutes a child would need to replace 10 minutes of time that would have otherwise been spent in SB, LIPA or sleep. Furthermore, including multiple movement behaviours in the same regression model often leads to multicollinearity.[15]

Second, when analyzing these four movement behaviours a researcher is dealing with data that represent the composition of a measurement period. Movement behaviours can therefore be expressed as proportions of the measurement period. Imagine a hypothetical scenario where one child’s composition is 4% MVPA, 18% LIPA, 40% SB, 38% sleep and another child’s composition is 5% MVPA, 12% LIPA, 50% SB, 33% sleep. It appears that the second child spends a higher proportion of their day in MVPA (5%) compared to the first child (4%) and a higher proportion of the second child’s day (50%) is spent in SB compared to the first child (40%). However, the ratio of the proportion of time spent in SB to the proportion of time spent in MVPA (SB/MVPA) would be 10 for both children. In other words, both of these children spend 10 fold more of their time in SB compared to MVPA. Importantly, this conclusion differs from the comparison of the individual behaviours which observed differences between the two children’s SB and MVPA. Focusing on one of these behaviours at a time conceals the co-dependencies between the movement behaviours. Furthermore, the two children spend different proportions of their time in LIPA and sleep.
Rather than analyzing ratios between pairs of behaviours these ratios can be computed to incorporate the entire array of movement behaviours at once using specific log-ratio transformations. This log-ratio analysis of the composition of a child’s day is at the heart of a field of applied mathematics known as compositional data analysis.[15,18] Compositional data analysis is a statistical approach that has been developed for analyzing data that is compositional in nature and constrained to some finite whole.[16] This approach has been used for years in other research fields such as nutrition (e.g., fatty acid composition of meat) and geochemistry (e.g., composition of minerals in rocks).[18–20] Because movement behaviours fit within a compositional paradigm, compositional data analysis holds great promise in the physical activity epidemiology field. The conceptual model in figure 1 highlights the compositional nature of the movement behaviours. The movement behaviors are made up of sleep, SB, LIPA and MVPA and form the composition of a 24 hour day. This composition is related to obesity. However, other variables such as diet and age are related to both the movement behaviours and obesity and can be thought of as potential confounders.

1.2 Objectives and Hypotheses

The objectives of my thesis research will be to use a compositional data analysis approach to estimate whether 1) the composition of time spent in sleep, SB, LIPA, and MVPA is associated with obesity measures among 10 to 13-year-olds, and 2) displacing an equal amount of time from one movement behaviour to another movement behaviour, such as 10 minutes of SB with 10 minutes of MVPA, is associated with changes in obesity measures among 10 to 13-year-olds.

It is hypothesized that: 1) the composition of time spent in different movement behaviours will be significantly associated with the obesity measures, 2) the relative amount of time spent in MVPA and sleep will be beneficially associated with the obesity measures while the time spent in SB and LIPA will be detrimentally associated with the obesity measures, and 3) the estimated change in the obesity measures
associated with displacing SB with MVPA will be larger than the estimated changes associated with
displacing SB with LIPA or sleep.

1.3 Scientific and Public Health Significance

Public health guidelines in physical activity, SB, and sleep have historically focused on promoting
an individual movement behaviour. Similarly, most movement behaviour interventions have focused on
changing the amount of time children spend in MVPA, SB, or sleep duration in isolation and have neglected
the rest of the composition of the day. Recent evidence suggests that adequate sleep, low SB and high
MVPA represents the ideal movement behaviour ‘soup’ and is beneficially associated with a myriad of
health markers. This thesis research will model the movement behaviour ‘soup’ using a compositional
paradigm. This new modelling approach could aid in making a case for adopting an integrated movement
behaviour paradigm and designing interventions that target the composition of a child’s day and not just a
single movement behaviour.

1.4 Thesis Organization

This thesis follows the guidelines set in place by the Queen’s University School of Graduate Studies
for a manuscript-based thesis. The second chapter provides a literature review of the effects of sleep, SB,
LIPA, MVPA, and combinations of these movement behaviour on obesity measures in children and
adolescents. The literature review also discusses methodological and statistical approaches that can be
used to examine how combinations of movement behaviours are associated with health. The third
chapter is the Manuscript, which investigates the compositional effects of sleep, SB, LIPA and MVPA on
obesity measures in 10-13-year-olds. Lastly, the fourth chapter consists of a general discussion of the
findings and their importance in the field of physical activity epidemiology and movement behaviour
research.
Figure 1: Conceptual Model for the relationship between the movement behaviours and obesity in children
1.5 References


Chapter 2

Literature Review

2.1 Introduction

The purpose of the Literature Review is to describe the scientific evidence examining the association between movement behaviours and combinations of these behaviours with obesity within school-aged children and adolescents. The literature review starts by summarizing the existing evidence on the relationship between individual movement behaviours and obesity. This is followed by a discussion of the evidence demonstrating how combinations of movement behaviours influence obesity. The methodological approaches used to examine these combined influences are critiqued and key gaps and limitations in this literature are highlighted.

2.2 Key Terms and Concepts

Before embarking upon the literature review it is important to define some of the key and recurring terms that will be used. Usually, a child is defined as a 5-11-year-old and an adolescent as a 12-17-year-old. Pre-adolescents refer to children aged 10-11 nearing adolescence. Youth can refer to adolescents and young adults up to the age of 25. While my thesis research focused on the pre and early adolescence period that occurs between the ages of 10-13 years, the literature review includes studies that sampled school-aged children and adolescents.

For the purposes of this thesis, sleep duration is defined as the length of time between when someone turns out the lights to go to bed to when they wake up in the morning. The remaining three movement behaviours occur during waking hours and they are often defined according to their intensity based on their metabolic equivalence (MET), where one MET is the amount of oxygen consumed while resting.[1] Sedentary behaviour (SB) refers to any waking behaviour characterized by an energy expenditure ≤1.5 METs.[2] Any waking behaviour at an intensity of 1.5 to 2.9 METs is considered light
Intensity physical activity (LIPA) and includes activities such as standing, slow walking, and playing an instrument. Any waking behaviour at or above 3.0 METs is considered moderate-to-vigorous physical activity (MVPA) and includes activities such as brisk walking and running. It should be noted that many activities that children and adolescents engage in contain combinations of different movement behaviours. For instance, while playing a soccer game a child partakes in SB (e.g., time spent on the bench), LIPA (e.g., standing during stops in play), and MVPA (e.g., running during game play).

Overweight and obesity are defined as excessive fat accumulation that may impair health. The body mass index (BMI) is a simple index of weight-to-height that is a commonly used obesity measure in people of all ages. For children and adolescents overweight is often defined as BMI-for-age greater than 1 standard deviation above the WHO Growth Reference median and obesity as greater than 2 standard deviations above the WHO Growth Reference median.[3] Also, waist circumference is an indicator of health risk associated with excess fat around the waist.[4] Overweight and obesity can also be assessed in terms of body fat mass or body fat percentage.

2.3 Importance of Obesity as a Measure of Health in Children and Adolescents

According to the Canadian Health Measures Survey, an estimated 1.6 million Canadian children were classified as overweight (19.8%) or obese (11.7%) in 2009 to 2011.[5] Obesity appears to progressively increase from childhood to adolescence. Based on estimates from 2012/2013, 8.5% of 5-to-9 years-olds, 12.9% of 10-to-14-year-olds and 18.2% of 15-to-17-year-olds have obesity.[6] A recent study found that the prevalence of overweight and obesity experienced a slight decline from 30.7% in 2004 to 27.0% in 2013. [7] However, the prevalence of obesity has been stable at about 13%.[7] Unfortunately, Canadian children and adolescents are still relatively heavy with median z-scores for BMI higher than those recommended by the WHO age and growth references.[7] A recent systematic review and meta-analysis using BMI to measure obesity found that compared with normal weight children, systolic and diastolic blood pressure, total cholesterol and triglyceride concentrations, and fasting insulin
and insulin resistance were significantly higher in children with overweight and obesity.[8] There is also prospective evidence showing that adolescents with obesity have an increased risk of cardiovascular disease and all-cause mortality in adulthood independent of adult obesity status.[9,10] Furthermore, young people with a BMI in the overweight/obese range are more likely to experience detrimental psychosocial and mental health including depression, teasing, social isolation and discrimination, diminished self-esteem, behavioural problems, dissatisfaction with body-image and reduced quality of life.[11,12] Prospective studies also demonstrate that adolescents with a high BMI are at a higher risk of developing major anxiety and depressive disorders later in life.[13] Thus, BMI is associated with a wide range of immediate and long-term health problems among children and adolescents.

Another method to quantify obesity is measuring the waist circumference. Waist circumference has been advocated as a simple measure of abdominal fat.[14] Among adults, abdominal fat is more strongly related to the development of cardiovascular disease, diabetes mellitus and premature death than is fat in other regions of the body, such as subcutaneous fat in the arms and legs.[15–19] In children, high waist circumference has been associated with lower good cholesterol (i.e., high density lipoprotein) and higher triglycerides, insulin, and abdominal subcutaneous and visceral fat.[18,20]

Most obesity research uses simple anthropometric measures, such as BMI and waist circumference, as proxies of body fat and abdominal fat. However, it is possible to measure body fat itself using various methods such as bioelectrical impedance (BIA) and dual-energy x-ray absorptiometry (DXA).[21] Body fat measures may provide a more sensitive measure of overweight/obesity related health risk than BMI since BMI gives no information on lean muscle mass versus fat mass. Also, movement behaviours, particularly MVPA, can alter body composition by decreasing fat mass and increasing muscle mass.[22] Because of these more direct measures of body fatness it is often assumed that body fat is a better predictor of adverse health outcomes than BMI. However, several studies have demonstrated that in children BMI is highly correlated with both body fat percentage (r=0.85) and body
fat mass \( r=0.95 \), and that the association between body fat and cardiovascular risk factors are not stronger than the associations between BMI and cardiovascular risk factors.[20,23] Thus, it remains unclear if it is important to measure body fat instead of or in addition to simple anthropometric measures of obesity such as BMI.

2.4 Associations Between Individual Movement Behaviours and Obesity

i) Sleep Duration

Average sleep durations in children and adolescents have declined by almost a minute per year over the last century.[24] The Canadian 24-hour Movement Behaviour Guidelines for Children and Youth recommend that school-aged children aged 6-13 years sleep for 9-11 hours per night and that 14-17 year olds sleep for 8-10 hours per night.[25] The Canadian Health Behaviour in School-aged Children Study (HBSC) found that almost one-third of Canadians in grades 6-10 had an average nightly sleep duration shorter than these recommendations.[26]

Recent evidence suggests that sleep duration is negatively associated with energy balance, body weight regulation and cardio-metabolic risk factors within children and adolescents.[27],[28,29] The results from a published systematic review indicate that children with the shortest sleep duration, who were defined as having a sleep duration at least 2 hours below the age specified sleep duration recommendations, had a 92% increased odds of overweight or obesity by comparison to children with sleep durations in the recommended range.[30] For each hour increase in sleep, the odds of overweight/obesity was reduced on average by 9% (pooled OR=0.91 95% CI: 0.84-1.00).[30] Furthermore, an overall negative association was observed \( (\beta=-1.34 \text{ 95\% CI:} -1.83,-0.83) \) between sleep duration and waist circumference from a recent meta-analysis which pooled 8 cross-sectional studies.[29]

Chaput et al. published the most recent systematic review of the relationship between sleep duration and health indicators in school-aged children and adolescents.[27] Only one randomized trial
was included in this review and it showed that increased sleep duration resulted in lower weight after a week compared with decreased (mean difference in weight of 0.24 kg, p<0.001).[31] There was 2.4-hour sleep duration difference between conditions (10.5 h vs 9.1 h for the increased and decreased sleep, respectively measured via accelerometry).[31]

Chaput and colleagues systematic review included 12 longitudinal studies in which 7 found negative associations between short sleep duration and adiposity gain, with only 2 of these studies using objective measures of sleep.[27] The two studies using objective measures and a longitudinal design had contrasting conclusions.[32,33] The FLAME study found that each additional hour of sleep at ages 3-5 was associated with a reduction in BMI z-score of 0.48 (95% C.I: 0.01 to 0.63) and a reduced risk of being overweight at age 7 of 0.39 (95% C.I: 0.24 to 0.63).[32] These estimates were adjusted for MVPA, television viewing, and diet. On the other hand, Hjorth et al. followed 10-year-old Danish children for 200 days and found no longitudinal relationship between changes in sleep duration and changes in adiposity after adjustment for MVPA and diet.[33] The most obvious differences between these longitudinal studies was that the Hjorth et al. study followed an older group of children for a much shorter period of time. Also, compared to the children from the FLAME study, the Hjorth et al. study examined children with lower BMI z-score (approximately 0.75 standardized units on average) and the FLAME study may have used a more robust measure of sleep duration (average of sleep duration at 3, 4 and 5 years of age) due to the repeated measures of sleep during the follow-up period.

A total of 50 cross sectional studies (out of 58) reported a negative association between short sleep duration and excess adiposity. For example, Chaput et al. conducted a study to determine if short sleep duration was independently associated with adiposity among 550 children with an average age of 9.6 years. Objective measures of adiposity (BMI Z-score, waist circumference and percent body fat), sleep duration, and MVPA were taken.[34] Children were categorized into four groups according to sleep duration: <10 hours, 10-10.9 hours, 11-11.9 hours and ≥12 hours of sleep per night. After adjusting
for a host of covariates including total energy intake and MVPA, short sleep duration (<10 hours) was associated with increased odds of being overweight or obese (OR: 2.05 95% C.I: 1.15-3.63) compared to sleeping between 11 and 12 hours.[34] Another study used a sample that included 6025 children (9-11 years) from 12 countries representing a wide range of human development. They found that for every standard deviation increase in sleep duration (50 minutes/day) the odds of obesity decreased to 0.75 (95% C.I: 0.69-0.82) after adjustment for MVPA and diet.[35] Virtually all cross sectional studies that use objective measures of sleep duration report detrimental associations between short sleep duration and adiposity.

The authors of the most recent comprehensive and systematic review of sleep duration and health concluded the quality of evidence is low due to a serious risk of bias (i.e., most studies used subjective measures of sleep with no psychometric or reliability properties recorded); however, many of the studies had large effects observed and there was evidence of a dose response gradient between short sleep duration and adiposity.[27] Overall, there appears to be evidence to support the relationship between longer sleep duration and lower adiposity indicators. However, studies in sleep epidemiology have typically relied on subjective measures.[27] Sleep questions used in epidemiologic studies do not agree well with objective measures of sleep as assessed using accelerometry (kappas range from -0.19 to 0.14).[36] There is a need for more accurate measures of sleep duration in future studies such as accelerometry, which is gaining more popularity for the assessment of sleep in epidemiologic research. Another consistent limitation in studies examining the association between sleep duration and obesity is the lack of consideration and/or adjustment for other movement behaviours, such as the time spent in MVPA and SB.[37]

The following paragraph will briefly discuss the potential mechanisms by which altered sleep duration can lead to obesity. One of those mechanisms is through a change in dietary intake. Hart et al. recently conducted a crossover randomized controlled trial in 8 to 11-year-old children. They found that
an experimental increase in nightly sleep of 2 hours and 21 minutes resulted in a reported 134 kcal/day (p<.05) reduction in caloric intake and body weight reduction of 0.22 kg (p<.05) after the 3-week intervention.[31] Observational studies in children and adolescents also lend support to the hypothesis that inadequate sleep affects dietary intake. Associations have been reported between short sleep and energy dense and sugar containing diets and intake of fast foods.[38,39] Furthermore, it may be that inadequate sleep duration affects energy expenditure through a reduction in MVPA or LIPA and thus total daily energy expenditure. Hart et al. found that when the children decreased their sleep they reported watching an additional hour of television each day (P<.001).[40] Also, during the decreased sleep condition children were less active on average during waking hours than they were during the increased sleep condition (p=0.03).[40]

**ii) Sedentary Behaviour (SB)**

Canadian school-aged children and adolescents spend 8.6 hours per day or 62% of their waking hours being sedentary.[41] These sedentary pursuits include screen time (TV, video games, computer use, etc.), classroom time and motorized transportation. Screen time has garnered the most research attention.[42],[43,44] Canadian public health guidelines stress that to avoid negative health outcomes children and adolescents should limit recreational screen time to 2 hours per day or less.[45] Only 24% of 5-17 year olds in Canada meet these guidelines.[46] A recent systematic review included a total of 162 studies that examined the relationship between sedentary behaviour (both objectively and subjectively measured) and obesity.[42] These studies consisted of a combination of prospective, case control and cross sectional designs. Overall, higher durations/frequencies of screen time and television viewing were associated with unfavourable body composition.[42] It is worth noting that these studies were ranked as “very low” according to the GRADE Quality of Evidence framework. [42] The low quality of evidence reflects that few of the studies described the psychometric properties of the screen time questionnaire items measured. Also, few of the studies adjusted their analysis for time spent in MVPA.
and/or sleep duration, which could confound the relationship between self reported screen time and obesity.

A recent randomized controlled trial was carried out to assess the effect of a screen time intervention on body composition. [47] Robinson et al. reported that elementary school children who were randomized to receive an intervention which aimed to reduce screen time without promoting MVPA experienced a 0.45 kg/m² decrease in BMI and a 2.3 cm reduction in waist circumference when compared to control students over a 6-month period. [47] Katzmarzyk et al. found that the odds ratio for obesity (BMI Z-score>2) increased by 1.12 (95% C.I: 1.04-1.19) for every unit increase in TV time score. [35] Chaput et al. conducted a study to examine the independent association of different movement behaviours on cardio-metabolic risk factors using a sample of 630 children from the QUALITY study. [48] Self-reported screen time was positively associated with waist circumference (β=0.89, 95% C.I: 0.45 to 1.33), independent of objectively measured MVPA. [48] Another study using baseline data from 736 Finnish children 6-8 years found that watching television and videos was positively associated with body fat percentage (β=0.077, p=0.076) and waist circumference (β=0.083, p=0.071) but with adjustment for total physical activity the relationship became marginally non-significant. [49] A drawback of this study was that they adjusted for total PA rather than MVPA. Sedentary behaviour is likely to be more strongly correlated with total PA than MVPA which would artificially inflate the standard error estimates thus potentially leading to the marginally non-significant p-value.

While most of the SB literature has examined screen time, screen time is not the only context in which children take up sedentary pursuits. Some recent studies have used accelerometers to objectively measure total SB. When examining the relationship between objectively measured total sedentary time and obesity, there appears to be a detrimental relationship for more time a child spends in sedentary pursuits. [37, 48, 50–53] However, after adjustment for other movement behaviours, and MVPA in particular, the relationship is attenuated and it is no longer significant. [41, 46–53] Thus, in school-aged
children and adolescents total SB does not have a consistent relationship with obesity that is
independent of MVPA.[56]

It may be that particular sedentary pursuits, particularly television viewing, have a negative effect on
health in children and adolescents rather than cumulative sedentary time. Potential mechanisms linking
television viewing to obesity in children include increased snack food consumption or exposure to food
advertisements that promote excess energy intake leading to weight gain.[57] Also, it may be that
television time has more between child variability than total sedentary time. For example, classroom
time, which is primarily sedentary, would be very similar for all children resulting in little between child
variability. This would lessen the statistical efficiency required to detect a meaningful relationship
between total sedentary time and adiposity. However, since television time would have a greater
between child variability it may allow a researcher the ability to make comparisons between different
body composition subgroups and detect statistically significant associations as compared to total
sedentary time. In other words, these p-value discrepancies may be a result of differing statistical
efficiencies between the exposure distributions of television time and total sedentary time rather than
pragmatic scientific effects.

iii) Light Intensity Physical Activity (LIPA)

While the energy expenditure rates per unit time are much lower for LIPA than for MVPA, LIPA
should not be discounted as an important source of physical activity energy expenditure.[58] This is
because the cumulative effect of LIPA over the entire day is often greater than that of MVPA since
people tend to spend far more time in LIPA than MVPA.[58] On average MVPA consists of <5% of a
child’s day whereas LIPA consists of anywhere between 15-20% of a child’s day.[59]

The literature surrounding the health impacts of LIPA are mixed. A recent systematic review of 12
studies found an equal proportion of favourable, unfavourable and null relationships between LIPA and
obesity.[60] Carson et al. conducted a longitudinal analyses examining the relationship between LIPA
and obesity in a sample of 841 children, aged 9-15 years. There was a trend for increasing BMI z-score and waist circumference comparing the 3rd (3.76 hours) and 4th (3.16 hours) quartile of LIPA to the 1st quartile of LIPA (2.19 hours) after 2 years of follow-up.[61]

Another two-year longitudinal study following 984 school-aged girls found no relationship between changes in LIPA and changes in BMI or body fat from the 6th to 8th grade. [62] Two cross-sectional studies divided LIPA into 2 subcategories; lower intensity LIPA (e.g., standing) and higher intensity LIPA (e.g., slow walking) and adjusted their analysis for MVPA.[63,64] Kwon et al. found that among boys, both low and higher intensity LIPA were negatively associated with fat mass at age 11, but not at age 5 or 8.[63] However, among girls only higher intensity LIPA was negatively associated with fat mass at age 11 and both intensities of LIPA were negatively associated with fat mass at age 8.[63] Carson et al. found no association between either intensity of LIPA and waist circumference amongst 1731 adolescents, aged 12-19 years [64]

These weak and mixed associations may be artefacts of the way in which LIPA is measured by accelerometers.[60] Accelerometers may not effectively differentiate LIPA from sedentary time and may cause misclassification of some SB as LIPA and vice versa.[60] Also, it may be that when LIPA displaces SB it has a positive effect on health whereas when LIPA displaces MVPA it has a deleterious effect. Overall, more research is needed to ascertain whether LIPA is an effective substitute for more sedentary pursuits and/or exerts beneficial effects on obesity and other health indicators independent of MVPA.

iv) Moderate-to-vigorous physical activity (MVPA)

The Canadian Physical Activity Guidelines for children and youth recommend at least 60 minutes/day of MVPA.[65] An estimated 9% of boys and 4% of girls in Canada meet this target on 6 or 7 days of the week, indicating that MVPA levels are low in young Canadians.[41] There is strong and consistent evidence based on hundreds of experimental and observational studies for several health outcomes, including obesity, that participating in as little as 2 or 3 hours of MVPA per week is associated
with health benefits. In their 2012 systematic review, Janssen and Leblanc demonstrated that there is a dose-response relation between MVPA and health indicating that the more MVPA, the greater the benefit. A more recent systematic review that only included studies with objective physical activity measures came to very similar conclusions. Specifically, Poitras et al. concluded that there was strong and consistent evidence of favourable relationships between total PA and adiposity markers and similar favourable relationships were observed for the different PA intensities but in general, higher intensities of physical activity (i.e., MVPA) were more frequently examined and had more consistent associations and stronger effect sizes than lower intensity physical activities (i.e., LIPA).

A major limitation of the studies examined in these reviews are that most examined MVPA in isolation and did not adjust for the possible confounding effects of the other movement behaviours. However, some studies have performed such adjustments. Specifically, four studies have reported finding inverse associations between time spent in MVPA and measures of adiposity in children, independent of objectively measured sedentary and sleep time, with the strongest associations found for participation of vigorous physical activity. In a longitudinal analysis, Mitchell et al. discovered a negative association between MVPA and change in BMI at the 90th BMI percentile. This negative association was progressively weaker moving towards the 10th BMI percentile. All of these associations were adjusted for objectively measured SB and sleep duration. Furthermore, a study using cross-sectional data from the Canadian Health Measures Survey found that an increase in 1 hour of MVPA was associated with a 1.2 kg/m² decrease in BMI and a 3.2 cm decrease in waist circumference. These associations were adjusted for objectively measured sleep duration and parent reported screen time. A recent pooled analysis of 14 studies from the International Children’s Accelerometry Database yielded comparable results. Time spent in MVPA was significantly and inversely associated with various cardio-metabolic outcomes such as waist circumference, fasting insulin, fasting triglycerides, HDL-cholesterol and resting systolic blood pressure even after adjusting for...
Overall, there appears to be a consistent and beneficial relationship between the time spent in MVPA and obesity, independent of the time a child spends in SB and/or sleeping.

2.5 Stability of Movement Behaviours and Obesity Over Time

A key component when defining an exposure in epidemiological research is the time period in which the exposure effects the outcome of interest, which is known as the exposure time window. The exposure time window in which movement behaviours exert effects on obesity is presumed to be across the lifetime. For example, the obesity status of a 13-year old can be thought of as a function of how physically active they are at age 13 as well as how physically active they were throughout childhood. However, there are pragmatic limitations of measuring movement behaviours across childhood and adolescence. Thus, in cross-sectional studies and longitudinal studies that measure the exposures at a single point in time certain assumptions must be made. The assumption being that movement behaviours are habitual and rather stable, indicating that the time a child spends in MVPA, SB and sleep tracks over time. In order to establish a habitual relationship between these movement behaviours and obesity, the stability of these movement behaviours over time must be investigated to approximate an exposure time window.

Several studies have attempted to quantify the relative stability of obesity and movement behaviours. In the epidemiological literature, the concept of persistence or relative stability of overweight/obesity and movement behaviours over time is often referred to as ‘tracking’. In general, three concepts are used to describe tracking: (i) the relationship (correlation) between measurements over time (ii) the maintenance of the relative position within a distribution of values in the observed population over time, and (iii) the predictability of future values by early measurements.

A review of epidemiological studies in Europe and the United States of the relations between obesity in childhood and adulthood reported that the risk of adult obesity was at least twice as high for
obese children as for non-obese children.[72] Magarey et al. followed healthy term infants from age 2 to age 20.[73] Tracking correlation coefficients were strong and highly significant indicating a high degree of temporal stability. For example, the tracking correlation between BMI at age 6 and BMI at age 11 was 0.84 and the correlations between BMI at age 11 and BMI at age 20 was 0.72.[73] Also, children who were overweight at 11 years of age had a 3.55 (95% C.I: 2.43-5.21) times greater risk of being overweight at age 20 compared to those of normal weight at age 11.[73] A study in Norway found that children who were overweight/obese at age 5-7 had a 11 (95% C.I: 6.4-19.2) times increased odds of being overweight/obese at age 15-17 compared to thin/normal weight children.[74] The positive predictive value of overweight/obese 5-7 year old children staying overweight/obese at 15-17 years old was 63%.[74] Furthermore, a systematic review which included 13 studies found that all studies reported an increased risk for overweight or obese children and youth to become overweight and obese adults.[71]

A recent review attempted to synthesize the body of literature which examined the tracking of MVPA and SB from early childhood (aged 0-5.9 years) to middle childhood (6-12 years).[75] Of the tracking coefficients (Pearson’s Correlation and Spearman’s Rank Correlation) for MVPA, 4% were large (≥0.5), 60% were moderate (0.3-0.49), and 36% were small (0.10-0.29).[75] Using the same coefficient cut-points for SB, 33% were large, 50% were moderate and 36% were small.[75] It is important to note that due to day-to-day variation, within instrumental measurement error and using subjective measures of activity, tracking coefficients of MVPA and SB tend to be biased downwards (i.e., underestimated coefficients).[75]

Unfortunately, no studies were found that assessed the tracking of sleep duration over time. However, the other results discussed in the section illustrate the relative stability of MVPA, SB and adiposity during the childhood, adolescent, and early adult years. Thus, it appears that measurement of
movement behaviours and obesity at one-time, such as during childhood in a cross-sectional study, may approximate the relevant exposure time window.

2.6 Multiple Movement Behaviours and Obesity

i) Independent variables in a regression model  The primary approach that researchers have used to try to determine whether multiple movement behaviours are associated with health is to include different movement behaviours as covariates in the same regression models. Studies examining the association between SB and obesity often include MVPA as a covariate. Most often only one of the remaining movement behaviours are controlled for as covariates. For example, Steele et al., found that objectively measured SB was positively associated with waist circumference and fat mass.[50] However, these associations were attenuated and no longer significant after MVPA was adjusted for.[50] In reality all of the movement behaviours have the potential to exert confounding effects and should be considered in a regression analysis. Given that sleep, SB, LIPA and MVPA account for 100% of a child’s day, traditional statistical approaches that look at independent associations may be inappropriate for analyzing all these behaviours simultaneously.[76–78] Time spent in the movement behaviours are co-dependent, since an increase in the time spent in one behaviour must result in a subsequent decrease in one or more of the other behaviours. Thus, these movement behaviours are not truly independent of one another.[8,12] This co-dependence is often quantified using the usual correlation coefficient, which becomes problematic given that these behaviours represent relative information (e.g., proportions of time in a 24-hour day) rather than absolute values. This concept goes back to Pearson’s observation of ‘spurious correlation’, where it has been demonstrated that relative amounts of time, which share the same denominator (i.e., a 24-hour) may not be independent even when they are found to be weakly correlated (such as time spent in MVPA and SB; \( r = -0.23 \)); as the usual correlation coefficient becomes an inconsistent measure of pair-wise relationships.[76,77,79–81] In other words, collinearity indices might
return values that suggest noncollinearity while the collinearity exists by nature.\[82\] Mutually adjusting a common regression model with sleep, SB, LIPA and MVPA induces multicollinearity which causes poor statistical adjustment, since these movement behaviours are not independent but rather co-dependant relative amounts of time.\[76,83\] Instead of searching for independent associations between movement behaviours a more appropriate approach could be examining the combined effects of these movement behaviours which more suitably represent the intrinsic co-dependence of the data.

ii) Combined Associations of Movement Behaviours and Obesity

Another approach that researchers have used to look at whether different movement behaviours influence health independent of other movement behaviours is to dichotomize the variables and then look at how combinations of these dichotomized variables relate to obesity. For instance, when examining the combination of MVPA and SB, comparisons can be made across 4 groups: high MVPA/high SB, low MVPA/high SB, high MVPA/low SB, and low MVPA/low SB.

Eight studies (1 longitudinal and 7 cross-sectional) have assessed the relationship between combinations of high and low MVPA and SB with adiposity.\[37,51,67,84–88\] All eight studies reported that individuals with the best combination (i.e., High MVPA/Low SB) had lower measures of adiposity and/or reduced prevalence of overweight/obesity than those with the worst combination (i.e., Low MVPA/High SB). Four studies found that for at least one sub-group of participants, those with a high MVPA and high SB had lower levels of adiposity when compared to those with low MVPA and high SB.\[51,67,87,88\] Moreover, especially among girls higher levels of adiposity were found for those with a high SB and high MVPA compared to those with low SB and high MVPA, whereas for boys engagement of high MVPA was of crucial importance and SB was of less importance for adiposity.\[87\],\[88\]

Fewer studies have looked at combinations of other movement behaviours or more than two combinations of movement behaviours. The studies that have been conducted have looked at combinations of high/low for MVPA, SB, and sleep. Because the SB and LIPA are so highly correlated (r=-
0.9), virtually all participants with a high SB have a low LIPA, so it becomes redundant to also include high/low LIPA groups in these comparisons.[64]

Three studies have reported that individuals with the most ideal combination of movement behaviours (e.g., High MVPA/Low SB/High Sleep) had lower adiposity and/or risk of overweight than those with the least ideal combination of movement behaviours (e.g., Low PA/High SB/Low Sleep).³⁶,⁴⁵,⁶⁴ Laurson et al. conducted an analysis of 674 elementary school-aged children and reported that children that failed to meet the three recommendations for sleep duration (self reported), screen time (self reported), and physical activity (steps/day via pedometer) had an 8.2 (95% CI: 3.2-32.1) times increased odds of obesity by comparison to children meeting all three guidelines.[89] The corresponding odds ratios for children meeting one or two guidelines only were 2.6 (95% CI: 1.1-6.5) and 4.7 (95% CI: 1.9-11.3), respectively.[89] A longitudinal analysis of 723 Danish 8-11-year-old children assessed the associations between different combinations of self-reported screen time and accelerometer measured MVPA, SB and sleep.[37] In comparison to children in the High Sleep/High MVPA group, children in the Low Sleep/Low MVPA group had a 2.17 kg/m² higher fat mass index.[37] However, there were no significant differences in fat mass index between the High Sleep/Low SB and Low Sleep/High SB groups irrespective of whether SB was self-reported or measured objectively.[37] The third study using data from 10 year olds from 12 countries found that children with the least healthy pattern (low PA/high SB/low sleep) had a 9.3% higher body fat percentage than those in the opposite pattern and similar associations were found for other adiposity outcomes such as BMI z-score and waist circumference.[53] Two studies investigated the associations between the proportion of participants who meet the MVPA, screen time and sleep duration recommendations (and combinations of these recommendations) with obesity.[90,91] The first study used an international sample of 6128 children (9-11 years old). Whereas the second study included 6 to 17-year-olds from the Canadian Health Measures Survey.[91] The results of the international study demonstrated that those who met the three
recommendations were 72% (95% C.I: 55%-82%) less likely to be obese (BMI z-score>2) than those who did not meet them.[90] Also, children who met only the MVPA recommendation were 55% (95% C.I: 48%-62%) less likely to be obese whereas meeting the MVPA and screen time or MVPA and sleep duration recommendations were 57% (95% C.I: 45%-67%) and 62% (95% C.I: 51%-71%) less likely to be obese, respectively.[90] When only the screen time and sleep duration recommendations were met obesity was 35% (95% C.I: 20%-46%) less likely.[90] The Canadian study found that children meeting none of the three recommendations had a higher BMI z-score (β=0.36, 95% C.I: 0.19 to 0.54) and log waist circumference (β=0.04, 95% C.I: 0.02 to 0.07) compared to those children and youth meeting all three recommendations.[91] The only intermediate combinations to reach statistical significance were for children failing to meet the MVPA recommendation only and children failing to meet both the screen time and sleep recommendations only. They had a 5% and 2% higher waist circumference than children meeting the recommendations, respectively.[91] These results indicate that it is most important to meet all three movement behaviour guidelines. However, the most important recommendation for children to meet is MVPA. Screen time and sleep duration may act synergistically to lower the odds of obesity but more so when MVPA is already sufficient.

Physical activity researchers are beginning to investigate the effects of multiple movement behaviours on obesity. This is a step forward in moving towards a more integrated and inclusive approach in regards to human movement.[92,93] However, there are still some inherent limitations of the research carried out thus far. The majority of studies compared only the best and worst combinations of behaviours (e.g., High PA/High Sleep/Low SB .vs. Low PA/Low Sleep/High SB), without directly comparing intermediate combinations.[94] However, comparing intermediate combinations also has inherent issues. For example, children meeting the sleep recommendation only, includes children who fall marginally below the physical activity and screen time recommendations along with children who fall severely below these recommendations. These crude classifications may mask the true
effects of these behaviours. Studying the relative amount of time spent in each of these behaviours on a continuum could yield important information.

iii) Isotemporal Substitutions

Another approach that researchers have used to examine how different movement behaviours are associated with obesity is to employ isotemporal substitution models using observational study data. Isotemporal substitution modeling is a regression approach that is used to estimate the extent to which substituting one movement behaviour with another movement behaviour, such as substituting 1 hour of SB with 1 hour of LIPA, is associated with changes in obesity or other health measures.[84,85,95,96] The covariates in an isotemporal substitution model include the time spent in each of the individual movement behaviour variables and the total time (i.e., sum of the time spent in all of the movement behaviours being examined).[95] Individual movement behaviours are then dropped from the model to estimate how replacing this behaviour would change the obesity outcome. For example, if SB is dropped from the regression model the regression coefficient for total time would represent the estimated effect of the omitted activity component, SB, on the outcome. The coefficients for the remaining movement behaviours would represent the estimated effect of substituting 1 hour of that movement behaviour for the omitted activity (e.g., LIPA instead of SB), while adjusting for the other behaviours in the exact same way as in standard multivariable regression.[95]

Three studies (3 cross-sectional and 1 prospective) have used this type of modelling to examine different movement behaviours and obesity among children and adolescents. In their cross-sectional studies, Loprinzi et al. and Aggio et al. reported that substituting 60 mins/day of SB or LIPA with MVPA would result in a 4-5% lower percent body fat among children but no significant change in body fat was found among adolescents.[84,85] Also, a recent study followed 386 Portuguese school aged children for one year.[97] Substituting 30 minutes of daily sedentary time with 30 minutes of MVPA was negatively associated with waist circumference ($\beta=-1.11$, 95% C.I: -2.16 to -0.06) and total body fat mass ($\beta=-0.48$, 95% C.I:
95% C.I: -0.87 to -0.06). Conversely, substituting SB with LIPA was not associated with any of the obesity measures among children or adolescents. One of the major limitations in this research is that none of the studies used sleep in there substitution models. Isotemporal substitution modelling provides a simple and interpretable means of examining the array of movement behaviours in relation to obesity. However, it suffers from the same poor statistical adjustments mentioned previously, since it relies on conventional regression approaches for its substitution across the entire array of movement behaviours.

iv) Compositional Data Analysis

The next step in movement behaviour research is to move beyond thinking about sleep, SB, LIPA and MVPA as individual exposures that have independent associations with obesity (and other health measures). Rather, we should be thinking about these movement behaviours collectively as compositional variables that have combined and/or compositional associations. Therefore, the pertinent information is in the relative distribution of time between behaviours, and not in their absolute values. That is, the amount of time spent in a behaviour is meaningful only in light of the time spent on other behaviours and not on its own.

Time spent in one movement behaviour must displace the time spent in at least one of the other behaviours. Thus, movement behaviour data represents co-dependant relative amounts of time which are constrained within the confines of a given period of time, such as a 24-hour day. Because the movement behaviour data are constrained to compositions of a whole (e.g., 24-hour day), they would ideally be analyzed using statistical approaches that are appropriate for compositional data.

This paragraph discusses the unique geometric and mathematical properties of compositional data and statistical approaches that can be used to analyze such data. Geometrically speaking, compositional data lives in an equilateral triangle which defines a constrained space known collectively as the simplex. Compositional data is inherently different from data that exist in standard...
Euclidean space that is unconstrained (e.g., x,y,z).[78] Two statistical approaches can be used with compositional data. The first is known as the staying-in-the-simplex approach. It operates in the simplex space ($S^D$, for D-part compositions) and uses statistical approaches based on Aitchison geometry.[78] These statistical approaches are not familiar to epidemiologists and are rarely used in health research. The second approach resorts to transforming the compositional data so that it maps onto the standard Euclidean space. This is typically done using a log-ratio transformation. After these transformations have been performed, the compositional data can be analyzed using standard regression methods that are familiar and commonly used in health research.[78,99][100]

Two studies have utilized the compositional data analysis framework to assess whether the composition of movement behaviours is associated with health outcomes.[77,82] These groundbreaking papers studied an adult sample (n=1937) from the cross-sectional 2005-2006 U.S. National Health and Nutrition Examination Survey and a children and adolescent sample (aged 5-17 years) from the Canadian Health Measures Survey (n=5217).[77,82] In both of these studies the day was partitioned in proportion of time spent in four movement behaviours: self-reported sleep duration and objectively measured time spent in SB, LIPA and MVPA. The proportion of time spent in each movement behaviour was then analyzed using the log-ratio transformation approach to map the movement behaviours as compositions in the standard real space. A plethora of cardio-metabolic risk factors were examined such as waist circumference, BMI, and LDL cholesterol. I have focused my discussion on the BMI results. After transforming the movement behaviour variables into compositional variables (via isometric log-ratio transformations), both studies used linear regression to examine the associations between the movement behaviours, BMI, and other cardio-metabolic risk factors.[77,82]

Chastin et al. showed that the relative distribution of time amongst the four movement behaviours as a whole was significantly associated with BMI.[77,82] This indicates that the composition of an adult’s day partitioned into each of the movement behaviours was associated with BMI.[77,82]
The proportion of time spent in each behaviour compared to the other three was detrimentally associated with SB (β=1.40, p=0.002) and LIPA (β =0.98, p=0.029) but favourably with sleep ( β=-1.40, p=0.009) and with MVPA (β=-0.098, p<0.001). These β values represents the mean change in BMI z-score associated with change in the log ratio of the time spent in that behaviour in relation to the time spent in the remaining movement behaviours. For example, the MVPA coefficient can be interpreted as when MVPA displaces an average of the other movement behaviours BMI declines. To further understand the role played by the relative proportion of time spent on each movement behaviour, Chastin et al. used the estimates from the linear regression model to predict the change that would occur at average BMI if 10 minutes of time were displaced from one behaviour to another one around the average composition (similar to the isotemporal substitution). The effect of re-allocating time from one behaviour to another was found to be small and not symmetric. For BMI the largest effect was found when 10 minutes of MVPA was displaced by 10 minutes of SB, this changed BMI by 1.21%. However, the opposite, replacing 10 minutes of SB with 10 minutes of MVPA, only changed BMI by -0.001%. Also, when 10 minutes of MVPA was displaced by 10 minutes of LIPA a 0.850% increase in BMI was observed whereas the opposite displacement was again miniscule. Lastly, when 10 mins of sleep was displaced by 10 mins of LIPA and SB there was only a 0.003% increase in BMI.

In their compositional analyses of movement behaviours, Carson et al. computed BMI z-scores in the children and adolescent sample. The proportion of time spent in each behaviour compared to the other three was detrimentally associated with SB (β= 0.58, p<0.011) and LIPA (β= 0.66 and p <0.001) but favorably associated with sleep duration (β =-0.93, p= 0.002) and MVPA (β= -0.32, p<0.001).[82] The largest effect was found when 10 minutes of MVPA was displaced with 10 minutes of the other behaviours, particularly SB.[82] This resulted in a 5.1%, 1.2%, and 1.1% increase in BMI z-score when taking 10 min away from MVPA and displacing it with SB, LIPA and sleep respectively.[82] Also, replacing 10 mins of SB, LIPA and sleep with 10 mins of MVPA only changed the BMI z-scores by less than 1%.
The two studies that used a compositional data analysis to model the movement behaviours are not free of limitations. Both studies used self reported sleep duration. Also, the Canadian study pooled children from ages 4-17. It is well known that movement behaviours such as MVPA change as a function of age. Future research should attempt to unravel these compositional relationships across smaller age ranges. Furthermore, no confidence intervals were reported for the movement behaviour displacements. This makes these estimates appear as if they were computed without error. In order to gain appreciation for the random variability that exists when performing inference prediction intervals around the estimates should be computed and interpreted as such.

2.7 Study Rationale

Canada has recently created the world’s first 24-hour Movement Behaviour Guidelines for Children and Youth.[92][101] These guidelines integrate all movement behaviours. These guidelines were developed in response to the recent trend of studying and thinking about movement behaviours collectively rather than individually. Although researchers are now conceptualizing movement behaviours as having combined and/or compositional effects, for the most part they are still using statistical approaches that are not appropriate for compositional data. A compositional paradigm opens the door for finding the optimum distribution in different movement behaviours and obesity in children and adolescents. While a compositional approach may seemingly only correct for a mere methodological issue, it represents a substantial shift in how we model multiple movement behaviours throughout the day.
2.8 References


43. Costigan SA, Barnett L, Plotnikoff RC, Lubans DR. The health indicators associated with screen-based


63. Kwon S, Janz KF, Burns TL, Levy SM. Association between light-intensity physical activity and


74. Evensen E, Wilsgaard T, Furberg A-S, Skeie G. Tracking of overweight and obesity from early


84. Loprinzi PD, Cardinal BJ, Lee H, Tudor-Locke C. Markers of adiposity among children and adolescents:
implications of the isotemporal substitution paradigm with sedentary behavior and physical activity patterns. J. Diabetes Metab. Disord. 2015;14:1–14.


93. Prochaska JO. Multiple Health Behavior Research represents the future of preventive medicine. Prev.


Chapter 3

The Compositional Effects of Time Spent in Sleep,
Sedentary Behaviour and Physical Activity on Obesity in
Children
3.1 Abstract

Purpose

Physical activity, sedentary behaviour (SB) and sleep have traditionally been studied as independent behaviours and not as co-dependent behaviours that are compositional in nature. This study used compositional data analyses to investigate the co-dependent relationships between time spent in movement behaviours (sleep, SB, light intensity physical activity (LIPA), and moderate-to-vigorous physical activity MVPA) and obesity among children. Methods

434 children aged 10-13 years were studied. Participants wore an Actical accelerometer for 7 days to determine time spent in SB, LIPA, and MVPA. Time spent sleeping was determined from the accelerometer and a log. The outcomes of interest were the body mass index, waist circumference, and fat mass index. Compositional data analysis was used to examine associations. This involved transforming the movement behaviours using an isometric log ratio transformation, using regression to model the associations, and back-transforming the regression coefficients to estimate how displacing time from one movement behaviour with another influenced the obesity measures.

Results

The composition of movement behaviours was associated with all three obesity measures (p<0.001). Relative to the other movement behaviours, time spent in MVPA was negatively associated with the obesity measures (p<0.01), time spent in LIPA was positively associated with the obesity measures (p<0.05), while time spent in SB and sleep were not associated with the obesity measures. The most meaningful time displacements were for MVPA, and these displacements were larger at lower MVPA levels. For example, reallocating 10 minutes of MVPA to 10 minutes of LIPA was associated with a 2.7% (95% CI: 2.4, 2.8), 2.0% (95% CI: 1.8, 2.1), and 1.5% (95% CI: 1.4,1.6) increase in BMI z-score at the 25th, mean, and 75th MVPA percentiles, respectively.
Conclusion

The composition of movement behaviours across the day was associated with the obesity measures. The displacement of time from MVPA to LIPA were associated with the most significant changes in the obesity measures.

3.2 Introduction

Moderate–to-vigorous physical activity (MVPA), light intensity physical activity (LIPA), sedentary behaviour (SB) and sleep are mutually exclusive intensities of movement that together account for the entire 24-hour day. Research examining these movement behaviours in isolation has demonstrated that they are all related to obesity and other health indicators within children and adolescents.[1–5] In recent years there has been an interest in studying the health effects of combinations of these movement behaviours.[6,7] The approach typically used in these multiple movement behaviour studies was to include two or more movement behaviours as covariates in the same regression model to determine if they are independently associated with the health outcome.[8] For instance, studies have reported that television viewing, a common sedentary behaviour, is associated with obesity after adjusting for MVPA and sleep as confounders.[9,10] Using common regression approaches to determine the independent associations for different movement behaviours is inappropriate because these behaviours are not independent of each other. Rather, they are co-dependant since an increase in time spent in one movement behaviour must displace an equal amount of time from one or more of the other behaviours.[8,12] Furthermore, common regression approaches were developed to deal with unconstrained variables that are free to range from negative infinity to positive infinity in Euclidean space. Movement behaviours are; however, constrained because the time spent in a given movement behaviour cannot exceed 24-hours in a day. When constrained variables are examined using common regression approaches the results can be misleading as the effects can be over or under estimated and some real effects obscured.[8,11]
Compositional data analysis is a statistical approach suitable for analyzing co-dependent data that is compositional in nature and constrained to some finite whole, such as movement behaviour data.[12] Although compositional data analysis has been used for years in other research fields such as nutrition (e.g., fatty acid composition of meat) and geochemistry (e.g., composition of minerals in rocks),[13–15] it has only recently been used in movement behaviour research. To our knowledge, only one movement behaviour study has applied compositional data analysis techniques in a pediatric population. That study found that the proportion of the 24-hour day spent in MVPA and sleep was beneficially associated with the body mass index (BMI) among 4-17 year olds, whereas the proportion of the day spent in SB and LIPA was detrimentally associated with BMI. Additional findings from that study suggest that displacing 10 minutes/day of MVPA with 10 minutes/day of SB would be associated with unfavourable changes in BMI. A key limitation of that study was that it relied on questionnaires to assess sleep duration, and the data obtained from such questions relate poorly to data obtained using objective measures (kappa coefficients range from -0.19 to 0.14).[17] Also, children were pooled from ages 4-17. It is well known that movement behaviours change as a function of age.[18–20] The objective of this study was to use a compositional data analysis approach to examine the association between objectively measured movement behaviours and obesity measures within 10-13 years olds. Specifically, this study estimated 1) whether the composition of time across the 24-hour day spent in MVPA, LIPA, SB and sleep is associated with obesity measures, and 2) the extent to which displacing an equal amount of time from one movement behaviour to another movement behaviour, such as 10 minutes/day of SB with 10 minutes/day of MVPA, is associated with changes in obesity measures.

3.3 Methods

Study Design and Participants
The study sample consisted of 458 pre and early adolescents who completed the cross-sectional Active Play Study. Inclusion criteria were that participants be 10-13 years old and live and attend school in Kingston, ON, Canada. Non-ambulatory and non English or French speakers were excluded. Participants were recruited by word of mouth, social media, and advertisements posted and distributed in local schools, stores, and community centres. An example advertisement is provided in Appendix A (p.95). Participant recruitment was balanced by age, sex, season, and Kingston’s 12 electoral districts to ensure proportional representation across these strata. All participants, and a parent or guardian, provided written informed consent prior to participation. The letter of information and consent forms are provided in Appendix B (p.97). The study was approved by the General Research Ethics Board at Queen’s University. Additional ethics clearance was obtained by the Queen’s University Health Sciences Research Ethics Board to perform the analyses included in this thesis (Appendix H, p.134).

**Overview of Data Collection**  
Participation in the study involved visiting the Physical Activity Epidemiology Laboratory at Queen’s University on two occasions, 8-11 days apart. During the first visit, participants underwent a series of anthropometric and body composition measurements (e.g., height, weight, % fat). They were also provided with verbal and written instructions on how to wear an Actical accelerometer (Philips Respironics, Murrysville, Pennsylvania, USA) (see Appendix C, p.111 ) and how to complete an accelerometer activity and sleep log (see Appendix D, p. 116). They were asked to wear the accelerometer on their right hip continuously for the next 7 days, except while bathing or participating in water activities. The devices were programmed to initialize at midnight following the first visit to the lab, and continue recording in 15-second epochs over the next 7 days. During the 7-day movement behaviour collection period participants were asked to record the time they woke up each morning and went to sleep each night on the log. Daily email and/or text messages were sent to participants and/or their parents reminding them to wear the accelerometer and to complete the log. Within a few days of completing the 7-day movement behaviour data collection, participants returned the accelerometer and
log to the lab and one of their parents completed a questionnaire on a tablet computer. Children were compensated $40 for completing the study; $20 of this was provided for returning the accelerometer in working condition and completing the log.

**Processing and Cleaning of Movement Behaviour Data**

The sleep times that were recorded in the logs were manually verified, and corrected as necessary, by visually inspecting the recorded log times against the Actical accelerometer data. An example of this visual data verification and correction process is shown in Appendix E (p.119). In our laboratory, this visual verification/correction process is highly reliable as 90% of the verified and corrected sleep times are within 10 minutes of each other based on repeated verification/correction attempts completed by different researchers. Using the adjusted wake and bed times, sleep duration was calculated for each night, and then an average sleep duration was calculated for each participant across the valid nights of observation.

The accelerometer data and corrected wake and bedtimes were imported into SAS statistical software (SAS Inc., Carry, NC) and processed using a specially designed program. Initially, all accelerometer epochs that occurred during sleep periods were flagged and removed, leaving only epochs that occurred during waking hours. Non-wear time accelerometer data was then identified and removed. Non-wear time was defined as ≥ 60 consecutive minutes of zero epoch counts, with allowance of 2 minutes of counts between zero and 100.[21] Also, non-wear time that was recorded on the log was removed. The SAS program then identified invalid days (i.e., < 10 hours of wear time during waking hours), and removed all accelerometer data from invalid days and all participants with < 4 valid days.[21] Each of the remaining epochs was categorized as MVPA (>1,499 counts per minute), LIPA (100-1,499 counts per minute), or SB (<100 accelerometer counts per minute).[21] For each day, time spent in each of these intensities was determined by summing the epochs spent in each of the intensities. Then, the average daily time spent in SB, LIPA, and MVPA was calculated across the valid days. Finally,
time spent in the four movement behaviours were summed and normalized to the proportion of the total time, which summed to 24 hours.

**Obesity Measures**

The outcomes of interest were the body mass index (BMI), waist circumference, and the fat mass index. Sitting and standing height were measured to the nearest 0.1 cm using a portable stadiometer (SECA model 213, SECA GmbH & Co., Hamburg, Germany) with the head in the Frankfurt Plane. Weight was measured to the nearest 0.1 kg using an electronic scale (Tanita scale model BF-689, Tanita Inc. Tokyo, Japan) after heavy clothing and shoes were removed. BMI values were calculated as weight in kg divided by height in m². World Health Organization (WHO) growth references were used to calculate age- and sex- specific BMI z-scores.[22] Waist circumference was measured to the nearest 0.1 cm midway between the lowest rib margin and the iliac crest.[23] Waist circumference was measured twice and the average used for analysis. A third measurement was obtained if the first two measurements were >0.5 cm apart and the average of the two closest measurements was used. Fat mass was estimated using a bioelectrical impedance analysis (BIA) scale (Tanita Model BF-689, Tanita Inc. Tokyo, Japan). BIA determines the electrical impedance or the opposition to the flow of an electrical current through body tissues, which is used to estimate total body water, which in turn be used to estimate fat-free body mass, which when subtracted from body mass provides an estimate of body fat mass.[24] The fat mass index was calculated as fat mass in kg divided by height in metres squared. As the fat mass index is relatively independent of fat-free mass, it was chosen over percent body fat.[25] For descriptive analysis, participants were categorized into 3 subgroups based on BMI z-scores: non-overweight (z-score <1), overweight (z-score between 1 and 2), or obese (z-score >2). Waist circumference and the fat mass index were divided into quartiles since standardized cut-points do not exist for these measures.

**Covariates**
Age (continuous), sex, race (white or non-white), family income ($ CDN per year ≤50 000, 50 001-100 000, >100 000, prefer not to say), parent education (high school or less, 2 year college, 4 year university/college), family structure (single or dual parent household), presence of a chronic health condition (yes or no), biological maturity, season of data collection (based on solstice and equinox dates), accelerometer wear time, frequency of fast food consumption, and frequency of snack food consumption in front of a screen were considered as potential confounders. Peak height velocity was used as a proxy measure for biological maturity.[26] It was calculated based on the child’s age and the ratio of their trunk and leg length. Accelerometer wear time was calculated as the average time that a child wore the device (MVPA + SB + LIPA + sleep). Frequency of snack food consumption was ascertained by two questions, “How many days of the week do you snack while watching TV (including videos, DVDs, Youtube?)” and “How many days of the week do you snack while working or playing on a computer or games console”. The responses for these two questions were combined to calculate an overall continuous frequency of snacking in front of a screen variable. Also, statistical interactions by sex and age were investigated via the inclusion of a product term in each of the regression models. As none of these interactions were found to statistically significant, all analyses are presented in boys and girls combined.

Statistical Analysis

Statistical analyses were performed using SAS version 9.4 (SAS Inc., Cary, NC) and the robCompositions package in RStudio version 3.2.4 (RStudio, Boston, MA).[27] Standard descriptive statistics (e.g., mean, prevalence) were computed to describe the participant characteristics. The main analyses followed the guide to compositional data analysis for movement behaviour research published by Chastin et al.[11] The initial step of the compositional analysis involved calculating the geometric mean for the proportion of time spent in each movement behaviour. The geometric mean is a better representation of central tendency for compositional data than the arithmetic mean.[13] Compositional
geometric mean bar plots were constructed to display the relative movement behaviour profiles across obesity groups (e.g., difference in movement behaviours across non-overweight, overweight, and obese groups). These bar plots display the ratio between the log geometric mean of a movement behaviour for a particular subgroup to the log of the overall sample geometric mean of that same behaviour (e.g., \( \ln(\text{MVPA}_{\text{Subgroup}}/\text{MVPA}_{\text{Overall}}) \)). Groups with bars > 0 spent more time in the respective behaviour than the sample average. The opposite holds true for bars < 0.

We then estimated the variability between behaviours using a variation matrix. Due to the intrinsic co-dependence between movement behaviours the variance of one behaviour on its own is meaningless. Therefore, the variation matrix was computed using the variances of the logs of all pairwise ratios between behaviours (e.g., variance of \( \ln(\text{MVPA}/\text{LIPA}) \)).[13] Values in the matrix that are closer to 1 indicate a high co-dependence between behaviours whereas values further from 1 represent a lower co-dependence between behaviours. The next phase of the compositional analysis involved using regression to examine the association between the compositional movement behaviours and the obesity measures. The fat mass index was log transformed prior to regression analyses to meet the assumption of normality of the residuals. Through residual diagnostic testing some participants with high leverage values were identified. Thus, robust regression was used instead of ordinary least squares regression. MM-Estimation along with iteratively reweighted least squares was employed to find estimates.[28] Prior to conducting the regression analyses, time spent in each movement behaviour were transformed into compositional variables via an isometric log ratio (ilr) transformation. This transformed the movement behaviours from their natural space, the constrained simplex (e.g., a 24-hour day for movement behaviours), onto the ordinary real space where standard statistical techniques are well characterized. All four movement behaviours acted as the input for the isometric log ratio transformation and 3 transformed variables were the output. Only the 1st ilr variable was interpreted whereas the 2nd and 3rd ilr variables were used to fit the regression models. This is because the first ilr
variable contained all the relevant information in a participant’s movement behaviour composition. Thus, four robust regression models were fit for each of the obesity markers, yielding a total of 12 models. A backwards elimination with a liberal p-value (0.2) was used to remove covariates not related to the obesity markers. Then with the reduced model a change in estimate approach was carried out to build a parsimonious model where covariates that changed the compositional movement behaviour coefficients by less than 5% were removed. The next paragraph explains how the results from these regression models were interpreted and used to create a change matrix.

An overall Chi-Squared test using the Robust Deviance statistic from the robust regression models was used to assess the overall significance of the composition of the day and the Robust $R^2$ was used to ascertain the amount of outcome variability explained by the composition of movement behaviours. The coefficients and p-values for the individual movement behaviours were used to determine if they were significantly associated with the obesity measures relative to the time spent in the other movement behaviours. Finally, coefficients from the regression models were used to estimate the effect of displacing 10 minutes/day of time from one movement behaviour to another. These displacements were computed in three steps. First, an inverse log ratio transformation was performed on the coefficients from the robust regression model and then a change prediction matrix was built by contrasting time spent in one movement behaviour with another.[11] Second, 10 minute displacements and 95% prediction intervals from one movement behaviour to another were calculated from the sample mean composition and from the 25th and 75th percentile of each of the movement behaviours. Third, effects were then expressed as a percentage change from the sample mean of the respective obesity marker. It is important to note that for the change matrix a modification was made to the Chastin et al. method.[11] Instead of using an absolute change between the 10 minute/day reallocated comparison and the observed composition, a relative change between the two compositions was used. For example, 10 minute/day reallocations of MVPA to SB and vice versa are difficult to compare because
SB consists of a significantly higher composition of the day compared to MVPA thus, dominating the ratio. Dividing the change in the ratio by the original composition scales the variables by time and eliminates the absolute time disparities between the two behaviours (Formula in Appendix F, page 130).

3.4 Results

Twenty four (5.2%) of the original sample of 458 had insufficient accelerometer data (i.e., <4 days of valid data) and were removed from the analyses. Characteristics of the 434 participants included in the analyses are presented in Table 1. The average age was 11.7 years, 50% were female, the majority were white (88%), and 27% were categorized as having overweight or obesity based on BMI.

The geometric means for the MVPA, LIPA, SB and sleep compositions were 54 mins/day, 176 min/day, 624 min/day, and 572 min/day, respectively. Approximately 3.8% of the 24-hour day was spent in MVPA, 12.2% in LIPA, 44.3% in SB, and 39.7% in sleep. Figure 1 illustrates the compositional geometric mean bar plots for BMI (left panel), waist circumference (middle panel), and the fat mass index (right panel). These plots illustrate the difference between the geometric mean of non-overweight, overweight, and obese groups vs. the geometric mean of the entire sample. By comparison to the sample mean, the group with the highest BMI, waist circumference, or fat mass index spent the lowest proportion of the 24-hour day in MVPA and LIPA and the highest proportion of the day in SB.

For the variation matrix, values closer to 1 indicate a high co-dependence between behaviours whereas values further from 1 indicate a lower co-dependence. The largest pair-wise log ratio variances were for sleep vs. SB (0.99), sleep vs. LIPA (0.97), and LIPA vs. SB (0.96). The lowest pair-wise log-ratio variances were for MVPA vs. SB (0.88), MVPA vs. sleep (0.89) and MVPA vs. LIPA (0.92). This indicates that MVPA is the least co-dependant with the other behaviours.

The associations between the combination of movement behaviours and obesity indicators are displayed in Table 2. The model p-values indicate that the composition of movement behaviours across the 24-hour day was significantly related to each of the obesity measures (p<0.001). Time spent in
MVPA relative to the other behaviours was negatively associated with BMI z-score ($\gamma = -0.39$, $p=0.01$), waist circumference ($\gamma = -2.79$, $p=0.005$) and log fat mass index ($\gamma = -0.23$, $p=0.001$). Time spent in LIPA relative to the other behaviours was positively associated with all three obesity measures ($p \leq 0.03$). The relationships for SB and sleep did not reach statistical significance in any of the models ($p \geq 0.2$). Change matrices of the estimated effect of reallocating 10 minutes/day of time from one movement behaviour to another are shown in Table 3 (BMI), Table 4 (waist circumference), and Table 5 (fat mass index). These changes are shown at the 25th percentile, geometric mean, and 75th percentile of each movement behaviour. The most meaningful estimates across the obesity measures occurred when 10 minutes/day of MVPA displaced 10 minutes/day of LIPA, or when 1 minutes/day of LIPA displaced 10 minutes/day of MVPA. The estimates suggested that reallocating 10 minutes/day of MVPA with 10 minutes/day of LIPA at the mean of each movement behaviour would be associated with a 2.04% (95% CI: 1.83%, 2.13%) increase in BMI z-score from the geometric mean (i.e., change of BMI z-score of 0.007 at the mean to 0.35 with a 10 minute/day displacement of MVPA to LIPA equals a relative change of 2.04%). The corresponding values were 0.06% (95% CI: 0.05,0.07) for waist circumference and 0.24% (95% CI: 0.21,0.27) for the fat mass index.

Note that the % change in BMI, waist circumference, and fat mass index associated with the time displacements are not directly comparable because of the different units of measure and the averages used as the denominator for the calculations (e.g., average = 0.35 z-score for BMI, 66.7 cm for waist circumference, 1.28 log kg/m² for fat mass index). Also note that the MVPA to LIPA (or LIPA to MVPA) displacements were not linear across the MVPA range. For instance, reallocating 10 minutes/day from MVPA to LIPA at the 25th MVPA percentile (i.e., change from 42 to 32 minutes/day) was estimated to result in a 2.70% (95% CI: 2.41%, 2.82%) increase in BMI z-score while reallocating 10 minutes/day from MVPA to LIPA at the 75th MVPA percentile (i.e., change from 73 to 63 minutes/day) was estimated to result in a 1.52% (95% CI: 1.35%, 1.58%) increase in BMI z-score.
The reallocations that occurred outside of the MVPA to LIPA (or LIPA to MVPA) were quite small. Reallocating 10 min/day of MVPA to 10 min/day of SB lead to a 1.12% (0.60%, 1.71%) increase in BMI z-score and the opposite reallocation resulted in 0.93% (0.49%, 1.40%) decrease in BMI z-score. Similar to LIPA, a non-linear pattern for SB was observed across the MVPA range. Furthermore, the displacements that involved sleep were small in strength and had very wide confidence limits which included 0. Lastly, when 10 minutes of LIPA were reallocated to SB, the obesity measures declined marginally. 3.5

Discussion

This study used a compositional analyses paradigm to help elucidate the co-dependent relationships between movement behaviours and obesity measures within 10- to 13-year-olds. Taken together, this study found that the composition of a child’s day made up of sleep, SB, LIPA and MVPA was significantly associated with the obesity measures. The amount of time spent in MVPA relative to the time spent in the other behaviours was beneficially associated with the obesity measures whereas the time spent in LIPA relative to the other movement behaviours was detrimentally associated with the obesity measures. Furthermore, the estimates suggested that displacing time in LIPA or SB with an equal amount of time in MVPA would be associated with a lower body weight, waist circumference, and body fat, particularly for children with low MVPA levels.

Carson et al. were the first to employ a compositional analysis approach to analyze movement behaviours and health in children and youth.[16] Their study was based on a large (N=4169) and representative sample of 6-17 year old Canadians. They found that MVPA and sleep were negatively associated with BMI z-score and waist circumference and that LIPA and SB were positively associated with BMI z-score and waist circumference.[16] Although the size of the regression coefficients of the movement behaviours were very similar between the Carson et al. study and the present study, in the present study the regression coefficients for SB and sleep were not statistically significant. While this could reflect the smaller sample size of the present study, the p-values for SB and sleep were > 0.2 and
do not support a trend towards statistical significance that would have been aided with more data. The discrepancies in findings between the two studies is more likely explained by key methodological differences. First, while the current study used an objective and robust estimate of sleep duration, the CHMS estimated sleep duration based on parent and youth reported data,[16] which could have led to misclassification and biased effect estimates. Second, the CHMS study captured accelerometer movement data in 1-minute epochs whereas the current study used 15- second epochs,[16] and 1-minute epochs capture more LIPA and less SB compared to 15-second epochs.[29] Differences in the geometric means between this study and the CHMS study demonstrate this disparity (LIPA = 176 vs 263 minutes/day, SB = 624 vs. 547 minutes/day).[16]

This study computed change matrices at the 25th and 75th percentile of each behaviour and not just at the sample average composition, as done in earlier work.[11,16] This allowed us to examine whether the time reallocations would differ at different starting points. For example, we estimated whether less active children would derive a greater benefit from increasing their MVPA than children who are already sufficiently active. The effects of the time reallocations for MVPA were larger at lower MVPA levels and got weaker as MVPA levels increased. Thus, it appears that removing 10 minutes of MVPA is more detrimental for a child with a low activity than for a child who is already quite active. The non linear patterns of the time reallocation estimates were in line with the literature which consistently shows curvilinear relations between MVPA and obesity measures, with larger changes in the obesity measures occurring with increases in MVPA at the low end of the MVPA scale.[4,30–33] The current study reinforces this curvilinear relationship and also takes into account the compositional nature of a 24-hour day.

Our finding that sleep was not associated with the obesity measures contradict those of past research, which suggest that sleep duration correlates with obesity.[2] Past research has primarily analyzed sleep duration in isolation or with only partial adjustment for other behaviours, such as MVPA.
or screen time. Thus, many of the relationships in these studies could have been plagued by residual confounding or improper adjustment of the movement behaviours using common regression approaches.[8,11,34] Although the evidence on the associations between total SB time and LIPA with obesity among children are mixed.[1,3] We were surprised to find that time spent in SB relative to the other behaviours was not associated with the obesity indicators. This could potentially be explained by the fact that there is far less between child variability in SB than in other movement behaviours, particularly MVPA. In our study there was only a 42% difference between the SB values at the 5th and 95th percentiles; the corresponding value for MVPA was 250%. The lack of variability for SB would lessen the statistical efficiency required to detect a meaningful relationship between SB and the obesity measures.

A key implication of this study is that movement behaviour interventions aimed at preventing obesity should contain a large MVPA component. However, more research is needed in applying compositional data analysis techniques to movement behaviours to further model and explore the composition of the day before the integrated movement behaviour approach be fully adopted into interventions. For example, breaking SB down into school time versus out of school time or categorizing LIPA into higher intensity and lower intensity LIPA are important aspects of a child’s day that could aid in unravelling some of the questions left unanswered from this study.

Strengths of this study are that it used a novel analytical approach to examine 24-hour movement data, it objectively and meticulously assessed all 4 movement behaviours, and it considered three objectively measured obesity outcomes. Furthermore, unlike most accelerometer studies, there was very little missing data and only 5% of the sample was removed from the analyses due to inadequate wear time. The limitations of this study include its cross-sectional design, which limits cause and effect relationships. Also, accelerometers underestimate the intensity of some physical activities, such as cycling and resistance training activities, which may cause an underestimation of a child’s
Furthermore, some activities in the LIPA range, particularly standing still, will produce accelerometer counts <100 counts per minute and will be misclassified as SB. This non-differential misclassification could have biased the effect estimates towards the null, particularly for SB and LIPA. Furthermore, the study was limited to obesity outcomes and other aspects of physical, mental, and social health need to be examined in future compositional analyses. Finally, the study was limited to 10- to 13-years-olds and the findings may not apply to other age groups.

3.6 Conclusion

Compositional data analyses can be used to provide insights into the co-dependent relationships between movement behaviours and obesity. The proportion of time spent in MVPA relative to the other movement behaviours was a key predictor of body weight and body fat in this study. Our estimates suggest that replacing LIPA with MVPA would reduce body weight and fat, especially for children who are inactive. Future research is needed to ascertain if the proportion of time spent in different intensities of LIPA, different types of SB (e.g., recreational screen time versus classroom time) and other sleeping behaviour measures (e.g., sleep efficiency) are important drivers of the composition of a child’s day and its relationship with obesity and other health indicators.
3.6 References


8. Pedišić Ž. Measurement issues and poor adjustments for physical activity and sleep undermine sedentary behaviour research - The focus should shift to the balance between sleep, sedentary behaviour, standing and activity. Kinesiology 2014;46;135–46.


<table>
<thead>
<tr>
<th>Characteristic</th>
<th>N</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Sex</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>216</td>
<td>49.8</td>
</tr>
<tr>
<td>Female</td>
<td>218</td>
<td>50.2</td>
</tr>
<tr>
<td><strong>Age (years)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>10</td>
<td>111</td>
<td>25.6</td>
</tr>
<tr>
<td>11</td>
<td>111</td>
<td>25.6</td>
</tr>
<tr>
<td>12</td>
<td>114</td>
<td>26.3</td>
</tr>
<tr>
<td>13</td>
<td>98</td>
<td>22.6</td>
</tr>
<tr>
<td><strong>Body mass index</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Non-overweight</td>
<td>316</td>
<td>72.8</td>
</tr>
<tr>
<td>Overweight</td>
<td>77</td>
<td>17.7</td>
</tr>
<tr>
<td>Obese</td>
<td>41</td>
<td>9.5</td>
</tr>
<tr>
<td><strong>Race</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>White</td>
<td>374</td>
<td>88.2</td>
</tr>
<tr>
<td>Non-white</td>
<td>50</td>
<td>11.8</td>
</tr>
<tr>
<td><strong>Family income ($ CDN per year)</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>≤50,000</td>
<td>66</td>
<td>15.2</td>
</tr>
<tr>
<td>50,001-100,000</td>
<td>117</td>
<td>27.0</td>
</tr>
<tr>
<td>&gt;100,000</td>
<td>200</td>
<td>46.1</td>
</tr>
<tr>
<td>No response</td>
<td>51</td>
<td>11.8</td>
</tr>
<tr>
<td><strong>Parental education</strong></td>
<td></td>
<td></td>
</tr>
<tr>
<td>High school or less</td>
<td>38</td>
<td>8.8</td>
</tr>
<tr>
<td>2-year college</td>
<td>131</td>
<td>30.2</td>
</tr>
<tr>
<td>4-year college/university</td>
<td>265</td>
<td>61.6</td>
</tr>
</tbody>
</table>
## Table 2. Compositional robust regression model estimates for the obesity measures.

<table>
<thead>
<tr>
<th>Obesity Measure</th>
<th>Model</th>
<th>R²</th>
<th>P-Value</th>
<th>MVPA</th>
<th>Model</th>
<th>R²</th>
<th>P-Value</th>
<th>LIPA</th>
<th>Model</th>
<th>R²</th>
<th>P-Value</th>
<th>SB</th>
<th>Model</th>
<th>R²</th>
<th>P-Value</th>
<th>Sleep</th>
<th>R²</th>
<th>P-Value</th>
</tr>
</thead>
<tbody>
<tr>
<td>BMI z-score</td>
<td>0.03</td>
<td>&lt;0.001</td>
<td>-0.39 (-0.68, -0.09)</td>
<td>0.01</td>
<td>0.80 (0.24,1.37)</td>
<td>0.005</td>
<td>0.46 (-0.37,1.31)</td>
<td>0.3</td>
<td>-0.60 (-1.49,0.30)</td>
<td>0.2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Waist circumference</td>
<td>0.04</td>
<td>&lt;0.001</td>
<td>-2.79 (-4.75, -0.82)</td>
<td>0.005</td>
<td>4.11 (0.33,7.87)</td>
<td>0.03</td>
<td>-0.82 (-6.45,4.81)</td>
<td>0.8</td>
<td>0.66 (-5.32,6.66)</td>
<td>0.8</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Log fat mass index</td>
<td>0.07</td>
<td>&lt;0.001</td>
<td>-0.23 (-0.36, -0.09)</td>
<td>0.001</td>
<td>0.29 (0.03,0.55)</td>
<td>0.03</td>
<td>0.21 (-0.18,-0.60)</td>
<td>0.3</td>
<td>-0.18 (-0.60,0.23)</td>
<td>0.4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

*Note: Adjusted for age, sex, biological maturity, season of data collection, accelerometer wear time and frequency of snack food consumption in front of a screen. Regression coefficients for each behaviour can be interpreted as the increase in the time spent in that behaviour relative to the time spent in the other behaviours.*
Table 3. Estimated percentage change (95% CI) in BMI z-score by displacing 10 minutes of movement behaviour in rows with 10 minutes of movement behaviour in columns.

<table>
<thead>
<tr>
<th>Displacements at 25th percentile</th>
<th>MVPA</th>
<th>LIPA</th>
<th>SB</th>
<th>Sleep</th>
</tr>
</thead>
<tbody>
<tr>
<td>MVPA(^a)</td>
<td>--</td>
<td>2.70</td>
<td>1.53</td>
<td>-0.81</td>
</tr>
<tr>
<td>LIPA(^b)</td>
<td>-1.87</td>
<td>-0.20</td>
<td>-0.37</td>
<td>-0.81</td>
</tr>
<tr>
<td>SB(^c)</td>
<td>-0.77</td>
<td>0.16</td>
<td>--</td>
<td>-0.81</td>
</tr>
<tr>
<td>Sleep(^d)</td>
<td>0.44</td>
<td>0.69</td>
<td>0.24</td>
<td>--</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Displacements at average values</th>
<th>MVPA</th>
<th>LIPA</th>
<th>SB</th>
<th>Sleep</th>
</tr>
</thead>
<tbody>
<tr>
<td>MVPA(^e)</td>
<td>--</td>
<td>2.04</td>
<td>1.12</td>
<td>-0.60</td>
</tr>
<tr>
<td>LIPA(^f)</td>
<td>-1.76</td>
<td>-0.47</td>
<td>-0.73</td>
<td>-0.73</td>
</tr>
<tr>
<td>SB(^g)</td>
<td>-0.93</td>
<td>0.17</td>
<td>--</td>
<td>-0.23</td>
</tr>
<tr>
<td>Sleep(^h)</td>
<td>0.50</td>
<td>0.70</td>
<td>0.24</td>
<td>--</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Displacements at 75th percentile</th>
<th>MVPA</th>
<th>LIPA</th>
<th>SB</th>
<th>Sleep</th>
</tr>
</thead>
<tbody>
<tr>
<td>MVPA(^i)</td>
<td>--</td>
<td>1.52</td>
<td>0.92</td>
<td>-0.32</td>
</tr>
<tr>
<td>LIPA(^j)</td>
<td>-1.45</td>
<td>-0.16</td>
<td>-0.65</td>
<td>-0.65</td>
</tr>
<tr>
<td>SB(^k)</td>
<td>-0.99</td>
<td>0.18</td>
<td>--</td>
<td>-0.23</td>
</tr>
<tr>
<td>Sleep(^l)</td>
<td>0.98</td>
<td>1.42</td>
<td>0.48</td>
<td>--</td>
</tr>
</tbody>
</table>

Note: All estimates have been adjusted for sex, age, maturity, season, snacking, and wear time.

\(^a\) Estimates based on the 25th percentile value for MVPA (42 min/day) and the predicted LIPA (170 min/day), SB (648 min/day), and sleep (581 min/day) values for that MVPA value.

\(^b\) Estimates based on the 25th percentile value for LIPA (156 min/day) and the predicted MVPA (53 min/day), SB (651 min/day), and sleep (580 min/day) values for that LIPA value.

\(^c\) Estimates based on the 25th percentile value for SB (587 min/day) and the predicted MVPA (67 min/day), LIPA (193 min/day), and sleep (593 min/day) values for that SB value.

\(^d\) Estimates based on the 25th percentile value for sleep (62 min/day) and the predicted MVPA (184 min/day), LIPA (184 min/day), and SB (648 min/day) values for that sleep value.

\(^e\) Estimates based on average values for MVPA (54 min/day), LIPA (176 min/day), SB (624 min/day), and sleep (572 min/day).

\(^f\) Estimates based on the 75th percentile value for MVPA (73 min/day) and the predicted LIPA (187 min/day), SB (571 min/day), and sleep (568 min/day) values for that MVPA value.

\(^g\) Estimates based on the 75th percentile value for LIPA (204 min/day) and the predicted MVPA (66 min/day), SB (602 min/day), and sleep (567 min/day) values for that LIPA value.

\(^h\) Estimates based on the 75th percentile value for SB (657 min/day) and the predicted MVPA (50 min/day), LIPA (165 min/day), and sleep (567 min/day) values for that SB value.

\(^i\) Estimates based on the 75th percentile value for sleep (612 min/day) and the predicted MVPA (56 min/day), LIPA (174 min/day), and SB (598 min/day) values for that sleep value.
Table 4. Estimated percentage change (95% CI) in waist circumference by displacing 10 minutes of movement behaviour in rows with 10 minutes of movement behaviour in columns.

<table>
<thead>
<tr>
<th></th>
<th>MVPA</th>
<th>LIPA</th>
<th>SB</th>
<th>Sleep</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Displacements at 25th percentile</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MVPA&lt;sup&gt;a&lt;/sup&gt;</td>
<td>--</td>
<td>0.08</td>
<td>0.01</td>
<td>0.03</td>
</tr>
<tr>
<td>LIPA&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-0.05</td>
<td>-0.01</td>
<td>--</td>
<td>-0.01</td>
</tr>
<tr>
<td>SB&lt;sup&gt;c&lt;/sup&gt;</td>
<td>-0.01</td>
<td>0.01</td>
<td>--</td>
<td>0.00</td>
</tr>
<tr>
<td>Sleep&lt;sup&gt;d&lt;/sup&gt;</td>
<td>-0.02</td>
<td>--</td>
<td>0.00</td>
<td>--</td>
</tr>
<tr>
<td><strong>Displacements at average values</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MVPA&lt;sup&gt;e&lt;/sup&gt;</td>
<td>--</td>
<td>0.06</td>
<td>0.01</td>
<td>0.01</td>
</tr>
<tr>
<td>LIPA&lt;sup&gt;f&lt;/sup&gt;</td>
<td>-0.05</td>
<td>--</td>
<td>--</td>
<td>-0.01</td>
</tr>
<tr>
<td>SB&lt;sup&gt;g&lt;/sup&gt;</td>
<td>-0.01</td>
<td>0.01</td>
<td>--</td>
<td>0.00</td>
</tr>
<tr>
<td>Sleep&lt;sup&gt;h&lt;/sup&gt;</td>
<td>-0.02</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
<tr>
<td><strong>Displacements at 75th percentile</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MVPA&lt;sup&gt;i&lt;/sup&gt;</td>
<td>--</td>
<td>0.04</td>
<td>0.01</td>
<td>0.02</td>
</tr>
<tr>
<td>LIPA&lt;sup&gt;j&lt;/sup&gt;</td>
<td>-0.03</td>
<td>0.01</td>
<td>--</td>
<td>-0.01</td>
</tr>
<tr>
<td>SB&lt;sup&gt;k&lt;/sup&gt;</td>
<td>-0.01</td>
<td>0.00</td>
<td>--</td>
<td>0.00</td>
</tr>
<tr>
<td>Sleep&lt;sup&gt;l&lt;/sup&gt;</td>
<td>-0.03</td>
<td>--</td>
<td>--</td>
<td>--</td>
</tr>
</tbody>
</table>

Note: All estimates have been adjusted for sex, age, maturity, season, snacking, wear time.

<sup>a</sup> Estimates based on the 25th percentile value for MVPA (42 min/day) and the predicted LIPA (170 min/day), SB (648 min/day), and sleep (581 min/day) values for that MVPA value.

<sup>b</sup> Estimates based on the 25th percentile value for LIPA (156 min/day) and the predicted MVPA (53 min/day), SB (651 min/day), and sleep (580 min/day) values for that LIPA value.

<sup>c</sup> Estimates based on the 25th percentile value for SB (587 min/day) and the predicted MVPA (67 min/day), LIPA (193 min/day), and sleep (593 min/day) values for that SB value.

<sup>d</sup> Estimates based on the 25th percentile value for sleep (62 min/day) and the predicted MVPA (184 min/day), LIPA (184 min/day), and SB (648 min/day) values for that sleep value.

<sup>e</sup> Estimates based on average values for MVPA (54 min/day), LIPA (176 min/day), SB (624 min/day), and sleep (572 min/day).

<sup>f</sup> Estimates based on the 75th percentile value for MVPA (73 min/day) and the predicted LIPA (187 min/day), SB (571 min/day), and sleep (568 min/day) values for that MVPA value.

<sup>g</sup> Estimates based on the 75th percentile value for LIPA (204 min/day) and the predicted MVPA (66 min/day), SB (602 min/day), and sleep (567 min/day) values for that LIPA value.

<sup>h</sup> Estimates based on the 75th percentile value for SB (657 min/day) and the predicted MVPA (50 min/day), LIPA (165 min/day), and sleep (567 min/day) values for that SB value.

<sup>i</sup> Estimates based on the 75th percentile value for sleep (612 min/day) and the predicted MVPA (56 min/day), LIPA (174 min/day), and SB (598 min/day) values for that sleep value.
Table 5. Estimated percentage change (95% CI) in log fat mass index by displacing 10 minutes of movement behaviour in rows with 10 minutes of movement behaviour in columns.

<table>
<thead>
<tr>
<th></th>
<th>MVPA</th>
<th>LIPA</th>
<th>SB</th>
<th>Sleep</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Displacements at 25th percentile</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MVPA&lt;sup&gt;a&lt;/sup&gt;</td>
<td>--</td>
<td>0.31 (0.27,0.35)</td>
<td>0.22 (0.13,0.31)</td>
<td>-0.02 (-0.42,0.39)</td>
</tr>
<tr>
<td>LIPA&lt;sup&gt;b&lt;/sup&gt;</td>
<td>-0.22 (-0.19,-0.24)</td>
<td>--</td>
<td>-0.01 (-0.03,0.00)</td>
<td>-0.07 (-0.19,0.04)</td>
</tr>
<tr>
<td>SB&lt;sup&gt;c&lt;/sup&gt;</td>
<td>-0.11 (-0.15,-0.06)</td>
<td>0.01 (-0.0,0.02)</td>
<td>--</td>
<td>-0.02 (-0.08,0.03)</td>
</tr>
<tr>
<td>Sleep&lt;sup&gt;d&lt;/sup&gt;</td>
<td>0.01 (-0.21,0.23)</td>
<td>0.06 (-0.03,0.16)</td>
<td>0.02 (-0.03,0.08)</td>
<td>--</td>
</tr>
<tr>
<td><strong>Displacements at average values</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MVPA&lt;sup&gt;e&lt;/sup&gt;</td>
<td>--</td>
<td>0.24 (0.21,0.27)</td>
<td>0.16 (0.09,0.23)</td>
<td>-0.01 (-0.31,-0.18)</td>
</tr>
<tr>
<td>LIPA&lt;sup&gt;e&lt;/sup&gt;</td>
<td>-0.21 (-0.23,-0.18)</td>
<td>--</td>
<td>-0.01 (-0.02,0.00)</td>
<td>-0.07 (-0.15,0.03)</td>
</tr>
<tr>
<td>SB&lt;sup&gt;e&lt;/sup&gt;</td>
<td>-0.13 (-0.18,-0.08)</td>
<td>0.01 (-0.02,0.02)</td>
<td>--</td>
<td>-0.03 (-0.07,0.03)</td>
</tr>
<tr>
<td>Sleep&lt;sup&gt;e&lt;/sup&gt;</td>
<td>0.01 (-0.24,0.26)</td>
<td>0.06 (-0.03,0.16)</td>
<td>0.02 (-0.03,0.07)</td>
<td>--</td>
</tr>
<tr>
<td><strong>Displacements at 75th percentile</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>MVPA&lt;sup&gt;f&lt;/sup&gt;</td>
<td>--</td>
<td>0.18 (0.15,0.20)</td>
<td>0.12 (0.07,0.16)</td>
<td>-0.01 (-0.22,0.21)</td>
</tr>
<tr>
<td>LIPA&lt;sup&gt;g&lt;/sup&gt;</td>
<td>-0.17 (-0.15,-0.19)</td>
<td>--</td>
<td>-0.01 (-0.02,0.00)</td>
<td>-0.06 (-0.15,0.03)</td>
</tr>
<tr>
<td>SB&lt;sup&gt;h&lt;/sup&gt;</td>
<td>-0.14 (-0.20,-0.08)</td>
<td>0.01 (-0.02,0.03)</td>
<td>--</td>
<td>-0.02 (-0.07,0.03)</td>
</tr>
<tr>
<td>Sleep&lt;sup&gt;i&lt;/sup&gt;</td>
<td>-0.02 (-0.23,0.25)</td>
<td>0.13 (-0.03,0.16)</td>
<td>0.05 (-0.03,0.07)</td>
<td>--</td>
</tr>
</tbody>
</table>

Note: All estimates have been adjusted for sex, age, maturity, season, snacking, and wear time.

<sup>a</sup> Estimates based on the 25<sup>th</sup> percentile value for MVPA (42 min/day) and the predicted LIPA (170 min/day), SB (648 min/day), and sleep (581 min/day) values for that MVPA value.

<sup>b</sup> Estimates based on the 25<sup>th</sup> percentile value for LIPA (156 min/day) and the predicted MVPA (53 min/day), SB (651 min/day), and sleep (580 min/day) values for that LIPA value.

<sup>c</sup> Estimates based on the 25<sup>th</sup> percentile value for SB (587 min/day) and the predicted MVPA (67 min/day), LIPA (193 min/day), and sleep (593 min/day) values for that SB value.

<sup>d</sup> Estimates based on the 25<sup>th</sup> percentile value for sleep (62 min/day) and the predicted MVPA (184 min/day), LIPA (184 min/day), and SB (648 min/day) values for that sleep value.

<sup>e</sup> Estimates based on average values for MVPA (54 min/day), LIPA (176 min/day), SB (624 min/day), and sleep (572 min/day).

<sup>f</sup> Estimates based on the 75<sup>th</sup> percentile value for MVPA (73 min/day) and the predicted LIPA (187 min/day), SB (571 min/day), and sleep (568 min/day) values for that MVPA value.

<sup>g</sup> Estimates based on the 75<sup>th</sup> percentile value for LIPA (204 min/day) and the predicted MVPA (66 min/day), SB (602 min/day), and sleep (567 min/day) values for that LIPA value.

<sup>h</sup> Estimates based on the 75<sup>th</sup> percentile value for SB (657 min/day) and the predicted MVPA (50 min/day), LIPA (165 min/day), and sleep (567 min/day) values for that SB value.

<sup>i</sup> Estimates based on the 75<sup>th</sup> percentile value for sleep (612 min/day) and the predicted MVPA (56 min/day), LIPA (174 min/day), and SB (598 min/day) values for that sleep value.
Figure 1. Compositional geometric mean bar plots comparing the geometric mean of the entire sample with the geometric mean of the respective obesity sub group for moderate-to-vigorous physical activity (MVPA), light intensity physical activity (LIPA), sedentary behaviour (SB) and sleep. BMI, body mass index. WC, waist circumference. FMI, fat mass index.
Chapter 4

General Discussion

4.1 Study Summary

The purpose of this thesis was to assess the relationship between objectively measured movement behaviours and obesity within children using a compositional data analysis approach. Data were obtained from a sample of 434 children aged 10-13 years. The movement behaviours were measured over 7 consecutive days using an Actical accelerometer and a sleep log. Obesity measures were measured directly and included the body mass index, waist circumference, and fat mass index. An isometric log ratio transformation was applied to the movement behaviours to transform them to an unconstrained space so that standard regression procedures could be applied appropriately [1]. Robust regression with compositional exposure variables were fit for each of the obesity markers. Model p-values were used to investigate whether the composition of movement behaviours in the day was significantly related to the obesity outcomes. Then, coefficients from the regression models were used to estimate the extent to which displacing 10 minutes/day of time from one movement behaviour to another would influence the obesity outcomes.

4.2 Summary of Major Findings

A major finding of this study was that the composition of a child’s day made up of sleep, SB, LIPA and MVPA was significantly associated with the obesity measures. The amount of time spent in MVPA relative to the time spent in the other behaviours was beneficially associated with the obesity measures whereas the time spent in LIPA relative to the other movement behaviours was detrimentally associated with the obesity measures. Furthermore, the estimates suggested that displacing time in LIPA or SB with an equal amount of time in MVPA would be associated with a lower body weight, waist circumference, and body fat, particularly for children with low MVPA levels.

The main findings from this research are in line with much of the past movement behaviour
literature. Thus, despite the methodological differences employed by taking up a compositional paradigm versus the common regression approaches used in the past the results were similar and suggest that MVPA is the movement behaviour mostly strongly associated with obesity. However, the interpretation of the results differs between approaches and within a compositional paradigm we can get at the true underlying associations for the movement behaviours which represent relative changes between the behaviours rather than isolated changes with one behaviour. For example, replacing 10 minutes/day of MVPA with LIPA was detrimental to body weight and fat whereas replacing 10 minutes of MVPA with sleep had a minimal effect.

4.3 Strengths

Strengths of this study are that it used a novel analytical approach to examine 24-hour movement data, it objectively and meticulously assessed all 4 movement behaviours, and it considered three objectively measured obesity outcomes. The careful measurement of the study variables limited the potential for misclassification and bias. Furthermore, unlike most accelerometer studies where upwards of 20% of the study sample is removed because of insufficient accelerometer data, there was very little missing data and only 5% of the sample was removed from the analyses due to inadequate accelerometer wear time [2–4]. Thus, the insidious issues associated with missing data are limited and the data retained for the analysis accurately represents the sample derived from the target population.

4.4 Internal Validity

Internal Validity refers to how accurately the study results reflect what is truly happening in the sample population, assuming that the results are not due to chance [5]. Common threats to internal validity in epidemiology are selection bias, information bias, and confounding.

i) Selection Bias
Selection bias would have occurred if the study participants differed systematically from the population they were meant to represent, namely 10- to 13-year-olds in Kingston, Ontario [5]. Although participant recruitment was balanced by age, sex, season, and Kingston’s 12 electoral districts to ensure proportional representation across these strata, participants were volunteers and that could have influenced the representativeness of the sample if there was a volunteer bias. A volunteer bias occurs when those who elect to participate in a study differ systematically from those who do not. While the Active Play Study had excellent study compliance from those who participated (i.e., 95% of participants had complete data), there is still the possibility that the children who volunteered to participate in the study are systematically different from children who did not participate. This becomes an issue when the volunteer bias is related to the exposure or the outcome of interest. The way in which volunteer bias could be related to the movement behaviours, obesity, and the association between the movement behaviours and obesity is discussed in the next few paragraphs.

The Active Play Study was advertised as a physical activity study in the recruitment materials. The main criticism of this approach is that it could have attracted participants who were more physically active, on average, than the target population. Also, children with overweight/obesity may have been less inclined to volunteer for a study where their body weight, waist circumference, and body fat were being measured. To determine the extent to which these biases may have occurred, I compared the physical activity and obesity in the study sample to the same estimates derived using comparable methods in a nationally representative sample of Canadian children who participated in the Canadian Health Measures Survey. In the current study 41.5% of children met the recommendation of a daily average of at least 60 minutes/day of MVPA and 9.5% were categorized as having obesity. The equivalent estimates for children in the Canadian Health Measures Survey were similar at 36.5% and 11.7%, respectively [6,7]. Self-reported data from the Canadian Community Health Survey suggest that the proportion of the population in the KFL&A health region who are physically inactive and who have obesity are very comparable to the Canadian average [6,7]. Combined, these data
suggest that the sample population of volunteers was similar to the target population for the exposure and outcomes being studied.

It is also important to keep in mind when discussing selection bias that the goal of the current study was to ascertain the etiological relationship between the movement behaviours and obesity measures. This means that selection bias is only of concern if the relationship between the movement behaviours and obesity measures differed systematically based on study selection. That is unlikely.

**ii) Information Bias**

Information error refers to any intentional or unintentional systematic error made in the measurement of a relevant exposure, outcome or covariate [5]. The most common type of information error is non-differential misclassification. This is when the misclassification of the outcome is not related to the exposure, or when the misclassification of the exposure is not related to the outcome [5]. Typically, non-differential misclassification reduces estimates in the direction of the null and reduces a study’s power to detect a statistically significant association. On the other hand, differential misclassification occurs when misclassification of the outcome is related to the exposure or vice versa [5]. As discussed above in the strengths section, the Active Play Study objectively and meticulously assessed all four movement behaviours using the best available techniques for field based assessments, and it considered three objectively measured obesity outcomes. All of the methods used have good validity and reliability. However, as explained below, there are still some potential sources of information error when measuring movement behaviours with accelerometers.

Although accelerometers are the “gold standard” approach for measuring physical activity in natural settings, they are not a perfect measure of physical activity [8,9]. Accelerometers worn around the hip are best at capturing step-based physical activities, which dominate much of the movement that people do; however, they underestimate the intensity of some physical activities such as upper body movement, cycling and swimming [9]. This would lead to an underestimate of children’s MVPA and misclassification that is likely non-differential. The only way in which this error could resort in a differential misclassification of MVPA is if
children with overweight/obesity spent a greater proportion of their total physical activity partaking in upper body exercises, cycling or swimming compared to normal weight children. This phenomenon has never been documented in the literature indicating that non-differential misclassification is likely the only type of information bias relevant for the measurement of accelerometry derived MVPA. Furthermore, accelerometers do not measure “sitting” and SB per se. Rather, they capture non-movement at the hip. Therefore, time spent in some light-intensity activities may be misclassified as SB. This is of particular concern for standing, a light intensity activity that results in little movement at the hip. This non-differential misclassification would have reduced effect estimates for LIPA and SB and reduced any associations for these movement behaviours towards the null. Also, wake up and bed times were recorded by participants in a log. The research team did visually inspect, and if necessary adjust, these recorded times by looking at the accelerometer data, which would have reduced self-reported error. Although this is a robust measure of the time a child spends in bed, it is only a proxy measure for actual sleep duration. It is possible that children were using cell phones, laptops or tablet computers while in bed resulting in misclassification of the sleep duration variables. It is well known that more overweight/obese children spend more time using screen-based devices throughout the day [10–12]. If this phenomenon also holds true before bed, then this would certainly bias the results (e.g., differential misclassification for sleep duration). In fact, this could explain why no association was observed between sleep duration and the obesity measures.

Finally, there is the potential for misclassification of the objectively measured obesity outcomes. The type of misclassification is due to random measurement error which would be considered non-differential misclassification. Height and weight are simple anthropometric measures to take and have very little measurement error when obtained in a laboratory environment. However, waist circumference is slightly more challenging. To combat this standardized protocols were used which involved taking 2 measurements and if they deviated by more than 0.5 cm a third measurement was taken and the closest two measurements were averaged [13]. Bioelectrical impedance was used to measure body fat and although it is an objective and robust measure of body fat percentage the hydration status of the participants could lead to inaccuracies in the
results [14]. Hydration status was not controlled for or monitored in the Active Play Study, which means that there could be some non-differential misclassification in the body fat percentage estimates.

Social Desirability bias occurs when participants intentionally or unintentionally over report characteristics that are seen as “good” and under-report those that are seen as “bad”. In the current study it is only relevant for the wake and bed times that the children recorded since this is the only self-reported data used. Children may have recorded that they went to bed earlier than they actually did in order to appease their parents who were asked by the research team to ensure and help their children fill out the sleep log. In order to correct for this potential misclassification, the sleep times that were recorded in the logs were manually verified, and corrected as necessary, by visually inspecting the recorded log times against the Actical accelerometer data. An example of this visual data verification and correction process is shown in Appendix E (p.119). In our laboratory, this visual verification/correction process is highly reliable as 90% of the verified and corrected sleep times are within 10 minutes of each other based on repeated verification/correction attempts completed by different researchers.

Accelerometer “reactivity” is another form of potential bias [15]. That is, children are aware that they were wearing a device that records physical activity, and this may have altered their physical activity levels in the positive direction (e.g., partaking in more physical activity or less SB than normal). Important steps were taken to combat this potential behaviour adaptation. Firstly, the research team asked participants to maintain their normal movement behaviours during the 7-day measurement period. Second, the accelerometers are “black boxes” that give no feedback or output, such as a step count, to participants. Third, participants were given accelerometers that initialized at midnight of the same day they were given the device. Accelerometer “reactivity” often occurs immediately after receiving the device, and it does not persist past the first day [16]. We did not start measuring their physical activity until the second day. While often raised as a potential concern, recent studies have found no evidence of accelerometer “reactivity” in children and adolescents across a 7-day monitoring period [15,16].
iii. Confounding:

Confounding occurs when a relationship of interest is distorted or hidden by the effects of a third factor that is related to both the exposure and outcome but not on the causal pathway [5]. I controlled for several potential confounders determined from past literature including age, sex, race, income, parental education, parental marital status, chronic health conditions, maturity, accelerometer wear time, season of data collection, frequency of fast food consumption and frequency of snack food consumption. It is; however, still possible that the results observed were due to residual confounding caused by imprecise measurement of any of the confounders. For example, diet is related to both obesity and to the movement behaviours [17,18]. The only dietary measures taken in the Active Play Study were self-reported frequency of fast food consumption and the frequency of snacking in front of a screen. While these dietary measures are related to obesity, on their own they do not capture the complexities of the diet, which means that there could have been residual confounding due to imprecise measurement of diet [5].

4.5 External Validity

External Validity is a term used to describe whether a study’s results can be generalized to other populations outside of the sample population [5]. The Active Play Study consisted of participants balanced by age, sex, season, and Kingston’s 12 electoral districts to ensure proportional representation across these strata. Also, as mentioned previously the proportion of children meeting the MVPA recommendations and the prevalence of obesity in the sample was close to the Canadian average. Furthermore, the relationship between the movement behaviours and obesity is biological in nature and consistent in boys and girls and in children of different ages and races [19,20]. Therefore, it is likely that the results can be applied to children outside of the sample population.

4.6 Causation
In 1965, Sir Austin Bradford-Hill proposed a series of nine criteria to aid researchers in deciding whether an observed association is likely to be causal. Five are still commonly used today and are discussed below.

i) Temporality

Temporality refers to the necessity that the cause precedes the effect in time. That is, the movement behaviours must precede the change in body weight or fat in order for the movement behaviours to cause body weight or fat gain. Since this was a cross-sectional study temporality cannot be ascertained. Furthermore, reverse causality is a possibility in this relationship, and there is evidence that changes in body weight or fat cause changes in the movement behaviours [21]. Thus, the study design does not allow for the disentanglement of temporality.

ii. Plausibility

Plausibility refers to the scientific plausibility of an association. Relationships between movement behaviours and obesity are plausible because excess weight and fat represents excess energy stores in the body and movement is an important source of energy expenditure. Body weight and fat will increase when there is an imbalance between energy intake and energy expenditure. Thus, when SB and lighter intensity activities dominate the composition of the day, this results in a lower overall energy expenditure and a potential energy surplus leading to weight gain and excess body fat accumulation. The biological mechanisms by which sleep duration is related to overweight/obesity has been proposed to be through changes in dietary intake such as increased consumption of energy and sugar containing foods or decreases in overall energy expenditure throughout the day [22,23].

iii. Strength

In the current study the strengths of the association between the composition of movement behaviours and the obesity measures were modest. Hill argued that strong associations are more likely to be
causal because it is “easier” to imagine an unmeasured or poorly measured confounder(s) as being responsible for weaker associations [5]. However, a strong association is neither necessary nor sufficient for absence of causality.

iv) Consistency

Consistency refers to the repeated observation of an association in different populations under different circumstances. Lack of consistency; however, does not rule out a causal association. Consistency serves to rule out hypotheses that the association is attributable to some factor that varies across studies [5]. It is important to note that a set of results in not inconsistent simply because some results are statistically significant and some are not. The effect estimates from a set of studies could all be identical even if many were significant and many were not. The difference in significance can arise solely because of differences in the standard errors or sample sizes of the studies [5]. The regression estimates of the current study were very similar to the regression estimates in Carson et al., which applied the compositional analysis techniques to the Canadian Health Measures Survey [24]. Also, as found in my thesis research, much of the past literature has demonstrated that MVPA is significantly negatively related to obesity whereas total SB is not related to obesity [25–29]. Lastly, the direction of the associations was consistent across all three obesity measures examined in my thesis.

v) Biologic Gradient

Biologic gradient refers to the presence of a dose-response curve with an expected shape. The dose-response shape does not need to be linear but merely monotonic [5]. The findings of the time reallocations were in line with past research consistently showing curvilinear relations between MVPA and obesity measures, with larger changes in the obesity measures occurring with increases in MVPA at the low end of the MVPA scale [30–34]. The current study reinforces this curvilinear relationship.

4.7 Public Health Implications
Public health guidelines in physical activity, SB, and sleep have historically focused on promoting an individual movement behaviour. Similarly, most movement behaviour interventions have focused on changing the amount of time children spend in MVPA, SB, or sleep duration in isolation and have neglected the rest of the composition of the day. Recent evidence suggests that adequate sleep, low SB and high MVPA represents the ideal movement behaviour ‘soup’ and is beneficially associated with a myriad of health markers [35]. This thesis research modelled the movement behaviour ‘soup’ using a compositional paradigm. A key implication of this thesis research was that movement behaviour interventions aimed at preventing obesity should contain a large MVPA component. However, more research is needed in applying compositional data analysis techniques to movement behaviours to further model and explore the composition of the day before the integrated movement behaviour approach be fully adopted into interventions.

4.8 Future Research Directions

This research contributes to the small but growing body of literature that has applied compositional analysis techniques to movement behaviour data. Applying compositional data analysis to cross-sectional studies has demonstrated that the composition of a child’s day and its relationship to different health markers is important. To gain a more causal appreciation for these compositional relationships, these compositional data techniques need to be developed and applied to longitudinal movement behaviour data from cohort and intervention studies. Furthermore, more research is needed to ascertain if the proportion of time spent in different types of LIPA (higher versus lower intensity LIPA), different modalities of SB (e.g., after school screen time versus classroom learning time) and other sleeping behaviours (e.g., sleep efficiency) are important drivers of the composition of a child’s day and its relationship with health.

4.9 Summary of MSc Research Experience

My experience as a master’s student has allowed me to broaden my knowledge and skills in the field of epidemiology, biostatistics and public health. Through my initial year of coursework, I had the opportunity to
explore several different applications of the study of epidemiology and biostatistics. Outside of the classroom, my role as a research assistant for the Active Play Study provided me with invaluable insight into study design and the benefits associated with primary data collection. In this position, which lasted the duration of my degree, I worked with child participants and their families to collect data (e.g., anthropometric, accelerometer, surveys). I also contributed to the data entry, cleaning, and processing for the Active Play Study.

In my second year, I developed, executed, and critically evaluated my own thesis research using data collected from the Active Play Study. I gained a comprehensive understanding of SAS statistical programming software through the complex formatting, manipulating and merging of datasets that I had to do to assemble my thesis dataset. I also developed a SAS program where a myriad of compositional data analysis techniques could be applied. I completed all of the statistical analyses, including the compositional regression analyses and change matrix predictions. I was also responsible for interpreting my results and preparing my work in written format for this thesis and future publication in the peer-reviewed literature. Finally, I was given the opportunity to orally present my thesis research at an international conference (International Society of Behavioural Nutrition and Physical Activity, June 2017). As a whole, these experiences have allowed me to develop and refine the skills I will need to successfully work in the field of epidemiology and public health.

4.10 Conclusion

Compositional data analyses can be used to provide insights into the co-dependent relationships between movement behaviours and obesity. The proportion of time spent in MVPA relative to the other movement behaviours was a key predictor of body weight and body fat in this study. My findings suggest that replacing LIPA with MVPA would reduce body weight and fat, especially for children who are inactive.
4.11 References


   https://www.kflaph.ca/en/research-and-reports/Physical-Activity-Youth.aspx?_mid_=116338


Appendix A

Example Recruitment Advertisement for the Active Play Study
Physical Activity in Kingston Children

We are looking for 10-13 year olds to participate in a physical activity study at Queen’s University.

Children who complete the study will earn $40!

This study will determine where and when children are physically active. It will also determine how different types of physical activity influence children’s health.

All 10-13 year olds who live and go to school in Kingston can participate.

Participation in this study involves the following:
1. Simple physical measures such as height, weight, and blood pressure.
2. Completing a survey on a computer
3. Wearing a small activity measurement device for 7 days

The total time commitment for participating is about 4 hours.

For more information please contact us:

Email: Queens.Physical.Activity@gmail.com
Phone: (613)533-6000 ext. 75401
Website: https://sites.google.com/site/paepilab/
Appendix B

*Child Participant and Parent/Guardian Letters of Information and Consent Forms*
LETTER OF INFORMATION / CONSENT FOR PARENTS/GUARDIANS

Physical Activity Levels in Kingston Children

Principal Investigator: Dr. Ian Janssen
School of Kinesiology & Health Studies, Queen’s University
Kingston, Ontario
Phone: (613)533-6000 ext. 78631
E-mail: ian.janssen@queensu.ca

Co-Investigator: Dr. Michael McIsaac
Department of Public Health Sciences, Queen’s University
Kingston, Ontario
Phone: (613)533-6000 ext. 77460
E-mail: mcisaacm@queensu.ca

Research sponsor: Heart and Stroke Foundation of Canada

Purpose of the study

You and your child are invited to take part in this study on children’s physical activity. Children’s physical activity levels have declined in recent years and we hope to better understand children’s physical activity so that we can better work to increase their physical activity levels.

The purposes of this study are:
1. To determine the amount of different types of physical activities children do such as outdoor active play, organized sport, and active transportation (walking and biking).
2. To determine where children are when they engage in outdoor active play, organized sport, and active transportation. Several locations will be considered including the child’s home, the homes of relatives and friends, streets, playgrounds, wooded areas, school grounds, sports facilities, etc.
3. To determine what factors of the family, home, and neighbourhood environment predict how much outdoor active play, organized sport, and active transportation children get.
4. To determine whether active play, organized sport, or active transportation predicts children’s physical and mental health.

**What will happen during the study?**

You and your child will be asked to come to the Physical Activity Epidemiology lab at Queen’s University (Room 501, 28 Division St) for two visits about 8-11 days apart. Each visit will last approximately 45 minutes. Your child’s physical activity will be measured over a 7 day period between the two visits.

During the first visit to the lab, details of the study will be explained to you and your child. The research team will answer any questions that you or your child have. We will then measure your child’s standing height, sitting height, weight, and waist circumference. We will also measure your child’s heart rate and blood pressure using an automated machine. These physical measurements are non-invasive and should not cause any pain or discomfort to your child.

At the end of the first visit, your child will receive two small electronic devices that they will wear for the next 7 days to measure their physical activity. The first electronic device is a physical activity monitor. It will measure how much physical activity your child gets. The physical activity monitor is worn around the hip on an elastic belt. It is very small (ie, smaller than a book of matches). However, it is not waterproof. Your child will be asked to wear the physical activity monitor for 24/hours day for 7 days except the times when they will be in water.

The second electronic device is a GPS logger. The GPS logger looks like a sports watch and is worn around the wrist. This device will record your child’s geographic location about every 30 seconds. After the data has been collected the research team will determine where your child was when they were being active. Your child will be asked to wear the GPS logger for 7 days. They will take the GPS logger off at night so that its battery can be charged. Please note that the research team cannot track where child is while they are wearing this GPS logger.

During the 7 days your child’s physical activity is being measured, they will be asked to write down the times they remove their physical activity monitor. They will also be asked to write down times they go to bed and wake up. We will give them a diary to write down this information. Also, the research team will contact you by phone, e-mail, or text message (whichever is your preference) every morning. This will let us remind your child
to wear the physical activity monitor and GPS logger. This will also allow you or your child to ask us any questions that may arise.

Following the 7 days of physical activity data collection, you and your child will be asked to return to the physical activity epidemiology lab for the 2\textsuperscript{nd} and final visit. At this time, your child will be asked to return the physical activity monitor and GPS logger. Your child will also be asked to complete a \textasciitilde 25 minute questionnaire on the computer. This questionnaire will ask them about different types of physical activity that they do, their feelings about these physical activities, other ways that they spend their time (e.g., watching TV, doing homework), their mental health, and some of their eating behaviours. You will also be asked to complete a \textasciitilde 25 minute questionnaire on the computer. This questionnaire will ask for information about your family, your child’s physical activity, as well as some home and neighbourhood factors that may influence the ability of your child to be physical active.

\textbf{Are there any risks to participating in the study?}

It is unlikely that participating in this study will be associated with any harms or discomforts beyond those experienced in everyday life. The physical measures that we will obtain (e.g., height, blood pressure) are routinely used in children and are not associated with any known risk or adverse effect. The devices that your child will wear to measure their physical activity are similar to a belt and watch. These devices present no additional risk beyond those encountered in daily life while wearing these accessories. Finally, some of the items on the questionnaires might be deemed personal or sensitive by some people. You and your child do not need to answer questions that you do not want to answer or that make you feel uncomfortable.

\textbf{Are there any benefits to participating in the study?}

The research will not benefit you or your child directly. However, by participating in this study we hope to learn more about the types of physical activity that children do. Ultimately, we hope that this research will help to increase physical activity levels in children.

\textbf{Payment for study participation}

Compensation will be provided to you for parking ($3 for each visit to the lab). Children will be compensated for their time with up to $40 in cash. $10 will be given to your child at the end of the first visit to the lab. $20 will be given to your child at the beginning of the 2\textsuperscript{nd} visit to the lab if they return the physical activity monitor and GPS logger in good condition. Finally, your child will receive $10 at the end of the 2\textsuperscript{nd} visit after they complete their questionnaire. If you or your child withdraw from the study before it is completed, your child will get to keep the money they have already received.
Confidentiality and privacy

Every effort will be made to protect (guarantee) your confidentiality and privacy. When we present the research findings we will not include names or any information that can be used to identify you or your child. No one other than the research team will know that you and your child participated in the study unless you tell them. The information we obtain will be de-identified, such that you and your child will receive a unique identification number and will be known by this number, not by name. All of the study data will be entered into password- and firewall- protected computers in the physical activity epidemiology lab, and will be only be available to the research team. We will keep the data here securely for several years, but will never allow anyone other than the research team to have access to the data.

Legally Required Disclosure

Although we will protect your privacy, if legal authorities request information we may be required to reveal it to them (e.g. cases of child abuse).

What if I change my mind about being in the study?

It is important to remember that all aspects of a research study are voluntary. Even after providing consent you and/or your child can withdraw from the study at any time prior to when you submit your final questionnaire responses. In cases of withdrawal, there will be no negative consequences any data you have provided will be destroyed if you want the research team to do so.

How do I find out what was learned in this study?

We expect to have this study completed by the spring of 2017. If you would like a brief summary of the results, please let us know in the consent form below how you would like it sent to you.

Questions about the study

Any questions about study participation may be directed to Dr. Ian Janssen with the contact information listed at the top of this letter. Any ethical concerns about the study may be directed to the Chair of the General Research Ethics Board at chair.GREB@queensu.ca or 613-533-6081.
This study has been granted clearance according to the recommended principles of Canadian ethics guidelines, and Queen's policies.
CONSENT FORM FOR PARENT/GUARDIAN – Participant’s copy

I have read the information presented in the information letter about “The Physical Activity and Active Play” study being conducted by Drs. Ian Janssen and Michael McIsaac of Queen’s University. I have had the opportunity to ask questions about my involvement, as well as my child’s involvement, and to receive additional details that I requested. I have been adequately informed of the confidentiality and privacy measures that will be undertaken by the research team to protect my identity and my child’s identity. I understand that if I agree to participate, and provide consent for my child to participate, that we may withdraw from the study at any time. I have been given a copy of this form. I agree to participate in the study and I provide consent for my child to participate in the study.

Signature: ________________________________

Name of adult participant (Printed) ________________________________

Name of child participant (Printed) ________________________________

Date: ________________________________
CONSENT FORM FOR PARENT/GUARDIAN – Research Team’s Copy

I have read the information presented in the information letter about “The Physical Activity and Active Play” study being conducted by Drs. Ian Janssen and Michael McIsaac of Queen’s University. I have had the opportunity to ask questions about my involvement, as well as my child’s involvement, and to receive additional details that I requested. I have been adequately informed of the confidentiality and privacy measures that will be undertaken by the research team to protect my identity and my child’s identity. I understand that if I agree to participate, and provide consent for my child to participate, that we may withdraw from the study at any time. I have been given a copy of this form. I agree to participate in the study and I provide consent for my child to participate in the study.

Signature: ______________________________________

Name of adult participant (Printed) ___________________________________

Name of child participant (Printed) ___________________________________

Date: __________________________________________________

Would you like to receive a summary of the study’s results?

☐ Yes, I would like to receive a summary of the study’s results.

Please send them to this E-mail address: ___________________________________

or to this mailing address:

_________________________________________

☐ No, I do not want to receive a summary of the study’s results.
Would you be willing to be contacted about a potential follow-up study, understanding that you can always decline the request?

☐ Yes. Please contact me by:

Phone: ________________________________

or E-mail: ________________________________

or Mail: ________________________________

☐ No
Physical Activity Levels in Kingston Children

Principal Investigator: Dr. Ian Janssen
School of Kinesiology & Health Studies, Queen’s University
Kingston, Ontario
Phone: (613)533-6000 ext. 78631
E-mail: ian.janssen@queensu.ca

Co-Investigator: Dr. Michael McIsaac
Department of Public Health Sciences, Queen’s University
Kingston, Ontario
Phone: (613)533-6000 ext. 77460
E-mail: mcisaacm@queensu.ca

Research sponsor: Heart and Stroke Foundation of Canada

Purpose of the study

We want you to participate in this study. It is about children’s physical activity. Children’s physical activity levels are getting worse. We want to know why.

The purposes of this study are:

1. To determine how much active play, sport, and walking and biking children do.
2. To determine where children get physically active. Several locations will be looked at. These include homes, streets, playgrounds, fields, forests, schools, and arenas.
3. To determine how families, friends, and neighbourhoods affect physical activity.
4. To determine how physical activity affects health.
What will happen during the study?

You and your parent will come to Queen’s University for two visits. The visits will be 8 to 11 days apart. Each visit will last about 45 minutes. Your physical activity will be measured for 7 days between the two visits.

At the first visit we will explain the study to you. We will answer any questions you have. We will measure how tall you are and how much you weigh. We will measure your belt size. We will measure your heart rate and blood pressure using a small machine. These measures should not cause any pain or discomfort.

At the end of the first visit we will give you two small electronic devices. You will wear them for 7 days. They will measure your physical activity. The first device will measure how much physical activity you get. You will wear it around your waist on a belt. The second device looks like a watch. It will record your location on a map about every 30 seconds. It will tell us where you got your physical activity.

On the 7 days your physical activity is measured you should write when you remove the electronic devices. You should also write down times you go to bed and wake up. We will give you a diary to write this down.

On the second visit to Queen’s University you will return the two electronic devices. You will also answer some questions on a computer. This will take about 25 minutes. The questions will ask about things you do in your free time. The questions will also ask about your health.

Are there any risks to participating in the study?

Participating should not cause any harms. You do not have to answer questions that make you uncomfortable.

Are there any benefits to participating in the study?

The research will not benefit you directly. We hope to learn more about physical activity in children. We hope this will help to us think of ways to get children to be more active.

Payment for participating

93
You will be given up to $40. You will receive $10 at the end of the first visit. You will be given $20 at the start of the 2nd visit if you return the electronic devices in good condition. You will be given $10 at the end of the 2nd visit. If you drop out of study, you can keep the money you have already received.

Confidentiality and privacy

We will make every effort to keep the information we obtain from you private. When we show the research findings we will not include private information about you. The information we obtain about you will be protected on our computers.

Legally required disclosure

Although we will protect your privacy, if the police request information we may be required to give it to them.

What if I change my mind about being in the study?

All parts of a research study are voluntary. You can drop out of the study at any time before it is done. There will be no penalties if you drop out. Also, any information you gave us will be destroyed if you choose.

Questions about the study

Questions can be asked to Dr. Ian Janssen. His contact information is shown at the top of this letter. Ethical concerns can be asked to the Chair of the General Research Ethics Board at chair.GREB@queensu.ca or 613-533-6081.

This study has been granted clearance according to the recommended principles of Canadian ethics guidelines, and Queen's policies.

Physical Activity Levels in Kingston Children
I have read and understood the attached information sheet or had it explained to me. I know that there may be no direct benefit to me for participating. I know that it is my choice to participate. I have been told about the study. I have had all of my questions answered. I know that any information collected about me will be kept private. No one will know that I participated in the study except for the research team. I know I am free to drop out of the study at any time. If I drop out it will not affect me or my family. I also know that I do not have to answer questions that make me feel uncomfortable. I have received a copy of the information sheet and consent form. I agree to participate in the study.

Your full name (Printed) ___________________________________

Your signature: __________________________________________

Date: __________________________________________________

Would you be willing to be contacted about a potential follow-up study, understanding that you can always decline the request?

☐ Yes

☐ No
I have read and understood the attached information sheet or had it explained to me. I know that there may be no direct benefit to me for participating. I know that it is my choice to participate. I have been told about the study. I have had all of my questions answered. I know that any information collected about me will be kept private. No one will know that I participated in the study except for the research team. I know I am free to drop out of the study at any time. If I drop out it will not affect me or my family. I also know that I do not have to answer questions that make me feel uncomfortable. I have received a copy of the information sheet and consent form. I agree to participate in the study.

Your full name (Printed) ________________________________

Your signature: ________________________________

Date: ________________________________

Would you be willing to be contacted about a potential follow-up study, understanding that you can always decline the request?

Yes

No
Appendix C

Actical Monitor and Activity Log Instructions
Instructions for Activity Monitor, Location Monitor, and Sleep & Activity Log

This study will measure your physical activity patterns over one week. In order to do this, we want you to wear an Activity Monitor and a Location Monitor for the next 7 days. We are interested in measuring your normal activity level. Please do not change your normal physical activity levels during the study.

Information and Instructions for the Activity Monitor and Sleep & Activity Log

An Activity Monitor is a small electronic device that records all daily activities as electronic signals. It does not need to be turned on or off. You do not need to change the batteries or recharge this device. Please start wearing the Activity Monitor as soon as your visit to the laboratory is over. We want you to keep wearing it for the 7 days and nights following your visit.

The Activity Monitor should be worn as shown in the picture to the right. You should wear it around your waist using the elastic belt we give you. It should be worn above your right hip. The Active Monitor should be positioned so that “RESPIRONICS” is at the top and “Actical” is at the bottom. It should be located half way between your stomach and back. You can wear it underneath or above your clothes.
It is very important that you wear the Activity Monitor as much as possible. You should take it off when you are having a bath or shower or when swimming since the Activity Monitor is not waterproof. If there are times that you need to take the Activity Monitor off, other than when having a bath or shower, we would like you to record this on the Activity Monitor and Location Monitor Diary. This should be recorded in the PINK columns of the diary.

We would also like you to keep the Activity Monitor on at night when you go to bed. The Activity Monitor will measure how much you move when you are sleeping. We would like you to record what time you wake up in the morning and what time you go to bed at night on the Sleep, Organized Sports, and Outside Chores Diary. This should be recorded in the YELLOW columns of the diary.

If you participate in organized sports or programs during the study (eg, hockey, soccer, karate, dance class), we would like you to record these sports and the times you participated in the Sleep, Organized Sport, and Outside Chores Diary. This should be done in the GREEN columns of the diary. Finally, if you do any chores or work outdoors during the study (eg, shovel snow, farming, cut grass), we would like you to record what time you did this work in the BLUE columns of the diary.

Information and Instructions for the Location Monitor

The Location Monitor is an electronic device that connects to satellites and records your location every few seconds. We will use the Location Monitor to determine where you are when you are being active. While you are using the Location Monitor during the study we will not know where you are. However, after the study is over the Location Monitor will tell us where you were throughout the week.

You will wear the Location Monitor on your wrist like a watch. You can wear it on your left or right wrist. You can wear the Location Monitor under long sleeved clothes such as a sweatshirt or coat.

The Location Monitor runs on a rechargeable battery that lasts for about 10 hours. We ask that you charge the Location Monitor tonight before you go to bed. You will need to do this again every night for the following 7 nights. Follow these 4 steps to charge the Location Monitor:

1) Plug the USB end of the charger into the USB adapter.
2) Plug the USB adapter in a regular outlet.
3) Look at the picture to the right. Align the charge posts on the charger with the contacts on the back of the Location Monitor. Then press the charger until it clicks.

4) Leave it plugged in overnight to charge.

You should start wearing the Location Monitor in the morning before you leave your house. On school days, put the Location Monitor on a few minutes before you leave for school. On weekends and holidays, try to put the Location Monitor on at around the same time you would do on school days. Alternatively, if you are leaving your house earlier in the day, put the Location Monitor on before you go.

When you start wearing the Location Monitor each morning, you will need to turn its recording function “on”. Follow these 4 steps:

1) Press the top right button on the Location Monitor. This is button ④ in the picture to the right.

2) Continue pressing this button until the display on the Location Monitor looks like the picture on the bottom right.

3) Press this button once more and the recording function will turn “on”. A large green triangle will appear on the display for 2 seconds immediately after the recording function is turned “on”. Also, the numbers under “Timer” will start to count up. Numbers may also start to appear at the top and bottom of the display once you start to walk around.

4) After the recording function is turned on, you can turn on the watch function by pressing the middle button on the left hand side of the display. This is button ② shown in the picture above.

Once the recording function is “on”, do not press the top right button of the Location Monitor again. If you do, the recording function will turn “off”. If this happens, press the top right button again to turn it back “on”. You will know the recording function is “on” when the timer in the display is counting up.

Let the recording function of the Location Monitor run continuously each day. The battery on the Location Monitor will usually run out of charge after about 10 hours. Therefore, please try to re-charge the battery for about 15 minutes in the late afternoon or early evening (eg, right after school, at supper time). After you re-charge the battery for a few minutes, please put the Location Monitor back on and turn “on” the recording function again. Right before you go to bed at night, you should take the Location Monitor off and charge it again for the next day.
If there are times that you leave home without the Location Monitor, we would like you to record this on the Activity Monitor and Location Monitor Diary. This should be recorded in the ORANGE columns of the diary.

It is important that you wear the Location Monitor as much as possible when it is turned on. Since the Location Monitor is waterproof, you can wear it when showering, bathing, or swimming. You should not wear the Location Monitor to bed at night as you should be charging it’s battery at that time. If you need to take the Location Monitor off when playing organized sports, please bring it with you to where you are playing. For example, if you need to take it off to play in a basketball game, take it off at the gym and put it back on after the game is over.
Appendix D

Sleep Log
Activity Monitor and Location Monitor Diary

Participant ID: _____________________                   Todays Date (day/month/year):

<table>
<thead>
<tr>
<th>Day</th>
<th>If you took the Activity Monitor off, what time did you take it off and put it back on?</th>
<th>Time Off</th>
<th>Time Back On</th>
<th>What were you doing when the Activity Monitor was off?</th>
<th>Time Left Home</th>
<th>Time Came Back Home</th>
<th>Where did you go without the Location Monitor?</th>
</tr>
</thead>
<tbody>
<tr>
<td>Example</td>
<td>4:00 pm</td>
<td>4:30 pm</td>
<td>karate</td>
<td>3:45 pm</td>
<td>4:45 pm</td>
<td>Kingston Karate Club</td>
<td></td>
</tr>
<tr>
<td></td>
<td>6:30 pm</td>
<td>7:30 pm</td>
<td>soccer</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day 3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day 5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day 6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day 7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
### Sleep, Organized Sport, and Outside Chores Diary

**Participant ID: _____________________**

**Todays Date (day/month/year):** ______________________

<table>
<thead>
<tr>
<th>Day</th>
<th>What time did you get out of bed in the morning?</th>
<th>What time did you go to sleep at night?</th>
<th>If you participated in organized sports or programs, what time did they start and stop?</th>
<th>What organized sports or programs did you participate in?</th>
<th>If you worked or did chores outside, what time did they start and stop?</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Time Start</td>
<td>Time Stop</td>
<td>Time Start</td>
<td>Time Stop</td>
<td>Time Start</td>
</tr>
<tr>
<td>Example</td>
<td>7:30 am</td>
<td>9:30 pm</td>
<td>4:00 pm</td>
<td>4:30 pm</td>
<td>karate</td>
</tr>
<tr>
<td>Day 1</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day 2</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day 3</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day 4</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day 5</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day 6</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Day 7</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>
Appendix E

Sleep Time Cleaning Protocols
Data Cleaning Guidelines: Sleep Times

Before You Start: Things to Keep in Mind

Sleep time refers to the duration someone sleeps at night. In the Active Play Study participants wore their accelerometer during both waking hours and sleep time, and it is important that we accurately distinguish between the two before we process the accelerometer data. To help us with this, participants were asked to record the time that they went to bed each night and the time they got up in the morning. The objective of the data cleaning outlined in this protocol is to correct errors in the recorded sleep times (e.g., the participant recorded that they went to bed at 9:30 p.m. but they actually went to bed at 10:00 p.m.).

Sleep time is recognizable in the Actical accelerometer data by a period of several hours of little or no movement with accelerometer counts at or close to zero. Because people move when they sleep (e.g., roll over in bed), there will be brief bursts of lower intensity movement during sleep time that are intermixed within long periods with no movement. Sleep time is generally preceded and followed by at least a few minutes of movement. For example, getting ready for bed (e.g., brushing teeth, going to the bathroom, walking to bedroom, changing clothes) will be recorded as light intensity movement by the accelerometer. In combination with the sleep diaries, this predictable movement pattern will help us determine exact sleeping times for study participants.

When you work on the time verification and correction, commit to verify and correct full days of all recorded sleep times, organized sport times, and non-wear times of a participant. Do Not stop in the middle of a day of a participant.

Sleep Time Verification

1. **Enter your name on the sleep time tracking sheet** pinned on the bulletin board in Room 501G every time after you start verifying the sleep time for a new participant. Select the next participant on the tracking sheet that has not been started by another researcher. Write down your name in the “Researcher Name” column on the tracking sheet.

2. **Obtain the photocopied Sleep and Activity Diary** of the Participant ID you wish to verify sleep time for. The photocopied Sleep and Activity diaries are located in the middle filing cabinets in Room 501G. Sleep times include get-up times and bed times.

3. **Ensure that you have a coloured pen** to make changes on the photocopied diary. All edits should be made on the photocopy and not on the original diary used by the participant.

4. **Open the Actical software and Actical accelerometer file.**
   a) Open the Actical 3.10 software.
   b) Click **File**, then click **Open**...
   c) Select and open the .AWC file of the participant ID you are verifying. These files can be found in the following directory: Epi-Server → EPI lab → Actical. For example, for participant 147, open the 0147.AWC file in the Epi-Server → EPI lab → Actical directory.
   d) Click **Tools**, then click **Actogram**
A new screen containing several activity graphs will appear

e) At the top of the screen above the activity graphs, ensure the *Identity* is the participant ID you are verifying.

f) Adjust the Scale value on the left hand side of the actogram to **1500**.
   - This will change the scale on each y-axis to show a maximum value of 1500, making it easier to observe low-intensity movements around the wake-up and sleep times

5. **Determine the correct Day 1 date of the participant you are verifying.**
   a) Open the *Database Access* file located in the **Epi-Server → EPI lab → Database** folder.
   b) Double click and open the *Visit #1* table
   c) In column two, search for the *Date of Visit* of the participant ID you are verifying. **This date + 1** will be the Day 1 date.

6. **Verify Get-up Time:**
   a) On the actogram, double click on the activity graph corresponding to the Day 1 date. You will now see an **Expanded Actogram** for Day 1. An example actogram is shown below in Figure 1.
   b) Ensure the date on the Expanded Actogram is the Day 1 date (see **A** on Figure 1).
   c) Adjust the *Display Center* time using the left and right arrows (see **B** on Figure 1) to match the get-up time recorded for Day 1 on the photocopied diary (i.e., **A** on Figure 1 matches **C** on Figure 2).

Figure 1.
d) Check to see if the get-up time that was recorded in the diary is accurate to within one minute of the time registered on the Actical accelerometer. In general, you are looking for the start point of continual movements that occurs around the get-up time that was recorded on the diary. These continual movement will indicate that the participant got up and started their day.

Keep in mind that the pattern of movements that occurred during the sleep period can help to determine whether the low intensity movements observed close to the recorded get-up times are part of the sleep period or indicate the participant has gotten up. Also, it may be useful to consider the get-up times recorded for the rest of the week. Children often have very similar get-up times on school days and on the weekend.

e) You are asked to **determine a reasonable get-up time for Day 8** (the day following the last day of study participation) based on your experience for the participant you are verifying times for.

f) If there is any day when the participant clearly did not wear the activity monitor to sleep, there are 2 options for this step.

Option 1 - you will not change the recorded get-up time if this time is within the non-wear period, as there is no evidence suggesting the recorded get-up time is wrong. Additionally, if the period from the recorded get-up time to the time when the first movement is seen on the Actogram is no longer than 20 minutes, please indicate this period in the non-wear period section. For example, if the recorded get-up time is 6:30 a.m., and the first movement is observed at 6:45 a.m., make sure that you write down 6:30 a.m. to 6:45 a.m. as a non-wear period. If this period is greater than 20 minutes, you do not need to indicate it on the non-wear period section.

Option 2 - if the recorded get-up time is outside the non-wear period, please change the get-up time to the point where first movement is seen. For example, if the data shows that the participant did not put the activity monitor back on until 6:30 a.m., but the participant indicated the get-up time for that morning was 6:45 a.m., please change the get-up time to 6:30 a.m., as the participant has to be awake to put the monitor back on.

*Three illustrative examples for verifying get-up times can be found in Examples 1-3 on pages 7-8.*
g) There are 2 options for this step. **Option 1** - If you determine that the recorded get-up time was accurate to the nearest minute, place a checkmark beside the get-up time on the photocopied diary. **Option 2** - If you determine that the recorded get-up time is different from what is recorded on the diary, use a coloured pen to write the corrected time underneath the original time on the photocopied diary. Please always write down the words *Day 8* in the white space at the bottom of the diary and aligned with the Column for days. Then put down the Day 8 get-up time you determined beside it.

*Note: if you are not sure of the times you have corrected, make a note of this in the “Issues occurred?” column of the tracking sheet. Please get a second opinion (ideally from Chao, Mike, or Emily) on this issue. The data should not be entered into database (Step 10) until the issue has been resolved.*

7. Verify Bed Time:

![Expanded Actogram](image)
a) Adjust the *Display Center* time using the right arrow to match the bed time recorded for Day 1 on the photocopied diary (i.e. D on Figure 3 matches E on Figure 4).

b) Check to see if the bed time that was recorded in the diary is accurate to within one minute of the time registered on the Actical accelerometer. Please keep in mind that we cannot determine the exact time when the participant fell asleep, so we are looking for the time they turned off the lights to go to sleep. Thus, if there is some low-intensity movement after the recorded bed time, we would consider the recorded bed time as accurate. Such low-intensity movements might indicate that the participant was trying to fall asleep (e.g., tossing and turning in bed). However, if there is any movement or epoch after the recorded bed time above 375 counts on the y-axis of the actogram, this would typically indicate that the participant was still out of bed doing some moderate intensity movements. During this step it may be useful to consider the bed times recorded for the rest of the days. Children often have the same bedtime on school nights, for example.

c) If there is any day when the participant clearly did not wear the activity monitor to sleep, there are 2 options for this step.  
*Option 1* - you will not change the recorded bed time if this time is within the non-wear period, as there is no evidence suggesting the recorded bed time is wrong. *Additionally*, if the period from the time when the last movement is seen on the Actogram to the recorded bed time is no longer than 20 minutes, please indicate this period in the non-wear period section. For example, if the last movement is observed at 9:45 p.m., and the recorded bed time is 10 p.m., make sure that you write down 9:45 p.m. to 10 p.m. as a non-wear period. If this period is greater than 20 minutes, you do not need to indicate it on the non-wear period section.

*Option 2* - if the recorded bed time is outside the non-wear period, please change the bed time to the point where last movement is seen. For example, if the data shows that the participant did not take off the activity monitor until 10 p.m., but the participant indicated the bed time for that night was 9:45 p.m., please change the get-up time to 10 p.m., as the participant has to be awake to take off the activity monitor.
Three illustrative examples for verifying bed times can be found in Examples 4-8 on pages 8-9.

d) There are 2 options for this step. Option 1 - If you determined that the recorded sleep time was accurate, place a checkmark beside the sleep time on the photocopied diary. Option 2 - If you determine that the recorded sleep time is different from what was recorded on the diary, use a coloured pen to write the corrected time underneath the original time on the photocopied diary.

Note: if you are not sure of the times you have corrected, make a note of this in the “Issues occurred?” column of the tracking sheet. Please get a second opinion (ideally from Chao, Mike, or Emily) on this issue. The data should not be entered into database (Step 10) until the issue has been resolved.

8. Repeat the Sleep Time Data Verification Process. The processes that were explained in Steps 6 and 7 for Day 1 should be repeated for Day 2 through Day 7 for the same participant ID.

9. Indicate that all Sleep Times has been verified and corrected on the data cleaning tracking sheet pinned on the bulletin board in Room 501G. Every time you have completed all the sleep time, organized sports time, and non-wear time verification and correction for a same day of a participant’s, put a check mark in the corresponding day in the “All 7 days verified & corrected?” column. The next time you start working on the data verification you should pick-up where you left off with this participant.

10. Enter Corrected Sleep Time Information into Database
   a. All of the sleep time information for all 7 days plus the Day 8 get-up time for the participant ID, including data on the diary that was accurate and data that was corrected, should be entered in the electronic study database. This should be entered in the “Sleep and Activity Diary Day [1-7] – Cleaned” table in the Database-Cleaned Access file located in the Epi-Server → EPI Lab → Database folder.
   b. Enter your name in the Researcher Name column beside the participant ID in the Database – Cleaned Access file.

11. Indicate that all verified and corrected data on the data cleaning tracking sheet pinned on the bulletin board in Room 501G. Every time you have entered all the verified and corrected sleep times, organized sports times, and non-wear times for a same day of a participant, put a check mark in the corresponding day in the “All data entered into database?” column. The next time you start working on the data entry you should pick-up where you left off with this participant.
Example 1:

The participant recorded 8:53 a.m. as their get-up time. However, the start point of the continual movements can be observed at 7:25 a.m. where the green arrow is pointing. Looking through this participant’s sleep (e.g., prior to 7:25), there are no similar movement patterns. Thus, we would change the get-up time of this day to 7:25 a.m. after zooming in the Display With to determine the exact minute.

Example 2:
The recorded get-up time for this actogram is 6:45 a.m., which looks accurate. Using the Display Width to zoom in, you observed that 6:45 a.m. is the closest minute. Thus, you will not change the get-up time for this day.

Example 3:

The participant put down 7 a.m. as their get-up time. However, continuous movement starts at 6:44 a.m., as noted by the green arrow. The intermittent movements around 6 a.m. and 6:15 a.m., are similar to what can be seen for this participant throughout the night, such as around 5:10 a.m. Thus, the get-up time would be corrected to 6:44 a.m. on this day.

Example 4:
The recorded bed time is 11 p.m. for this day. 11 p.m. appears to make sense as there is some movement in the half hour proceeding and a long string of 0 counts after. In this case, the recorded bed time would not be changed.

**Example 5:**

11 p.m. was recorded as the bed time, but light to moderate intensity movements are detected well after 11 p.m. Thus, when zoomed in, 11:27 p.m. (see the green arrow) will be considered as the more accurate bed time and the diary would be corrected to this time.

**Example 6**
Appendix F

Example Change Matrix Calculation (Relative versus Absolute)
Chastin et al Method (Absolute Change)

Displace 10 minutes of Sedentary behavior with 10 mins of MVPA:

Let $b_i$ represent the sample geometric mean of MVPA and $b_j$ represent the sample geometric mean of SB
Let $b_i^*$ represent the $b_i+10$ and $b_j^*$ represent $b_j-10$.
c$_{ij}$ represent the results of the inverse transformation of the regression coefficients for MVPA and SB

$$e^1\left[\left(\frac{b_i^*}{b_j^*}\right) - \left(\frac{b_i}{b_j}\right)\right]c_{ij}$$

Modified Method (Relative Change)

Displace 10 minutes of Sedentary behavior with 10 mins of MVPA:

Let $b_i$ represent the sample geometric mean of MVPA and $b_j$ represent the sample geometric mean of SB
Let $b_i^*$ represent the $b_i+10$ and $b_j^*$ represent $b_j-10$.
c$_{ij}$ represent the results of the inverse transformation of the regression coefficients for MVPA and SB

$$e^1\left[\left(\frac{b_i^*}{b_j^*}\right) - \left(\frac{b_i}{b_j}\right)\right]c_{ij}$$

$$\left[\frac{b_i}{b_j}\right]$$
Appendix G

Power Calculation
**Power**

The ‘pwr’ package from the Comprehensive R Archive Network was used for the power calculations.\(^8^5,8^6\) For linear regression models power can be calculated by specifying the desired significance level, the degrees of freedom for the numerator and denominator, and the desired effect size (Cohen’s \(f^2\)). All of my power calculations were based on a significance level of 0.05. I assumed that 15 covariates would be included in the final regression model, based on my exposure and covariates section, and that my final sample size would be 450. Therefore, the power calculation was based on having 14 degrees of freedom for the numerator (\(u=\# \text{ of continuous and dummy variables } -1\)) and 435 degrees of freedom for the denominator (\(v=\text{sample size-}\# \text{ continuous and dummy variables}\)). Cohen’s \(f^2\) is an effect size measure that is used when both the exposure and outcome variables are continuous, and it is derived from the formula \(f^2=R^2/1-R^2\), where \(R^2\) is the squared multiple correlation.\(^8^6\) Cohen has suggested that a small, medium and large effect size can be represented by the values 0.02, 0.15 and 0.35, respectively, and these effect sizes are commonly used in the behavioural epidemiology literature.\(^8^6\) The following formula was used to calculate power: \(\Lambda=f^2*(u+v+1)\). For a small effect size I will have a power of 41.2%, for a medium effect size a power of 99.9% and for a large effect size a power of 100%. 

---

118
Appendix G

Ethics Letter of Approval For This Thesis
Mr. Robert Talarico  
Department of Public Health Sciences  
Queen’s University 

**ROME0/TRAQ: #6019271**  
Department Code:  EPID-565-16  
Study Title:  Unravelling the Compositional Effects of Time Spent in Sleep, Sedentary Behaviour and Physical Activity on Obesity Measures in Children  
Co-Investigators:  Dr. I. Janssen  
Review Type:  Delegated  
Date Ethics Clearance Issued:  September 27, 2016  
Ethics Clearance Expiry Date:  September 27, 2017 

Dear Mr. Talarico,  

The Queen's University Health Sciences & Affiliated Teaching Hospitals Research Ethics Board (HSREB) has reviewed the application and granted ethics clearance for the documents listed below. Ethics clearance is granted until the expiration date noted above. 

- Thesis Proposal 

**Documents Acknowledged:**  

- CORE Certificate – R. Talarico  
- GREB Clearance Letter – GPHE-178-14 – October 17, 2014  
- GREB Renewal Clearance – September 22, 2015  
- PRE-Study Data Collection Sheet  
- Child Survey  
- Parent Survey  
- Sleep Activity and Monitor Diary  
- Physical Activity Monitor Instructions  
- Visit 1 Data Collection Sheet  
- Visit 2 Data Collection Sheet  
- Information/Assent Form – Child  
- Information/Consent Form - Parent  

**Amendments:** No deviations from, or changes to the protocol should be initiated without prior written
clearance of an appropriate amendment from the HSREB, except when necessary to eliminate immediate hazard(s) to study participants or when the change(s) involves only administrative or logistical aspects of the trial.

**Renewals:** Prior to the expiration of your ethics clearance you will be reminded to submit your renewal report through ROMEO. Any lapses in ethical clearance will be documented on the renewal form.

**Completion/Termination:** The HSREB must be notified of the completion or termination of this study through the completion of a renewal report in ROMEO.

**Reporting of Serious Adverse Events:** Any unexpected serious adverse event occurring locally must be reported within 2 working days or earlier if required by the study sponsor. All other serious adverse events must be reported within 15 days after becoming aware of the information.

**Reporting of Complaints:** Any complaints made by participants or persons acting on behalf of participants must be reported to the Research Ethics Board within 7 days of becoming aware of the complaint. *Note:* All documents supplied to participants must have the contact information for the Research Ethics Board.

Investigators please note that if your trial is registered by the sponsor, you must take responsibility to ensure that the registration information is accurate and complete.

Yours sincerely,

*Albert L. Clark*
Chair, Health Sciences Research Ethics Board

*The HSREB operates in compliance with, and is constituted in accordance with, the requirements of the TriCouncil Policy Statement: Ethical Conduct for Research Involving Humans (TCPS 2); the International Conference on Harmonisation Good Clinical Practice Consolidated Guideline (ICH GCP); Part C, Division 5 of the Food and Drug Regulations; Part 4 of the Natural Health Products Regulations; Part 3 of the Medical Devices Regulations, Canadian General Standards Board, and the provisions of the Ontario Personal Health Information Protection Act (PHIPA 2004) and its applicable regulations. The HSREB is qualified through the CTO REB Qualification Program and is registered with the U.S. Department of Health and Human Services (DHHS) Office for Human Research Protection (OHRP). Federalwide Assurance Number: FWA#:00004184, IRB#:00001173*

*HSREB members involved in the research project do not participate in the review, discussion or decision.*