Disentangling the combined effects of 24-hour time-use behaviours on childhood obesity: A compositional data analysis

Leila Hedayatrad

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Department of Behavioural Nutrition and Physical Activity

School of Sport and Recreation

Faculty of Health and Environmental Sciences

Thesis Abstract

Obesity in children is a worldwide health problem, and New Zealand is no exception. One in three New Zealand children is overweight or obese. Thus, identifying modifiable determinants of obesity in children is essential to inform future interventions. Evidence shows that time-use behaviours, including physical activity, sedentary behaviour, and sleep, are related to obesity in children. However, the associations between these individual time-use behaviours and obesity shown in past research have been criticised for failing to appropriately adjust for time spent in each of the other behaviours. The emerging research field of time-use epidemiology suggests that interactions among these time-use behaviours may impact health in ways that cannot be explained by studying these behaviours in isolation (e.g., increasing one behaviour displaces another). This has prompted a global shift in behavioural epidemiology research where an integrated approach focusing on complete (24-hour) days is now a research priority.

The overall aim of this PhD thesis was to advance the area of time-use research in children through four studies, guided by the Viable Integrative Research in Time-Use Epidemiology (VIRTUE) framework. Study 1 investigated the concurrent validity of two accelerometers (i.e., ActiGraph GT3X+ and Axivity AX3) for measuring children's time-use behaviours against direct observation. Both accelerometers reached 65% to 97% balanced accuracy for detecting various postures and physical activity intensities, with the AX3 offering slightly better accuracy than the GT3X+ accelerometer. These findings showed that the AX3 device could effectively measure activity type and intensity in child populations.

Studies 2–4 utilised data from a sample of children who participated in the 8-year wave of the Growing Up in New Zealand cohort study. Study 2 investigated if the 24-hour AX3-measured time-use behaviours (measured from activity intensity and activity type

perspectives) and reallocation of time across these behaviours were associated with obesity-related outcomes using compositional data analysis. The 24-hour time-use composition was significantly associated with body mass index (BMI). More time spent in light-intensity physical activity (LPA) and walking (relative to the other behaviours) was associated with lower BMI. Study 3 examined how these children clustered based on their lifestyle behaviours (including time-use behaviours and diet) and associations between cluster membership and obesity. Three unique clusters were identified, with children in the healthiest cluster (lowest sedentary time and sitting time, healthiest diet) had the lowest BMI compared to other clusters. Study 4 examined which sociodemographic factors were associated with adherence to the New Zealand 24-hour Movement Guidelines. Only a small number of children met these guidelines, and child gender, ethnicity, mother's education, and household area (urban vs rural) were associated with guideline adherences.

Overall, the studies in this thesis have made significant contributions to time-use research by providing insight into the structure of time-use behaviours and their relationship with measures of obesity in New Zealand children. It is hoped that these findings will assist in developing and tailoring future interventions to improve child health.

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Attestation of Authorship

I hereby declare that this submission is my own work and that, to the best of my knowledge and belief, it contains no material previously published or written by another person (except where explicitly defined in the acknowledgements), nor material which to a substantial extent has been submitted for the award of any other degree or diploma of a university or other institution of higher learning.

Leila Hedayatrad, September 2022

Co-authored works

Peer-reviewed journal publications:

Hedayatrad, L., Stewart, T., & Duncan, S. (2020). Concurrent validity of ActiGraph GT3X+ and Axivity AX3 accelerometers for estimating physical activity and sedentary behaviour. *Journal for the Measurement of Physical Behaviour*, *4*(1), 1-8. doi: 10.1123/jmpb.2019-0075.

Hedayatrad, L., Stewart, T., Paine, SJ., Marks, E., Walker C., & Duncan, S. (2022) Sociodemographic differences in 24-hour time-use behaviours in New Zealand children. *International Journal of Behavioural Nutrition and Physical activity,* 19(1), 131. doi: 10.1186/s12966-022-01358.

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Hedayatrad, L., Stewart, T., Marks, E., Walker C., & Duncan, S. (under review). Clustering of lifestyle behaviours and obesity in New Zealand children: A compositional data analysis approach.

Research chapter contributions

Chapters 3–6 of this thesis are either published in a peer-review journal or under review.

The percentage contribution of each author is presented below.

Chapter 3: Concurrent validity of ActiGraph GT3X+ and Axivity AX3 accelerometers for estimating physical activity and sedentary behaviour.

Leila Hedayatrad…………………………………………………………… 80%
Tom Stewart……………………………………………………………….... 15%
Scott Duncan……………………………………………………………… 5%

Chapter 4: Utilising compositional data analysis to compare 24-hour time-use behaviours and obesity in New Zealand children.

Leila Hedayatrad…………………………………………………………… 80%
Tom Stewart……………………………………………………………….... 15%
Scott Duncan…………………………………………………………….... 5%

Chapter 5: Clustering of lifestyle behaviours and obesity in New Zealand children: A compositional data analysis approach.

Leila Hedayatrad…………………………………………………………… 80%
Tom Stewart……………………………………………………………….... 15%
Scott Duncan……………………………………………………………… 5%

Chapter 6: Patterns and sociodemographic correlates of 24-hour time-use behaviours in New Zealand children.

Leila Hedayatrad…………………………………………………………… 80%
Tom Stewart……………………………………………………………….... 15%
Scott Duncan……………………………………………………………… 5%

Tom Stewart Scott Duncan

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Chapter 1- Introduction

Background

Childhood obesity represents a major public health concern of the 21st century [1]. Worldwide obesity and overweight in children have increased by 47% over the last four decades [2]. According to the New Zealand Ministry of Health, about one in three New Zealand children aged 2–14 years is overweight or obese [3]. The rate of New Zealand children classified as overweight or obese has remained almost consistent over the past ten years, from 31.6 % in 2011/2012 to 30.8 % in 2020/2021 [4]. The results from the 2020/2021 New Zealand Health Survey show that the rate of obesity in children has increased from 9.5% in 2019/2020 to 12.7% in 2020/2021 [3]. This is concerning as childhood obesity is associated with several comorbidities that track to adulthood [5]. Evidence shows that children with obesity are at higher risks of cardiovascular and all-cause mortality in adulthood [5]. In 2006, the healthcare costs on overweight and obesity in New Zealand was estimated at USD 424 million, corresponding to 4.4% of the country's total healthcare costs [6]. Treating obesity once being established in children is challenging, highlighting the importance of obesity prevention. In addition to healthy eating behaviours [7], favourable daily time-use behaviours (i.e., regular physical activity [8], reduced sedentary time [9], and sufficient sleep [10]) have been identified as key lifestyle behaviours in obesity prevention.

A substantial body of evidence links time-use behaviours (i.e., physical activity, sedentary behaviour, and sleep) to overweight and obesity in children [8-10]. However, most of this evidence comes from research assessing and analysing these behaviours individually, where the fundamental co-dependency between these behaviours has been largely overlooked [11]. As the duration of any given day is fixed and limited to 24 hours, any changes in time spent in one behaviour (increase or decrease) is inevitably accompanied by equal and opposite changes in the time available for one or more of the remaining behaviours [12]. Thus, the health outcome claimed to be associated with increasing or decreasing time in one behaviour may be the result of changes in the remaining behaviour within the 24-hour time-use composition [13]. Consequently, collective examinations of all these behaviours within the 24-hour time-use composition rather than single isolated behaviours is more relevant to the real world. This has resulted in behavioural researchers moving away from focusing on a single behaviour to an integrated approach targeting all behaviours collectivity [13].

The shift has led to integrating physical activity, sedentary behaviour, and sleep research into a unified research area called *time-use epidemiology* [12]. To progress research in this new field, a theoretical framework has been proposed called the Viable Integrative Research in Time-Use Epidemiology (VIRTUE framework) [12]. This framework encompasses five categories of research: 1) methodological research in time-use epidemiology (i.e., measurement, surveillance, data processing and analysis), 2) outcomes of health-related time-use compositions, 3) time-use compositions (i.e., optimal balance, prevalence, and trends), 4) determinants and correlates of optimal time-use, and 5) time-use interventions (Figure 1-1) [12].

To progress time-use research within this framework, capturing 24-hour time-use behaviours is the first step [12]. Accelerometers are commonly used to measure these behaviours; however, there are challenges [14]. These include the ever-growing availability of various accelerometer devices and the lack of standardised procedures to collect and analyse the accelerometer-derived data, which limit the comparability between studies [15]. Therefore, establishing the validity of available accelerometers and the comparability between different models, and developing standardised data collecting and processing procedures are critical for advancing time-use research.

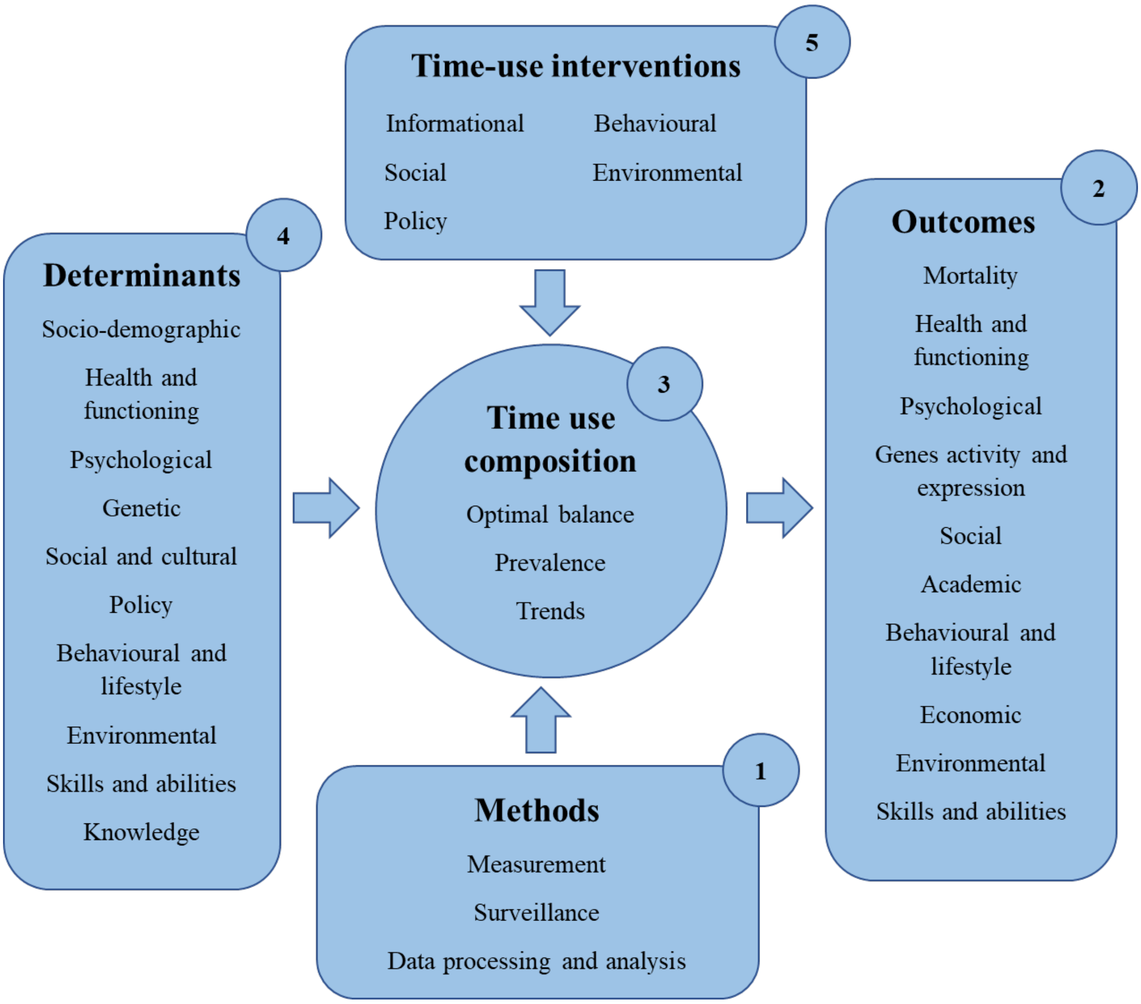

Figure 1-1. Viable Integrative Research in Time-Use Epidemiology (VIRTUE framework).

Thesis Rationale

The recent paradigm shift in behavioural research, focusing on time-use behaviours collectively within the 24-hour context, is accompanied by two challenges: 1) measuring time-use behaviours 24 hours a day, including accurately classifying each behaviour of interest, and 2) applying appropriate statistical methods that acknowledge the compositional properties of these data.

Continuous and accurate measurement of 24-hour time-use behaviours is clearly the first step for understanding the influence of time-use behaviours on health. This has been identified as the first research area within the VIRTUE framework (i.e., methods) for future research in time-use epidemiology [12]. Over the past decade, accelerometers have been commonly used to measure time-use behaviours. However, previous measurement protocols were not designed to capture the entire 24-hour day. Following the traditional measurement protocols, individuals were generally not required to wear accelerometer devices for the whole 24-hour period, but usually for 8 to 12 hours a day [16]. With the new focus on 24-hour time-use data, there has been a movement towards 24-hour wear protocols and different wear locations (e.g., wrist and thigh), which has resulted in higher compliance rates (approximately 24 hours) [15], compared to an average of 10 hours wear time in previous studies [17].

In addition to collecting time-use data for 24 hours, classifying these acceleration data into time-use behaviours is not without challenges. Count-based approaches are commonly used to categorise accelerometer-derived data into various activities based on their intensities. Here, acceleration data are converted into 'activity counts' before cut points are applied to these counts to estimate time spent in different activity intensities [14]. However, there are various sets of cut points available for different accelerometer brands, referred to as the 'cut point conundrum'. Depending on which cut-point is used, the estimate of each activity may differ, which ultimately reduces the comparability between studies [15]. More recently, machine learning techniques have gained attention for detecting various activity types from raw accelerometer data and offer promise for exploring time-use behaviours in more detail [18, 19].

The time spent in each behaviour is exclusive and exhaustive parts of a constrained whole (24-hour). Consequently, these times are co-dependent and represent compositional data in that each component carries relative information [20]. Due to these specific properties, compositional data such as time-use data should be handled with an appropriate statistical methodology, called compositional data analysis (CoDA)[13].

Using CoDA, researchers have begun to explore 24-hour time-use behaviour patterns and their collective impacts on various health outcomes in several countries within different age groups [21]. Investigating the health outcomes of time-use behaviours is outlined as the second area of research in the VIRTUE framework [12]. Preliminary evidence from these studies suggests that 24-hour time-use compositions are associated with various health outcomes in children, including obesity [21]. To date, there is limited evidence on the relationship between 24-hour time-use behaviours and obesity in New Zealand children. In reality, children engage in these time-use behaviours in a particular way (i.e., children with more of one behaviour may have less of another). Therefore, it is of importance to explore how these children's time-use behaviours cluster into distinct groups. This information may inform more specific interventions for obesity prevention among children.

Realising the importance of 24-hour time use behaviours in the health and wellbeing of children, the New Zealand Ministry of Health released a revised set of physical activity, sedentary behaviour, and sleep guidelines for children and young people. These recommendations advocate a favourable combination of sleep, physical activity, and sedentary behaviour within a given 24-hour period [22]. However, there is currently no evidence to illustrate the adherence to these 24-hour Movement Guidelines among New Zealand school-aged children and whether these time-use patterns vary among different sociodemographic subgroups. Exploring the prevalence of time-use compositions and their determinants are highlighted as the third and fourth areas of future research in the VIRTUE framework [12].

Purpose of Research

Following the VIRTUE framework, the overall goal of this thesis research was to explore how time-use behaviours were related to obesity in New Zealand children. This thesis consists of four studies covering the first four research areas in the VIRTUE framework. The specific objectives of each study are as follows:

Study 1: To investigate the accuracy of device-based measures of time-use behaviours (VIRTUE Research Area 1).

- ❖ To assess the concurrent validity of ActiGraph GT3X+ and Axivity AX3 accelerometers for measuring time-use behaviours against direct observation.

Study 2: To examine the associations between 24-hour time-use behaviours and obesity-related outcomes in children using compositional data analysis (VIRTUE Research Area 2).

- ❖ To determine the cross-sectional associations between 24-hour time-use compositions and obesity in children using compositional multiple linear regression.
- ❖ To determine the associations between reallocations of time among time-use behaviours and obesity in children using compositional isotemporal substitution.

Study 3: To explore whether lifestyle behaviours (i.e., 24-hour time-use and diet behaviours) cluster among New Zealand children and the relationships between cluster memberships and obesity using compositional analysis techniques (VIRTUE Research Areas 2 and 3).

- ❖ To determine clusters of lifestyle behaviours among children using compositional cluster analysis.
- ❖ To examine the associations between cluster membership and obesity among children.

Study 4: To determine patterns of 24- hour time-use behaviours in New Zealand children and the associated sociodemographic correlates (VIRTUE Research Areas 3 and 4).

- ❖ To describe the 24-hour time-use patterns in children, and the associated sociodemographic factors.
- ❖ To determine the proportion of children who meet the New Zealand 24-hour Movement Guidelines and the sociodemographic factors related to guidelines adherence.

Thesis Structure

This thesis consists of seven chapters, as shown in Figure 1-2. Chapter 2 includes a literature review examining the relationships between time-use behaviours and obesity in children. Chapters 3–6 are distinct publications adapted in chapter format, either published in peer-reviewed journals or under review. Lastly, Chapter 7 provides a general discussion, including a summary of key findings, overall limitations, and future directions.

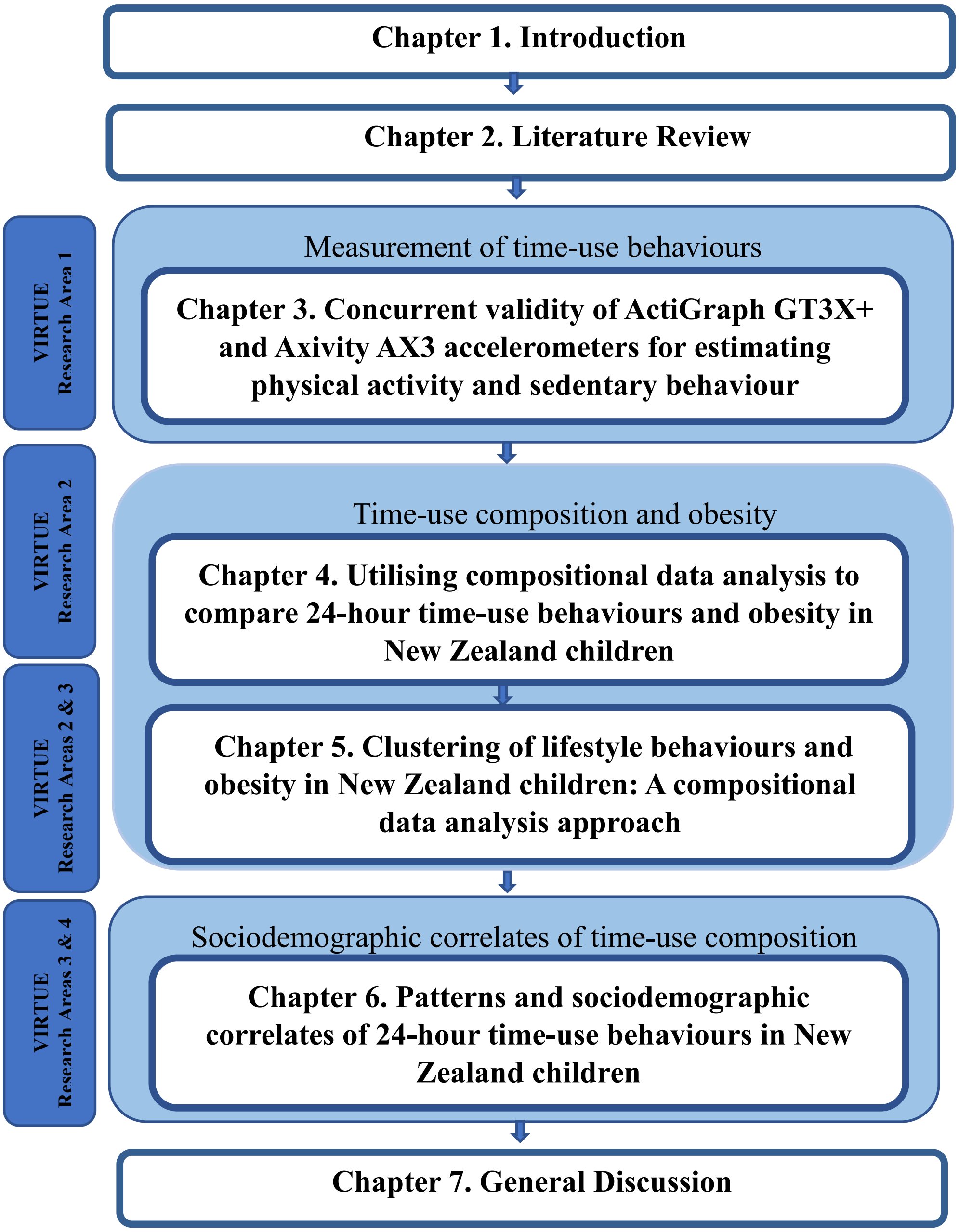

Figure 1-2. Thesis structure and flow.

Thesis Organisation

Context

This research consists of two main sections. The first section (Chapter 3) is a validation study investigating the concurrent validity of two accelerometers (i.e., Axivity AX3 and ActiGraph GT3X+) for detecting various activity intensity and activity types against direct observation. This study was conducted among 41 children and 33 adults. The ethics approval for this study was received from the AUT University Ethics Committee (17/220) (Appendix A).

The second section is divided into three studies (Chapters 4–6), which utilise data from *Growing Up in New Zealand* (GUiNZ), a birth cohort study of New Zealand children-tracking the lives of nearly 7,000 children and their families from before birth until they are young adults. This is a diverse but nationally representative sample with adequate numbers among ethnic and gender groups. This cohort study was launched in 2008 by recruiting pregnant women (estimated delivery in 2009/2010) residing in Auckland, Counties-Manukau, and Waikato District Health Boards [23]. Currently, six main Data Collection Waves (DCW) have been carried out, including Antenatal, Nine Month, Two Year, Four Year, Six Year, and Eight Year waves. The Antenatal DCW happened before the child's birth in which the pregnant mother and her partner completed a face-to-face Computer Assisted Personal Interview (CAPI), followed by another CAPI with the mother and her partner in the Nine Months DCW. The Two Year DCW (children aged two years old) included a CAPI with the parents, direct observations, and developmental and anthropometric assessments of the children. The Four and Six DCW happened when the children were four and a half and six years old, which involved interviews with the parents, child observations and biological sampling. The Eight Year DCW (children aged eight years old) included a parent online questionnaire, a child CAPI, direct child observations, developmental and anthropometric assessments, and biological sampling.

In this DCW, 24-hour time-use behaviours were measured for the first time, using a novel dual-accelerometer protocol designed and tested by the researchers at the Human Potential Centre, Auckland University of Technology. The research presented in this thesis utilises data from a sub-sample (n = 623) of the Eight Year DCW of this cohort study.

Candidate contributions

For the first section, the candidate assisted with the data collection, organised, and prepared the data (i.e., video coding and checking), analysed the data, and wrote the manuscript (Chapter 3). For the second section, the candidate prepared a project proposal outlining the objectives of the study, as well as the required datasets, which was submitted to the GUiNZ data access committee (DAC) for approval. The proposal was also presented by the candidate before the GUiNZ DAC members. Following the project approval by the DAC, the candidate completed a formal Data Access Application to access datasets for this research project (Appendix B). The candidate led the data checking, analysis procedures, results presentation, and interpretation, and writing the manuscripts (Chapters 4–6).

Chapter 2 - Literature Review

This chapter is organised into two main sections. The first section reviews the relationships between time-use behaviours and obesity in children. This section covers the individual and combined relationships between physical activity, sedentary behaviour, and sleep and obesity. Measurement of each individual behaviour is also included in the first section, whereas the second section focuses on the methods of measuring and analysing of time-use behaviours within their 24-hour context.

Health-related outcomes of time-use behaviours

Associations between individual time-use behaviours and obesity

Physical activity and obesity

A recent systematic review looked at the relationship between objectively measured physical activity (PA) and adiposity in children and youth aged 5–17 years old [8]. This review included 72 studies, of which 62 were observational (14 longitudinal, 48 cross-sectional) and 13 experimental studies. The majority of the cross-sectional studies showed consistent, favourable associations between total PA (18/22 studies), vigorous-intensity physical activity (VPA) (14/15 studies), and moderate-to-vigorous-intensity physical activity (MVPA) (26/30 studies) and at least one adiposity indicator. Relationships between light-intensity physical activity (LPA) and adiposity variables have also been explored in several studies showing equal proportions of favourable, unfavourable and null relationships (i.e., favourable associations between at least one adiposity indicator in 3/9 studies, at least one unfavourable association in 3/9 studies and null association in 3/9 studies). This review demonstrated that most of the physical activity research in children has explored the health benefits of higher PA intensities (VPA and MVPA) rather than LPA.

Accumulation of evidence on the benefits of PA on health, specifically MVPA, led to the establishment of physical activity guidelines. The physical activity guidelines are meant to deliver a simplified message to the general public regarding the health-enhancing benefits of physical activity [24]. In the late 1980s, The American College of Sports Medicine pioneered delivering such messages by issuing an opinion statement that children and youth should obtain 20–30 minutes of vigorous exercise every day for optimal health [25]; however, this statement and following guidelines [26-28] were all based on evidence linking physical activity with health risk factors in adults and not children [29]. The first child-focused physical activity guidelines based exclusively on evidence from child studies were developed in 1998 [30], recommending that children and youth should be engaged in at least 60 minutes of moderate-intensity physical activity per day. According to the current global physical activity guidelines for children and youth (aged 5–17 years old), the accumulation of at least 60 minutes of MVPA daily, including various aerobic activities, is needed for optimal health [31].

As mentioned, historically, most of the physical activity research in children has explored the health benefits of higher PA intensities (i.e., MVPA), but over the years, increased interest has been paid to LPA, which represents the majority of children's physical activity accumulated during waking hours [32]. Emerging evidence suggests that LPA may also be necessary for optimal health and disease prevention [33-35]. This evidence of the potential health benefits of all intensities of PA, including LPA, has led to a broader focus beyond only one hour of MVPA in 24 hours [8]. Accordingly, recent Canadian physical activity guidelines (as part of 24-hour movement guidelines) have included recommendations for several hours of structured and unstructured LPA in addition to 60 minutes of MVPA for children and youth [36]. This approach has been since adopted by other countries, including New Zealand [22].

There is a favourable relationship between meeting PA guidelines (60 minutes of MVPA daily) and several health indicators, including adiposity [8]. Despite this, there is concern that many children are insufficiently active worldwide, including in New Zealand [37, 38]. Only two-thirds of New Zealand children reach the recommended level of MVPA (i.e., at least 60 minutes daily) on most days of the week [39]. As a global health concern, physical inactivity (i.e., not meeting the recommended level of MVPA) is identified by the World Health Organisation (WHO) as a major modifiable risk factor for noncommunicable disease, and it is also associated with other significant health outcomes, including obesity [31]. Therefore, promoting PA in this age group is essential, but this requires accurate measurement of PA to determine the prevalence of PA and efficiency of PA intervention programmes [16].

Physical activity measurement

Accurate assessment of PA is essential for determining the prevalence of PA, and identifying the proportion of the population who meet the recommended level according to the PA guidelines. Accurate measurement is also necessary to quantify the relationships between PA levels and health outcomes and evaluate the effectiveness of physical activity intervention programmes [40]. Several methods exist to measure PA, typically categorised as subjective and objective [40]. Subjective methods are the most convenient and include self- or proxy-report questionnaires, reports or interviews, providing useful information about physical activity context, but they are prone to flaws due to low validity and biased reports [41]. Conversely, it has been demonstrated that accelerometers can provide reliable and valid objective measures of PA in children and youth. Accelerometers are now widely used in large-scale epidemiological and interventional studies for objectively assessing free-living physical activity [14]. Multiple accelerometers are available, with ActiGraph being the most commonly used device in PA research [16]. These wearable monitors provide an objective measure of frequency, intensity, and duration of physical activities by recording the acceleration of body parts to which they are attached (e.g., waist, hip, wrist) during movement [42]. Accelerometers can detect acceleration in different planes of movement; one (uniaxial), two (biaxial) or three (triaxial) [40]. Although recall bias is not an issue when assessing PA by accelerometers, there are methodological challenges related to accelerometer data collection and analysis [16].

The validity of objective estimates of PA using motion-based accelerometers (e.g., ActiGraph and Actical) might be constrained due to technical-related shortcomings, significant non-wearing time, non-objectivity and choice of intensity cut-points [43]. Technical shortcomings such as the inability of hip- or wrist-worn accelerometers to capture activities such as cycling [44] and water-based activities might result in underestimating physical activity. Additionally, studies using accelerometers have reported low wear-time compliance, potentially resulting in missing data, producing a picture that may not represent an individual's habitual physical activities [45]. Another issue with using accelerometers is non-objectivity; objective measurement of acceleration by accelerometers is supposed to be independent of human-related factors. However, individuals in free-living settings can interfere with the outcome by not wearing the device deliberately, changing their routine behaviour, changing device placement or shaking the device [43] .

While using accelerometers to access PA, methodological decisions made by researchers before and after data collection may drastically change the outcome. These decisions include determining data collection interval (epoch length), non-wear criteria, defining a valid day, specifying a minimum number of valid days for a valid dataset, choosing intensity cut-points, and algorithms [46]. Differences between studies in these decisions may lead to variabilities in results and mislead research [47]. For example, children and youth accelerometer-derived estimations of PA intensities can be significantly affected by epoch lengths; however, this may not be an issue when total accumulated PA per day is the outcome of interest [48]. Six different epoch lengths have been used in children and youth studies, varying from 2 to 60 seconds, with the majority using a 60-second epoch [16]. For example, based on 401 adolescents, Aibar et al. (2014) compared the impact of different epoch lengths ranging from 3 to 60 seconds for estimating PA intensities (using the ActiGraph GT3X). They indicated that using shorter epochs resulted in higher estimation of MVPA, consequently, higher compliance with PA guidelines (40.7% for 3-second vs 24.4% for 60-second epoch lengths), which potentially creates errors when studies using different studies epoch lengths are compared [49]. Similarly, another study reported that longer epoch length (e.g., 60 sesonds) provided smaller estimates for higher intensities PA (i.e., MPA, VPA, and MVPA) compared to shorter epoch lengths [50].

Non-wear time is the duration of time when the accelerometers are removed for specified reasons (i.e., sleeping, showering, or being involved in water-based activities) or for no reason. Non-wear duration can be determined by adding up the number of consecutive zero counts, and then wear time can be calculated by subtracting non-wear time from the total amount of time [16]. Non-wear time is not included in the final analysis, assuming the remaining wear time is representative of the entire measurement duration. The ideal non-wear criteria may differ based on the type of accelerometer and the study population due to having diverse PA and sedentary time patterns [51]. Six different non-wear definitions have been reported, ranging from 10 to 180 minutes of continuous zero counts, with 10–20 minutes criteria most common in children and youth studies [16]. The choice of non-wear time criteria affects the estimation of the level of PA. For example, in a sample of 891 11-year-old children, Aadland et al. (2018) compared ten different definitions of non-wear time (i.e., 10, 20, 30, 45, 60 and 90 minutes of consecutive zero counts without allowance of interruptions, and 60 and 90 minutes with allowance of 1 to 2 minutes of interruptions). They found that non-wear criteria influenced estimation of total PA (10% difference, 591 to 649 counts per minute), but estimates for time spent in different PA intensities were similar between different criteria [51].

Variability in defining non-wear time may also have an impact on the number of valid days; for example, it was reported that the number of participants having four valid days (minimum of 10 hours of daily wearing time) differed from 38% to 84%, using 10 minutes or 60 minutes of consecutive zero counts criteria to calculate non-wear time, respectively [52]. A possible solution to overcome ambiguity surrounding non-wear time is using skin-taped accelerometers with an inbuilt skin temperature sensor such as the Axivity AX3, with which wear time is estimated based on the temperature readings [53].

Other accelerometer-derived data processing decision rules are to determine the minimum number of daily wearing hours for a valid day to be representative of a typical day and the minimum number of wearing days for reliable and valid data showing habitual PA levels of individuals [54]. Regarding the definition of a valid day, 12 different criteria have been used in children studies ranging from 6 to 12 hours, with a minimum of 10 valid hours of wearing as the most commonly used criteria [16]. These decisions ultimately affect the reliability of the physical activity level obtained [16].

While processing accelerometer-derived data, detected raw acceleration data are converted into dimensionless units called "counts" using proprietary algorithms and then are summed over a user-specified period, known as epoch (e.g., 1, 10, or 60 seconds) [14]. Subsequently, cut-points are applied to these counts to distinguish between different PA intensities. Generally, these cut-points have been determined based on calibration studies [14]. Referred to as the "cut point conundrum"[55], there are various and often conflicting sets of cut points to estimate the amount of MVPA, LPA and sedentary time, reducing comparability across studies [56]. Diversity in using different PA intensity cut-points can lead to inconsistencies between findings; for example, the results from the National Health and Nutrition Examination Survey comparing five different child-derived cut points showed that the choice of PA intensity cut-points can influence the proportion of individuals who meet the PA guideline, as well as the relationship between PA and various health outcomes [57]. Additionally, in a study by Carson et al. (2013), a positive association was observed between high LPA cut-points (800 counts/min) and cardiometabolic biomarkers, but not with low LPA cut-points (100–799 counts/min) [33]. The lower cut-point thresholds may not accurately differentiate between LPA and sedentary behaviours, producing inconsistent findings. To address the limitations of cut-point thresholds, applying machine learning or pattern recognition methods on raw accelerometer data is increasingly used as an alternative approach, providing high accuracy for recognition of PA type and intensities [58]. Accelerometers such as ActiGraph GT3X+ and Axivity AX3 can record raw acceleration data [59, 60]. Shifting from a count-based approach to extracting features from raw-data accelerometers will increase researchers' control over the steps involved in processing accelerometer-derived data [61].

Sedentary behaviour and obesity

Although engaging in 1 hour of MVPA daily is beneficial for health, it accounts for a small proportion of the 24 hours. Within the remaining 23 hours, children and youth spend a considerable amount of their waking hours (about 50–60%) in sedentary behaviour (SB) [62, 63]. There is growing support for the importance of limiting sedentary behaviour, particularly screen-based activities for health promotion and disease prevention in children [9]. According to the recent Sedentary Behaviour Research Network (SBRN)-Terminology Consensus Project, SB is referred to any waking behaviour with an energy expenditure of ≤1.5 METS in a sitting, reclining or lying position [64], and is characterised by the SITT formula; Sedentary behaviour frequency (number of bouts with specific duration), Interruption (breaks), Time (period of sitting), and Type (mode of sedentary behaviour such as watching TV, computer, video games) [65]. An occupational physician first noticed an unfavourable relationship between SB and health outcomes in the 17th century [66]. However, a proliferation of research on the health outcomes of SB has been seen from nearly two decades ago [12], when researchers started to treat SB as a separate and distinct construct from physical inactivity (i.e., insufficient level of MVPA) [67-69]. Accumulating evidence suggests that engaging in SB is associated with poor physical and psychological health status in both adults and children, which has been demonstrated to be statistically independent of the level of MVPA [70-72]. As sedentary behaviour habits in the paediatric population tend to persist in adulthood [73], determining safe and healthy amounts of these behaviours is essential, especially in children.

The association between SB and adiposity in children has been primarily examined, with the majority focusing on screen-based sedentary behaviour, particularly TV viewing [74]. One of the first studies in 1985 by Dietz and Gortmaker investigated the health outcomes of watching TV. This landmark study recognised watching TV as a potential risk factor for obesity in children and adolescents. Using two cross-sectional and one longitudinal sample of children and adolescents, an association was observed between obesity (defined as a triceps skinfold equal or greater than 85th percentile) and time spent watching TV in both study designs. It was reported that obesity prevalence was the highest among adolescents aged 12–17 years who had watched TV for 5 hours or more daily at age 6–11 years old. However, it was acknowledged that TV viewing only accounted for a small proportion of the variance of childhood obesity [75]. More recently, another study with over 1000 children aged 5–15 years old from New Zealand supported these findings by showing a positive prospective relationship between weekly hours of television viewing and BMI status in adulthood [76].

In a review by Tremblay et al. (2011), a total of 152 observational studies (119 cross-sectional and 33 longitudinal) and 18 experimental studies (8 randomised control trials (RCTs) and 10 other interventions) have examined the relationships between SB and various measures of body composition (i.e., body mass index (BMI), body fat percentage (BF%), the sum of skinfolds, waist circumference (WC)). The majority of the observational studies (about 75%) reported a significant positive relationship between sedentary time (particularly time spent watching TV) and higher BMI, weight status, or fat mass and increased risk for being overweight or obese. Meta-analysis of the RCTs showed that a decrease in sedentary time led to a mean reduction in BMI of -0.89 kg/m^2 (95% CI = -1.67, -0.11, p = 0.03) [71]. However, most of the included studies used subjective measurements of sedentary behaviour (i.e., self-report or proxy report), which are prone to bias [77]. Carson and colleagues conducted similar systematic reviews to Tremblay et al. (2011) in a five-year update. They found 162 new studies (157 observational and 5 experimental) [9] that had examined the association between SB and body composition. In agreement with Tremblay and colleagues' findings, this review indicated a significant unfavourable relationship between higher duration of screen time and TV viewing and body composition measures across all the study designs. This review provided updated information for recent Canadian sedentary behaviour guideline, integrated with other guidelines (i.e., sleep and physical activity), forming the 24-hour Movement Guidelines [36].

A recent systematic review of reviews has been conducted to analyse the links between SB and adiposity or weight status [78]. Based on the evidence from cross-sectional studies, a small relationship was reported between self-reported TV viewing, screen time (i.e., a combination of TV viewing, video game/computer use), and adiposity in children and youth. However, reviews on the association between computer usage and adiposity reported mixed findings, with some reporting an association [79], while others did not [80, 81]. Although TV viewing or screen-based entertainment is the most favourable sedentary behaviour during leisure time, it is not necessarily an appropriate proxy of total sedentary time in other contexts such as sitting time in school or passive commuting [82].

Since the advent of wearable technology such as accelerometers, the research focus has been expanded from screen-based sedentary behaviour to total sedentary time. Several studies have examined the association between accelerometer-derived total sedentary time and body composition. Although these studies' findings primarily show a null association between total sedentary time measured using accelerometers and body composition [9, 71, 78], it is essential to note that the findings of these studies need to be interpreted with caution due to methodological issues. More specifically, using a regression model to examine the relationship between total sedentary time and body composition while adjusting for physical activity might produce inaccurate results [20] as this model assumes independence between sedentary time and physical activity. Recent evidence indicates that time spent in time-use behaviours, including physical activity, sedentary behaviour, and sleep, is interdependent. A recent study among Canadian children aged 6–17 years old used compositional data analysis instead of traditional regression analysis to address this issue. A positive association between sedentary time and obesity markers was reported [83]. Therefore, studies with novel analytical approaches such as compositional data analyses, compatible with the interdependent components of 24-hour time-use behaviours, are needed to provide further insights into this association.

It appears that the association between SB and health outcomes is being influenced by the way that sedentary behaviour is measured [84]. Until recently, hip-mounted accelerometers (e.g., ActiGraph) were the most commonly used device to objectively measure sedentary time [82]. However, these accelerometers may not be sensitive enough to differentiate between sitting and upright postures with restricted movements, such as passive standing [85, 86] potentially having significant impacts on the relationship between SB and health outcomes.

Sedentary behaviour measurement

Earlier studies have frequently used subjective methods to quantify sedentary time, such as self- or proxy-reported screen time [71]. However, this approach may not accurately represent total sedentary time, given that screen time is only a sub-component of total SB [84]. For example, it was shown in a nationally representative survey of 2,200 children aged 9–16 years old that only 60% of total sedentary time was allocated to screen time, with a moderate correlation between screen time and total sedentary time ($r = 0.53$), illustrating that screen time may not be an appropriate proxy of total sedentary time [87]. Although subjective measures of SB have been preferred in large-sample studies due to their practicality, low costs and burden, these self-reported measurements of SB may introduce errors and bias. Conversely, objective measures may provide more reliable and valid estimates of SB [88].

Objective measurements of SB have increased in recent years using two devices, including energy expenditure devices and posture classification devices. While most of these devices are based on the same underlying technology (accelerometry), data are interpreted using different algorithms to estimate energy expenditure or body posture [88]. Accelerometers such as ActiGraph GT3X are an example of energy expenditure devices. This small triaxial accelerometer measures human movement by recording acceleration in three orthogonal planes using vertical, horizontal, and perpendicular axis within user-determined periods (epoch) at different sampling frequencies (e.g., 30 Hz). These data are then converted into counts via proprietary algorithms and software [88]. Generally, the amount of sedentary time is determined using a threshold of fewer than 100 counts per minute, which corresponds to energy expenditure levels of sedentary behaviour (≤1.5 METs) [88]. While providing valid and reliable estimates of PA, there are issues in using these waist/hip-mounted accelerometers for measuring SB as they estimate sedentary time based on lack of movement using cut-point protocols rather than posture [89], which is not congruent with the conceptual definition of sedentary behaviour by SBRN - any waking behaviour with an energy expenditure of ≤1.5 METs in a sitting, reclining or lying position [64]. Using a cut-point based approach, a study showed 0% accuracy for ActiGraph GT3X in distinguishing standing from sitting, misclassifying 100 % standing time as sitting [90]. Additionally, it has been demonstrated that different cut-points might influence the association between SB and health outcomes [91]. Alternatively, posture-based accelerometers such as activPAL, a small and thigh-worn monitor, which are equipped with an inclinometer, appears to be an accurate monitor to estimate SB defined by posture [89]; however, it fails to account for the energy expenditure component of the SBRN sedentary behaviour definition (i.e., less than 1.5 METs) [92]. Accelerometer-derived information about acceleration and thigh position are used to determine body posture and transition between postures using proprietary algorithms [93]. A laboratory-based study in school-aged children found a perfect correlation (r = 1.00) between direct observation and activPAL in time spent sitting/lying, standing and walking, and an approximately perfect correlation (r = 0.99) in posture transition (i.e., sit-to-stand and stand-to-sit) [94]. Energy expenditure or posture-based accelerometers are specialised to measure one component of SB, highlighting the need for measurement tools that can simultaneously provide information about both dimensions of SB (i.e., posture and energy expenditure). Notably, no single device is capable of measuring both components [95]. However, a novel technique called the "multi-method" approach integrating data from multiple accelerometers (i.e., energy expenditure and posture-based monitors) have shown to provide a more accurate measure of SB [96] and physical activity intensities [97]. Furthermore, in a recent laboratory-based study using Axivity AX3 accelerometer to classify PA and SB, dual accelerometers (one attached to the lower back and one on thigh) showed greater accuracy in classifying SB than a single one back or thigh accelerometer [19].

Regardless of whether energy-expenditure or posture classification devices are used to measure sedentary time objectively, it is likely that error is introduced at any stage of the data generation process from the initial steps in measuring raw acceleration through the use of algorithms to decisions on criteria such as cut-points, the definition of non-wear time, a valid day of wear and determining the minimum number of days for a valid data set [88]. While processing accelerometer data, non-wear time is detected and eliminated based on continuous zero counts, which can occur for various reasons, including legitimate removal of the accelerometer (e.g., showering, sleeping) or without any reason (i.e., non-compliance) and prolonged sitting time, making it difficult to accurately discriminate between non-wear time and wear time [98]. This issue leads to biased estimation of sedentary time, as shown in a study by Choi et al. (2011) that 50 minutes of misclassification of wear time as non-wear time resulted in underestimating sedentary time by 8 % [98].

Sleep and obesity

Sleep is defined as a natural and reversible rest state of body and mind. It occurs due to inhibition of sensory activities and voluntary muscles, reduced engagement with surroundings and consciousness [99]. It has been argued that sleep is as critical for health as physical activity and diet [100]. Sleep duration may lead to obesity through mechanisms affecting energy intake and energy expenditure [101]. Reduced sleep duration might lead to increased energy intake due to hormonal imbalances or more time to eat, especially if this time is replaced by sedentary activities such as watching TV, during which snacking is common [102]. Accordingly, the Canadian 24-hour Movement Guidelines recommend 9–11 hours of nightly sleep for children aged 6–13 and 8–10 hours of sleep for adolescents aged 14–17 years old to maximise health benefits [36].

A recent systematic review by Chaput et al. (2016) included a total of 71 (70 observational and 1 experimental) studies that examined the relationship between sleep duration and adiposity in school-aged children and youth [10]. The only randomised controlled trial with 37 children aged 8–11 years old found that an experimental increase of children's nightly sleep duration led to a lower weight after three weeks of intervention (mean difference in weight of 0.24 kg, $p<0.001$)[103]. There was 141 minutes difference between accelerometer-derived sleep duration between the increase and decrease conditions, 10.5 h vs 8.1 h sleep hours, respectively. Among the longitudinal studies, 7 out of 12 studies reported a significant negative association between short sleep duration and adiposity gain, while the remaining studies reported a null association. Only three of the included longitudinal studies (2 unique samples) used an objective assessment of sleep duration [104-106] and reported mixed findings. Hjorth et al. (2014) found no prospective association between accelerometer-derived sleep duration, fat mass index (FMI) and WC over a 200-day follow-up period of children aged 8–11 years old [105, 106]. In contrast, another study found that compared to children with 7.5–9 hours/night or ≥9 hours/night sleep, children with ≤7.5 hours of sleep at age 6–12 years old had higher body weight in early adolescence (5 years later) ($p<0.01$). Furthermore, children with ≤7.5 hours of sleep had higher odds of being obese (≥95th BMI percentile) at follow-up than children who slept ≥9 h/night (OR = 3.3, 95% CI = 1.09, 9.66, $p<0.05$) [104]. In this study, sleep duration was assessed by PSG for a single night only, and these estimates were not adjusted for PA, SB, or diet.

Another longitudinal study with objectively-measured sleep duration (not included in the above-mentioned systematic review) reported that each additional hour of nightly sleep in children aged 3–5 years old was associated with a 0.56 kg/m^2 reduction in BMI at age 7. However, the association was no longer significant once analyses adjusted for diet and physical activity (p=0.053) [107]. This study also showed that each extra hour of sleep at ages 3–5 resulted in a reduced risk of being overweight (BMI ≥85th centile) by 0.39 (0.24–0.63) while adjusting for various confounders, including physical activity and fruit/vegetable intake. Among the cross-sectional studies included in the previous systematic review, 50 out of 58 studies reported a significant association between short sleep duration and adiposity, while eight studies reported no association. However, relatively few studies used objective measurement of sleep (i.e., accelerometry). Sleep duration was negatively associated with BMI in 6–10-year-old Swedish children (r = -0.085, p<0.01) [108], and FMI in 8–11–year–old Danish children (r = -0.17, p<0.001) [105]. In contrast, the study on 507 Canadian children 9–11 years of age reported that the relationship between sleep duration and BF% was no longer significant after adjustment for MVPA and total sedentary time [109]. Overall, the authors of the most recent systematic review of the association between sleep duration and adiposity in children and youth found a consistent relationship between longer sleep duration and lower adiposity markers. However, the quality of evidence was low as most of the studies have used subjective assessment of sleep [10].

In addition to sleep duration, there is growing evidence that other sleep characteristics, including sleep timing, quality, and variability, may also be necessary for optimal health [110]. Recent evidence found that sleep timing (i.e., the combination of wake up and bedtime) is associated with an unfavourable weight status profile and lower level of physical activity [111], as well as poor diet quality [112] in children, independent of sleep duration. More specifically, children who went to bed late and woke up late were 2.16 times more likely to be obese and 1.77 times more likely to have low MVPA [111], and had lower diet quality ($p<0.001$) [112] compared to those who went to bed early and woke up early. Likewise, results from a recent study involving 439 children aged 9–11 years old from New Zealand showed that children with a later sleeping timing were less active and had a poorer diet than children with an earlier sleeping time. Those children with a late sleep and late wake schedule had lower weekly consumption of fruit and vegetables (-2.9, 95% CI = -4.9, -0.9, $p<0.05$) and higher consumption of sweetened beverages (1.8, 95% CI = 0.2, 3.3, $p<0.05$) compared with those in the early sleep/early wake category. In addition, children in the late sleep and late wake group accumulated fewer minutes of MVPA per day than those in the early bedtime and early wake group (-9.4, 95% CI = -15.3, -3.5, $p<0.05$) [113].

Sleep measurement

Polysomnography (PSG) is the most reliable method (gold standard test) for measuring sleep, which is a multi-parametric test measuring biophysiological parameters of sleep [95]. However, its application is limited to small population studies due to high costs, being time-consuming, and burden to the participants [114]. While PSG remains the gold standard for assessing sleep and diagnosing sleep-related disorders [115], a limitation is that one-night PSG may not represent habitual sleep. On the other hand, sleep diaries are more feasible and cheaper for measuring sleep duration over multiple days in large-scaled population research, yet are subject to recall bias [116]. There has been an increase in the development and use of accelerometers over the last decade for the measurement of sleep [117, 118]. These affordable, non-obstructive wearable devices are recognised as a valid method to measure sleep [119]. However, the lack of standardised accelerometer-related methodological decisions including device selection, device placement, and classification techniques remains a challenge for quantifying sleep-related behaviours, particularly beyond simple ‘sleep duration’ measures [46, 120].

There is still controversy regarding the best device placement for measuring sleep using accelerometry. Findings from a recent study comparing ActiGraph GT3X+ and Actical wrist and hip worn accelerometers for sleep in children, suggests that there may not be a single best placement for detecting all sleep variables (i.e., sleep quantity and sleep quality metrics) [121]. While ActiGraph GT3X+ placed at the hip outperformed the more traditional wrist placement for estimating sleep duration, the wrist positioned was superior for sleep quality metrics including sleep efficiency [121].

There are several proposed sleep detection algorithms for estimating sleep-related behaviours in children depending on the placement of the accelerometer. It has been recommended that the Tudor_Locke algorithm [122] to be applied for the hip placement and Sadeh algorithm [123] for the wrist [46].

Recently, it has been shown that machine learning techniques applied to raw data from Axivity Ax3 accelerometers were capable of classifying sleep with 97% accuracy in adults [124]. In another recent study sleep classification technique have been developed for waist-worn ActiGraph accelerometer in preschool-aged children using machine learning methods, which has shown a high accuracy (96%) for quantifying both day and night sleep [125] .

The shift towards 24-hour time-use composition

Within a 24-hour period, individuals spend their time sleeping, in sedentary behaviour (e.g., watching TV), quiet standing or physical activity [12]. Time spent in these daily activities are compositional by nature as they are : 1) components of a finite total (i.e., 24-hour day or any other fixed period of time), so total time spent daily in MVPA, LPA, sitting and sleeping is always equal to 24 hours, 2) mutually exclusive components of a 24-hour period, so an individual can only spend time in one of these activities at the same time [13]. These components of time use are perfectly collinear, which means that due to the closed nature of a 24-hour period, any change in the total amount of time spent in one of these activities causes an opposite change in the total amount of time spent in one or all of the remaining activities [12].

However, traditionally, researchers tend to examine the relationship between time spent in each of these time-use behaviours throughout the day and health in isolation, or with partial adjustment for remaining behaviours (using traditional statistical methods), ignoring the co-dependency of all these time-use behaviours [20]. For example, in an analysis of 54 cohort studies on the health impacts of sedentary behaviour, it was reported that none of the reviewed studies adequately adjusted for total physical activity (MVPA and LPA) and sleep duration [11].

Additionally, in a recent systematic literature review on the relationship between combinations of time-use behaviours and various health outcomes [126], it was revealed that most of the included studies assessed combinations of two time-use behaviours (typically PA and SB, excluding sleep), and only four studies (three unique samples) examined combinations of all three time-use behaviours [105, 106, 109, 127], with one study focused on screen time (not total sitting time) [127], and the other three focused on MVPA (not total PA including LPA) [105, 106, 109]. One of these studies study involving

507 Canadian children aged 9–11 years old reported that %BF was 9.3% ($p<0.05$) lower among children in the higher tertile for MVPA, lower tertile for SB, and higher tertile of sleep, compared with children in the opposite group [109]. Similarly, in another study of 785 Danish children (8–11 years old), those with a healthy pattern of time-use behaviours (higher quartile of MVPA, lower quartile of SB, higher quartile of sleep) had 3.44 units lower FMI ($p<0.001$) compared with children with unhealthy time-use patterns (lower quartile of MVPA, higher quartile of SB, lower quartile of sleep)[105]. However, findings of these studies in which time spent in each time-use behaviour were studied in isolation or with partial adjustment for time spent in the remaining behaviours (i.e., MVPA and screen time) using traditional regression (not compositional data analysis) are potentially biased due to not acknowledging the collinearity of 24-hour daily time-use behaviour components.

Emerging methodological advances have encouraged research on the amount of time spent in daily activity behaviours including sleep, sedentary behaviour, and physical activity (LPA and MVPA) as health-related components of time-use. These advancements have being integrated into a novel field of public health research known as time-use epidemiology [12]. This is defined as the study of determinants, incidence, prevalence and effects of health-related time-use patterns in populations and ways to prevent unhealthy time-use patterns [12]. Time-use epidemiology covers sleep, physical activity, and sedentary behaviour research, but not necessarily all the topics such as physical activity policy, attitudes towards physical activity, and sleep disturbances. In addition to daily activity behaviours, other time-use variables in relation to health such as family/peer time, housework, and leisure time are also being incorporated in time-use epidemiology.

Proposing the Activity Balance Model (AB model), Pedisic (2014) called for an integrative approach whereby researchers in behavioural epidemiology should investigate the relationships between time-use behaviours and health by studying the health impacts of time spent in PA, SB and sleep collectively rather than in isolation [11]. In this paradigm, a composition of time spent in each of the time-use behaviours are treated as explanatory variables and health outcomes are considered dependent variables, with the possibility of adjusting for potential confounders where necessary. Besides emphasising an integrated approach, the author of this paper also highlighted the necessity of using appropriate statistical analysis (i.e., compositional data analysis) for these perfectly collinear time-use data with compositional properties.

Recently there has been a shift towards a new paradigm in which all components of time-use behaviours are considered as a 24-hour composition rather than individual domains. Acknowledging the compositional nature of 24-hour time-use behaviours, this approach may improve the understanding of how these behaviours may concurrently relate to health outcomes. In response to this paradigm shift, a limited number of studies in children have assessed collective effects of physical activity (LPA and MVPA), sedentary behaviour (total sitting time with or without screen time), and sleep on various outcomes including body composition using compositional data analysis [32, 83, 128-131]. Carson et al. conducted a study among children aged 6–17 years old [83]. They found that the proportion of time spent in MVPA and sleep was negatively associated. In contrast, the time spent in LPA and sedentary behaviour was positively associated with BMI and WC ($p<0.05$). In a similar study (3–4 years old pre-schoolers), a significant association was found between the composition of time-use behaviours and BMI but not with WC. Further, in contrast with the older age group, no association was observed between each component relative to the time spent in other components [128]. In both studies, PA and SB were measured objectively with an accelerometer, while sleep was self or parent-reported.

In an analysis of data from the International Study of Childhood Obesity, Lifestyle and the Environment among children aged 9–11 years old from 12 countries, participants with similar behavioural characteristics were categorised into four clusters named Junk Food Screenies, Actives, Sitters, and All-Rounders, using compositional cluster analysis. Children with highest sedentary time and lowest PA (Sitters cluster) were shown to have the highest BMI, largest waist-to-height ratio and BF%, compared with participants in the Actives cluster who had the lowest BMI [131] . However, a key limitation of these studies is using hip-mounted accelerometers (i.e., ActiGraph or Actical) in measuring 24-hour time-use behaviours, which may contribute to biased estimate, given the poor accuracy of these devices in differentiating between postures (sitting vs. standing still) [83].

Advocating this paradigm shift towards 24-hour time-use behaviours, Canada pioneered the 24-hour Movement Guidelines for children and youth, which integrated the previous separated guidelines for each behaviour [36]. This has been followed by other countries, including New Zealand [22]. These guidelines contain integrated recommendations on daily amounts of moderate-to-vigorous physical activity (MVPA) (at least 60 minutes), screen time (not more than 2 hours), and sleep (9–11 hours for 5–13-year-old children and 8–10 hours for those aged 14–17-year-old) for optimal health and wellbeing in children aged 5–17 years old [22]. Several studies have examined the adherence to these guidelines among children in different countries and the associated sociodemographic correlates [132-136]. However, currently, there is no comprehensive evidence on the prevalence of meeting these guidelines among New Zealand school-aged children and the associated sociodemographic factors.

Methods of measuring and analysing time-use behaviours

Measurement of 24-hour time-use behaviours

Traditional waking-hour accelerometer protocols required an individual to wear an accelerometer while awake and remove it at bedtime; however, missing data during non-wear time may not provide an accurate representation of 24-hour time-use behaviours. Alternatively, 24-hour monitoring protocols (i.e., wearing accelerometers continuously) eliminate issues with non-wear time and may offer a more accurate measure of daily activities within 24 hours [17, 20]. Compared to waking hour protocols, a 24-hour accelerometer protocol may result in higher compliance [45], reducing the need for arbitrary decisions to identify non-wear time duration. Measuring 24-hour time-use behaviours is difficult, and this challenge might be a reason for the lack of studies on the impacts of combinations of 24-hour time-use behaviours on health. The emergence of water-proof accelerometers such as ActiGraph GT3X and Axivity AX3, which can be worn continuously without the need of removal while bathing or playing water sports, is of great importance in achieving 24-hour monitoring.

In addition to 24-hour monitoring, accurate estimates of 24-hour time-use behaviours are needed to capture actual daily activities. Recent technological advances have seen the release of the Axivity AX3, the smallest research-grade physical activity monitor capable of collecting raw acceleration information [137]. When attached to the thigh and lower back, it has been shown that these devices can precisely classify various activity types in children (e.g., sitting, standing, lying, walking, running) [19]. An inbuilt temperature sensor removes the ambiguity surrounding sensor use and wear time compliance and allows the development of robust sedentary behaviour profiles [138].

Analysis of time-use data

Compositional data analysis (CoDA) proposed by Aitchison [139] has been used in various scientific fields such as geology, chemistry and nutritional epidemiology to study data that is compositional in nature: data that are proportions of a whole [140]. Compositional data have three key properties: 1) they are scale invariant (the analysis results remain the same regardless of the scale in which the components are being expressed, 2) they show sub-compositional coherence (the relationship between each components remains regardless of including or excluding other components), and 3) they are permutation invariant (the results remain the same regardless of which sequence the components are being reported) [141]. Due to constant-sum constraints of compositional data, all components of a compositional dataset are codependent on each other and therefore convey relative information. This is why traditional statistical methods, which are intended for absolute values cannot be used [13]. Therefore, CoDA is a more fitting statistical approach to deal with this type of data such as time-use data by respecting their relative nature [142].

Through this statistical approach, compositions (representing data in a simplex data space with absolute values) are expressed as sets of log-ratios (representing data in a real space that are infinite and can take any value). Then these transformed data can be analysed using any traditional statistical methods including regression models [142]. There areeveral algorithms for log transformation of compositional data such as additive log-ratio (alr), cantered log-ratio (clr), and isometric log-ratio (ilr) transformations [143]. The ilr transformation is most commonly used which preserves all metric properties of data [143].

Although CoDA is the best-suited statistical approach for analysing time-use data and is being increasingly used in time-use research, there are challenges that remain [13]. One of the main challenges of CoDA is dealing with zero values in the compositional parts since the log-ratio transformation cannot be applied to zero [144]. There are three replacement methods to address zero problems in time-use epidemiology including simple, multiplicative, and log-ratio Expectation-Maximization (lrEM) [145]. The lrEM method has been shown to outperform the other replacement methods, which preserves the relative structure of time-use data [145]. Another challenge of CoDA is the interpretation of results. This is because the statistical analyses are applied to log-transformed data, making it difficult to interpret the results which are expressed on a log-scale [140].

Different compositional techniques have been developed, including compositional multivariate analysis of variance (MANOVA): to compare compositions across groups [146], compositional isotemporal substitution: to test predicted changes in an outcome after reallocation of time [147], compositional linear regression models: to examine general associations between a composition and outcome (and vice versa) [142], and compositional cluster analysis: to examine how time-use data can be organised into distinct groupings [131, 148]. A further disadvantage of using CoDA analysis methods is the composition of time use behaviours is comprised of the time spent in various behaviours (e.g., minutes per day). This means that current research has been unable to capture the relationship between other variables that are not duration-based. For example, multi-dimensional sleep health variables (e.g., sleep quality measures) are generally not included as part of a composition, only sleep duration.

Chapter 3 - Concurrent validity of ActiGraph GT3X+ and Axivity AX3 accelerometers for estimating physical activity and sedentary behaviour

Preface

Following the Research Area 1 within the VIRTUE framework (measurement and methods), this chapter explores the validity of AX3 and GT3X+ accelerometer for measuring time-use behaviours in terms of activity intensity and activity types in children. The full paper from this chapter is currently published in the March 2021 issue of the *Journal for the Measurement of Physical Behaviour*.

Abstract

Background: Accelerometers are commonly used to assess time-use behaviours related to physical activity, sedentary behaviour, and sleep; however, as new accelerometer technologies emerge, it is important to ensure consistency with previous devices. This study aimed to evaluate the concurrent validity of the commonly-used accelerometer, ActiGraph GT3X+, and the relatively new Axivity AX3 (fastened to the lower back) for detecting physical activity intensity and body postures when using direct observation as the criterion measure.

Methods: A total of 41 children (aged 6–16 years) and 33 adults (aged 28–59 years) wore both monitors concurrently while performing 10 prescribed activities under laboratory conditions. GT3X+ data were categorised into different physical activity intensity and posture categories using intensity-based cut points and ActiGraph proprietary inclinometer algorithms, respectively. AX3 data were first converted to ActiGraph counts before being categorised into different physical activity intensity categories, while activity recognition models were used to detect the target postures. Sensitivity, specificity, and the balanced accuracy for intensity and posture category classification was calculated for each accelerometer. Differences in balanced accuracy between the devices and between children and adults were also calculated.

Results: Both accelerometers obtained 74% to 96% balanced accuracy with the AX3 performing slightly better (~4% higher, $p<0.01$) for detecting postures and physical activity intensity. Error in both devices was greatest when contrasting sitting/standing, sedentary/light intensity, and moderate/light intensity.

Conclusions: In comparison with the GT3X+ accelerometer, AX3 was able to detect various postures and activity intensities with slightly higher balanced accuracy in children and adults.

Introduction

Time-use behaviours related to physical activity, sedentary behaviour, and sleep are associated with a number of important health outcomes in children and adults, including adiposity, cardiometabolic health, and cardiorespiratory fitness [21]. Accelerometers are currently the preferred method of assessing these behaviours in free-living settings. As there are many types of accelerometers available, it is of importance to investigate the comparability between different devices. The ActiGraph GT3X+ accelerometer is one of the most commonly-used motion sensing devices to assess physical activity and sedentary behaviour in epidemiological research, particularly when worn on the hip [59], and it is consequently often utilised in investigations of sensor-based time-use [149, 150]. Using the ActiGraph system, 'counts' are translated into different physical activity intensity categories using cut-points [14]. Count-based approaches can result in all non-ambulatory activities (i.e., lying, sitting, and standing still) being classified as sedentary behaviour [151]. This may confound the assessment of the health-related effects of these non-ambulatory activities [20, 152], highlighting the importance of the accurate differentiation between activities for understanding the true relationships between time-use behaviours and health.

The addition of an inclinometer feature to the GT3X+ accelerometer makes it possible for the data to be characterised as lying, sitting, standing and device removal [153]. This development may provide richer information on daily time-use activities by estimating both activity intensity (based on activity counts) and posture (based on inclinometer information) simultaneously. Methodological shortcomings include a typically low compliance rate when placed on the hip (~10 hours per day)[17], lack of waterproofing, and difficulty differentiating between non-wear time and a true sitting time [51]. The Axivity AX3, on the other hand, is a relatively new accelerometer that is waterproof, has a temperature sensor (which can help to remove the ambiguity around wear time estimation), and appears to result in reasonable wear time compliance (median of 168 hours/week in adults, and 160 hours/week in children) when taped directly to the skin [53, 138]. The AX3 has demonstrated relatively high accuracy in detecting activity and postures in children and adults using machine learning techniques [19, 154].

The AX3 has been attached to the lower back (and thigh) in several recent studies to assess physical activity, including the large HUNT4 cohort study in Norway [155], the TEACHOUT study in Denmark [156] and the Growing Up in New Zealand study [53]. Despite the several large studies using the AX3 on the lower back, only one study has compared the AX3 (worn on the lower back) and GT3X+ (worn on the hip) in a small free-living study in adults [157]. The study reported poor agreement between AX3 (lower back) and GT3X+ (hip) for epoch-by-epoch physical activity intensity estimates. No existing studies have compared the AX3 and GT3X+ against a criterion measure, or compared postural information obtained from AX3 with the inclinometer output of the GT3X+. This information will be useful when comparing physical activity estimates between studies that use these different devices at the lower back and hip placement sites. Therefore, the aim of the present study was to investigate the concurrent validity of these two devices for detecting activity intensity and postures in both children and adults.

Methods

Participants

After this study received ethical approval from the AUT University Ethics Committee (17/220), children from a local school and their parents were invited to participate in the present study. A total of 33 parents (17 female; aged 28 to 59 years) and 41 children (22 female; aged 6 to 16 years) agreed to take part. Written informed consent was received from each parent, who also provided parental consent for their child. Assent was also obtained from all child participants.

Instrumentation

The ActiGraph GT3X+ (ActiGraph LLC, Pensacola, FL, USA) and the Axivity AX3 (Axivity, York, UK) are accelerometers that measure movement across three axes: vertical (Y-axis), anterior-posterior (X-axis), and medio-lateral (Z-axis). ActiLife (version 6.11.9, ActiGraph, Pensacola, FL) and OmGui (version 1.0.0.30, open Movement, Newcastle University, UK) software were used to initialise and download the data from the GT3X+ and AX3, respectively. Both the GT3X+ and AX3 were set to record raw data at a sampling rate of 100 Hz, and all devices were initialised on the same computer. To create an indicator for the alignment of the accelerometer data with the video record, an identifiable spike was created in the accelerometer data. This was done by firstly placing the accelerometers in a bag, remaining stationary for a short period, before carefully striking the bag with the researcher's hand, while in the view of the three cameras.

Procedure

Participants performed 10 activities during a single laboratory visit. Table 3-1 shows each activity, the duration and the assigned posture, and the activity intensity. All walking and running activities were performed on a treadmill (slow walk, 2 mph; fast walk, 2.5 mph; run, 4 mph). Participants started on the treadmill from a stationary position, but the acceleration and deceleration periods were not included in the trial. These speeds were selected to accommodate the age range of the sample. These were performed in a randomised order by participants while simultaneously outfitted with two accelerometers placed at the centre of the mass: the GT3X+ at the top of their iliac crest (fixed by an elastic waist belt), and the AX3 on their lower back, offset from the spine (adhered with foam pouches or medical tape) [138]. Each data collection session took approximately one hour per participant. The instruction for starting and finishing each activity was given by one observer who was responsible for recording the start and finish time of each activity. Each session was recorded with three cameras to cover all angles of the laboratory setting.

Table 3-1. Activities performed by each participant.

Activities	Duration (min)	Assigned posture/activity intensity
Sitting (chair)	6	Sitting/sedentary
Sitting (floor) in children only	6	Sitting/sedentary
Sitting (stool) in adults only	6	Sitting/sedentary
Lying (supine)	2	Lying/sedentary
Lying (prone)	2	Lying/sedentary
Lying (side)	2	Lying/sedentary
Reclining	6	Sitting/sedentary
Standing	6	Standing/sedentary
Slow walking (2 mph)	2	Standing/LPA
Fast walking (2.5 mph)	2	Standing/MPA
Running (4 mph)	2	Standing/VPA

LPA= Light intensity physical activity; MPA = Moderate-intensity physical activity; VPA= Vigorous-intensity physical activity.

Data treatment

ActiGraph

The GT3X+ data were collapsed to 5-second epochs and converted to time spent sitting, lying and standing, or off (non-wear) using ActiGraph's proprietary inclinometer algorithms. The 5-second epoch was chosen to align with the AX3 posture recognition model requirements (see "Axivity" section). Running and walking activities were considered as a standing posture. Next, the sum of activity counts from the vertical axis (VA) was obtained before being scored into four intensity categories: sedentary, light-intensity physical activity (LPA), moderate-intensity physical activity (MPA), and vigorous-intensity physical activity (VPA). The Freedson [158] and Evenson [159, 160] cut-points were used for adults and children, respectively.

Axivity

To generate comparable data from the AX3, the raw data were first resampled to 30Hz and then converted to ActiGraph counts using recently published algorithms [161]. This method aggregates raw data into 1-second epochs using an eight-step process, including applying filters, down sampling to 10Hz, truncation, rectification and conversion to 8-bit resolution. The authors suggest the estimated error is −0.11 ± 0.97 (mean ± SD) counts per 10 seconds. This approach was chosen as there are no published intensity detection algorithms specific to the AX3 when attached to the lower back. The counts were then collapsed to 5-second epochs before the Freedson and Evenson cut-points were applied. To obtain sitting, standing, and lying postures, activity recognition models developed specifically for the AX3 placed on the lower back were used [18, 19].

Video criterion

The start and end of each activity were noted from the video data. Each activity block (duration presented in Table 1) only contained one activity type. The first and last epoch in each activity block were removed (if less than 5-seconds) to ensure that all epochs were 5-seconds in duration. The physical activity type obtained from direct observation was treated as the criterion measure. Each 5-second segment of the video record (synchronised with the accelerometer data) was assigned an activity type corresponding to one of the activities shown in Table 1. The criterion measure of intensity was based on calculated metabolic equivalent (MET) values for each activity. Firstly, the Physical Activity Compendium was used to assign MET values to each activity type for adults [162]: slow walk (2 mph) = 2 METs, fast walk (at 2.5 mph) = 3 METs, and run (at 4 mph) = 6 METs. For children, the Youth Compendium was used to assign MET values to walking and running activities specific for each age group: slow walk (2.5 – 2.9 METs), fast walk (4.6 – 5.1 METs), and run (6.6 –7.7 METs) [163]. Finally, each 5-second segment was assigned an intensity category using MET intensity thresholds for children and adults (i.e., for children: sedentary behaviour: ≤1.5 METs, LPA 1.5 – 4 METs, MPA: >4 – 6 METs and VPA: ≥6 METs and for adults: sedentary behaviour: ≤1.5 METs, LPA 1.5 – 3 METs, MPA: >3 – 6 METs and VPA: ≥6 METs).

Statistical Analysis

To determine the concurrent validity of GT3X+ and AX3 for detecting different activity intensity categories and postures, each 5-second epoch of accelerometer data was compared with the corresponding 5-second segment of the video criterion. Both the calculated postures (sitting, standing, lying) and the estimated intensity category (sedentary, LPA, MPA, and VPA) were compared. The sensitivity, specificity and balanced accuracy (i.e., the mean of sensitivity and specificity) were calculated. Sensitivity refers to the proportion of actual positive cases that are correctly identified as such (e.g., sitting as sitting), while specificity refers to the actual negative cases that are correctly identified as such (e.g., non-sitting as non-sitting). Confusion matrices with overall accuracy were calculated for each posture and activity intensity category. Kappa statistics were also reported for the intensity outcomes. The differences in balanced accuracy between adults and children were examined using independent-samples t-tests, while differences between the GT3X+ and AX3 accelerometers were examined using paired t-tests. All statistical analyses were performed in R (version 3.6.1, RStudio, Boston, MA).

Results

Forty-one children (22 females) and 33 adults (17 females) participated in the study. In total, 25.6 hours of data (18,396 epochs) was obtained from the child sample, and 20.6 hours (14,801 epochs) from the adult sample. Table 3-2 and Table 3-3 present the sensitivity, specificity, and balanced accuracy of the AX3 and the GT3X+ for posture and activity intensity detection when compared with direct observation. In the combined sample, the balanced accuracy for posture detection by the AX3 was ≥ 81.6% for both sitting and standing positions, and > 96 % for lying. The balanced accuracy for GT3X+ was ≥ 74.9 % for sitting and standing, and > 88% for lying position. AX3 achieved slightly higher balanced accuracy compared with GT3X+ for detecting all four activity intensities. The AX3 balanced accuracy was ≥ 95% for both sedentary and VPA, 90% for LPA, and 81.4 % for MPA. These values for GT3X+ were ≥ 92 for sedentary and VPA, 86% for LPA, and 73.7% for MPA.

Table 3-2. Concurrent accuracy of ActiGraph GT3X+ and Axivity AX3 accelerometers for detecting posture in children and adults when compared with direct observation.

Metric	Sitting		Standing		Lying		Off (non-wear)	
	ActiGraph GT3X+	Axivity AX3	ActiGraph GT3X+	Axivity AX3	ActiGraph GT3X+	Axivity AX3	ActiGraph GT3X+	Axivity AX3
Children (n = 41)								
Sensitivity	65.2	86.3	75.1	62.6	78.6	98.4		
Specificity	82.4	75.0	78.6	94.6	96.2	95.8	96.9	N/A
Balanced accuracy	73.8	80.7	76.9	78.6	87.4	97.1		
Total time (device)	508	646	374	303	201	242		
Total time (video)	779		498		256		0	
Adults (n = 33)								
Sensitivity	67.2	77.2	78.5	80.2	89.0	97.6		
Specificity	85.4	86.0	87.6	90.2	91.0	94.1	97.7	N/A
Balanced accuracy	76.3	81.6	83.0	85.2	90.0	95.9		
Total time (device)	412	467	324	325	184	195		
Total time (video)	613		414		206		0	
Combined (n = 74)								
Sensitivity	66.0	82.3	76.6	70.6	83.2	98.0		
Specificity	83.8	80.0	82.6	92.7	93.8	95.0	97.3	N/A
Balanced accuracy	74.9	81.8	79.6	81.6	88.5	96.6		

All values are presented as percentages except for total time (in minutes).
Total time (video) is the total minutes of each posture observed, while total time (device) is the total number of minutes of each posture classified by each accelerometer during this period.
N/A = not available in AX3 output.

Table 3-3. Concurrent accuracy of ActiGraph GT3X+ and Axivity AX3 accelerometers for detecting physical activity intensity in children and adults when compared with direct observation.

Metric	Sedentary		LPA		MPA		VPA	
	ActiGraph GT3X+	Axivity AX3	ActiGraph GT3X+	Axivity AX3	ActiGraph GT3X+	Axivity AX3	ActiGraph GT3X+	Axivity AX3
Children (n = 41)								
Sensitivity	92.1	93.8	80.2	92.7	31.1	49.6	89.2	90.8
Specificity	93.0	97.8	89.0	92.0	99.5	99.4	99.9	99.7
Balanced accuracy	92.6	95.9	84.6	92.3	64.6	74.5	94.6	95.3
Total time (device)	1204	1226	64	74	25	42	55	56
Total time (video)	1340		82		87		62	
Adults (n = 33)								
Sensitivity	97.1	98.3	81.4	82.3	72.2	79.1	77.2	92.4
Specificity	93.1	94.1	95.8	97.4	99.1	99.4	100	100
Balanced accuracy	95.1	96.2	88.6	89.8	85.6	89.3	88.6	96.2
Total time (device)	1011	1023	55	56	47	51	37	55
Total time (video)	1041		68		65		60	
Combined (n = 74)								
Sensitivity	94.3	95.8	80.2	85.1	48.1	63.6	84.0	91.7
Specificity	93.0	96.2	92.0	94.6	99.0	99.3	99.9	99.7
Balanced accuracy	93.7	96.0	86.0	89.9	73.7	81.4	92.0	95.7

All values are presented as percentages except for total time (in minutes).

Total time (video) is the total minutes of each activity intensity observed, while total time (device) is the total number of minutes of each activity intensity classified by each accelerometer during this period.

LPA = Light-intensity physical activity; MPA = Moderate-intensity physical activity; VPA = Vigorous-intensity physical activity.

Table 3-4 presents differences in balanced accuracy between the AX3 and GT3X+ for detecting intensity and posture. Compared with GT3X+, The AX3 showed higher balanced accuracy in detecting various postures and activity intensities (~4%, $p < 0.01$). Table 3-5 presents differences in balanced accuracy between AX3 and GT3X+ for detecting posture and activity intensity compared between children and adults. Both GT3X+ and AX3 showed higher balanced accuracy for assessing posture and intensity among adults, although the only significant difference between adults and children was observed for GT3X+ intensity output ($p<0.01$).

Table 3-4. Mean balanced accuracy difference between Axivity AX3 and ActiGraph GT3X+ in estimating intensity and posture.

Metric	Axivity AX3 (n=74)	ActiGraph GT3X+ (n=74)	Paired difference (95% CI)	*t* value	df	*P*-value
Intensity (%)	91.0	87.0	- 3.8 (-5.6 – -2.1)	- 4.44	73	**<0.01**
Posture (%)	87.7	82.2	- 5.5 (-7.6 – -3.4)	- 5.33	73	**<0.01**

CI = Confidence interval.

Table 3-5. Mean balanced accuracy difference between Axivity AX3 and ActiGraph GT3X+ in estimating intensity and posture between children and adults.

Metric	Children	Adults	Difference (95% CI)	*t* value	df	*P*-value
ActiGraph GT3X+						
Intensity (%)	84.6	90.2	5.6 (1.3 – 9.8)	2.65	63	**< 0.01**
Posture (%)	81.0	84.1	3.1(- 0.6 –7.5)	1.70	72	0.09
Axivity AX3						
Intensity (%)	89.7	92.6	2.9 (-1.1 – 6.9)	1.44	65	0.15
Posture (%)	87.0	89.0	2.0 (-1.5 – 5.1)	1.08	46	0.28

CI= Confidence interval.

Figure 3-1 and Figure 3-2 illustrate the percentage of correct and incorrect 5-second epochs detected by each accelerometer for each posture and activity intensity category in children and adults. Compared with GT3X+, the AX3 showed higher overall accuracy and a higher kappa statistic for detecting posture and activity intensity. Overall, the accuracy for detecting activity intensity was ≥91.2% (Kappa = 71.2–86.3%) for the AX3 and ≥88 % for the GT3X+ (Kappa = 61.2–78.9%). The accuracy for detecting posture was lower, with ≥80.6% for the AX3, and ≥70.4% for the GT3X+. The main misclassifications for posture were between sitting and standing for both devices (Figure 3-1). For intensity, the main areas of confusion were between sedentary/light intensity (light intensity was commonly misclassified as sedentary), and between moderate/light intensity (moderate intensity was frequently misclassified as light intensity) (Figure 3-2).

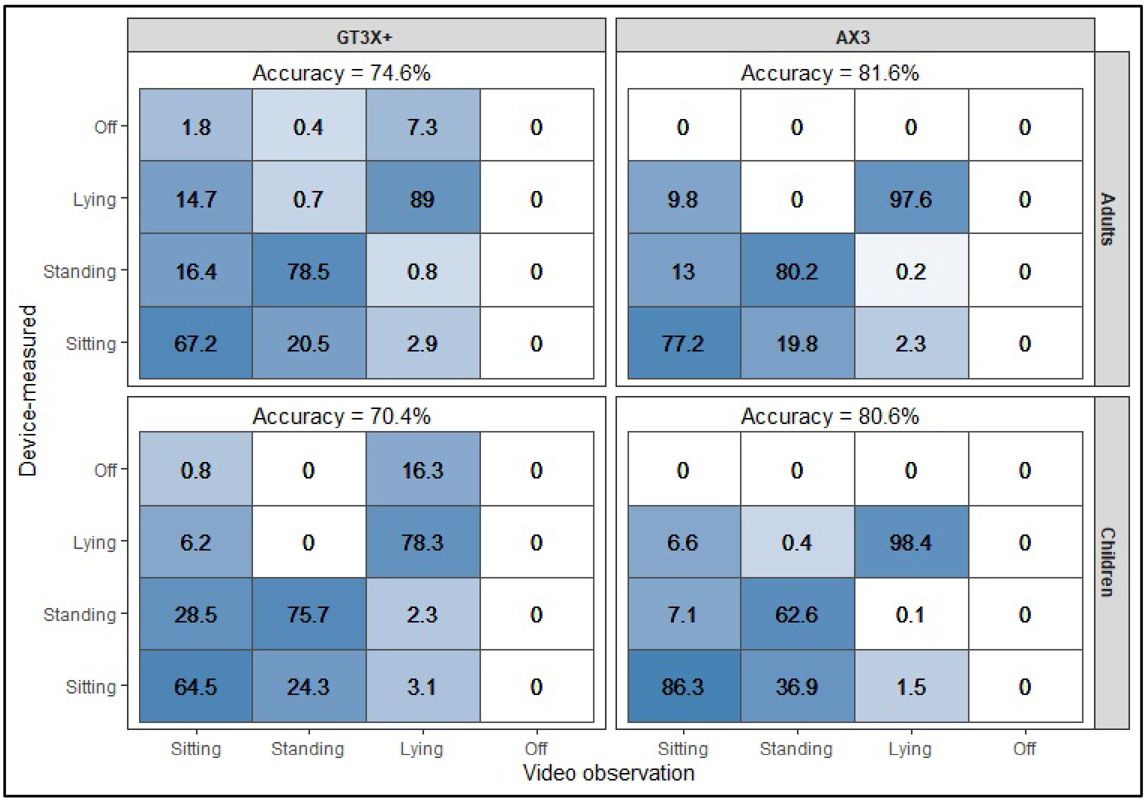

Figure 3-1. Confusion matrices for posture detection between ActiGraph GT3X+ and Axivity AX3 in adults and children (values represent the percentage of cases correctly classified or misclassified in each category).

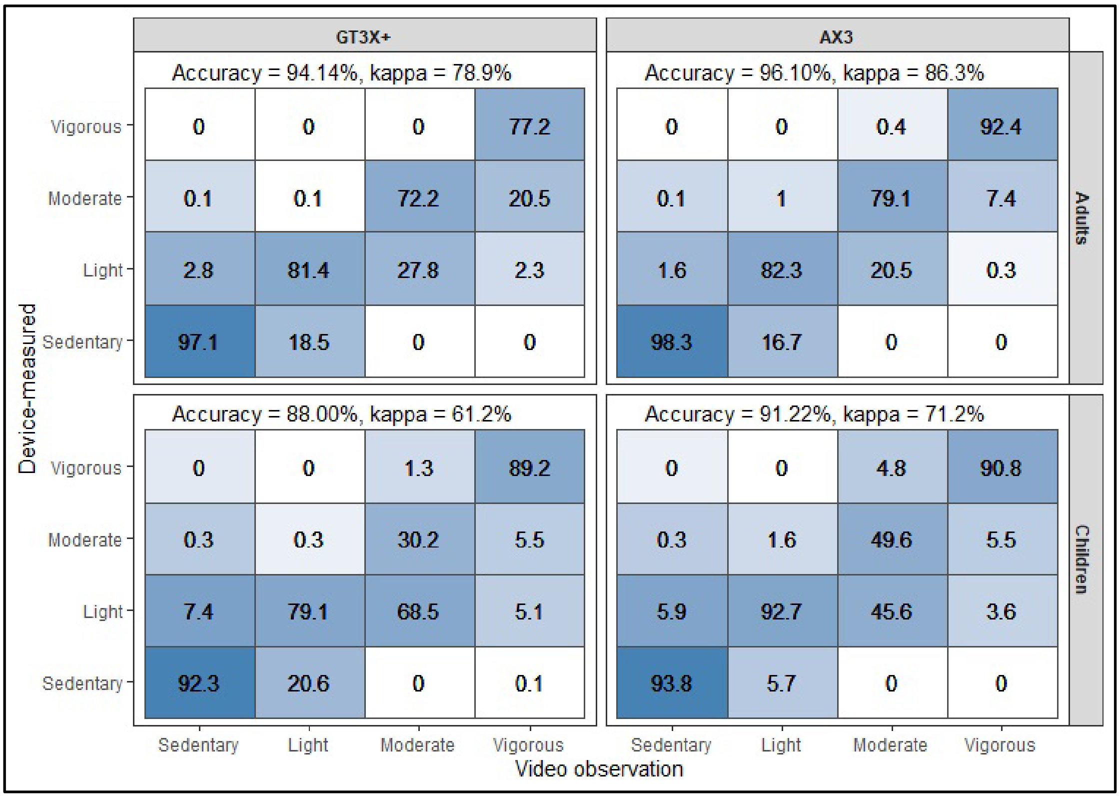

Figure 3-2. Confusion matrices for activity intensity detection between ActiGraph GT3X+ and Axivity AX3 in adults and children (values represent the percentage of cases correctly classified or misclassified in each category).

Discussion

This study represents the first investigation of the concurrent validity of GT3X+ and AX3 for detecting posture and activity intensity in both children and adults. Overall, the findings of this study showed both accelerometers were able to identify different postures and activity intensities with the balanced accuracy ranging from 74% to 96%, with the AX3 performing slightly better than GT3X+ for recognising postures (especially for lying and sitting) and physical activity intensity.

Previous findings investigating the accuracy of ActiGraph GT3X/GT3X+ for detecting postures in children are contrasting, with an accuracy of 15%, 20% and 94% for lying, standing and sitting in one study [153], and the equivalent values of 48%, 99.5%, and 54.6% in another study [164]. Given the similarity between these studies in terms of the study protocol and sample population, the difference between these two studies might be due to differences between GT3X and GT3X+, which was also pointed out by the authors. A limited number of studies have investigated the validity of the inclinometer function of waist-worn ActiGraph (GT3X or GT3X+) in children [153, 164] and adults [86, 165-171]. Compared with the only published study investigating the accuracy of GT3X+ in children aged 11–15 years old [164], our findings provided evidence for higher accuracy of GT3X+ inclinometer for detecting sitting and lying postures and lower accuracy for standing posture detection. These inconsistencies might be due to the different age ranges of the participants and the prescribed activity trials. In previous lab-based studies in adults, the accuracy of GT3X+ ranged from 58–65% for sitting, 60.6–93.7% for standing, and 66.7–80.8% for lying postures [86, 167, 170]. Consistent with previous studies, it was observed that some of the sitting and lying times were wrongly classified as non-wear (off). [86, 164, 166]. ActiGraph's proprietary inclinometer algorithms seem to detect some stationary periods as 'off' time. As seen in Figure 3-1, this primarily occurred during the lying activity, particularly in children.

Compared with the GT3X+, the AX3 showed higher sensitivity in detecting all three types of postures in both children and adults except for standing in children (which was 13% less accurate), although the balanced accuracy was still higher compared with the GT3X+. Unlike most of the studies examining the validity of the ActiGraph inclinometer, we reported the balanced accuracy (mean of sensitivity and specificity) and kappa statistics, along with other measures of accuracy. This may provide a better estimation of the accuracy, particularly since there were an unequal number of observations within each activity category. Both the AX3 and the GT3X+ were able to detect lying better than sitting and standing, which were commonly confused. The ability of back- or hip-worn accelerometers to detect lying better than standing and sitting is due to the distinct back orientation when lying (i.e., horizontal) versus sitting and standing (i.e., both vertical). To overcome this measurement challenge, physical activity researchers have used an extra accelerometer to take into account leg orientation as a way of differentiating between standing and sitting postures. When using dual AX3 accelerometers (one on the thigh and one on the lower back), sitting and standing postures have been classified with high balanced accuracy (greater than 98 %) in both children and adults [19].

In terms of intensity output, both accelerometers performed similarly, with sedentary and vigorous intensities classified with the highest accuracy. Compared with one study investigating the accuracy of GT3X+ for detecting sedentary and light physical activity in adults, we found similar accuracy for categorising walking slowly (1.0 mph) as light intensity activity (75%) and slightly higher accuracy for sedentary behaviour (88–96%) [86]. Although both devices showed high accuracy for detecting sedentary and vigorous categories, they both performed poor for detecting other intensities, especially MPA, which was commonly misclassified as LPA. A similar study has compared epoch-level activity counts between an AX3 on the lower back and a GT3X+ on the hip [157]. The authors concluded that despite reasonably similar day-level averages, the epoch-by-epoch activity counts varied, as did the time spent in each intensity category. Count-based approaches are commonly used to derive activity intensity estimates from accelerometers; however, researchers have started to use other approaches such as machine learning techniques on raw data, which is promising but requires further exploration [154].

This study has several limitations that should be considered. Firstly, the measurement took place in a lab-based setting with a standardised protocol. Although we tried to include many types of activities, the findings may not be generalisable to free-living settings. This also means that the standardised treadmill speeds used in this study may not represent the typical walking or running speeds of each participant. Secondly, while the AX3 placed on the lower back has been shown to produce reasonably similar day-level estimates compared to the GT3X+ on the hip [157], it is possible that any differences in posture and intensity observed in this study could be confounded by sensor placement. Thirdly, we did not consider participants weight status, which has been shown to have an influence on posture prediction via inclinometer [172]. Additionally, MET values from the Compendium of Physical Activities were used as the criterion measurement of activity intensity, which are absolute values that do not take into account individual characteristics such as weight, sex, and physical fitness [173]. Finally, as seen with the GT3X+ inclinometer data, it is possible that some activities can be incorrectly classified as non-wear time. As a specific non-wear protocol was not part of this study, we are unable to say how this may have impacted the results.

Conclusions

This lab-based study provides evidence of the accuracy of the relatively new AX3 accelerometer for detecting posture and activity intensity (when attached to the lower back) and how this compared with the widely-used GT3X+ accelerometer. Overall, compared with the GT3X+, the AX3 (placed at the lower back) showed slightly higher accuracy for classifying various postures (87.7% vs 82.2 %) and activity intensities (91.0 % vs 87.0%) in children and adults.

Chapter 4 - Utilising compositional data analysis to compare 24-hour time-use behaviours and obesity in New Zealand children

Preface

In the previous chapter, the validity of the Axivity AX3 accelerometer (placed on the lower back) was established for measuring time-use behaviours in children. In that study it was shown that an AX3 placed on the lower back performs similarly compared to the most-commonly used accelerometer (i.e., ActiGraph GT3X+) for measuring time-use behaviours from both activity intensity and activity type perspectives. Accordingly, in the subsequent Chapters, which are focused on AX3-measured time-use behaviours and obesity in children, data from AX3 on the lower back was used to derive children's time-use behaviour profiles based on activity intensity. However, for activity type profiles, data from both lower back and thigh AX3s were utilised, which previously were shown to be more accurate compared to a single AX3 on the lower back when detecting various activity types [18, 19].

This chapter focuses on the Research Area 2 of the VIRTUE framework (the link between time-use behaviours and outcomes) by examining the relationships between AX3-measured 24-hour time-use behaviours and obesity-related outcomes among New Zealand children. These relationships are examined using a compositional data analysis approach, as recommended from the reviewed literature. The paper from this chapter is currently under review at the *International Journal of Behavioural Nutrition and Physical Activity*.

Abstract

Background: In recent years, compositional data analysis (CoDA) has emerged as the preferred method for understanding the health-related associations of time-use behaviours. This statistical approach acknowledges the compositional properties of time-use data, properties that are often overlooked in behavioural analyses. Using CoDA, a limited number of studies have investigated the effects of 24-hour time use behaviours on obesity in children, typically quantifying daily behaviours by intensity (i.e., sedentary behaviour (SB), light-intensity physical activity (LPA), moderate-to-vigorous physical activity (MVPA) and sleep). The present study examined associations between 24-time use behaviours, measured from two perspectives (activity intensity and activity type), and obesity outcomes in children. We also investigated the theoretical changes in the obesity outcomes associated with the reallocation of time between these time-use behaviours.

Methods: Data from the 8-year wave of the longitudinal *Growing Up in New Zealand* study were used (n = 623, age =7.8). Axivity AX3 accelerometers were used to measure time-use behaviours over seven consecutive 24-hour periods. Obesity measures included body mass index (BMI) z-score, waist circumference, and waist-to-height ratio. Compositional linear regression and compositional isotemporal substitution methods were used to explore associations among 24-hour time-use behaviours and obesity-related outcomes.

Results: A significant negative (favourable) relationship was observed between LPA (relative to the remaining behaviours) and BMI z-score (p = 0.005), while time spent in SB, MVPA and sleep was not associated with any of the obesity outcomes. For the activity type composition, time spent walking and running, relative to the other behaviours, had a significant negative association with BMI z-score (p = 0.002). No other significant associations were observed. More time reallocated to LPA, walking, and running (from each of the remaining behaviours) was significantly associated with favourable changes in BMI z-score ($p <0.05$).

Conclusions: The present findings showed that increasing LPA (within the activity intensity composition) and walking and running (within the activity type composition) may be the most effective way to reduce BMI z-scores in New Zealand children. Given the cross-sectional nature of this study, these findings require further investigation using longitudinal data.

Introduction

Child obesity has become a worldwide epidemic, increasing tenfold over the past four decades [174]. New Zealand is no exception, with one in every three children being overweight or obese [3]. Obesity in children is associated with short- and long-term adverse health outcomes [5]. These accelerating and concerning trends underscore the need for further research on modifiable lifestyle factors that can inform effective intervention strategies.

Existing research has shown that lifestyle behaviours such as time spent in physical activity, sedentary behaviour, and sleep are associated with adiposity in children [8-10]. However, the majority of previous studies have examined these behaviours as individual domains, independent from each other, yet intrinsic dependencies exist between these behavioural constructs [11]. Across a day, the total time spent in each of these behaviours sums up to a finite total (i.e., 24 hours), meaning that any changes in time spent in one behaviour is compensated with an equal and opposite change in the duration of the remaining behaviour(s). Accordingly, a new paradigm of research called time-use epidemiology has emerged, urging researchers to examine these time-use behaviours relative to each other within a 24-hour context rather than in isolation [12]. As 24-hour time-use data are compositional in nature, they are not compatible with traditional data analysis techniques [13]. An alternative statistical approach called compositional data analysis (CoDA) has been recently applied in time-use research to accommodate the properties of these data [13].

Some studies have investigated the impacts of daily time-use compositions on obesity among children and youth using a compositional paradigm [21]. For example, in 434 Canadian children aged 10–13 years, the more time spent in moderate-to-vigorous physical activity (MVPA) relative to the other behaviours (i.e., light physical activity

(LPA), sedentary behaviour (SB), and sleep) was favourably associated with body mass index (BMI) z-score and waist circumference (WC). In contrast, an unfavourable association was observed for additional LPA. There was no association between time spent in SB or sleep (relative to the other behaviours) and obesity markers [129]. In 4,169 Canadian children aged 6–17 years, the proportion of time spent in MVPA and sleep were beneficially associated with BMI z-score and WC, while a detrimental association was seen between time spent in SB or LPA [83].

The 24-hour time-use compositions of children in these studies have been described as a 4-part composition based on the intensity of activities using accelerometer 'counts'. With advances in technology and the utilisation of machine learning techniques, researchers have detected activity types from raw accelerometer data with excellent accuracy and resolution [18, 19]. This is important given the limitations associated with the validity of count-based methods for classifying ranges of physical activity intensity and SB [14]. Previously, we identified how New Zealand children structure their 24-hour time-use composition from an activity intensity (based on counts) and an activity type (based on machine learning) perspective [175] ; however, the associations of these 24-hour activity compositions with obesity measures have yet to be explored.

The aims of the present study were (1) to determine the associations between time-use compositions and obesity in children while adjusting for diet quality and selected sociodemographic variables, and (2) to examine how the reallocation of time among selected behaviours is associated with changes in obesity outcomes in a sample of New Zealand children.

Methods

Participants

The present study utilised data from the 8-year data collection wave of the *Growing Up in New Zealand* (GUiNZ) birth cohort study. A detailed profile of the cohort and study design has been reported elsewhere [23]. Briefly, GUiNZ is a large longitudinal study of New Zealand children recruited via enrolment of their pregnant mothers with an estimated delivery date between April 2009 and March 2010. A total of 5,556 children participated in the 8-year wave of this study; however, accelerometers were only worn by a subsample of children. In total, 952 children wore accelerometers, although the final analytic sample used in this study was 623 children. Ethical approval for GUiNZ was received from the Ministry of Health Northern Y Regional Ethics Committee (NTY/08/06/055).

Measurements

24-hour time-use behaviours

24-hour time-use behaviours were captured continuously over seven days using two Axivity AX3 accelerometers. These sensors were attached directly to the thigh and lower back skin using medical dressing or purpose-built foam pouches [53]. Accelerometry data were downloaded using the Open Movement Software (OMGUI, version 1.0.0.30, open Movement, Newcastle University, UK). Wear time was assessed using the inbuilt temperature sensor described elsewhere [53, 138]. Children with at least one day of 24-hour wear time were included for analyses. The 24-hour time-use composition of each child was described from two perspectives: the activity intensity composition (i.e., SB, LPA, MVPA, and sleep) and the activity type composition (i.e., sitting, standing, walking, running, lying). To derive the activity intensity composition, the accelerometer data from the lower back sensor were converted to counts congruent with the ActiGraph GT3X+

accelerometer [161, 176]. Subsequently, each 5-second epoch was categorised as SB, LPA, or MVPA using the Evenson cut-points [159]. The Tudor-Locke algorithm was applied to detect sleep duration [122]. Sleep duration was calculated from 12am to 12 am. Finally, the minutes accumulated in each behaviour were averaged across valid days. For the activity type composition, each 5-second epoch from both thigh and lower back sensors were categorised into various activity types using machine learning algorithms developed to classify activity types in children. These algorithms have shown ≥97% accuracy in the lab [19] and ≥ 90 % accuracy in free-living settings [18].

Obesity measures

In the present study, body mass index (BMI) z-score, waist circumference (WC), and waist-to-height ratio (WHtR) were considered as obesity markers. Weight was measured using a digital scale (Seca) to the nearest 0.1 kg. Height was measured with a wall-mounted laser stadiometer (Seca) to the nearest millimetre. WC was measured using a tape measure to the nearest millimetre at the midpoint between the lowest rib and the top of the iliac crest. WHtR was calculated as WC (cm) divided by height (m). BMI was calculated as weight (kg) divided by squared height (m^2) and was transformed into z-scores following the age-and sex-specific World Health Organisation reference data [177].

Covariates

Covariates included gender, ethnicity, deprivation, mother's education, and diet behaviours, given these are known confounders of the primary associations of interest (time use behaviour and obesity) [83, 129]. Mothers reported their child's daily consumption of fruits and vegetables (from ‘never’ to ‘four or more’ servings), weekly consumption of soft drinks and fast food (from ‘never’ to ‘six times or more’), and frequency of breakfast consumption (‘never’ to ‘7 days’). Child ethnicity was classified into the following major ethnic groups: 1) European, 2) Māori, 3) Pacific, 4) Asian, 5) Middle Eastern, Latin American and African (MELAA), and 6) Other. MELAA and Other were combined as “Other” due to small numbers in each group. Children who answered, “I don’t know” to the ethnicity question were also categorised as “Other”. Socio-economic deprivation was estimated using the New Zealand Index of Deprivation 2013 [178]. Households were categorised into three categories: low deprivation (deciles 1–3), medium (deciles 4–7) and high deprivation (deciles 8–10). Mother’s education was derived from the antenatal dataset and was reported as 1) “less than a bachelor’s degree” or 2) “bachelor’s degree or higher”.

Statistical Analysis

All statistical analyses were performed in R software (version 3.6.1; The R Foundation for Statistical Computing, Vienna, Austria). Standard descriptive statistics were calculated for demographic and diet variables. Time-use behaviours were treated as compositional data, and therefore compositional data analysis approaches were used for explanatory analyses using the *compositions* [179] and deltacomp (github.com/tystan/deltacomp) R packages. Firstly, missing values and parts of each composition that contained zeros were imputed using log-ratio expectation-maximisation [180]. This method of zero imputation has been shown to produce the least bias [145]. The average daily minutes spent in each 24-hour time-use behaviour was reported as both arithmetic and geometric means. The geometric mean of each behaviour was normalised to 1440 minutes to calculate compositional means.

The associations between 24-hour time-use composition and each obesity outcome were assessed using compositional multiple linear regression models. Firstly, the 24-hour activity intensity and activity type compositions were expressed as isometric log-ratio (ilr) coordinates. These ilr coordinates were created using the sequential binary partition (SBP) process [142] with the following sign matrix:

$$
\begin{array}{ccccc}
 & x_1 & x_2 & x_3 & x_4 \\
ilr_1 & +1 & -1 & -1 & -1 \\
ilr_2 & 0 & +1 & -1 & -1 \\
ilr_3 & 0 & 0 & +1 & -1
\end{array}
$$

where x_1, x_2, x_3, and x_4 are the four parts for the activity intensity composition, and ilr_1, ilr_2, and ilr_3 are the resulting ilr coordinates. The first ilr coordinate (ilr_1) represents the time spent in behaviour x_1 relative to all other behaviours. The second ilr coordinate (ilr_2) represents the ratio of x_2 in relation to x_3 and x_4, while ilr_3 is the ratio of x_3 to x_4. As the primary contrast of interest is one behaviour relative to the remaining behaviours, the above sign matrix was subsequently permuted, such that each part of the composition was represented as x_1 [142]. A similar process was used for the activity type composition, but this resulted in four ilr coordinates, given the 5-part composition. The SBP and sign matrix for the activity type composition is shown below:

$$
\begin{array}{cccccc}
 & x_1 & x_2 & x_3 & x_4 & x_5 \\
ilr_1 & +1 & -1 & -1 & -1 & -1 \\
ilr_2 & 0 & +1 & -1 & -1 & -1 \\
ilr_3 & 0 & 0 & +1 & -1 & -1 \\
ilr_4 & 0 & 0 & 0 & +1 & -1
\end{array}
$$

The corresponding first ilr coordinates (ilr_1) were used as explanatory variables in the regression models, while obesity indictors (i.e., BMI z-score, WC, and WHtR) were treated as dependent variables. All models were then adjusted for potential confounders:

gender, ethnicity, mother's education, deprivation index, fruit intake, vegetable intake, frequency of fizzy drink and fast-food consumption, and breakfast consumption. Finally, using compositional isotemporal substitution, we also examined the theoretical changes in obesity indicators through "one-to-remaining" reallocation, where time was proportionally reallocated from/to one behaviour to/from the remaining behaviours within the composition (-60 to +60 minutes in 15-minute increments around the mean composition of each behaviour) [147]. For this analysis, time spent walking and running was combined, given the small volume of running observed in the dataset. These models also adjusted for the covariates described above.

Results

Table 4-1 summarises the characteristics of the study population. The mean age of the participants was 7.8 years. The majority were NZ European (43.8%) and were from low or medium deprived households (80.0%). Sociodemographic characteristics varied between our analytical sample (those with accelerometer data) and those participated in the 8 year wave but excluded due to not having accelerometer data (results presented in Chapter 6 (Table 6-1)). Of the participants, almost 78.0% ate between 1–3 servings of fruits and vegetables daily, 47.4% ate fast food at least one time per week, and 46.0% consumed fizzy drink 1–3 times per week. Most participants ate breakfast every day (90.0%).

Table 4-1. Participants characteristics.

Characteristics	Number (%)
Gender	
Boy	302 (48.5)
Girl	321 (51.5)
Ethnicity	
European	273 (43.8)
Māori	119 (19.1)
Pacific	45 (7.2)
Asian	74 (11.9)
Other	107 (17.2)
Missing	<10 (0.8)
Household deprivation	
Low	222 (35.6)
Medium	276 (44.3)
High	122 (19.6)
Missing	<10 (0.5)
Mother's education	
Less than a bachelor's degree	300 (48.2)
Bachelor's degree or higher	323 (51.8)
Missing	0
Fruit intake (per day)	
Never	11 (1.8)
<1serving	32 (5.1)
1 serving	126 (20.2)
2 servings	233 (37.4)
3 servings	128 (20.6)
4 servings	71(11.4)
Missing	22 (3.5)
Vegetable intake (per day)	
Never	13 (2.1)
<1 serving	34 (5.5)
1 serving	109 (17.5)
2 servings	199 (31.9)
3 servings	198 (31.8)
4 servings	48 (7.7)
Missing	22 (3.5)
Fizzy drink consumption (per week)	
Never	248 (39.8)
1 time	180 (28.9)
2 or 3 times	110 (17.7)
4 or 5 times	17 (2.7)
6 times or more	18 (2.9)
Missing	50 (8)
Fast food consumption (per week)	
Never	120 (19.3)
1 time	295 (47.4)
2 or 3 times	160 (25.7)
4 or 5 times	11 (1.8)
6 times or more	<10 (0.6)
Missing	33 (5.2)
Breakfast consumption (per week)	
Never	<10 (0.6)
1 or 2 days	<10 (0.6)
3 or 4 days	10 (1.6)
5 or 6 days	24 (3.9)
7 days	560 (89.9)
Missing	21 (3.4)

Table 4-2 shows the arithmetic and compositional means of time spent in each component of the activity intensity and activity type compositions. Relative to all other behaviours, children spent most of their time asleep, followed by SB, LPA and MVPA. From an activity type perspective, most of the day was spent lying and sitting postures, followed by standing, walking, and running.

Table 4-2. Arithmetic and compositional means of time spent in each component of the activity intensity and activity type compositions.

24-hour time-use composition	Arithmetic mean Minutes/day (%)	Compositional mean Minutes/day (%)
Activity intensity composition		
SB	427 (29.7)	427 (29.7)
LPA	307 (21.3)	307 (21.3)
MVPA	98 (6.8)	94 (6.5)
Sleep	608 (42.2)	612 (42.5)
Activity type composition		
Sitting	480 (33.3)	481 (33.4)
Standing	160 (11.1)	153 (10.6)
Walking	108 (7.5)	105 (7.3)
Running	9 (0.6)	7(0.5)
Lying	686 (47.5)	694 (48.2)

SB = Sedentary behaviour; LPA= Light-intensity physical activity; MVPA= Moderate-to-vigorous intensity physical activity.

Tables 4-3 and 4-4 present results from regression models examining the association between 24-hour activity intensity and activity type compositions (respectively) and obesity outcomes. Time spent in SB ($p = 0.007$), LPA ($p = <0.001$), and MVPA ($p = 0.005$), relative to the remaining behaviours, was associated with BMI z score; however, after adjustment for covariates, only time spent in LPA ($p=0.005$) had a significant negative (favourable) association with BMI z-score (relative to the remaining behaviours). Time spent in SB was positively associated with WC, and time spent in LPA was negatively associated with WC; however, these associations were no longer statistically significant after adjusting for covariates. No association was observed between time spent in any component of the activity intensity composition and WHtR.

For the activity type composition, time spent walking relative to the other behaviours had a significant negative (favourable) association with the BMI z-score. No associations were observed between time spent in any other activity type behaviours and WC or WHtR. Additionally, results from a sensitivity analysis where the analysis sample required at least three valid days of 24-hour time-use data (n = 482) revealed similar associations between the 24-hour activity intensity and activity type time-use compositions and obesity-related outcomes among these children (Supplementary Tables S1 and S2).

Table 4-3. Relationship between activity intensity compositions (expressed as isometric log-ratio coordinates) and obesity outcomes.

Obesity outcomes	Isometric log-ratio predictor	Unadjusted model ß– coefficient	*P*-value	Model R squared	Adjusted model ß– coefficient	*P*-value	Model R squared
BMI z-score	ilr SB/LPA*MVPA*SLEEP	0.725	**0.007**		0.283	0.336	
	ilr LPA/SB*MVPA*SLEEP	−1.123	**<0.001**	0.025	− 0.913	**0.005**	0.086
	ilr MVPA/SB*LPA*SLEEP	0.450	**0.005**		0.314	0.110	
	ilr SLEEP/SB*LPA*MVPA	− 0.053	0.868		0.315	0.367	
WC	ilr SB/LPA*MVPA*SLEEP	4.331	**0.012**		0.726	0.700	
	ilr LPA/SB*MVPA*SLEEP	−7.117	**<0.001**	0.023	− 3.931	0.061	0.086
	ilr MVPA/SB*LPA*SLEEP	2.686	**0.009**		0.737	0.558	
	ilr SLEEP/SB*LPA*MVPA	0.100	0.960		2.466	0.270	
WHtR	ilr SB/LPA*MVPA*SLEEP	0.019	0.092		− 0.001	0.931	
	ilr LPA/SB*MVPA*SLEEP	− 0.023	0.058	0.003	− 0.014	0.336	0.038
	ilr MVPA/SB*LPA*SLEEP	0.008	0.239		0.003	0.773	
	ilr SLEEP/SB*LPA*MVPA	− 0.004	0.736		0.013	0.416	

ilr = isometric log-ratio, is the first isometric log-ratio coordinate representing each time-use behaviour relative to the remaining behaviours; BMI z-score = Body mass index z-score; WC = Waist circumference; WHtR= Waist-to-height ratio; SB = Sedentary behaviour; LPA= Light-intensity physical activity; MVPA= Moderate-to-vigorous intensity physical activity. Models were adjusted for gender, ethnicity, deprivation, mother's education, fruit intake, vegetable intake, frequency of fizzy drink and fast food consumption, and breakfast consumption. Bold values represent significant associations.

Table 4-4. Relationship between activity type compositions (expressed as isometric log-ratio coordinates) and obesity outcomes.

Obesity outcomes	Isometric log-ratio predictor	Unadjusted model ß–coefficient	*P*-value	Model R squared	Adjusted model ß–coefficient	*P*-value	Model R squared
BMI z-score	ilr Sit/Stand*Walk*Run*Lie	0.157	0.411	0.011	– 0.033	0.872	0.088
	ilr Stand/Sit*Walk*Run*Lie	0.140	0.362		0.311	0.072	
	ilr Walk/Sit* Stand*Run*Lie	– 0.594	**0.003**		– 0.641	**0.002**	
	ilr Run/Sit* Stand*Walk*Lie	0.119	0.076		0.094	0.204	
	ilr Lie/Sit* Stand*Walk*Run	0.176	0.407		0.268	0.242	
WC	ilr Sit/Stand*Walk*Run*Lie	1.696	0.167	0.007	0.504	0.703	0.082
	ilr Stand/Sit*Walk*Run*Lie	–1.180	0.229		0.283	0.798	
	ilr Walk/Sit* Stand*Run*Lie	–1.353	0.294		–1.891	0.169	
	ilr Run/Sit* Stand*Walk*Lie	0.430	0.316		0.336	0.481	
	ilr Lie/Sit* Stand*Walk*Run	0.406	0.764		0.766	0.602	
WHtR	ilr Sit/Stand*Walk*Run*Lie	0.013	0.105	0.005	0.003	0.709	0.040
	ilr Stand/Sit*Walk*Run*Lie	0.004	0.460		0.008	0.281	
	ilr Walk/Sit* Stand*Run*Lie	– 0.016	0.052		– 0.016	0.092	
	ilr Run/Sit* Stand*Walk*Lie	0.002	0.353		0.002	0.519	
	ilr Lie/Sit* Stand*Walk*Run	– 0.004	0.656		0.002	0.824	

ilr = isometric log-ratio, is the first isometric log-ratio coordinate representing each time-use behaviour relative to the remaining behaviours; BMI z-score = Body mass index z-score; WC = Waist circumference; WHtR= Waist-to-height ratio.

Models were adjusted for gender, ethnicity, deprivation, mother's education, fruit intake, vegetable intake, frequency of fizzy drink and fast food consumption, and breakfast consumption. Bold values represent significant associations.

Figure 4-1 illustrates the predicted theoretical changes in the obesity outcomes when time from one behaviour is reallocated to the remaining behaviours within activity intensity and activity type compositions. With regards to activity intensity composition, reallocating more time to LPA from the remaining behaviours was significantly associated with favourable changes in BMI z-score ($p < 0.05$). When the time was reallocated to sleep and MVPA (from all the other behaviours), this was related to unfavourable changes in all the obesity measures. Adding time to sedentary (from the remaining behaviours) resulted in unfavourable changes in BMI z-score and WC, but favourable changes in WHtR; however, none of these trends were significant. Reallocating more time to sitting from all the remaining behaviours was associated with unfavourable obesity measures. Conversely, increasing the time spent walking and running showed a significant favourable association with BMI z-score ($p < 0.05$). Increasing standing time was detrimentally associated with BMI z-score and WHtR but beneficially associated with WC. Adding more time to lying had beneficial impacts on BMI and WHtR while negatively affecting WC (although not statistically significant). These predicted changes have been reported in Tables 4-5 and 4-6. Additionally, the results for the reallocation of time as a percentage difference are presented in Supplementary Tables S3 and S4. These results align with the previous results (in terms of statistically significant reallocations) when using minutes across the behaviours.

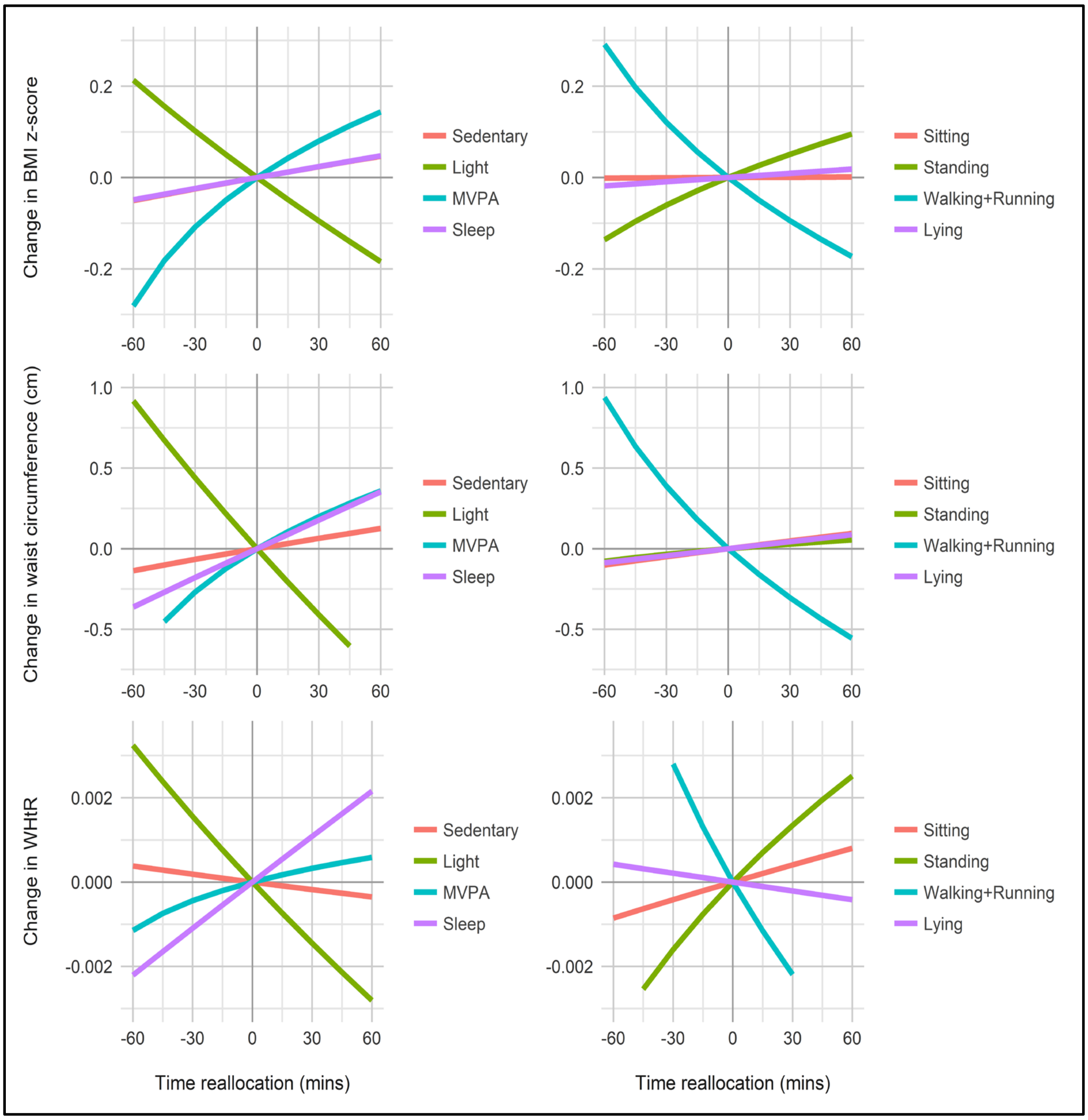

Figure 4-1. Estimated changes in obesity outcomes associated with reallocating ± 60 minutes in 15 mins to/from one behaviour to/from the remaining behaviours within activity intensity and activity type compositions.
Results are adjusted for gender, ethnicity, deprivation, mother's education, fruit intake, vegetable intake, frequency of fizzy drink and fast food consumption, and breakfast consumption.
BMI z-score = Body mass index z-score, WHtR= Waist-to-height ratio, Sedentary = Sedentary behaviour; Light = Light-intensity physical activity; MVPA= Moderate-to-vigorous intensity physical activity.
Note: the sedentary estimate is directly underneath the sleep estimate in the top left panel.

Table 4-5. Predicted change (95% CI) in obesity outcomes following reallocation of time between behaviours within the activity intensity composition.

Obesity outcomes	Changes in behaviour (minutes/day)	SB to/from remaining	LPA to/from remaining	MVPA to/from remaining	Sleep to/from remaining
BMI z-score					
	-60	0.05 (-0.15 –0.05)	**0.21 (0.06 – 0.36)**	-0.28 (-0.64 – 0.08)	-0.05 (-0.15 – 0.05)
	-45	-0.04(-0.11 –0.04)	**0.16 (0.04 – 0.27)**	-0.18 -0.41 – 0.05)	-0.04 (-0.11 – 0.04)
	-30	-0.02 (-0.08 – 0.03)	**0.10 (0.03 – 0.17)**	-0.11 (-0.24 – 0.03)	-0.02 (-0.07 – 0.03)
	-15	-0.01 (-0.04 –0.01)	**0.05 (0.01 – 0.09)**	-0.05 (-0.11 – 0.01)	-0.01 (0.04 – 0.01)
	0	0	0	0	0
	15	0.01 (-0.01 – 0.04)	**-0.05 (-0.08 – -0.01)**	0.04 (-0.01 – 0.10)	0.01 (-0.01 – 0.04)
	30	0.02 (-0.03 –0.07)	**-0.10 (-0.16 – -0.03)**	0.08 (-0.02 – 0.18)	0.02 (-0.03 – 0.07)
	45	0.04 (-0.04 – 0.11)	**-0.14 (-0.24 – -0.04)**	0.11(-0.03 – 0.26)	0.04 (-0.04 – 0.11)
	60	0.05 (-0.05 – 0.14)	**-0.18 (-0.31 – -0.05)**	0.14 (-0.04 – 0.33)	0.05 (-0.05 – 0.15)
WC					
	-60	-0.14 (-0.81– 0.54)	0.92 (-0.05 – 1.88)	-0.70 (-3.00 – 1.59)	-0.36 (-1.03 – 0.31)
	-45	-0.10 (-0.60 – 0.40)	0.67 (-0.03 – 1.38)	-0.45 (-1.94 –1.03)	-0.27 (-0.77 – 0.23)
	-30	-0.07 (-0.40 – 0.26)	0.44 (-0.02 – 0.90)	-0.27 (-1.15 – 0.61)	-0.18 (-0.51 – 0.15)
	-15	-0.03 (-0.20 – 0.13)	0.22 (-0.01– 0.44)	-0.12 (-0.52 – 0.28)	-0.09 (-0.25 – 0.08)
	0	0	0	0	0
	15	0.03 (-0.13 – 0.19)	-0.21 (-0.43 – 0.01)	0.11 (-0.24 – 0.45)	0.09 (-0.08 – 0.25)
	30	0.06 (-0.25 – 0.38)	-0.41 (-0.84 – 0.02)	0.20 (-0.45 – 0.85)	0.18 (-0.15 – 0.50)
	45	0.09 (-0.38 – 0.56)	-0.60 (-1.24 – 0.03)	0.28 (-0.64 – 1.21)	0.27 (-0.22 – 0.75)
	60	0.13 (-0.50 – 0.75)	-0.79 (-1.63 – 0.04)	0.36 (-0.81 –1.53)	0.35 (-0.30 –1.00)
WHtR					
	-60	0 (-0.004 – 0.005)	0.003 (-0.003 – 0.010)	-0.001(-0.017 – 0.015)	-0.002 (-0.007 – 0.002)
	-45	0 (-0.003 – 0.004)	0.002 (-0.003 – 0.007)	-0.001(-0.011 – 0.010)	-0.002(-0.005 – 0.002)
	-30	0 (-0.002 – 0.002)	0.002 (-0.002 – 0.005)	0 (-0.007 – 0.006)	-0.001 (-0.003 – 0.001)
	-15	0 (-0.001 – 0.001)	0.001(-0.001 – 0.002)	0 (-0.003 – 0.003)	-0.001 (-0.002 –0.001)
	0	0	0	0	0
	15	0 (-0.001 – 0.001)	-0.001 (-0.002 – 0.001)	0 (-0.002 – 0.003)	0.001 (-0.001 – 0.002)
	30	0 (-0.002 – 0.002)	-0.001 (-0.004 – 0.002)	0 (-0.004 – 0.005)	0.001(-0.001 – 0.003)
	45	0 (-0.004 – 0.003)	-0.002 (-0.007 – 0.002)	0 (-0.006 – 0.007)	0.002 (-0.002 – 0.005)
	60	0 (-0.005 – 0.004)	-0.003 (-0.009 – 0.003)	0.001 (-0.008 – 0.009)	0.002 (-0.002 – 0.007)

BMI z-score = Body mass index z-score, WC = Waist circumference, WHtR =Waist-to-height ratio.
SB = Sedentary behaviour; LPA = Light-intensity physical activity; MVPA= Moderate-to-vigorous intensity physical activity.
Bold values refer to significance values at $p<0.05$.

Table 4-6. Predicted change (95% CI) in obesity outcomes following reallocation of time between behaviours within the activity type composition.

Obesity outcomes	Changes in behaviour (minutes/day)	Sitting to/from remaining	Standing to/from remaining	Walking and running to/from remaining	Lying to/from remaining
BMI z-score					
	-60	0.00 (-0.07 – 0.07)	-0.14 (-0.30 – 0.03)	**0.29 (0.04 – 0.54)**	-0.02 (-0.10 – 0.06)
	-45	0.00 (-0.05 –0.05)	-0.10 (-0.21 – 0.02)	**0.20 (0.03 – 0.37)**	-0.01 (-0.07 – 0.04)
	-30	0.00 (-0.04 – 0.03)	-0.06 (-0.13 – 0.01)	**0.12 (0.02 – 0.22)**	0.01 (-0.05 – 0.03)
	-15	0.00 (-0.02 – 0.02)	-0.03 (-0.06 – 0.01)	**0.06 (0.01 – 0.10)**	0.00 (-0.02 – 0.01)
	0	0	0	0	0
	15	0.00 (-0.02 – 0.02)	0.03 (-0.01 – 0.06)	**-0.05 (-0.09 – -0.01)**	0.00 (-0.01 – 0.02)
	30	0.00 (-0.03 – 0.03)	0.05 (-0.01 – 0.11)	**-0.09 (-0.18 – -0.01)**	0.01 (-0.03 – 0.05)
	45	0.00 (-0.05 – 0.05)	0.07 (-0.01 – 0.16)	**-0.14 (-0.25 – -0.02)**	0.01 (-0.04 – 0.07)
	60	0.00 (-0.07 – 0.07)	0.10(-0.02 – 0.21)	**-0.17 (-0.32 – -0.03**)	0.02 (-0.06 – 0.10)
WC					
	-60	-0.10 (-0.56 – 0.36)	-0.08 (-1.13 – 0.97)	0.94 (-0.66 – 2.54)	-0.09 (-0.59 – 0.41)
	-45	-0.08 (-0.42 – 0.27)	-0.06 (-0.80 – 0.69)	0.63 (-0.45 – 1.72)	-0.07 (-0.44 – 0.31)
	-30	-0.05 (-0.28 – 0.18)	-0.03 (-0.50 – 0.43)	0.39 (-0.27 – 1.05)	-0.04 (-0.29 – 0.21)
	-15	-0.02 (-0.14 – 0.09)	-0.02 (-0.24 – 0.21)	0.18 (-0.13 – 0.49)	-0.02 (-0.15 – 0.10)
	0	0	0	0	0
	15	0.02 (-0.09 – 0.13)	0.02 (-0.19 – 0.22)	-0.16 (-0.43 – 0.11)	0.02 (-0.10 – 0.15)
	30	0.05 (-0.17 – 0.27)	0.03 (-0.36 – 0.42)	-0.30 (-0.82 – 0.21)	0.04 (-0.20 – 0.29)
	45	0.07 (-0.26 – 0.40)	0.04 (-0.53 – 0.61)	-0.44 (-1.18 – 0.31)	0.06 (-0.31 – 0.44)
	60	0.09 (-0.34 – 0.53)	0.05 (-0.68 – 0.79)	-0.56 (-1.50 – 0.39)	0.09 (-0.41 – 0.58)
WHtR					
	-60	-0.001 (-0.004 – 0.002)	-0.004 (-0.011– 0.004)	0.007 (-0.004 – 0.018)	0 (-0.00 – 0.004)
	-45	-0.001 (-0.003 – 0.002)	-0.003 (-0.008 – 0.003)	0.005 (-0.003 – 0.012)	0(-0.002 – 0.003)
	-30	0 (-0.002 –0.001)	-0.002 (-0.005 – 0.002)	0.003 (-0.002 – 0.007)	0 (-0.002 – 0.002)
	-15	0 (-0.001 – 0.001)	-0.001 (-0.002 – 0.001)	0.001 (-0.001 – 0.003)	0 (-0.001 – 0.001)
	0	0	0	0	0
	15	0 (-0.001 – 0.001)	0.001(-0.001 – 0.002)	-0.001 (-0.003 – 0.001)	0 (-0.001 – 0.001)
	30	0 (-0.001 – 0.002)	0.001(-0.001 – 0.004)	-0.002 (-0.006 – 0.001)	0 (-0.002 – 0.002)
	45	0.001 (-0.002 – 0.003)	0.002 (-0.002 – 0.006)	-0.003 (-0.008 – 0.002)	0 (-0.003 – 0.002)
	60	0.001 (-0.002 – 0.004)	0.003 (-0.003 – 0.008)	-0.004 (-0.011 – 0.003)	0 (-0.004 – 0.003)

BMI z-score = Body mass index z-score; WC =Waist circumference; WHtR= Waist-to-height ratio.
Bold values refer to significance values at $p<0.05$.

Discussion

The present study utilised CoDA to investigate associations between both 24-hour activity intensity and activity type compositions and obesity measures in New Zealand children. We found that within a 24-hour activity intensity composition, only the relative time spent in LPA had a significant negative (favourable) association with BMI z-score after adjusting for covariates. For activity types, only time spent walking (relative to other behaviours) was favourably associated with BMI z-score in the fully adjusted models. Compositional isotemporal substitution was also used to examine the theoretical changes in obesity outcomes associated with time reallocation between behaviours. Reallocating more time to LPA and walking (proportionally taking time away from other behaviours) was associated with favourable changes in BMI z-score. No significant differences were observed for other behaviours.

No significant associations were observed between time spent in SB and any of the obesity measures (in the fully adjusted models). This is in line with some [129, 181] but not all the previous compositional studies [83, 142]. However, it should be noted that these studies focused on total sitting time and did not take sitting patterns into account. As shown in previous studies, prolonged sitting time is associated with higher adiposity [182]. A recent CoDA-based study found that sitting patterns, not total sitting time, were significantly associated with adiposity among school-aged children [183]. In particular, time spent in sedentary bouts of 10–29 minutes in duration was associated with higher fat mass and visceral adipose tissue in children [183]. This highlights the importance of considering sitting patterns in future compositional time-use studies to better understand the effect of SB on obesity in children.

Our analyses revealed favourable associations between LPA time (relative to other behaviours) and BMI z-score. This is in contrast with findings of previous CoDA-based studies where detrimental impacts were reported between time spent in LPA (relative to other behaviours) and BMI (or BMI z-score) [83, 129, 142, 181]. As evidenced by a recent CoDA study, these inconsistencies might be related to the patterns in which LPA is accumulated (i.e., short bouts versus long bouts) [184]. Higher levels of LPA in short bouts could be associated with a lower BMI z-score and waist circumference, while longer bouts of LPA have been associated with a higher BMI z-score and waist circumference among children [184]. The use of different LPA cut points between studies could be another reason behind these different results. Considering other measurement techniques, such as machine learning without arbitrary threshold decisions, might be beneficial in this regard. Accordingly, in the current study, we also measured children's time-use behaviours in terms of activity types. Results from analysing the activity type compositions showed that only the time spent walking was favourably associated with BMI z-score. To our knowledge, this represents the first work to have examined the associations between 24-hour activity type composition and obesity outcomes in children.

Results from compositional isotemporal substitution analysis showed that the BMI z-score could be reduced by increasing LPA time at the expense of other behaviours. Contrary to this finding, previous compositional studies have reported unfavourable impacts on obesity when LPA substitutes other behaviours [129, 142, 181]. For example, Taylor et al. reported that 10% more time in LPA was associated with a higher BMI z-score among New Zealand children aged 6–10 years old [181].

In contrast to previous compositional studies [32, 129, 130, 185], we observed that reallocating more time to MVPA from other behaviours was associated with unfavourable obesity outcomes. Although not statistically significant, this could be due to the higher compositional mean of MVPA (98 minutes/day) in our sample compared to previous similar compositional studies. Therefore, these unfavourable estimates in the obesity measures may not be necessarily due to more time in MVPA, but less time in other activities such as sleep. Although we did not observe any association between sleep and obesity outcomes in this study, it has been shown that shorter sleep duration may increase the odds of obesity in children [10]. It is important to note that the null association between time spent in MVPA, sleep, and sedentary behaviour with obesity-related outcomes in this study do not imply that these behaviours are not related to adiposity. This means that, for example, the amount of time in MVPA in relation to the trade-offs in time from other behaviours (i.e., sleep and sedentary behaviour) is neutral in relation to obesity-related measures [186].

Strengths and limitations

The main strengths of our study include the use of CoDA to examine the 24-hour time-use composition and the assessment of time-use compositions from two separate perspectives (intensity and type of activities) using dual accelerometers. Additionally, the regression models were adjusted for various covariates, including diet. This study also has several limitations. Firstly, the cross-sectional design of this study precludes any casualty from being inferred; however, given the longitudinal nature of the GUiNZ study, changes in 24-hour time-use behaviours over time and their associations with adiposity (and other health outcomes) could be examined. Secondly, although we considered three different indicators to measure obesity, no direct measurement of body composition was included in the current study. Moreover, the 24-hour time-use data in this study may not represent habitual time-use behaviours given the inclusion of children with a minimum of one 24-hour day of wear time. Further, the Tudor-Locke sleep algorithm was developed for a hip-worn accelerometer placement, but we applied this algorithm to the lower back. Although this still represents the centre of mass, it is possible this decision affect sleep estimates. Lastly, it is possible the associations we observed with LPA (as opposed to MVPA) could be due to misclassifications of activity type and activity intensity (Chapter 3).

Conclusions

Using compositional data analysis, we found that the 24-hour time-use behaviours of children were associated with BMI z-score. For activity intensity, LPA relative to other behaviours was associated with favourable changes in BMI z-score. In terms of activity type, time spent walking was the key behaviour associated with favourable BMI z-scores. Additionally, reallocating additional time to LPA (from the remaining behaviours) was associated with a reduced BMI z-score among children. Similar results were observed when reallocating time to walking and running from the remaining behaviours. These findings need to be confirmed in future longitudinal studies to provide more robust evidence on how time use could be optimised to obtain the most favourable impacts on obesity measures in children.

Chapter 5 - Clustering of lifestyle behaviours and obesity in New Zealand children: A compositional data analysis approach

Preface

The preceding chapter revealed that 24-hour time-use compositions are associated with BMI in children and reallocating more time to LPA was associated with lower BMI. However, in reality, children tend to engage in particular patterns of lifestyle behaviours (including time-use and diet behaviours), so reallocating time from one behaviour to another might be more (or less) realistic for some groups of children. Thus, this chapter explores how New Zealand children cluster in terms of their lifestyle behaviours, and examines the association between cluster membership and measures of obesity. This study is primarily aligned with the Research Area 3 in the VIRTUE framework (patterns, prevalence, and optimal balance), but also contributes to Research Area 2 given the obesity focus. The paper from this chapter is currently under review at the *International Journal of Behavioural Nutrition and Physical Activity*.

Abstract

Background: Physical activity, sedentary behaviour, sleep, and dietary intake are individually associated with obesity in children. However, less is known about how these modifiable lifestyle behaviours cluster in children, and whether there is an association between the cluster of these behaviours and obesity.

Methods: Cluster analysis was used to identify distinct behavioural clusters among 623 children from the 8-year wave of the *Growing Up in New Zealand* cohort study. Clustering input variables included 24-hour time-use behaviours (in terms of activity intensity and activity type) along with screen time and dietary behaviours. Time-use behaviours were treated as compositional data and were expressed as isometric log-ratios. Obesity-related measures (i.e., body mass index z-score (BMI z-score), waist circumference (WC), waist-to-height ratio (WHtR) were compared among clusters using ANOVA.

Results: Three distinct lifestyle behaviour clusters were identified separately for activity intensity and activity type compositions: For activity intensity: Cluster 1 (41% of the sample, lowest sedentary behaviour and screen time), Cluster 2 (31% of the sample, highest moderate-to-vigorous physical activity (MVPA) and highest unhealthy diet score), and Cluster 3 (28% of the sample, highest sedentary behaviour and screen time score, lowest healthy diet score). For activity type: Cluster 1 (41% of the sample, lowest sitting time, lowest screen time and highest standing time), Cluster 2 (31% of the sample, high sitting time, lowest standing time, and highest unhealthy diet score), and Cluster 3 (28% of the sample, highest sitting time and screen time score, lowest healthy diet score). For both activity intensity and activity type compositions, Cluster 2 had the highest BMI z-score, WC, and WHtR, and the highest proportion of overweight and obese children.

After adjusting for potential covariates (i.e., gender, ethnicity, and deprivation), only the BMI z-score remained significantly different between the clusters.

Conclusions: Distinct patterns of lifestyle behaviours exist among New Zealand children. The cluster with the highest MVPA and highest unhealthy diet score (from an activity intensity perspective) and the cluster with high sitting time and highest unhealthy diet score (from an activity type perspective) were associated with poorer obesity-related outcomes.

Introduction

Child obesity is a significant health problem and is increasingly prevalent worldwide [174, 187], including in New Zealand, where one in three children are currently classified as overweight or obese [3]. Although obesity is related to sociodemographic factors such as gender, ethnicity, and socioeconomic deprivation [188], it is well established that modifiable lifestyle behaviours such as physical activity (PA), sedentary behaviour (SB) (including screen time), sleep, and dietary intake are individually associated with obesity in children [8-10]. In reality, these behaviours occur as clusters (or patterns) of behaviours and not in isolation [131, 189]. Therefore, understanding patterns of these behaviours and their relationship with obesity in children is imperative in developing more effective interventions to tackle the obesity epidemic.

Using data reduction techniques such as cluster analysis, previous research has explored patterns of lifestyle behaviours among children [190]. However, to date, a limited number of studies have investigated the clustering of all these lifestyle behaviours together (i.e., PA, SB, sleep, and diet) and their associations with obesity in children [131, 191-194]. However, most of these studies were based on proxy or self-reported measures of time-use behaviour (i.e., PA, SB, and sleep). Only one study has used 24-hour accelerometer to measure all these time-use behaviours and explored how these behaviours (including diet) cluster in children [131]. The findings showed four distinct lifestyle behaviour clusters among 5,710 children from 12 countries, and cluster membership was associated with Body Mass Index (BMI) [131]. This study also treated time-use behaviours as compositional data during the cluster analysis to account for the compositional properties of time-use behaviours. This is important as daily time-use behaviours are bound to 24-hours per day, and the time spent in one behaviour is co-dependent on the remaining behaviour(s) [13].

Until now, the clustering approach has mainly been used to examine time-use compositions in terms of intensity (i.e., moderate-to-vigorous intensity activity and sedentary behaviour) and not activity type (i.e., sitting, standing, walking, running, lying). Activity type information may be more sensitive to identifying patterns of behaviour and associated health outcomes. For example, different patterns of sitting and standing are known to have different physiological effects [64], but these types of behaviour are commonly grouped as sedentary, particularly when using device-based measures [91].

Two previous studies have discovered distinct clusters of behaviours among New Zealand adolescents [195, 196]; however, to our knowledge, there is no study on how New Zealand children cluster their lifestyle behaviours. Therefore, by using compositional cluster analysis, this study aimed (1) to identify how lifestyle behaviours in children (i.e., 24-hour time use behaviour in terms of both activity intensity and activity type, along with screen time and diet) cluster, and (2) to examine the associations between these clusters and obesity measures in a sample of New Zealand children.

Methods

Participants

Participants in this study were from the 8-year wave of the *Growing Up in New Zealand* (GUiNZ) cohort study [23]. This is a large longitudinal study of New Zealand children who were recruited via enrolment of their pregnant mothers with an estimated delivery date between April 2009 and March 2010. Further details about this study can be found elsewhere [23]. The study protocol was approved by the Ministry of Health Northern Y Regional Ethics Committee (NTY/08/06/055). A total of 5,556 children participated in the 8-year wave of this study; however, accelerometers were only worn by a subsample of children (n =952). The final analytic sample used in this study consisted of 623 children aged eight years.

Measurements

24-hour time-use behaviours

Time-use behaviours were measured using a dual Axivity AX3 accelerometer continuously for seven consecutive days. Two AX3 devices (one on the lower back and one on the thigh) adhered to the skin with medical tape or a foam patch [53]. Open Movement Software (OMGUI, version 1.0.0.30, open Movement, Newcastle University, UK) was used to set up the devices and download the accelerometer data. Wear time was determined using the inbuilt temperature sensor described elsewhere [53, 138]. A day with 24 hours of accelerometer wear time was considered valid, and children with at least one valid day of accelerometer data were included in the analysis. Children's 24-hour time-use behaviours were described in terms of activity intensity and activity types. For activity intensity, accelerometer data from the lower back sensor were converted to ActiGraph GT3X+ counts following the procedures explained elsewhere [161, 176]. Then each 5-second epoch was classified as sedentary behaviour (SB), light-intensity physical activity (LPA), or moderate-to-vigorous physical activity (MVPA) using the scaled Evenson cut-points [159]. Sleep duration was estimated using the Tudor-Locke algorithm [122]. Sleep duration was calculated from 12am to 12 am. Finally, the total minutes spent in these activities were summed and averaged over valid days to derive the 24-hour activity intensity composition. To identify activity types, we used algorithms derived from machine learning techniques to classify each 5-second epoch into sitting, standing, walking, running, or lying. These algorithms have shown high levels of accuracy for detecting activity types in children [18, 19]. The minutes spent in these activities were combined to obtain the 24-hour activity type composition. Using the 24-hour Movement Guidelines for New Zealand children [22], participants were classified as meeting the MVPA guideline if they had accumulated, on average, 60+ minutes of MVPA daily. Children with 9–11 hours of sleep per 24-hours were categorised as meeting the sleep guideline.

Screen time

Mothers were asked to indicate the time (hours and minutes) that their child spent (1) watching television, including free-to-air, online, and pay-tv or DVDs, either on TV or other screen-based devices, and (2) doing activities or tasks (e.g., homework, playing games, or sending messages) on any screen-based devices including computers, laptops, tablets, smartphones, or gaming devices. These questions were asked for a typical weekday and a weekend day. From this, the daily average of screen time (in hours) was obtained. Children with an average of less than two hours of daily screen time were categorised as meeting the screen time guideline [22].

Dietary behaviour

Children's dietary habits were assessed by asking five questions from their mothers. The mothers reported on average how many servings of (1) fruits and (2) vegetables their children ate per day (less than 1 serving, 1 serving, 2 servings, 3 servings, 4 or more servings). They were also asked about the number of days in the last week that their children (3) had a fizzy or soft drink, and (4) ate any food purchased from a fast-food place or takeaway shop. Finally, they reported the number of days each week that their child (5) eats breakfast (one day to seven days). To identify dietary habits among the children, an exploratory factor analysis was conducted, which resulted in two distinct components, (1) healthy dietary habits (i.e., positive loadings for fruits, vegetables, and breakfast consumption), and (2) unhealthy dietary habits (i.e., positive loadings for fast food and fizzy drink consumption)[131].

Obesity measures

Height was measured without shoes to the nearest millimetre using a wall-mounted laser stadiometer (Seca), and weight was measured to the nearest 0.1 kg with a digital scale (Seca). Body mass index (BMI) was calculated as weight (kg) divided by square of height (m^2) and transformed to z-scores according to the age- and sex-specific World Health Organisation (WHO) reference data [177]. Each child was categorised as normal weight, overweight, or obese using the WHO classification [177]. Waist circumference (WC) was measured at the midpoint between the lowest rib and the top of the iliac crest to the nearest millimetre. The waist-to-height ratio (WHtR) was calculated as weight (cm) divided by height (m).

Covariates

Covariates included gender, ethnicity, and deprivation. Child ethnicity was classified into the following major ethnic categories: (1) European, (2) Māori, (3) Pacific Island, (4) Asian, (5) Middle Eastern, Latin American and African (MELAA), and 6) Other. MELAA and Other were combined as "Other" due to small numbers in each group. Children who answered, "I don't know" to the ethnicity question were also categorised as "Other". Deprivation was estimated using the New Zealand Deprivation Index 2013 (NZDep2013) [178]. NZDep2013 reflects the area-level deprivation status for each meshblock (small geographic census unit) based on nine variables from the 2013 census data. Each meshblock is assigned a deprivation score ranging from 1 (least deprived) to 10 (most deprived).

Statistical Analysis

Using the *compositions* and *cluster* R packages, cluster analysis was conducted to identify how lifestyle behaviours aggregate in children. As children's 24-hour time-use behaviours represent compositional data, activity compositions were first converted to isometric log-ratio (ilr) coordinates using the isometric log-ratio transformation [142]. These ilr coordinates, along with screen time, healthy diet, and the unhealthy diet z-scores, were used for clustering. The cluster analysis process was performed separately for the activity intensity and activity type compositions. Firstly, agglomerative hierarchical clustering was performed. Dissimilarity was measured using Euclidean distance, and total within-cluster variance was minimised using Ward's minimum variance method. Next, *k*-means clustering was performed, with *k* set to the optimal number of clusters. Visual inspection of the dendrogram and silhouette value and gap statistic were used to determine the optimal number of distinct clusters [131]. This process aligns with compositional cluster analyses performed previously. Obesity measures were compared among the clusters using ANOVA, and adjusted models were then computed by adding child gender, child ethnicity and deprivation as covariates (ANCOVA). For both models, estimated means and contrasts between each cluster were performed using the *emmean*s R package, with multiple comparisons adjusted using the Holm correction. Lastly, the proportion of overweight and obese children and the proportion of children meeting the MVPA, screen time, and sleep guidelines were compared among the clusters using chi-squared tests.

Results

From 623 children with accelerometer data, 24-hour activity intensity and activity type compositions were extracted for 620 and 602 children, respectively. The mean age of the participants was 7.8 years (51.5% girls, 43.8% NZ European, 19.1% Māori, 7.2% Pacific, 11.9% Asian, 17.2% Other). Sociodemographic characteristics varied between our analytical sample (those with accelerometer data) and those participated in the 8 year wave but excluded due to not having accelerometer data (results presented in Chapter 6 (Table 6-1)).

Cluster analysis on behavioural data revealed three distinct clusters among the participants. Table 5-1 and Table 5-2 show the characteristics of the three clusters separately for the activity intensity and activity type compositions. For the activity intensity composition, the first cluster accounted for 41% of the sample (n = 253) and had the lowest SB and screen time score and the longest sleep duration. This cluster also had the highest rates of meeting all three 24-hour movement guidelines (20.2 %). The second cluster (31%, n = 192) was characterised by the highest level of MVPA (88% of this cluster met the MVPA daily recommendation) and the highest unhealthy diet score. Cluster 3 (28%, n = 175) was characterised by the highest sedentary behaviour and screen time score and the lowest healthy diet score. For activity type, Cluster 1 (41%, n = 244) had the lowest sitting time and screen time scores and the highest standing time. The second cluster (31%, n= 188) had a higher sitting time compared to the first cluster but had the lowest standing time among the three clusters. This cluster also had the highest unhealthy diet score. Cluster 3 (28%, n = 170) was characterised by the highest sitting time and the highest screen time score with the lowest healthy diet score.

Table 5-1. Characteristics of activity intensity clusters.

	Cluster 1	Cluster 2	Cluster 3	*P*-value
N	253	192	175	
Time-use behaviours (minutes/day)				
SB	414	432	442	
LPA	309	309	301	
MVPA	93	97	90	
Sleep	624	603	607	
Meeting 24-hour Movement Guidelines n (%)				
MVPA recommendation	170 (67.1)	170 (88.5)	151 (86.3)	**0.048**
Screen time recommendation	60 (29.5) (n =203)	10 (7.5) (n=132)	5 (3.7) (n=135)	**<0.001**
Sleep recommendation	170 (67.2)	119 (62.0)	98 (56.0)	0.062
MVPA + Screen time + Sleep	41 (20.2)	7 (3.6)	2 (1.5)	**<0.001**
Screen time (mean z-score)	-0.58	0.20	0.61	
Dietary behaviour (mean z-score)				
Healthy diet score	0.54	0.74	-1.59	
Unhealthy diet score	-0.81	1.49	-0.46	
Overweight/obese n (%)	51 (20.1)	68 (35.4)	51 (29.1)	**0.001**

SB = Sedentary behaviour; LPA= Light-intensity physical activity; MVPA= Moderate-to-vigorous intensity physical activity.

Values are presented as a compositional mean for time-use variables.

Note: The actual sample sizes for the screen time comparisons are indicated in superscripts as screen time information was not available for all the participants.

Table 5-2. Characteristics of activity type clusters.

	Cluster 1	Cluster 2	Cluster 3	*P*-value
N	244	188	170	
Time-use behaviours (minutes/day)				
Sitting	469	486	492	
Standing	161	146	151	
Walking	108	104	101	
Running	8	7	6	
Lying	694	698	690	
Screen time (mean z-score)	-0.57	0.18	0.60	
Dietary behaviour (mean z-score)				
Healthy diet score	0.50	0.77	-1.61	
Unhealthy diet score	-0.82	1.48	-0.46	
Overweight/obese n (%)	49 (20)	69 (36.7)	51 (30)	**0.001**

Values are presented as a compositional mean for time-use variables.

Table 5-3 shows the obesity measures across the activity intensity and activity type clusters. For the activity intensity clusters, Cluster 2 was associated with the highest BMI z-score and had the highest proportion of overweight or obese children. Cluster 2 also had the highest WC and WHtR (significantly different from Cluster 1). In terms of activity type, similar results were observed for Cluster 2, having the highest BMI z-score (significantly different from Cluster 1 and 3) and the highest WC and WHtR (significantly different from Cluster 1).

Table 5-3. Associations between activity intensity and activity type clusters and obesity outcomes (unadjusted).

	Cluster 1	Cluster 2	Cluster 3
Activity intensity clusters			
BMI z-score	0.22 (0.07 – 0.36)	0.69 (0.52 – 0.85)[a]	0.41 (0.24 – 0.58)
WC	57.6 (56.7 – 58.5)	60.1 (59.0 – 61.1)[b]	58.4 (57.3 – 59.5)
WHtR	0.44 (0.43 – 0.45)	0.46 (0.45 – 0.46)[b]	0.45 (0.44 – 0.46)
Activity type clusters			
BMI z-score	0.21 (0.07 – 0.36)	0.72 (0.55 – 0.89)[a]	0.42 (0.25 – 0.60)
WC	57.7 (56.7– 58.6)	60.0 (59.0 – 61.1)[b]	58.4 (57.3 – 59.6)
WHtR	0.44 (0.43 – 0.45)	0.46 (0.45 – 0.46)[b]	0.45 (0.44 – 0.46)

BMI z-score = Body mass index z-score; WC = Waist circumference; WHtR= Waist-to-height ratio.
Values are estimated means (95% confidence interval).
a: Significant difference from Clusters 1 and 3 ($p < 0.05$).
b: Significant difference from Cluster 1 ($p < 0.01$).

After adjusting for potential covariates (Table 5-4), only the BMI z-score remained significantly different between the clusters. Specifically, for activity intensity, Cluster 2 membership was associated with the highest BMI z-score, which was significantly different from Cluster 1. For the activity type composition, the BMI z-score of Cluster 2 was significantly higher than both Cluster 1 and 3. We also undertook a sensitivity analysis where participants had three or more days of valid wear time (n = 482). This also resulted in three distinct clusters among participants. The patterns of associations between cluster membership and obesity-related outcomes were in alignment with our initial results from participants with at least one day of 24-hour time-use data (Supplementary Tables S5 and S6).

Table 5-4. Associations between activity intensity and activity type clusters and obesity outcomes after adjusting for gender, ethnicity and household deprivation.

	Cluster 1	Cluster 2	Cluster 3
Activity intensity clusters			
BMI z-score	0.44 (0.27 – 0.61)[a]	0.78 (0.61 – 0.95)	0.53 (0.35 – 0.70)
WC	59.2 (58.2 – 60.3)	60.8 (59.8 – 61.9)	59.2 (58.2 – 60.3)
WHtR	0.45 (0.44 – 0.46)	0.46 (0.45 – 0.47)	0.45 (0.45 – 0.46)
Activity type clusters			
BMI z-score	0.45 (0.27– 0.62)[a]	0.83 (0.66 – 1.00)[b]	0.54 (0.36 – 0.72)
WC	59.3 (58.2 – 60.4)	60.9 (59.8 – 62.0)	59.3 (58.1 – 60.4)
WHtR	0.45 (0.45 – 0.46)	0.46 (0.45 – 0.47)	0.45 (0.45 – 0.46)

BMI z-score = Body mass index z-score; WC = Waist circumference; WHtR= Waist-to-height ratio.
Values are estimated means (95% confidence interval).
a: Significant difference from Cluster 2 ($p < 0.01$).
b: Significant difference from Cluster 3 ($p < 0.05$).

Discussion

This study utilised cluster analyses to examine the grouping of lifestyle behaviours and their associations with obesity-related outcomes in a sample of New Zealand children. We found that children in this study could be grouped into unique clusters based on their lifestyle behaviours. Cluster patterns characterised by longer sedentary time, longer screen time and the unhealthiest diet score (or the lowest healthy diet score) were associated with worse obesity-related outcomes.

To our knowledge, this study provided the first evidence of how New Zealand children cluster based on their lifestyle behaviour. However, there are two previous studies, which have explored lifestyle behaviour clusters among New Zealand adolescents [195, 196]. Consistent with our results, they identified distinct clusters of lifestyle behaviours, which were associated with weight status. For example, using 24-hour time-use recall, Ferrar et al. (2013) found three different time-use behaviour clusters among boys (labelled as techno active, quiet movers, and social studious) and girls (labelled as social, sporty, screenie tasker, and super studious). In that study cluster membership was linked to weight status among girls but not boys [195].

A recent systematic review on the clustering of lifestyle behaviours among children [190] has identified five studies that have focused on the same lifestyle behaviours as in the present study (i.e., physical activity, sedentary behaviour and or screen time, sleep and diet) using cluster analysis [131, 192, 193] or latent class analysis [191, 194]. In those studies, distinct patterns of lifestyle behaviours have been grouped in two clusters [193, 194], three [191], four [131], and five clusters [192]. Additionally, all except one study [193] observed that children with specific patterns of behaviours were more likely to be overweight or obese. Specifically, clusters of children characterised with high sedentary time [131, 191], high sedentary time and poor diet quality [194], and short sleep and inactive patterns [192] had a higher risk of being overweight or obese compared to the other identified clusters. In line with these findings, we found three distinct clusters of lifestyle behaviours among New Zealand children. The cluster categorised with high sedentary time and the highest unhealthy diet score (Cluster 2) had the highest BMI z-score, WC and WHtR, and the highest proportion of overweight or obese children. Children in this cluster also had the highest rate of meeting MVPA guidelines relative to the other clusters. In a study by Periira et al. (2015), a similar cluster characterised by high PA, high screen time, and poor diet quality, labelled as "active, low diet quality", has been identified among 9–11-year-old children [194]. Meeting the MVPA guideline but having unhealthy eating patterns has also been seen among 5,873 children aged 9–11 years from 12 countries [197]. This observation of clustering health impairing behaviours (e.g., unhealthy diet or sedentary behaviour) with health-enhancing behaviours (e.g., engaging in physical activity) in children highlights the importance of considering the patterns of lifestyle behaviours rather than focusing on individual behaviours.

In addition to the activity intensity compositions, we also clustered children's lifestyle behaviours from a 24-hour activity type perspective. Although similar cluster grouping and patterns were observed between these two perspectives, this was the first attempt to cluster children's lifestyle behaviours based on their 24-hour activity type composition. We observed that children with the lowest sitting time, highest standing time, lowest screen time and overall healthy diet had the most favourable obesity measures compared to the other clusters.

Key strengths of this study include the measurement of 24-hour time-use behaviours, both in terms of activity intensity and activity type using 24-hour accelerometry. Another strength is the use of compositional data analysis to respect the compositional properties of time-use data, which has been overlooked in many previous lifestyle behaviour cluster studies. However, this study also has several limitations. Firstly, the cross-sectional design of the study precludes any causal relationships between behaviour and obesity to be inferred. Secondly, screen time and children's dietary behaviours were parent-reported and therefore may be subject to recall bias. Finally, due to the inclusion of children with a minimum of one day of 24-hour accelerometer data, the 24-hour time-use composition data might not represent children's habitual time use over a longer period.

Conclusions

Of the three lifestyle behaviour clusters that were identified (for both activity intensity and activity type), the cluster with a favourable combination of sedentary time (or sitting time), screen time, and diet was related to the most favourable obesity-related outcomes, while clusters of unhealthy behaviours were related to poorer obesity outcomes. Although adjustment for sociodemographic variables attenuated some of these associations, the relationship between cluster membership and BMI z-score remained significant. This emphasises the need to consider lifestyle behavioural patterns in children rather than focusing on individual behaviours.

Chapter 6 - Patterns and sociodemographic correlates of 24-hour time-use behaviours in New Zealand children

Preface

The preceding chapters demonstrated that time-use behaviours are associated with BMI in children. In particular, children with the healthiest combination of time-use and diet behaviours had the most favourable obesity measures and were more likely to meet the New Zealand 24-hour Movement Guidelines. Thus, it is essential to identify the prevalence of time-use behaviours (and guideline adherence) among New Zealand children and sociodemographic factors that are associated with these behaviours. Identifying these factors is necessary to develop and tailor preventive interventions. This chapter explores the patterns of time-use behaviours, adherence to the 24-hour Movement Guidelines, and the associated sociodemographic factors, covering the Research Areas 3 (patterns, prevalence, and optimal balance) and 4 (determinants) within the VIRTUE framework. The full paper from this chapter is currently published in the October 2022 issue of the *International Journal of Behavioural Nutrition and Physical Activity*.

Abstract

Background: The time that children spend in physical activity, sedentary behaviour, and sleep each day (i.e., 24-hour time-use behaviours) is related to physical and mental health outcomes. Currently, there is no comprehensive evidence on New Zealand school-aged children's 24-hour time-use behaviours, adherence to the New Zealand 24-hour Movement Guidelines, and how these vary among different sociodemographic groups.

Methods: This study utilises data from the 8-year wave of the *Growing Up in New Zealand* longitudinal study. Using two Axivity AX3 accelerometers, children's 24-hour time-use behaviours were described from two perspectives: activity intensity and activity type. Compositional data analysis techniques were used to explore the differences in 24-hour time-use compositions across various sociodemographic groups.

Results: Children spent on average, 31.1%, 22.3%, 6.8%, and 39.8% of their time in sedentary behaviour, light physical activity, moderate-to-vigorous physical activity, and sleep, respectively. However, the daily distribution of time in different activity types was 33.2% sitting, 10.8% standing, 7.3% walking, 0.4% running, and 48.2% lying. Bothe the activity intensity and activity type compositions varied across groups of child ethnicity, gender, and household income or deprivation. The proportion of children meeting each of the guidelines was 90% for physical activity, 62.5% for sleep, 16% for screen time, and 10.6% for the combined guidelines. Both gender and residence location (i.e., urban vs. rural) were associated with meeting the physical activity guideline. Whereas, child ethnicity, mother's education, and residence location were associated with meeting the screen time guideline. Only child ethnicity was significantly associated with the adherence to the combined 24-hour movement guidelines.

Conclusions: This study provided comprehensive evidence on how New Zealand children engage in 24-hour time-use behaviour, adherence to the New Zealand 24-hour

Movement Guidelines, and how these behaviours differ across key sociodemographic groups. These findings should be considered in designing future interventions for promoting healthy time-use patterns in New Zealand children.

Introduction

There has been growing evidence that time-use behaviours comprised of physical activity [8], sedentary behaviour (including screen-based activities) [9] and sleep [10] are linked with physical and mental health outcomes in school-aged children and youth. However, most of this evidence is based on studies examining the time spent in each behaviour in isolation, ignoring the intrinsic interplay between them [11]. Since daily time-use behaviours are bound to 24-hours per day, the time spent in one behaviour is co-dependent on the remaining behaviour(s) [11]. That is, an increase in the time allocated to one behaviour (e.g., physical activity) leads to less time for the remaining behaviours (e.g., sedentary behaviour and/or sleep). Favourable health outcomes (e.g., decreased body mass index) might not be merely due to the increase in one activity (e.g., physical activity) but changes in the remaining activities (less sedentary and/or more sleep). To fully understand the relationships between health and time-use behaviours, researchers are moving away from investigating these behaviours as independent correlates of health and towards an integrated approach exploring the associations between compositions of behaviours and health [21]. This integrated approach has been conceptualised in a newly established health research area called time-use epidemiology [12].

Advocating this approach, Canada pioneered the 24-hour Movement Guidelines for children and youth, which integrated the previous distinct guidelines for each behaviour [36]. This has been followed by other countries, including New Zealand [22]. These guidelines contain integrated recommendations on daily amounts of moderate-to-vigorous physical activity (MVPA) (at least 60 minutes), screen time (not more than 2 hours), and sleep (9–11 hours for 5–13-year-old children and 8–10 hours for those aged 14–17 years old) for optimal health and wellbeing in children aged 5–17 years old [22]. Meeting these guidelines has been associated with favourable health indicators in children [5], yet international studies suggest that only a small proportion of children regularly meet these recommendations. For example, findings from a 12-country study indicate that only 7% of children aged 9–11 years met all three guidelines [136]. Findings from limited studies suggest that sociodemographic factors and parental factors (age and education) were associated with adherence to these guidelines [132, 133]. These findings on the potential sociodemographic correlates of the time-use behaviours can help tailor future interventions to promote optimal time-use patterns. Currently, there is no comprehensive evidence on the prevalence of meeting these guidelines among New Zealand school-aged children and the associated sociodemographic factors.

To date, accelerometers have been commonly used to derive the daily activity compositions in 24-hour time-use research, with the majority of the studies focusing on quantifying the time spent in different activity intensities (i.e., sedentary behaviour (SB), light-intensity physical activity (LPA), MVPA, sleep) using count-based methods [32, 150, 185, 198]. Here, the acceleration data are converted into "activity counts" using proprietary algorithms [14]. Subsequently, cut-points are applied to these counts to distinguish between different activity intensities. There are various and often conflicting sets of cut-points to estimate the amount of MVPA, LPA and SB, reducing the comparability across studies [15]. To help address this issue, extracting activity type and posture from raw accelerometer data through machine learning and other algorithms is gaining interest [154]. These techniques are capable of detecting postures (i.e., sitting, standing, lying) and other ambulatory activities (i.e., walking, and running) with high accuracy in the lab and free-living settings [18, 19]. However, to the best of our knowledge, no study has yet quantified complete 24-hour time-use behaviours in terms of activity type in children (i.e., sitting, standing, walking, running, lying).

Activity researchers are increasingly using compositional data analysis (CoDA) to analyse 24-hour time-use behaviours to adequately account for the compositional properties of time-use data [13]. Using this statistical approach, the aims of this study were 1) to describe the 24-hour time-use behaviours of New Zealand children, both in terms of activity intensity and activity type, 2) to examine differences in 24-hour time-use behaviours among different sociodemographic groups, and 3) to determine the adherence to the individual and combined 24-hour Movement Guidelines for New Zealand children.

Methods

Participants

This study is a secondary analysis of children participating in the 8-year data collection wave (when the children were 8 years old) of the *Growing Up in New Zealand* study (GUiNZ) – an ongoing longitudinal cohort study started in 2009. In the GUiNZ study, data have been collected at several time points. However, the current study uses the 8-year dataset, and several sociodemographic variables collected at birth (antenatal dataset). Additional details regarding this study are available elsewhere [23]. A total of 5,556 children participated in the 8-year wave of this study; however, accelerometers were only worn by a subsample of children. In total, 952 children wore accelerometers, although the final analytic sample used in this study was 623 children. The GUiNZ study was approved by the Ministry of Health Northern Y Regional Ethics Committee (NTY/08/06/055).

Measurements

24-hour time-use behaviours

The Axivity AX3 accelerometer was used to assess the 24-hour time-use behaviours. A pair of Axivity AX3 accelerometers were placed on the dominant thigh and lower back using medical dressing or purpose-built foam pouches [53]. Participants were asked to wear these monitors for seven consecutive days. The devices were initialised to collect data at a sampling rate of 100 Hz and were downloaded using the Open Movement Software (OMGUI, version 1.0.0.30, open Movement, Newcastle University, UK). Wear/non-wear time was detected using the in-built temperature sensor following procedures described elsewhere [53, 138]. To be included in the study, children needed to have valid accelerometer data (both thigh and lower back) for at least one day over the seven days of measurement. A valid day was defined as 24-hours of concurrent wear time for both sensors. Two separate 24-hour time-use compositions were created, one for activity intensity (based on energy expenditure) and one for activity type (based on posture). For the activity intensity composition, raw data from the back sensor were converted into counts congruent with the ActiGraph GT3X device, using published algorithms [161]. The scaled Evenson cut-points were then applied to categorise each 5-second epoch as SB, LPA or MVPA [159]. Sleep duration was derived using the Tudor-Locke algorithm for the centre of mass [122], which was calculated from 12am to 12 am. The minutes of each behaviour per day were averaged over the number of valid days for each participant. For the activity type composition, machine learning models were applied to each 5-second epoch from the thigh and lower back monitors. These models were previously developed and tested in both lab and free-living settings in children [18, 19]. The activity intensity composition was comprised of the following four parts: SB, LPA, MVPA, and sleep. For activity type, a 5-part composition was created containing: sitting, standing, walking, running, and lying.

24-hour Movement Guidelines adherence

Using the 24-hour Movement Guidelines for New Zealand children, participants were classified as meeting the MVPA guideline if they had accumulated on average 60+

minutes of MVPA daily. To assess adherence to the screen time guideline, each child's mother was asked to report the hours and minutes that their child usually 1) watched television, including free-to-air, online, and pay-tv or DVDs, either on TV or other screen-based devices, 2) spent time doing activities or tasks (e.g., homework, playing games, or sending messages) on any screen-based devices including computers, laptops, tablets, smartphones or gaming devices, separately for a weekday and weekend day. The responses to these two questions were summed to calculate total screen time (for the weekday and weekend days separately). Subsequently, the average of these values was calculated to obtain the average daily screen time. Children who engaged in less than 2 hours of screen time per day were categorised as meeting the screen time recommendation. Finally, children with 9–11 hours of sleep per 24-hours were classified as meeting the sleep guideline.

Sociodemographic variables

The child's age at the time of data collection was calculated using their date of birth, and the mother's age was calculated at the date of delivery (i.e., age of the mother when the child was born). Child ethnicity was classified into the following major ethnic groups: 1) European, 2) Māori, 3) Pacific, 4) Asian, 5) Middle Eastern, Latin American and African (MELAA), and 6) Other. MELAA and Other were combined as "Other" due to small numbers in each group. Children who answered, "I don't know" to the ethnicity question were also categorised as "Other". Household annual income and New Zealand Deprivation index 2013 (NZDep2013) [178] were used as a proxy for household socioeconomic status. Mothers were asked to report their household income over the past 12 months, categorised into four groups: (NZD <$70,000, 70,000 –100,000, 100,000 – 150,000, and >150,000). NZDep2013 reflects the area-level deprivation status for each meshblock (small geographic census unit) based on nine variables from the 2013 census data. Each meshblock is assigned a deprivation score ranging from decile 1 (least deprived) to decile10 (most deprived). From these scores, three categories were created: 1) low deprivation (deciles 1–3), 2) medium deprivation (deciles 4–7), and 3) high deprivation (deciles 8–10). The residence location was categorised as either urban or rural.

Information on the mother's highest level of education was obtained from the antenatal dataset (as it is not available in the 8-year dataset). Mothers were asked about their highest qualification at the time. They could choose from the following categories: 1) without a secondary school qualification, 2) secondary school/National Certificate of Educational Achievement (NCEA) levels 1–4, 3) diploma/Trade certificate/NCEA levels 5–6, 4) bachelor's degree 5) higher degree. These categories were dichotomised into 1) "less than a bachelor's degree" and 2) "bachelor's degree or higher". Mother's weekly work hours were obtained from the 8-year dataset and subsequently categorised as <15, 15–30, 30–40 and ≥40 hours. Information on the family structure was classified as either: 1) single parent 2) both parents 3) parent(s) with extended family or parent(s) living with non-kin.

Statistical Analysis

All the analyses were carried out in R (version 3.6.1; The R Foundation for Statistical Computing, Vienna, Austria). Descriptive characteristics, including frequency (categorical variables) and means (continuous variables), were calculated. Sociodemographic differences between children with and without accelerometer data at the 8-year time point were compared using Chi-squared tests and independent samples t-tests for continuous variables. This study used a compositional data analysis approach. Firstly, missing values and parts of each composition that contained zeros were imputed using log-ratio expectation-maximisation [180]. This method of zero imputation has been shown to produce the least bias [145]. For descriptive statistics, the geometric mean was calculated for time spent in each activity intensity and activity type component and then normalised to 1440 minutes (24-hours) to obtain the compositional mean for each activity over a 24-hour period. Compositional multivariate analysis of variance (MANOVA) was used to compare activity intensity and activity type components among different sociodemographic groups (i.e., gender, ethnicity, mother's age, mother's education, mother's work hours, household structure, household income, household deprivation, and residence location) [146]. Compositional parts were first transformed using the isometric log-ratio transformation, before being entered into each model as the dependant variable. For each model, partial eta squared (η_p^2) was calculated as an indication of effect size. Hoteling's T-square tests with the Holm adjustment were applied as post-hoc comparisons for sociodemographic variables with more than two levels [146]. To identify the specific component(s) of each composition responsible for significant overall differences, between-group log-ratio differences along with bootstrapped 95% confidence intervals were estimated for each component [146]. These estimated log-ratio differences were back-transformed into percentages using the following formula:

(exp (log-ratio difference) – 1) * 100. These differences were also visualised using compositional geometric mean bar plots.

Lastly, the association between meeting each component of the 24-hour movement guidelines and sociodemographic factors was assessed using Chi-squared tests. In cases where the expected cell counts were less than 5 (six occurrences), the Fisher's exact test was used instead. For each test, Cramer's V was calculated as an indication of effect size. Statistical significance was set at 0.05 for all analyses.

Results

Of the 5,556 participants in the 8-year wave of GUiNZ, 623 (51.5% girls, mean age = 7.8 (0.24) years old) had valid accelerometer data for at least one complete day (24 hours wear time) for both sensors simultaneously, making them eligible for this study. Other reasons for exclusion were: only had data from one sensor (n = 79; either due to the child only consenting to wearing one sensor, a lost sensor, or data were unable to be downloaded), corrupt raw data or failure to time synchronise the thigh and back sensors (n = 30). The mean number of valid days was 4.9, which contained, on average, 1.3 weekend days. Table 6-1 describes the characteristics of the GUiNZ participants with and without accelerometer data. Sociodemographic characteristics varied between those with and without accelerometer data in terms of child age, ethnicity, mother's age, mother's education, mother's working hours, household income, and household deprivation. No significant differences were seen for gender, residence location, or household structure.

Table 6-1. Characteristics of the participants in the 8-year wave of the GUiNZ (with/without accelerometer data).

Variables	Participants without accelerometer data n (%) or mean n = 4856	Participants with accelerometer data n (%) or mean n = 623	*P*- value*
Age (years)	7.6	7.8	**<0.001**
Gender			0.117
Boy	2516 (51.8)	302 (48.5)	
Girl	2340 (48.2)	321 (51.5)	
Ethnicity			**0.003**
European	1623 (38.2)	273 (44.2)	
Māori	968 (22.8)	119 (19.3)	
Pacific	470 (11.1)	45 (7.3)	
Asian	460 (10.8)	74 (12.0)	
Other	727 (17.1)	107 (17.3)	
Missing	608	<10	
Mother's age at delivery (years)			**< 0.001**
≤20	276 (5.7)	13 (2.1)	
≤25	720 (14.8)	66 (10.6)	
≤30	1284 (26.4)	155 (24.9)	
≤35	1585 (32.6)	237 (38.0)	
≤40	864 (17.8)	137 (22.0)	
>40	126 (2.6)	15 (2.4)	
Missing	<10	0	
Mother's level of education			**< 0.001**
Less than a bachelor's degree	2804 (63.0)	300 (48.2)	
Bachelor's degree or higher	2039 (37.0)	323 (51.8)	
Missing	13	0	
Mother's work hours (weekly)			**0.001**
<15	1807 (41.2)	181 (31.5)	
15 – 30	819 (18.7)	121 (21.0)	
30 – 40	731(16.7)	107 (18.6)	
≥ 40	1030 (23.4)	166 (28.9)	
Missing	469	48	
Household structure			0.176
Single parent	433 (9.5)	62 (10.0)	
Both parents	3172 (69.5)	447 (72.2)	
Parent(s) with extended family or non-kin	958 (21.0)	110 (17.8)	
Missing	293	<10	

Table 6-1. (continued).

Variables	Participants without accelerometer data n (%) or mean n = 4856	Participants with accelerometer data n (%) or mean n = 623	*P*- value*
Household income			**0.001**
≤70 k	1092 (29.9)	118 (21.0)	
70 –100k	655 (18.0)	120 (21.4)	
100 –150k	860 (23.6)	141 (25.1)	
>150k	1040 (28.5)	183 (32.6)	
Missing	1209	61	
Household deprivation**			**<0.001**
Low (1 – 3)	1576 (35.1)	222 (35.8)	
Medium (4 – 7)	1639 (36.5)	276 (44.5)	
High (8 – 10)	1280 (28.5)	122 (19.7)	
Missing	361	<10	
Residence location			0.350
Urban	3973 (88.4)	540 (87.1)	
Rural	522 (11.6)	80 (12.9)	
Missing	361	<10	
Screen time (minutes/day)	278	272	0.607
Missing	1949	151	

*Chi-square test (categorical variables) or independent sample t-test (continuous variables).
** According to the New Zealand Index of Deprivation 2013.

Of the 623 children with valid accelerometer data, information on activity intensity and activity type compositions could be extracted for 620 and 602 children, respectively (due to algorithm or imputation errors). Table 6-2 shows the compositional means of time spent in each component of the activity intensity and activity type compositions for the total sample, and separately by gender, ethnicity, and other sociodemographic factors. From the activity intensity perspective, children spent, on average, 31.1%, 22.3%, 6.8%, and 39.8% of their time in SB, LPA, MVPA and sleep, respectively. However, the daily distribution of time in different activity types was 33.2 % sitting, 10.8% standing, 7.3% walking, 0.4% running, and 48.2% lying do

Table 6-2. Compositional means (in minutes) for different components of activity intensity and activity type compositions by gender, ethnicity, and sociodemographic status.

	Activity intensity components (n = 620)				Activity type components (n = 602)				
	SB	**LPA**	**MVPA**	**Sleep**	**Sitting**	**Standing**	**Walking**	**Running**	**Lying**
Total	448	321	98	573	479	155	106	7	694
Gender									
Boy	450	311	109	570	486	137	109	8	700
Girl	446	331	89	575	476	170	101	5	688
Ethnicity									
European	443	322	99	576	476	152	106	7	698
Māori	449	320	101	569	482	142	108	7	701
Pacific	458	307	103	572	507	141	93	5	694
Asian	458	334	91	556	496	172	100	5	666
Other	445	319	96	580	474	160	104	7	695
Mother's age at delivery (years)									
≤20	484	294	93	569	530	132	91	4	682
≤25	452	321	98	570	495	151	97	6	690
≤30	439	328	101	571	465	160	106	7	702
≤35	448	325	97	571	480	154	107	7	693
≤40	452	312	98	578	486	148	106	7	692
>40	454	317	85	584	511	152	89	5	683
Mother's education level									
Less than a bachelor's degree	452	319	97	571	487	153	102	6	692
Bachelor's degree or higher	444	323	98	574	488	153	102	6	691

Table 6-2. (continued).

	Activity intensity components (n = 620)				Activity type components (n = 602)				
	SB	LPA	MVPA	Sleep	Sitting	Standing	Walking	Running	Lying
Mother's work hours									
<15	453	319	97	571	480	151	102	6	701
1 5 – 30	438	322	99	581	465	159	109	7	701
30 – 40	446	318	100	576	502	145	99	7	688
≥ 40	449	327	98	566	479	158	109	8	686
Household structure									
Single parent	462	309	92	576	487	141	97	6	710
Both parents	443	323	99	575	478	155	106	7	693
Parents with extended family or living with non-kin	460	321	96	563	489	151	102	6	691
Household income									
<70K	455	310	97	578	479	152	99	6	704
70 –100k	455	320	96	570	488	157	101	6	687
100 –150k	432	333	100	575	475	165	109	7	685
>150k	446	324	99	571	477	148	107	8	701
Household deprivation									
Low	449	320	97	574	476	154	108	8	694
Medium	442	324	100	574	474	155	106	7	698
High	461	320	93	566	505	149	96	5	686
Residence location									
Urban	451	321	97	572	484	152	104	7	694
Rural	431	326	104	578	460	167	111	7	694

SB = Sedentary behaviour; LPA= Light-intensity physical activity; MVPA= Moderate-to-vigorous intensity physical activity.

Activity intensity composition

Table 6-3 presents the results for the MANOVA tests, which were used to compare these compositions among sociodemographic groups. For the activity intensity composition, there were significant overall differences between gender ($p < 0.001$; $\eta p2 = 0.19$), with girls spending significantly less time in MVPA (-18%, 95% CI = -22 – -14%) but more time in LPA (6%, 95% CI = 3–8%), compared to boys. However, no significant difference in sedentary and sleep time between gender was observed (Figure 6-1 C).

The overall intensity composition was different among groups based on child ethnicity ($p = 0.003$; $\eta p2 = 0.16$), and the Hoteling's post hoc test revealed that Asian children had significantly different compositions compared to European ($p = 0.015$), Māori ($p = 0.028$) and Pacific ($p = 0.004$) children. As shown in Figure 6-2, Asian children were involved in more LPA compared to European (4%, 95% CI = 0.2–7%), Māori (4%, 95% CI = 0.2–9%) and Pacific (9%, 95% CI = 3–16%) children. They also slept less than European (-3.5%, 95% CI = -6 – -1%) and Pacific (-3%, 95% CI = -6 – -0.5%) children.

Lastly, overall intensity compositions were different among annual household income groups ($p = 0.04$; $\eta p2 = 0.01$), with post hoc tests revealing differences between <$70k and $100–150k groups ($p = 0.022$). Children from households with an annual income of $100–150K were less sedentary (-5%, 95% CI = -8 – -1%) and involved more in LPA (7%, 95% CI = 3–11%) compared to those from households with a $70k annual income. (Figure 6-3).

We also carried out a sensitivity analysis where participants had three or more days of valid time-use data ($n = 482$). Aligning with our initial results, similar patterns of differences between activity intensity and activity type compositions between gender, ethnicity, household income, and household deprivation groups were observed (Supplementary Table S7).

Table 6-3. Results of compositional MANOVA of differences in daily activity intensity and activity type compositions between sociodemographic factors.

	Activity intensity composition					Activity type composition				
	Pillai's trace	**F**	**df**	***P*-value**	**η_p^2**	**Pillai's trace**	**F**	**df**	***P*-value**	**η_p^2**
Gender	0.187	47.26	3, 616	**<0.001**	0.187	0.171	30.87	4, 597	**<0.001**	0.171
Ethnicity	0.048	2.48	12, 1830	**0.003**	0.160	0.069	2.60	16, 2368	**<0.001**	0.017
Mother's age at delivery	0.032	1.33	15,1842	0.178	0.011	0.037	1.48	15,1788	0.106	0.012
Mother's education level	0.003	0.66	3, 616	0.575	0.003	0.010	1.57	4, 597	0.179	0.010
Mother's work hours	0.018	1.16	9,1704	0.313	0.006	0.025	1.55	9,1653	0.126	0.008
Household structure	0.019	2.03	6, 1224	0.057	0.009	0.014	1.07	8, 1186	0.374	0.007
Household income	0.031	1.96	9, 1668	**0.040**	0.010	0.039	1.79	12, 1617	**0.044**	0.013
Household deprivation	0.014	1.48	6, 1226	0.181	0.007	0.035	2.70	8, 1188	**0.005**	0.017
Residence location	0.010	2.15	3, 613	0.092	0.010	0.010	1.62	4, 594	0.167	0.010

The levels of each factor can be seen in Table 6-2.
Bold values represent significant differences.

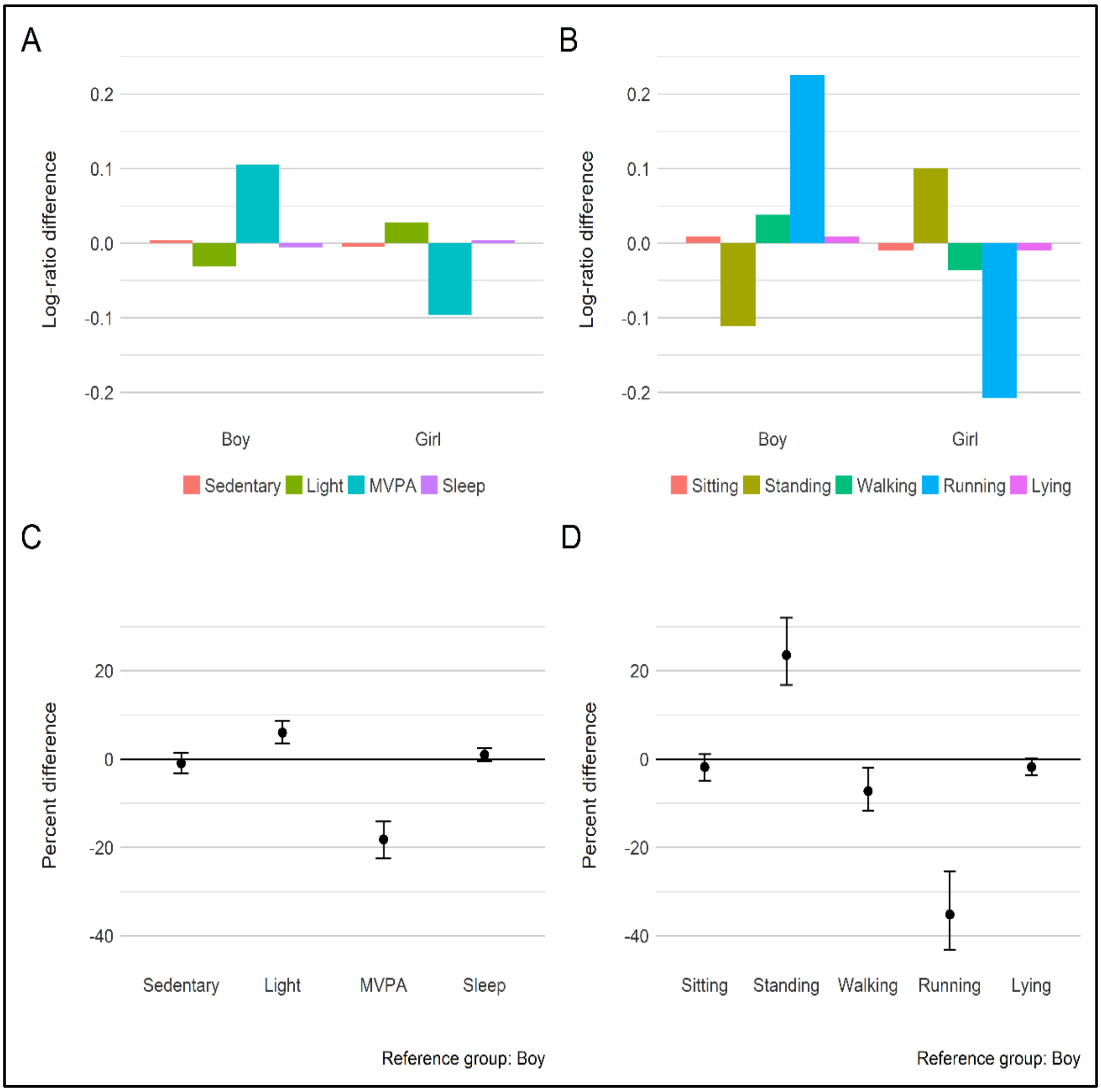

Figure 6-1. A and **B**: Compositional geometric mean bar plots comparing the geometric mean of the entire sample and the geometric mean of each activity intensity and activity type components by gender. **C** and **D**: The percentage differences (with 95% confidence interval) in times spent in each activity intensity and activity type components between genders. Estimates above the reference line mean girls have a higher proportion of an activity, relative to boys (reference group).

Light = Light-intensity physical activity; MVPA = Moderate-to-vigorous intensity physical activity.

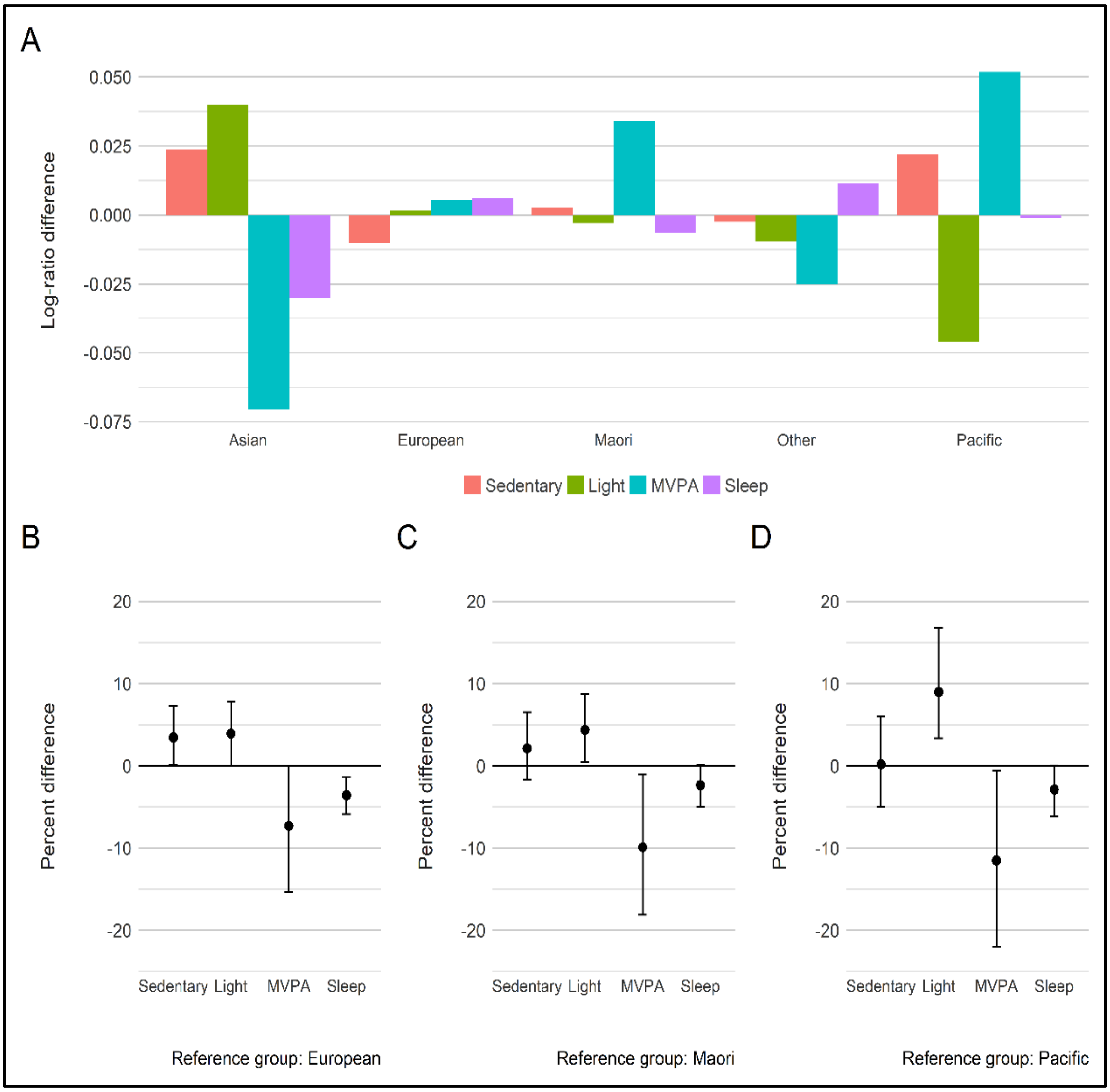

Figure 6-2. A: Compositional geometric mean bar plots comparing the geometric mean of each activity intensity component for each child ethnicity group with the geometric mean of the entire sample. **B**, **C** and **D**: The percentage differences (with 95% confidence interval) in time spent in each activity intensity component between Asian and European, Asian and Māori, and Asian and Pacific, respectively. Estimates above the reference line mean that ethnic group has a higher proportion of an activity, relative to the reference group.

Light = Light-intensity physical activity; MVPA = Moderate-to-vigorous intensity physical activity.

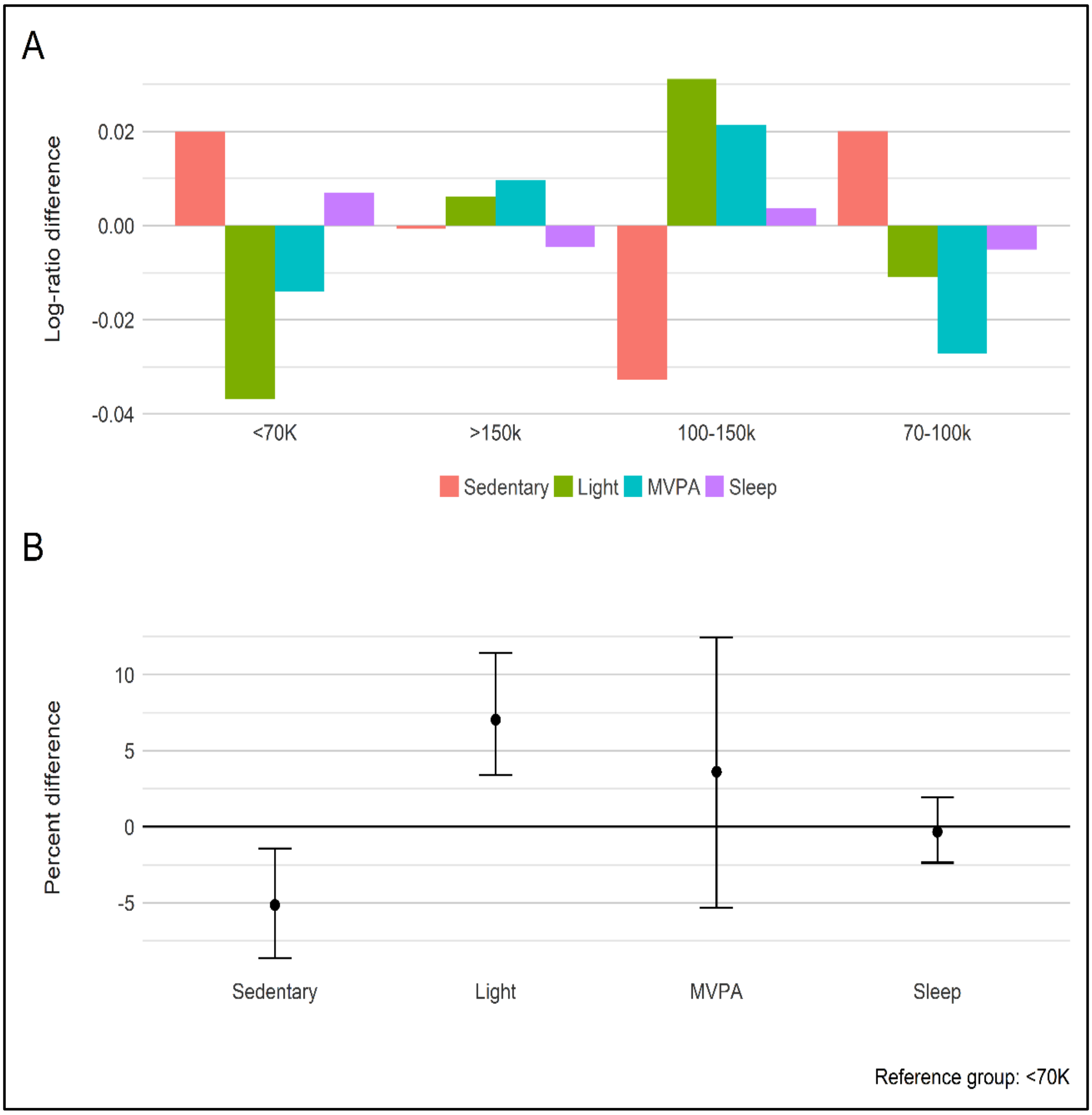

Figure 6-3. A: Compositional geometric mean bar plots comparing the geometric mean of each activity intensity component for each household income category group with the geometric mean of the entire sample. **B**: The percentage differences in time spent in each activity intensity component between households with less than NZ$70K annual income and households with NZ$100–150k annual income. Estimates above the reference line mean households with NZ$100–150k annual income have a higher proportion of an activity, relative to <70k (reference group).

Light = Light-intensity physical activity; MVPA = Moderate-to-vigorous intensity physical activity.

Activity type composition

Significant differences also existed between gender for the overall activity type composition ($p < 0.001$; $\eta p2 = 0.17$). The percentage differences in Figure 6-1 D suggest that girls spent significantly more time (23%, 95% CI = 17–31%) and less time walking (-7%, 95% CI = -12– -1%) and running (-35%, 95% CI = -44 – -25%) compared to boys. The overall activity type composition was different among groups based on child ethnicity ($p < 0.001$; $\eta p2 = 0.02$), and the Hoteling's post hoc test revealed Asian and European ($p = 0.002$), and Asian and Māori ($p = 0.003$) were different. Figure 6-4 shows spent more time standing (13%, 95% CI = 3–23%) and less time running (-25%, 95% CI = -40 – -3%) and lying down (-5%, 95% CI = -8 – -1%) compared to European children. Asian children also spent more time standing (21%, 95% CI = 8–34%) and less time running (-24%, 95% CI = -44 – -0.3%) and lying down (-5%, 95% CI = -9 – -1%) compared to Māori children.

Household deprivation was also related to the overall activity type composition ($p = 0.005$; $\eta p2 = 0.02$); specifically, children from highly deprived areas were different from those in areas of low ($p = 0.002$) and medium ($p = 0.012$) deprivation. Children from the most deprived areas spent more time sitting (6%, 95% CI = 2–11%) and less time walking (-11%, 95% CI = -17 – -3%) and running (-31%, 95% CI = -46 – -16%) compared to those from areas of low deprivation. Similar contrasts were seen for medium to high deprivation (Figure 6-5).

Although the MANOVA showed possible significant differences between household income groups for activity type compositions, results from the post hoc analyses did not show any significant differences between household income groups for activity type compositions after adjusting for multiple comparisons.

Results from the sensitivity analysis revealed overall significant differences for activity type composition between gender, and among ethnicity, mother's age at delivery, and household deprivation groups.

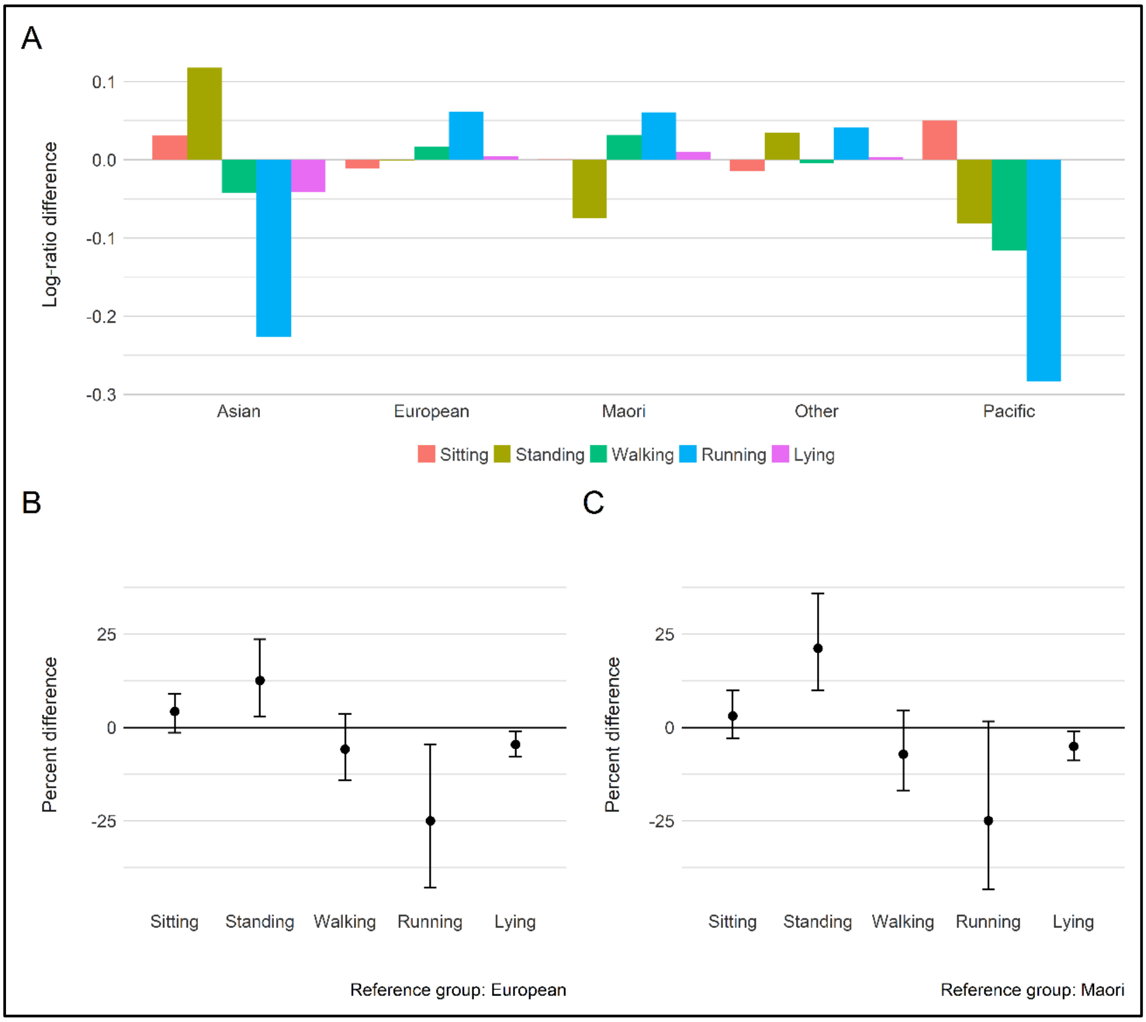

Figure 6-4. A: Compositional geometric mean bar plots comparing the geometric mean of each activity type component for each child ethnicity group relative to the entire sample. **B** and **C**: The percentage differences in time spent in each activity intensity component between Asian and European, Asian and Māori, respectively. Estimates above the reference line mean that ethnic group has a higher proportion of an activity, relative to the reference group.

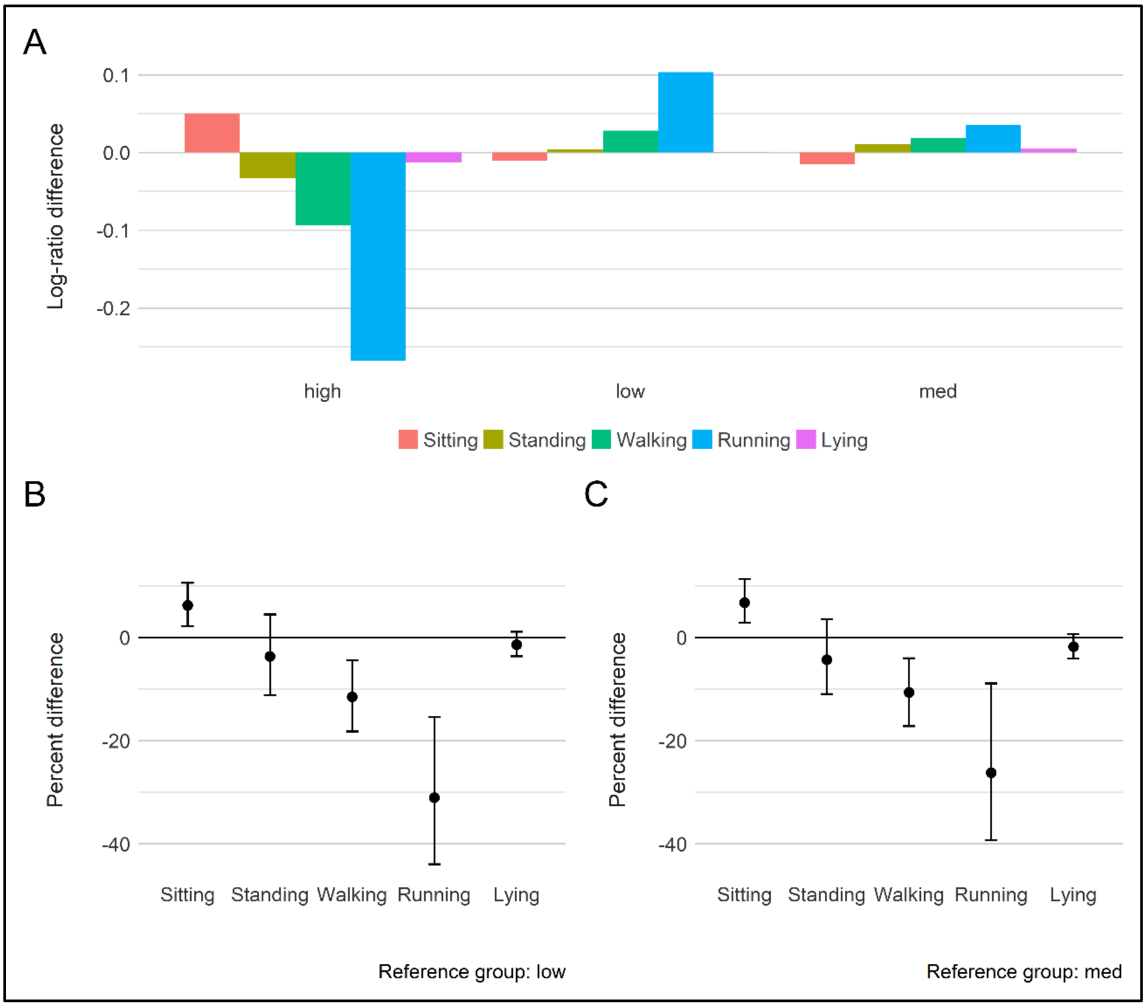

Figure 6-5. **A**: Compositional geometric mean bar plots comparing the geometric mean of each activity type component for each household deprivation category relative to the entire sample. **B** and **C**: The percentage differences in time spent in each activity intensity component between low and high, and medium and high levels of deprivation, respectively. Estimates above the reference line mean that level of deprivation has a higher proportion of an activity, relative to the reference group.

Adherence to 24-hour Movement Guidelines

Table 6-4 provides information on the proportion of children who met the individual and combined components of the 24-hour movement guidelines, as well as the associated sociodemographic factors. Significantly, more boys (93.3%) than girls (86.6%) met the PA guideline ($p = 0.006$; Cramer's $V = 0.11$). The percentage of children meeting the PA guideline was significantly different between children from rural and urban areas (97.5% vs. 88.6%, $p = 0.015$; $V = 0.10$). Meeting the screen time guideline was also associated with the child's ethnicity ($p = 0.021$; $V = 0.15$), mother's level of education ($p = 0.006$; $V = 0.12$ and residence location ($p = 0.033$; $V = 0.10$). A higher proportion of European (20.4%) and Asian children (20%), met the screen time guideline compared to Māori (7.1%) and Pacific (6.2%). Mother's education ($p = 0.017$) and child's ethnicity ($p = 0.008$; $V = 0.16$) were related to meeting the combined 24-hour guidelines.

Table 6-4. Proportion of children meeting the MVPA, screen time, and sleep recommendations and combinations of these recommendations, and associated sociodemographic factors.

	MVPA			Screen time			Sleep			MVPA+ Screen time + Sleep		
	Met	Not met	*p [V]*	Met	Not met	*p [V]*	Met	Not met	*p [V]*	Met	Not met	*p [V]*
Gender			**0.006** [0.11]			0.89 [0.01]			0.786 [0.01]			0.305 [0.05]
Boy	279 (93.3)	20 (6.7)		37 (15.9)	196 (84.1)		185 (61.9)	114 (38.1)		28 (12.1)	203 (87.9)	
Girl	278 (86.6)	43 (13.4)		39 (16.3)	200 (83.7)		202 (62.9)	119 (37.1)		22 (9.2)	217 (90.8)	
Child ethnicity			0.182* [0.10]			**0.021** [0.15]			0.562 [0.07]			**0.008*** [0.16]
European	245 (90.1)	27 (9.9)		44 (20.4)	172 (79.6)		176 (64.7)	96 (35.3)		32 (14.9)	183 (85.1)	
Māori	112 (94.9)	<10		<10	78 (92.9)		68 (57.6)	50 (42.4)		<10	80 (96.4)	
Pacific	41(91.1)	<10		<10	30 (93.8)		31 (68.9)	14 (31.1)		0	32 (100)	
Asian	62 (84.9)	11(15.1)		11 (20.0)	44 (80.0)		43 (58.9)	30 (41.1)		<10	50 (90.9)	
Other	94 (87.9)	13 (12.1)					66 (61.7)	41(38.3)		10 (12.3)	71 (87.7)	
Mother's age (years)			0.823* [0.06]			0.76* [0.08]			0.087 [0.12]			0.260* 0.12]
≤20	11 (84.6)	<10		0	<10		<10	<10		0	<10	
≤25	61 (92.4)	<10		<10	41 (89.1)		50 (75.8)	16 (24.2)		<10	44 (95.6)	
≤30	141(91.6)	13 (8.4)		20 (16.8)	99 (83.2)		93 (60.4)	61 (39.6)		10 (8.4)	109 (91.6)	
≤35	209 (88.6)	27 (11.4)		29 (15.7)	156 (84.3)		136 (57.6)	100 (42.4)		21 (11.4)	163 (88.6)	
≤40	121 (89.0)	15 (11)		19 (18.4)	84 (81.6)		92 (67.6)	44 (32.4)		14 (13.7)	88 (86.3)	
>40	14 (93.3)	<10		<10	10 (76.9)		<10	<10		<10	10 (76.9)	
Mother's education			0.940 [<0.01]			**0.006** [0.12]			0.184 [0.05]			**0.017** [0.11]
Less than a bachelor's degree	268 (89.9)	30 (10.1)		24 (11.1)	193 (88.9)		178 (59.7)	120 (40.3)		15 (6.9)	201 (93.1)	
Bachelor's degree or higher	289 (89.8)	33 (10.2)		52 (20.4)	203 (79.6)		209 (64.9)	113 (35.1)		35 (13.8)	219 (86.2)	

Table 6-4. (continued).

	MVPA			Screen time			Sleep			MVPA+ Screen time + Sleep		
	Met	**Not met**	***p [V]***	**Met**	**Not met**	***p [V]***	**Met**	**Not met**	***p [V]***	**Met**	**Not met**	***p [V]***
Mother's work hours			0.524 [0.06]			0.162 [0.11]			0.115 [0.10]			0.610 [0.06]
<15	166 (92.2)	14 (7.8)		22 (17.5)	104 (82.5)		113 (62.8)	67(37.2)		14 (11.1)	112 (88.9)	
15 – 30	110 (90.9)	11 (9.1)		21 (21.2)	78 (78.8)		82 (67.8)	39 (32.2)		12 (12.1)	87 (87.9)	
30 – 40	93 (86.9)	14 (13.1)		10 (11.8)	75 (88.2)		72 (67.3)	35 (32.7)		<10	76 (9.4)	
≥ 40	147 (89.6)	17 (10.3)		15 (11.7)	113(88.3)		91 (55.5)	73 (44.5)		<10	117 (92.9)	
Household structure			0.851 [0.02]			0.217 [0.08]			0.177 [0.08]			0.156* [0.09]
Single parent	56 (91.8)	<10		<10	40 (88.9)		43 (70.5)	18 (29.5)		<10	41 (91.1)	
Both parents	400 (89.9)	45 (10.1)		61 (17.8)	282 (82.2)		280 (62.9)	165 (37.1)		42 (12.3)	299 (87.7)	
Parents with extended family or living with non-kin	98 (89.1)	12 (10.9)		<10	72 (88.9)		62 (56.4)	48 (43.6)		<10	77 (95.1)	
Household income			0.698 [0.05]			0.442 [0.08]			0.094 [0.11]			0.519 [0.07]
<70K	105 (89.7)	12 (10.3)		<10	71 (88.8)		82 (70.1)	35 (29.9)		<10	74 (93.7)	
70 –100k	107(89.2)	13 (10.8)		13 (13.8)	81 (86.2)		65 (54.2)	55 (45.8)		<10	85 (90.4)	
100 –150k	131(92.9)	10 (7.1)		23 (19.2)	97 (80.8)		88 (62.4)	53 (37.6)		15 (12.5)	105 (87.5)	
>150k	163 (89.6)	19 (10.4)		25 (17.0)	122 (83.0)		112 (61.5)	70 (38.5)		17 (11.6)	129 (88.4)	
Household Deprivation			0.776 [0.03]			0.551 [0.05]			0.179 [0.07]			0.311 [0.07]
Low	201 (91.0)	20 (9.0)		25 (13.7)	157 (86.3)		134 (60.6)	87 (39.4)		14 (7.7)	167 (92.3)	
Medium	246 (89.1)	30 (10.9)		37 (17.8)	171 (82.2)		182 (65.9)	94 (34.1)		25 (12.0)	183 (88.0)	
High	107 (89.2)	13 (10.8)		13 (16.0)	68 (84.0)		68 (56.7)	52 (43.3)		10 (12.5)	70 (87.5)	
Residence location			**0.015** [0.10]			**0.033** [0.10]			0.198 [0.05]			0.058 [0.09]
Urban	476 (88.6)	61 (11.1)		59 (14.5)	348 (85.5)		329 (61.3)	208 (38.7)		38 (9.4)	367 (90.6)	
Rural	78 (97.5)	29 (2.5)		16 (25.0)	48 (75.0)		55 (68.8)	25 (31.2)		11 (17.2)	53 (82.8)	

MVPA = Moderate-to-vigorous intensity physical activity; V = Cramer's V effect size; *Fisher's exact test.
Bold values represent significant differences.

Discussion

This study provided a detailed description of 24-hour time use behaviours in New Zealand school-aged children. The prevalence of meeting the New Zealand 24-hour movement guidelines, and the association with selected sociodemographic factors was also investigated. Overall, 24-hours activity intensity and activity type compositions differed by children's gender, ethnicity, household income and household deprivation. Although most children met the PA recommendation, only 62.5% and 16% met the sleep and screen time recommendations, respectively. The compliance to the combined 24-hour movement guidelines was even lower (10.6%). Meeting the individual and combined 24-hour Movement Guidelines was also associated with several sociodemographic factors.

24-hour activity intensity and activity type compositions

From an activity intensity perspective, children spent 31.1 % of their day sedentary (448 minutes), 29.1% in physical activity (419 minutes; 6.8% MVPA) and 39.8% sleeping (573 minutes). These figures are comparable to the findings from a recent study in 690 New Zealand children aged 6–10 years [181]. Compared to Canadian children aged 6–17 years old, children in our study were less sedentary (~100 minutes less), more physically active (~47 more minutes in MVPA and ~58 minutes in LPA), and had similar amounts of sleep [83]. Similarly, children in our study were less sedentary (~33–125 minutes less) and more engaged in MVPA (~29–55 minutes more) compared to 9- to 11-year-old children from 12 countries [150]. These results suggest New Zealand children obtain almost the same amount of sleep as Australian and UK children, but more than Canadian, European, American, Asian and African children [150].

Children's 24-hour activity intensity compositions have been linked with various physical and mental health outcomes [83, 129, 150]. However, using count-based approaches to derive these activity intensity compositions is not without challenges; specifically, the detection of sedentary behaviour where all non-ambulatory activities, including standing, are potentially misclassified as sedentary behaviour [151]. This error in estimating sedentary behaviour may ultimately confound the true health-related impacts of the 24-hour time-use compositions. On the other hand, activity type recognition models have shown high accuracy in detecting sitting, standing, and other activity types [18, 19]. Using these models, we also described the 24-hour activity type compositions of children, which, to our knowledge, is the first study where the 24-hour compositions of children have been described from an activity type perspective.

Sociodemographic correlates of 24-hour activity intensity and activity type compositions

In this study, boys spent significantly more time in MVPA (20 minutes) and less time in LPA (20 minutes) than girls, which is in accordance with previous studies identifying gender as a correlate of physical activity in children [199, 200]. In terms of activity type, girls had less walking and running time and more standing time than boys. Measuring daily activities of Malaysian children (aged 9–11 years) using activPAL, it was shown that on average, girls had more standing time than boys, which aligns with our findings. However, in the aforementioned study, girls had significantly less lying/sitting time compared to boys [201]. This is distinct from our observations, where no gender differences were observed for sitting or lying time. These inconsistencies could be attributable to different accelerometers and methods for measuring daily activity types.

Differences in children's activity intensity compositions were observed across ethnicities. Asian children spent less time in MVPA and sleep than other ethnicities while engaged in more LPA and sedentary time. In Taylor et al.'s study of New Zealand children (aged 6–10 years), Asian children were less active (less MVPA and LPA) and more sedentary compared to all other ethnicities and had shorter sleep duration compared to European and Māori children [181]. This is congruent with findings from previous international studies where minoritised ethnic groups had more sitting [202, 203] and lower PA [203].

Additionally, children from high-income households ($100–150K) spent significantly more time in LPA and were less sedentary than children from low-income households ($70k and less). No association was identified between the amounts of MVPA across the household income categories. In a study of Australian children (aged 9–11 years), a weak positive association was observed between household income and MVPA, but no association was observed between household income and sedentary time [204]. In that study, parental education was used jointly with household income as an indicator of social-economic status. It showed no association between parental education and MVPA or sedentary time, which aligns with our findings. Contrary to these findings, a weak negative association was found between parental education and sedentary time in a study of UK school-aged children [205].

The activity intensity compositions did not differ among children from different areas of deprivation, a finding consistent with that reported by Taylor et al. [181]. In contrast, we found that the activity type compositions were significantly different between children from high deprivation and those from low to medium deprived households. Specifically, children from a high level of deprivation had less running and walking time and more sitting time than their peers from less deprived areas. This finding highlights the importance of assessing activity type, in addition to activity intensity, in order to provide a better understanding of 24-hour time-use behaviours in children.

24-hour Movement Guidelines adherence and associated sociodemographic factors

Regarding the proportion of children meeting the individual and combined 24-hour movement guidelines, the majority met the MVPA recommendation (90%), while 62.5% and 16% met the sleep and screen time recommendations, respectively. Significant differences were observed in meeting the MVPA guideline between genders, with higher adherence in boys than girls (93.3% vs 86.6%). This is supported by previous evidence on children from Canada [206] and Mozambique [133]. We also observed that a higher proportion of children residing in rural areas met the MVPA guideline than those living in urban areas (97.5% vs 88.6%). A similar study among children (9–11 years) in Mozambique also showed a higher prevalence of meeting the MVPA guideline among rural children [133].

Adherence to the screen time guideline was extremely low (16%). In a study investigating the temporal patterns of meeting the screen time guideline among the same population at an earlier age, a decrease of 26% in adherence rate of children at age 54-months (18.4%) was observed compared to 24-months (44.4%) [207] Collectively, this decreasing trend in screen time adherence among New Zealand children warrants immediate attention considering the detrimental health impacts associated with high screen time [9]. Consistent with other studies [208, 209], children with mothers who have higher educational qualifications had a greater adherence rate to screen time guideline. Additionally, children's screen time was significantly associated with the child's ethnicity, with European being more likely to meet the screen time guideline than other ethnicities. Similar observations were made in other studies in New Zealand [207] and other countries [210], where minoritised ethnic groups were more likely to exceed the screen time recommendations. We also found that those residing in rural areas had higher odds of meeting the screen time guideline. Others have also found that rural children tend to have less screen time than their urban peers [133]. This observation might mean that children in rural settings have higher opportunities to spend time outdoors and, therefore, are less engaged in screen-based activities than urban children.

In this study, 62.5% of the children met the sleep duration recommendation, which is less than Australian and UK children [136] but higher than American, Canadian, Chinese, African [136], and Chilean children [211]. Only a small proportion of children (10.6%) met the combined 24-hour movement guidelines. This observation of low adherence to these guidelines among children is in agreement with previous evidence from several countries showing that only 5–15% of children aged 9–11 met all three recommendations in the 24-hour movement guidelines [136, 211, 212].

This study is one of only a small number to investigate the sociodemographic factors of meeting the 24-hour movement guidelines. In our study, meeting the combined 24-hour movement guidelines was associated with the child's ethnicity and mother's education. As shown in a recent review [21], a limited number of studies have examined sociodemographic correlates of meeting the combined 24-hour movement guidelines among children [132, 133]. These studies suggest an association between parental education, outdoor time, school location (urban vs rural), maternal activity level, and TV viewing time before pregnancy and meeting the combined 24-hour movement guidelines [132, 133]. More studies need to investigate the sociodemographic correlates of meeting these guidelines to provide evidence for developing more effective interventions targeting those more likely to engage in unhealthy time-use patterns.

There are several strengths to this study. We used 24-hour accelerometry to measure 24 time-use behaviours. The 24-hour time-use compositions of children were described from two perspectives: activity intensity (using accelerometer-derived counts) and activity type (using machine learning algorithms). Additionally, we applied CoDA to investigate sociodemographic differences in 24-hour time use behaviours. To our knowledge, this is the first study in which CoDA methods have been applied to determine the group differences in time-use compositions among children. Adequately accounting for the compositional nature of time-use behaviours, these methods should be used while dealing with compositional data [13]. There are also several limitations that need to be considered. Firstly, there were significant differences between sociodemographic characteristics of those included and excluded in this study, which could reduce the generalisability of the findings. Also, screen time was parent-reported, which is prone to bias [77], and 25% of the children were missing screen time data which may limit the representativeness of the screen time results. Additionally, as children with at least one day of valid accelerometer data were included in the analysis, potential variability between weekday and weekend time-use patterns, and individual vs. multiple days, were not taken into account.

Also, the limited amount of higher intensity physical activity observed (particularly running) meant that the confidence intervals for these activities were much wider, and the estimates less precise. Hence, these results should be interpreted with caution. We were also not able to tease out how the interrelationships between socioeconomic status and ethnicity in children might impact our findings, which should be examined in the future time-use research. Finally, the cross-sectional design of the study precludes any causative conclusions from being drawn regarding the sociodemographic correlates of 24-hour time-use patterns.

Conclusions

In this study, child gender, ethnicity, household income, and household deprivation were associated with the 24-hour activity intensity and activity type compositions in New Zealand children. Girls were more at risk of lower MVPA (and walking and running) compared to boys. Asian children had higher LPA, but less sleeping time compared to the other ethnicity groups. Children from high deprived households were at higher risk of spending more time sitting and less time walking or running compared to the children from less deprived households. Overall, a small proportion of New Zealand school-aged children met the combined 24-hour Movement Guidelines. Sociodemographic factors including child gender, ethnicity, mother's education, and household area were associated with meeting these Guidelines. These findings may help to design more effective future interventions to promote optimal 24-hour movement patterns for New Zealand children.

Chapter 7 - General Discussion

The overall aim of this PhD thesis was to explore how time-use behaviours were related to obesity in New Zealand children by performing a series of studies guided by the VIRTUE framework. To address Research Area 1 in this framework (i.e., methods), a laboratory-based validation study was carried out to investigate the concurrent validity between two accelerometers (i.e., Axivity AX3 and ActiGraph GT3X+) for measuring time-use behaviours in terms of activity intensity and activity type (Chapter 3). Subsequently, the relationships between AX3-measured 24-hour time-use behaviours and obesity, as well as the patterns and determinants of these behaviours among school-aged children were explored in three separate cross-sectional studies (Chapters 4–6), fitting within Research Areas 2, 3, and 4 of the VIRTUE framework.

Summary of Research

Chapter 3 provided the first investigation of the concurrent validity of GT3X+ (waist-worn) and AX3 (attached to the lower back) against direct observation for classifying various postures and activity intensity in children and adults under laboratory conditions. The most significant measurement error was observed for both devices when contrasting sitting/standing, sedentary/light intensity, and moderate/light intensity. Both devices demonstrated 65% to 97% balanced accuracy for detecting various postures and physical activity intensities in children, with the AX3 performing slightly better than the GT3X+ accelerometer. The findings showed that the AX3 device could be effectively used to identify activity type and intensity in child populations.

Chapter 4 investigated the relationship between 24-hour time-use behaviours (measured in terms of activity intensity and activity type), as well as the reallocation of time between these behaviours, and obesity-related outcomes (i.e., BMI z-score, waist circumference (WC), and waist-to-height ratio (WHtR) among New Zealand school-aged children using compositional data analysis (CoDA). From an activity intensity perspective, time spent in LPA, relative to other behaviours, was negatively associated with BMI z-score and WC. Time spent in SB (relative to other behaviours) was positively associated with BMI z-score and WC. However, after adjusting for gender, ethnicity, and deprivation, only the relationship between LPA and BMI z-score remained significant. From an activity type perspective, time spent in walking and running (relative to other behaviours) were negatively associated with BMI z-score. Additionally, reallocation of time to LPA and walking and running (from the other behaviours) were associated with reduced BMI z-score among children. These findings demonstrated the importance of allocating time to targeted time-use behaviours to improve favourable obesity-related outcomes.

To further our understanding of the relationships between time-use behaviours and obesity in New Zealand children, Chapter 5 examined how these 24-hour time-use behaviours (measured from two perspectives of activity intensity and activity type) cluster with other modifiable lifestyle behaviours, including dietary behaviours and screen time. The relationship between these cluster memberships and obesity-related outcomes were also examined. Three distinct lifestyle clusters were identified, and cluster membership was associated with BMI z-score, WC, and WHtR among New Zealand children. Children from the cluster with favourable combinations of sedentary time, screen time, and dietary behaviour had more favourable obesity-related outcomes than those with unhealthy behaviours (unhealthy diet and high sedentary time). This study highlighted the importance of considering lifestyle behavioural patterns rather than focusing on isolated behaviours.

Chapter 6 investigated the sociodemographic correlates of 24-hour time-use behaviours among New Zealand children and adherence to the New Zealand 24-hour Movement Guidelines. Behaviour patterns were measured from two perspectives: activity intensity and activity type. Child gender, ethnicity, household income, and deprivation were associated with the 24-hour activity intensity and activity type compositions. While most children met the physical activity recommendation, 62.5% and 16% met the sleep and screen time recommendations, respectively. Failing to meet the screen time recommendation was the driving factor for very low compliance to all three recommendations (10.6%). Child gender, ethnicity, mother's education, and household area (urban vs. rural) were associated with meeting each of these guidelines individually and collectively. This study showed that some sociodemographic groups are at higher risk of engaging in suboptimal time-use compositions, which should be taken into account when developing future interventions.

Significance of Findings

This body of work makes significant contributions to time-use research in children by addressing several research areas in the VIRTUE framework. These important contributions specific to each research area within this framework are highlighted and discussed in the following sections:

Methods of assessing and analysing time-use behaviours (VIRTUE Research Area 1)

Measuring time-use behaviour is one of the main topics within the first stage of the VIRTUE framework [12]. Accurate measurement of these behaviours is clearly the first step for advancing the field of time-use epidemiology. Accelerometers are widely used to quantify time-use behaviours [14]. Therefore, it is essential to investigate the accuracy of these accelerometers and the comparability between different devices for measuring various components of time-use behaviour. The results presented in Chapter 3 of this thesis represent the first validation study of a widely used accelerometer, ActiGraph GT3X+, and a newer accelerometer, Axivity AX3, by comparing these devices against direct observation for measuring time-use behaviours from both activity intensity (using activity counts) and activity type (using machine learning) perspectives. Most accelerometer-derived intensity-based measures of time-use behaviour (including sedentary behaviour (SB), light physical activity (LPA), and moderate-to-vigorous physical activity (MVPA)) rely on activity counts and involve arbitrary decisions with regards to cut points and epoch lengths [14]. These arbitrary decisions could lead to different estimates of intensity-based components of time-use behaviours and ultimately different findings [14]. For example, in Chapter 4, we observed that LPA was associated with favourable obesity-related outcomes, which is contrary to most previous time-use studies that found the amount of time spent in MVPA, not LPA, was associated with most favourable obesity-related outcomes [83, 129, 181]. A possible reason for these inconsistencies could be the use of different cut-points and other data processing decisions. On the other hand, deriving activity type from postural information using raw accelerometer data could offer a solution to overcome this challenge.

Investigating the health-related impacts of time-use behaviours measured from an activity type (postural) perspective is essential, as different activity types such as sitting and standing still can trigger different metabolic responses [64]. These estimates could be overlooked when count-based approaches are applied, as activities with limited movements are all grouped and reported as sedentary behaviour [151]. Moreover, interpreting activity types might provide more understandable estimates of time-use behaviours. For example, in Chapter 4, we showed that reallocating time to LPA (from an intensity-based perspective), and to walking and running (from an activity type perspective) were associated with favourable obesity-related outcomes. The latter (walking and running) could be a more interpretable behaviour to understand and promote in interventions targeting childhood obesity prevention in the future.

Chapter 3 demonstrated that a single AX3 accelerometer (attached to the lower back) was slightly better for detecting postures than the waist-worn GT3X+. However, the overall accuracy was still much lower for detecting activity type when compared to using two AX3 accelerometers worn simultaneously at different body placements [18, 19]. Therefore, when detecting time-use behaviours that contain postural information, two sensors are preferred, which is the method utilised in the 8-year wave of the Growing Up in New Zealand (GUiNZ) cohort study. These accelerometer data were used in Chapters 4–6 of this thesis to investigate 24-hour time-use behaviour patterns and their collective impacts on obesity-related outcomes in New Zealand children.

Another key topic in the first area of research within the VIRTUE framework is the use of appropriate analytical methods for time-use data [12]. In particular, the use of compositional data analysis (CoDA) instead of traditional statistical methods to investigate time-use behaviours. This is because time-use data are compositional in nature, and these properties are appropriately acknowledged within the CoDA framework

[13]. When compositional data are not treated as compositional, it can lead to spurious correlations and incorrect inferences [12]. In the current research, various CoDA methods have been applied (including compositional regression, compositional isotemporal substitution, compositional MANOVA, and compositional cluster analysis) to investigate the patterns of 24-hour time-use behaviours and to disentangle the combined impacts of these behaviours on obesity-related outcomes in children. The results presented in this thesis are among the first compositional estimates of these time-use behaviours and their associations with obesity in New Zealand children.

Health outcomes of time-use behaviours (VIRTUE Research Area 2)

There has been a recent conceptual shift in behavioural research towards an integrated time-use approach, focusing on the relationships between health and time-use behaviours collectively within their 24-hour context [12]. This shift in time-use research acknowledges the natural co-dependency between these behaviours as parts of 24-hour time-use compositions [13]. The second research area in the VIRTUE framework is focused on exploring the health impacts of all these time-use behaviours relative to each other within a compositional framework, rather than in isolation [12]. In Chapter 4 of this thesis, we used CoDA to explore the relationship between accelerometer-measured 24-hour time-use behaviours and indicators of obesity in New Zealand children. A novel aspect of this study was to quantify children's time-use behaviours from an activity type perspective, in addition to the traditional measure of activity intensity. We observed that the amount of time spent in LPA and walking, relative to the other behaviours, was favourably associated with BMI z-score (but not WC and WHtR). The only other study to investigate New Zealand children's time-use composition and obesity-related outcome found MVPA as the most important component associated with a lower BMI z-score [181]. It should be noted that findings from our study show that how theoretical reallocations across activities within 24-hour time-use compositions affect obesity indicators; however, whether these modifications are practical in the real world are yet to be examined in the future intervention studies. The ultimate goal of the VIRTUE framework is to develop interventions for promoting healthy time-use, and our findings could be utilised to develop such time-use interventions for childhood obesity prevention. According to our findings, future interventions should aim at increasing LPA (or walking and running) for favourable obesity-related outcomes in school-aged children. Although, these cross-sectional findings need to be firstly confirmed in the future longitudinal studies before being used for developing interventions.

Results from Chapter 5 revealed that different clusters of lifestyle behaviours exist among these children and cluster membership was related to obesity. These findings have also important implications for developing and tailoring future interventions targeting childhood obesity. For example, children from one cluster with specific patterns of behaviours may not equally benefit from the same interventions as children from another clusters. Therefore, a different intervention may be applied depending on what behavioural cluster every individual fall into. To our knowledge, only one other study has explored the cross-sectional relationship between clusters of these behaviours and obesity in children using a compositional approach [131]. Thus, future longitudinal studies are warranted for stronger evidence.

This research also provides valuable evidence for developing future 24-hour Movement Guidelines. The current guidelines are mainly based on evidence from studies that examined the health-related effects of time-use behaviours individually, ignoring their co-dependency on each other. Therefore, studies using CoDA to examine the collective health impacts of time-use behaviours are critical for informing future guidelines. Additionally, findings from this research offer evidence for developing specific recommendations on daily time that should be spent in LPA and total sedentary behaviour (not only screen-based activities) for children, which are not currently included in the 24-hour Movement Guidelines.

Prevalence and patterns of time-use behaviours (VIRTUE Research Area 3)

The third research area in the VIRTUE framework is dedicated to investigating the prevalence, optimal balance, as well as trends of time-use behaviours. In Chapter 6, we explored how New Zealand children spend their time, on average, within a 24-hour day. This was also the first study to assess the adherence to individual and integrated New Zealand 24-hour Movement Guidelines in school-aged children. Overall, the proportion of individuals meeting all the New Zealand 24-hour Movement Guidelines was very low (10.6%). This low figure was predominantly due to the low adherence to the screen time guideline (16%). Therefore, strategies to limit screen time among New Zealand children are warranted.

Importantly, individuals engage in particular patterns of these behaviours. By exploring how these lifestyle behaviours cluster, we were able to identify the most healthy and unhealthy patterns (Chapter 5). This evidence is among the first on lifestyle patterns among children using an appropriate statistical approach (CoDA). We observed that the healthiest cluster (healthy diet and being less sedentary) had the lowest rate of meeting MVPA guideline. This co-occurrence of healthy and unhealthy lifestyle behaviours indicates the need for future childhood obesity prevention interventions, to be designed to target patterns of lifestyle behaviours (rather than being single behaviour focused).

Determinants and correlates of time-use behaviours (VIRTUE Research Area 4)

Identifying determinants (including sociodemographic determinants) of time-use behaviours is advocated in the fourth research area in the VIRTUE framework. In Chapter 6, we used CoDA to explore the cross-sectional relationship between sociodemographic factors and children's 24-hour time-use. To our knowledge, this was the first attempt to understand how sociodemographic correlates influence time-use behaviours collectively within their 24-hour context rather than in isolation in New Zealand children. The associated sociodemographic factors with adherence to the individual and integrated New Zealand 24-hour Movement Guidelines were also determined. Differences observed in 24-hour time-use patterns by gender, ethnicity, household income, and household deprivation among these children. This highlights the need for the future interventions to be tailored to be gender, ethnicity, and socioeconomic status specific, for promoting healthy time-use patterns among New Zealand children.

Study limitations and future directions

There are several limitations in this thesis that need to be acknowledged. Firstly, the estimates of children's 24-hour activity intensity compositions in this research were derived from the lower back-worn AX3 through count-based approaches, which has been shown to perform poorly in differentiating between LPA and MVAP [176] (results shown in Chapter 1). Although capturing activity intensities through application of machine-learning algorithms on raw accelerometer data might be superior to count-based approaches, such activity-intensity detection algorithms specific to the lower-back mounted AX3 is yet to be developed and published (to our knowledge). Therefore, future time-use research might consider using AX3 on different placement sites such as wrist, which has been shown to outperform traditional count-based approaches when detecting activity intensity [213]. Moreover, future work on examining the health-related impacts of 24-hour activity type compositions in children, might also consider including other activity types, such as cycling, swimming, and dynamic standing. There is evidence showing that these activities could be detected with high accuracy using AX3 [18]. It should be acknowledged that applying machine learning techniques for extracting activity intensity and activity type information from raw accelerometery data requires high level of mathematical and programming skills, and thus, developing methods for making these techniques readily accessible to all the researchers without specialist programming/coding skills is warranted.

Secondly, this research used a cross-sectional design to investigate the relationships between time-use behaviours and obesity in children using secondary data from the 8-year wave of the GUiNZ cohort study (Chapters 4–6). This study design limits the ability to determine cause and effect relationships from the findings. However, GUiNZ is a longitudinal study that allows future longitudinal research to combine data from multiple data collection waves. This means it may be possible to investigate the trends of these behaviours over time and to explore causal relationships between time-use behaviours and health in the future research. This is particularly important as evidence from longitudinal time-use studies in children suggests that children tend to involve in less MVPA and more sedentary behaviour as they get older [214, 215]. Additionally, inherent to the nature of the secondary data analysis, the selection of time-use correlates and covariates in this research was constrained to the availability of such data in the 8-year GUiNZ dataset. Thus, future time-use research in New Zealand children should consider examining the potential impacts of other correlates of time-use such as parental time-use profiles, mode of travel to school, and geographical location of school (rural vs. urban).

These have been shown as significant correlates of time-use patterns and meeting the 24-hour Movement Guideline in the previous time-use research in children [21, 133, 141].

Participants in the 8-year wave of the GUiNZ study were required to wear the accelerometers continuously for seven days. For this thesis, however, every participant with at least one day of 24-hour accelerometer data was included in the analyses (the average accelerometer wear time was 4.9 days, of which 1.3 days were weekend days). Due to this short duration of time-use measurement, we were not able to consider the variations between weekdays and weekend days' time-use, or across seasons. Research has demonstrated differences in time-use between weekday, weekend, and across seasons [216]. As a result, time-use data presented in this research may not be representative of habitual time-use in this population. Therefore, future research with a longer measurement period is required to better understand the time-use patterns in children and their relationship with health outcomes, including obesity. It should be noted that we have also rerun the analyses in Chapters 4–6 where participants had three or more days of valid time-use data (as opposed to at least one day of wear time). Overall, the results have remained the same, with slightly wider confidence intervals in some cases (as expected with a lower sample size). Given these almost identical results, therefore, we have included participants with at least one day of valid wear time in the analyses. This decision led to a larger sample size (623 vs. 482), and narrower confidence intervals, and hence higher confidence in the model estimates. The full sensitivity analysis results are shown in Supplementary Tables S1, S2 and S5 – S7.

In this research, we did not consider the way in which children accumulated their time spent in SB and PA (i.e., shorter vs. more prolonged bouts). As evidence from recent compositional studies suggests that different PA and SB accumulation patterns might be associated with adiposity status in children [13, 14], future research is encouraged to consider these behavioural patterns when investigating their collective impacts on health outcomes. Additionally, in this study, we only examined sleep in terms of duration, but as other characteristics of sleep such as quality, timing, and day-to-day variability might be of relevance to health [217]. Researchers should consider these factors in future time-use studies. In this research, we predominantly focused on the relationships between obesity and daily structure of time-use in children in terms of duration of time spent in each activity. However, developing future compositional data analysis methods which could cope with integrating different layers of information such as type and context of each behaviour, timing of each behaviour (e.g., time of day or weekday/weekend), and geographical data (e.g., neighbourhood context) could further provide insights into links between time-use and health outcomes.

Future CODA studies may also explore the optimal 24-hour time-use composition for favourable obesity-related outcomes in children. While findings are gradually accumulating on the optimal time-use for various health outcomes including adiposity among children [198, 218, 219], more evidence is needed to establish how a 24-hour day (or even a week) should look like for optimal health outcomes. Emerging findings, however, show that ideal 24-hour time-use might differ depending on the health outcomes of interest. For example, optimal durations of time-use for favourable adiposity might not be the same for other health outcomes such as mental wellbeing. This highlights the need for moving away from one-size-fits-all healthy time-use recommendations provided by the current guidelines, towards more personalised recommendations depending on individual's health and well-being priorities. Recently a decision-making tool had been developed, which could be used to customise time-use recommendations according to personal or public health preferences [218, 219].

Conclusions

This PhD thesis aimed to understand children's time-use behaviour patterns and if these patterns differed between different sociodemographic groups, as well as their cross-sectional association with measures of obesity. Together, the four studies presented in this thesis contribute to the growing body of knowledge in time-use research in children. For measurement of time-use behaviours, we found that both GT3X+ and AX3 accelerometers could be used to measure various activity intensity and activity types, with the AX3 performing slightly better. We demonstrated that 24-hour time-use was significantly associated with indicators of obesity in children, and reallocating more time to LPA, and walking and running, was associated with a favourable BMI in this population. It was also observed that 24-hour time-use behaviours and diet behaviours occur together in distinct clusters, and cluster membership was associated with obesity-related outcomes in children. Despite the important role of time-use behaviours in adiposity, only a small minority (10.6%) of New Zealand children met all three recommendations in the New Zealand 24-hour Movement Guidelines. Sociodemographic factors, including child ethnicity and mother's education were associated with meeting the combined 24-hour Movement Guidelines. This thesis provided insight into time-use behaviours and measures of obesity in children, and it is hoped that these findings will assist in the development and tailoring of future interventions.

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Appendixes

Appendix A. Ethical approval

AUT

AUTEC Secretariat

Auckland University of Technology
D-88, WU406 Level 4 WU Building City Campus
T: +64 9 921 9999 ext. 8316
E: ethics@aut.ac.nz
www.aut.ac.nz/researchethics

12 July 2017

Scott Duncan
Faculty of Health and Environmental Sciences

Dear Scott

Ethics Application: 17/219 **Measuring physical activity and sedentary behaviours in children**

I wish to advise you that the Auckland University of Technology Ethics Committee (AUTEC) has **approved** your ethics application at its meeting of 10 July 2017.

This approval is for three years, expiring 10 July 2020.

Standard Conditions of Approval

1. A progress report is due annually on the anniversary of the approval date, using form EA2, which is available online through http://www.aut.ac.nz/researchethics.
2. A final report is due at the expiration of the approval period, or, upon completion of project, using form EA3, which is available online through http://www.aut.ac.nz/researchethics.
3. Any amendments to the project must be approved by AUTEC prior to being implemented. Amendments can be requested using the EA2 form: http://www.aut.ac.nz/researchethics.
4. Any serious or unexpected adverse events must be reported to AUTEC Secretariat as a matter of priority.
5. Any unforeseen events that might affect continued ethical acceptability of the project should also be reported to the AUTEC Secretariat as a matter of priority.

Non-Standard Conditions of Approval

1. In the Child Information Sheet, replace the word 'sedentary' with 'sitting';
2. Inclusion in the lab protocol when the video will start and finish

Please quote the application number and title on all future correspondence related to this project.

AUTEC grants ethical approval only. If you require management approval for access for your research from another institution or organisation then you are responsible for obtaining it. You are reminded that it is your responsibility to ensure that the spelling and grammar of documents being provided to participants or external organisations is of a high standard.

For any enquiries please contact ethics@aut.ac.nz

Yours sincerely,

Kate O'Connor
Executive Manager
Auckland University of Technology Ethics Committee

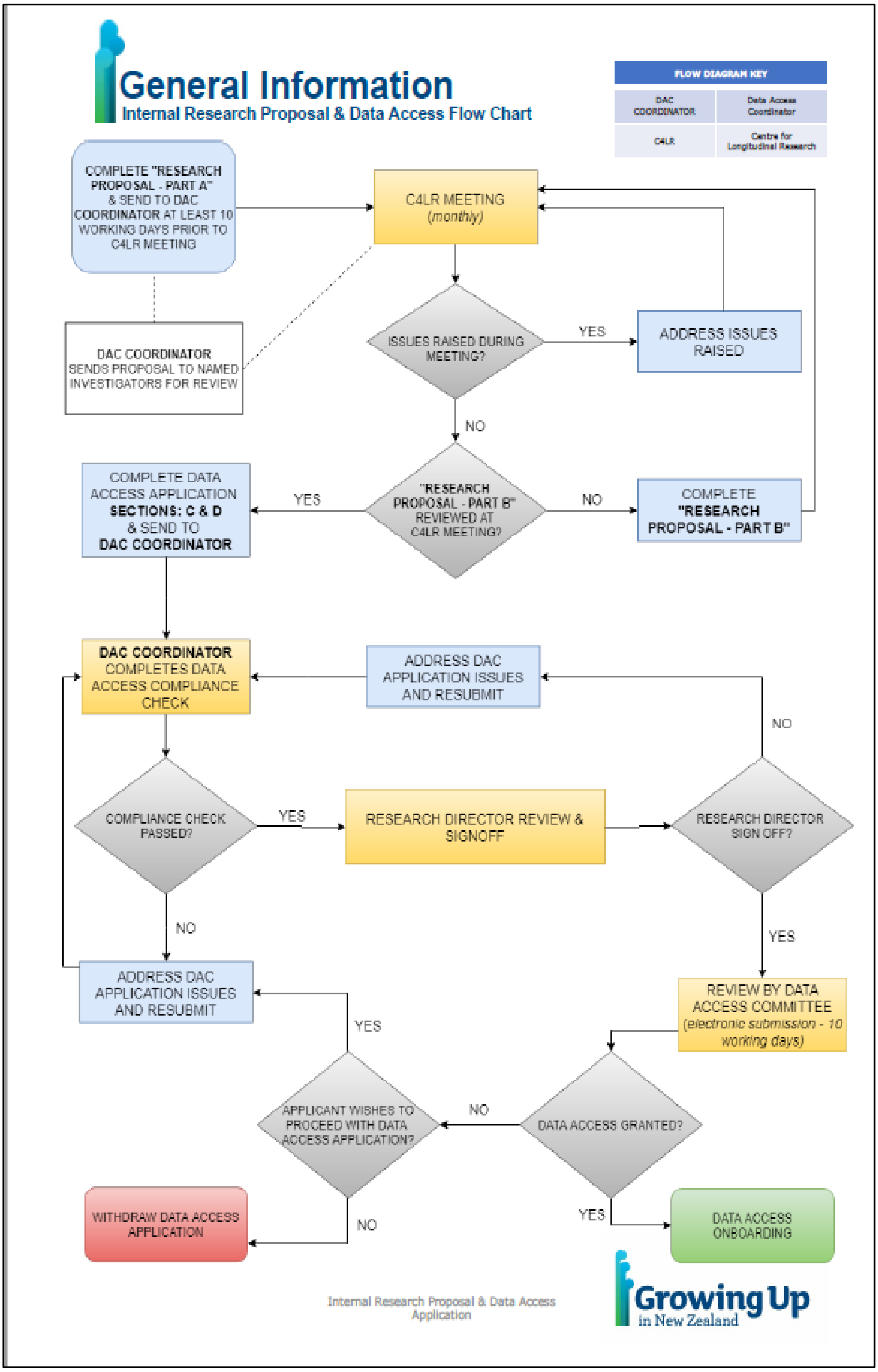
Cc: Tom Stewart; Roselinde van Nee; jono@qsportstechnology.com

Appendix B. Growing Up in New Zealand data access application

Growing Up in New Zealand

Internal Research Proposal & Data Access Application

CONTENTS


General Information
Internal Research Proposal & Data Access Flow Chart
FLOW DIAGRAM KEY
DAC COORDINATOR
Data Access Coordinator
C4LR
Centre for Longitudinal Research
COMPLETE "RESEARCH PROPOSAL - PART A" & SEND TO DAC COORDINATOR AT LEAST 10 WORKING DAYS PRIOR TO C4LR MEETING
C4LR MEETING (monthly)
DAC COORDINATOR SENDS PROPOSAL TO NAMED INVESTIGATORS FOR REVIEW
ISSUES RAISED DURING MEETING?
YES
ADDRESS ISSUES RAISED
NO
COMPLETE DATA ACCESS APPLICATION SECTIONS: C & D & SEND TO DAC COORDINATOR
YES
"RESEARCH PROPOSAL - PART B" REVIEWED AT C4LR MEETING?
NO
COMPLETE "RESEARCH PROPOSAL - PART B"
DAC COORDINATOR COMPLETES DATA ACCESS COMPLIANCE CHECK
ADDRESS DAC APPLICATION ISSUES AND RESUBMIT
NO
COMPLIANCE CHECK PASSED?
YES
RESEARCH DIRECTOR REVIEW & SIGNOFF
RESEARCH DIRECTOR SIGN OFF?
NO
YES
ADDRESS DAC APPLICATION ISSUES AND RESUBMIT
YES
REVIEW BY DATA ACCESS COMMITTEE (electronic submission - 10 working days)
APPLICANT WISHES TO PROCEED WITH DATA ACCESS APPLICATION?
NO
DATA ACCESS GRANTED?
WITHDRAW DATA ACCESS APPLICATION
NO
YES
DATA ACCESS ONBOARDING
Internal Research Proposal & Data Access Application
Growing Up in New Zealand

General Information
Guardianship & Responsibilities

Data Guardianship & Responsibilities		
Sensitivity Levels	**Requirements**	**Outputs**
EXISTING DATA	**Steps:** • Initial proposal to C4LR • Final proposal to DAC	**Must provide:** • Derived Variables • Documentation • Publications/Dissemination
EXISTING DATA + LINKED DATA (CLEANED)	**Steps:** • Initial proposal to C4LR • Final proposal to DAC	**Must provide:** • Derived Variables • Documentation • Publications/Dissemination
EXISTING DATA + NEW LINKAGE (WITH EXISITNG CONSENT)	**Steps:** • Initial proposal to C4LR • Linkage proposal (review guardianship, potential identifiers, any additional ethics) • Final proposal to DAC (+ ethics if required)	**Must provide:** • Cleaned linked data • Derived Variables • Documentation • Publications/Dissemination
EXISTING DATA + BIOSAMPLES	**Steps:** • Initial Biosampling proposal (rationale for sample request) • Advisory Group input • Initial Biosampling proposal to C4LR • Final Biological DAC form to DAC	**Must provide:** • Cleaned biological information • Derived Variables • Documentation • Publications/Dissemination
CONTACTING COHORT PARTICIPANTS	**Steps:** • Initial discussion (to be determined – in/out DCW, research questions, participant burden, logistics, operations, additional ethics) • NI agreement (in writing) • Initial proposal to C4LR • Final proposal to DAC (+ ethics if required)	**Must provide:** • New data • Derived Variables • Documentation • Publications/Dissemination

General Information
Derived Variables & Kaitiaki Principle

Derived Variables and Technical Documentation

Derived variables that have utility for other users and related technical documents are to be provided to the **Data Access Coordinator** at the end of the research project; these may be included in future *Growing Up in New Zealand* data sets. Documentation must include the methodologies used to create the derived variables in sufficient detail for the work to be independently verified by the *Growing Up in New Zealand* Biostatistics Team.

Kaitiaki Principle

The *Growing Up in New Zealand* Guardianship/Kaitiaki Principle states:

- Guardianship requires that the data are analysed, interpreted, reported and published in culturally appropriate ways;
- Data contributed to the study by **Māori study participants**, and other contributions to the study that draw on Māori knowledge and expertise are taonga whose value are to be preserved and protected and used productively and for the benefit of Māori; and
- Data contributed to the study, and other contributions to the study, by members of other cultural groups are to be similarly valued and protected.

In order to describe your approach, we recommend you consider the following questions:

- How does the proposed purpose and/or research question provide benefit for Māori?
- How does the proposed purpose and/or research question provide benefit for other cultural groups?
- How does the proposed purpose and/or research question create any potential risks for Māori, and if potential risks for Māori are identified, how may these be mitigated?
- How does the proposed purpose and/or research question create any potential risks for other cultural groups, and if potential risks are identified, how may these be mitigated?
- How will culturally appropriate analyses and interpretations be conducted? Examples:
- How do you intend to use and interpret ethnic identity variable(s)?
- Is ethnic identity intended to be used as an explanatory variable?
- Is there an intention to consider both strengths-based and risk-based variables?
- How will the results be interpreted in order to maximise utility for Maori and other cultural groups?

Treatment of Outputs/Publications
In accordance with the Kaitiaki Principle, *Growing Up in New Zealand* expect publications/outputs to be reviewed by: appropriate next-user(s), end-user(s), and stakeholder(s) before Data Access Committee review.

SECTION A – RESEARCH PROPOSAL

Research Plan – Project Proposal

Project working title

Disentangling the combined effects of 24-hour time use behaviours on childhood physical and mental wellbeing: a compositional data analysis

Proposed funding source *(if required)*

Project start date	**Project end date**
December 2019	November 2020

Research Domains *(please select the applicable research areas & themes for this project)*

- [ ] Family & Whānau
- [ ] Societal Context
- [x] Health & Wellbeing
- [ ] Psychosocial & Cognitive Development
- [ ] Culture & Identity
- [ ] Education
- [ ] Ethnic Specific *(please specify)* ________

Will your project require access to **biological samples** and/or **externally linked data**? [ ] YES [x] NO

If "Yes" please refer to ***"Data Responsibilities"*** *(**General Information**)*

Brief overview of the research project, question and proposed analyses.
Up to 250 words summarising the research objectives, methods and anticipated outputs. This overview will be made available to the public and should be written for a general audience.

Physical inactivity, prolonged sedentary behaviour, and insufficient sleep are three prevalent lifestyle factors that contribute to an increased risk of obesity and mental health problems in children. Studies have largely investigated these distinct but strongly interrelated behaviours as independent entities; however, the emerging evidence suggests that the interactions among these behaviours may impact health in ways that cannot be explained by studying each behaviour in isolation. This has prompted a global shift in behavioural research where an integrated movement approach focusing on complete (24-hour) days is now a research priority. Recently, the Ministry of Health released a revised set of physical activity, sedentary behaviour, and sleep guidelines for children and young people. These new guidelines, adapted from the Canadian 24-Hour Movement Guidelines for Children and Youth, advocate a favourable combination of sleep, physical activity, and sedentary behaviour time within a given 24-hour period. Despite this positive step forward, no objective data that describes these patterns in children currently exist, and there is a lack of evidence stipulating how a favourable 24-hour day is comprised. This study will use accelerometer-measured behaviour along with time use diary data from children participating in the 8-year data collection wave. The aims are 1) to determine the 24-hour behaviour patterns (e.g., physical activity intensities, sitting time, sleep, time use behaviours) of New Zealand children, and 2) to examine how different combinations of these behaviours – and the reallocation of time between them – are related to obesity, and behavioural, social, and mental health outcomes in children using compositional data analysis techniques.

SECTION A – RESEARCH PROPOSAL

Research Plan – Ethics Requirements and Research Team Overview

Does this proposal require an additional ethics application? ☐ Yes ☑ No

Ethics Requirements *(please explain the potential ethics requirements for this project)*

This project has been discussed with the AUT ethics committee and with the GUiNZ team, and additional ethical approval is not required (given this project only uses anonymised secondary data).

Principal Investigator Details

Family name	First name
Hedayatrad	Leila
Work phone	Mobile

Email

leila.hedayatrad@aut.ac.nz

Proposed Team

Name	Role	FTE	Organisation	Justification
Associate Prof. Scott Duncan	Primary supervisor		AUT	Supervisor / child behaviour and health expert
Dr Caroline walker	Secondary supervisor		University of Auckland	Supervisor/ behaviour and health expert
Dr Tom Stewart	Tertiary Supervisor		AUT	upervisor / physical activity & time-use data / compositional analysis proficiency
Dr Sarah-Jane Paine	Advisor		University of Auckland	Advisor / sleep research expert

SECTION B – RESEARCH PROPOSAL

Research Questions, Aims & Objectives

Research questions, aims and objectives
Up to 1500 words

This study will form the basis of a PhD thesis. This study will be organised into two parts based on the two main aims:

Aim 1:

To determine the 24-hour behaviour patterns of NZ children, both in terms of energy expenditure (i.e., light intensity physical activity (LPA), moderate-to-vigorous intensity physical activity (MVPA), sedentary behaviour, and sleep) and behaviour type (i.e., physical activity, chores, self-care, socio-cultural, transport, screen time, etc.) – and how these patterns differ between various sociodemographic groups (e.g., ethnicity, gender, family structure, socioeconomic status).

Aim 2:

To examine how different combinations of time use behaviours – and the reallocation of time between them – are related to obesity, social, behavioural, and mental wellbeing using compositional data analysis techniques.

SECTION B – RESEARCH PROPOSAL

Research Methodology

Research methodology and proposed analyses
Include specific details of the analyses that will be carried out. This includes which *Growing Up in New Zealand* data sets are being requested and how they will be linked (if at all), details on how complex longitudinal design issues will be taken into account in the analysis, and any data from other sources that will be used in the analysis, and how this will be linked. Up to 1500 words.

Aim 1

Measures:
The 24-hour behaviour patterns of each child (outcome variable) will be obtained via accelerometers and time use diaries. Accelerometers were used in a sub-sample of the 8-year cohort. These data were used to derive several variables related to 24-hour movement behaviours (e.g. LPA, MVPA, sedentary behaviour, and sleep) using machine learning algorithms [1, 2]. Secondly, time use diary data collected during the 8-year wave (for one weekday and one weekend day) will be used to obtain the duration of different types of behaviour (e.g. physical activity, chores, self-care, socio-cultural, transport, screen time). These two sources of data will be used to create 24-hour time-use compositions for each child. Lastly, the total energy expenditure of the 24-hour day will be estimated using the physical activity compendium, which provides a MET value for each activity type [3].
Sociodemographic information (independent, grouping variables) used for subgroup comparisons (e.g., ethnicity, gender, family structure, socioeconomic status) will be obtained via questionnaire or interview data (either the 8-year time point, or earlier time points where necessary – such as gender).

Analysis:
Daily time-use data sum to exactly 24 hours each day and are therefore compositional (meaning these data are incompatible with traditional multivariate statistical methods) [4]. Therefore, compositional data analysis methods will be used.
Firstly, the compositional mean of each 24-hour movement behaviour will be estimated by computing the geometric mean. The variation matrix (equivalent of standard deviation) will be used to estimate the variability of the composition. Compositional differences between groups (e.g., gender, SES, ethnicity, family structure) will be assessed using compositional multivariate analysis of variance (compositional MANOVA), and 95% confidence intervals of the mean difference will be determined using the bootstrapping method [4]. Using the 'compositions' R package, the compositional parts will be expressed as isometric log-ratio coordinates (ilrs) prior to fitting the MANOVA model, in line with compositional theory [4].

Aim 2

Measures:
The time use measures described above in Aim 1 will be treated as independent variables, while a range of health and behaviour variables will be treated as outcome (dependant) variables. These include physical, behavioural, social, and psychological variables from parental proxy interview responses and standardised, individually-administered tests. Specifically:

(1) Physical: Body mass index (BMI), Waist circumference (WC), Waist-height-ratio (WHtR)
(2) Quality of life: Quality of life Questionnaire (Child Questionnaire)
(3) Behavioural: Conduct and behaviour (Child Proxy Questionnaire)
(4) Social: Peer relationships (Child Questionnaire), Social skills and relationships (Child Proxy Questionnaire), Self-concept and perceived competence (Child Questionnaire)
(5) Mental-wellbeing: Depression and anxiety (Child Questionnaire)
(6) Covariates: Diet quality, sociodemographic characteristics (e.g., gender, SES, ethnicity, family structure)

Analysis:
Compositional descriptive statistics will be computed as per Aim 1. Using the 'compositions' R package, time use behaviours will be expressed as isometric log-ratio coordinates (ilrs), enabling the use of traditional regression models. Using generalised linear models (GLMs), the resulting ilr coordinates will be used as explanatory (independent) variables, and BMI, WC, WHtR, quality of life, behavioural, social, and mental health variables will be treated as outcomes, while adjusting for potential confounders (gender, diet quality, ethnicity, SES). For each outcome, the effect of reallocation of time between behaviours will be assessed using a compositional isotemporal substitution methodology [5], which can provide information about dose-response relationships.

References:

[1] Stewart et al. (2018). A dual-accelerometer system for classifying physical activity in children and adults. MSSE, 50(12).
[2] Narayanan et al. (In Press). A dual-accelerometer system for detecting human movement in a free-living environment. MSSE.
[3] Ainsworth et al. (2011). Compendium of Physical Activities: a second update of codes and MET values, MSSE, 43(8).
[4] Fernández et al. (2015). On the interpretation of differences between groups for compositional data. SORT 39(2).
[5] Dumuid et al. (2017). The compositional isotemporal substitution model: A method for estimating changes in a health outcome for reallocation of time between sleep, physical activity and sedentary behaviour. SMMR, 28(3).

SECTION B – RESEARCH PROPOSAL

Data Requested

Please clearly state the Variables, and their source, required for your research proposal:
Note: Please refer to the data dictionary for appropriate references.

The data required (as described below) are from the 8-year data collection wave. These have been broken down into three categories: (1) accelerometer/time use diary data, (2) anthropometry data, and (3) questionnaire/interview data. The question numbers refer to the code in the original questionnaire/interview protocol.
(1) The 24-hour behaviour patterns of each child will be obtained from the accelerometer data (variables already in the 8 year dataset; no raw accelerometer data required), and time use diaries.
(2) Anthropometry data (weight, height, waist circumference) from the physical measurements.
(3) Sociodemographic variables (age, ethnicity, gender, socio-economic status, family structure) - Quality of life (Child Questionnaire Q 2.1- 2.11) - Peer relationships (Child Questionnaire Q 5.1-5.18) - Self-concept and perceived competence (Child Questionnaire Q6.1 -6.12) - Behavioural conduct (Child Proxy Questionnaire Q 14.1 -14.27) - Social skills and relationships (Child Proxy Questionnaire Q 15.1-15.72) - Psychological wellbeing (Child Questionnaire Q12.1-12.10 and Q 13.1- 13.10) - Media use (Child Proxy Questionnaire Q 11.1 -11.17) - Sleep habit (Child Proxy Questionnaire Q 8.1 -8.5) - Diet quality (Child Proxy Questionnaire Q 2.1 - 2.5 and Q 3.1)

Please clearly state the Scales, and their source, required for your research proposal:
Note: Please refer to the data dictionary for appropriate references.

See variables section above.

Which data sets are required?
Please indicate which of the data sets you require. Additional information regarding the Mother, Partner and Child data sets are provided in the *Growing Up in New Zealand* Data Dictionaries.

☐ Antenatal Mother	☐ 9-month Mother	☐ 2-year Mother	☐ 54-month Mother	☐ 72-month Mother	☑ 8 Year Mother
☐ Antenatal Partner	☐ 9-month Partner	☐ 2-year Partner	☐ 54-month Mother-Child		☑ 8 Year Mother - Child
☐ Antenatal Child Linkage	☐ 9-month Child	☐ 2-year Child			☑ 8 Year Child

Software Request
Please select your preferred software for accessing the data set(s)

☐ STATA ☐ SPSS ■ R

Justification for data request
Justify why you need *Growing Up in New Zealand* data and demonstrate the value and benefits of your proposed use of this data. Please clarify how this research aligns with *Growing Up in New Zealand's*, overarching research questions and high level objectives.

Despite the recent Ministry of Health physical activity, sedentary behaviour, and sleep guidelines for children, there is no objective data that describe 24-hour behaviour patterns in NZ children. The Growing Up in New Zealand sample with accelerometer and time use data will allow us to answer out research questions. Using novel compositional data analysis techniques, this research will lead to a comprehensive understanding of how time use patterns cluster to affect the health and development of New Zealand children, which aligns with a key objective of Growing Up in New Zealand: to map the developmental pathways that determine the health status of children across the life course. Additionally, these findings will have direct implications for public policy by informing national activity and sleep guidelines, and by providing evidence for behaviour change initiatives in New Zealand and overseas.

SECTION B – RESEARCH PROPOSAL

Ethics, Guardianship and Dissemination Plan

Kaitiaki Principle
Please outline your approach to protecting the *Growing Up in New Zealand* Guardianship/Kaitiaki Principle, as described under **"Kaitiaki Principle" (General Information).**

By investigating the relationship between daily time use patterns and health outcomes in different ethnic groups including Māori and Pacific Island children, the outcomes of this research may help to identify the pathways and mechanisms that lead to ethnic inequities in health including those that are disproportionately experienced by Māori and Pacific children in NZ.

Dr. Sarah-Jane Paine is Kaupapa Māori epidemiologist and the NZ expert in sleep health inequities. She will provide advice on the use and analysis of ethnicity data in this study and contribute to the interpretation of findings.

Ethics approval for this research has already been discussed with the AUT ethics committee. We will ensure that our protocol aligns with expectations for equity in health research and health outcomes under the Treaty of Waitangi, and to mitigate potential risks for Māori participants in GUiNZ and communities more broadly.

Dissemination Plan
Describe your intentions for using any of the results from the data set(s). This may include, but not limited to, reports, journal papers, working papers, conferences, other public presentations, and other documents.

Two articles will be submitted in peer-reviewed journals as follows:

1) 24- hour movement patterns of New Zealand children using time use diary and dual accelerometers

2) Relationships of 24-hour movement behaviours with physical and mental health outcome in children

***Note: All forms of dissemination to be published** require a completed **Application to Publish Form**. The dissemination and form must be sent to the **Data Access Coordinator,** for review by the Growing Up in New Zealand Research Team, 14 days prior to submission to the **Data Access Committee**.*

SECTION C – RESEARCH TEAM

Team Member Details & Disclosure *(complete for each team member)*

Project role Primary Supervisor	
Brief biography, role description & justification *(a URL link or attached biography/academic CV is acceptable)* https://www.aut.ac.nz/profiles?id=scduncan https://orcid.org/0000-0002-8402-2930	
Family name Duncan	First name Scott
University/institution AUT	Department/section School of Sport and Recreation
Work phone 09 921 9999 ext 7678	Mobile
Email scott.duncan@aut.ac.nz	
Mailing address Auckland University of Technology, Private Bag 92006, Auckland 1142, New Zealand	

I require access to the data set(s)	✓	Yes	☐	No

Protecting the Principles of the Data Access Protocol

Each team member named in this application must read, understand and agree to uphold the principles of the **Data Access Protocol.** Failure to adhere to the **Data Access Protocol** may result in data access being terminated for this project and all other projects I am named.

Please signal your understanding and acceptance of these principles by checking this box. ✓

Please confirm you have attended a relevant data workshop or familiarised yourself with the workshop materials and technical documents (data dictionaries and data user guides) by checking this box. ✓

Are you a student or research assistant?	☐	Yes	✓	No

*If you selected "**Yes**" above, please sign the **Declaration** below and complete the **Student & Research Assistant Declaration.***

Declaration: I declare that the information provided is timely and accurate to the best of my knowledge.

[redacted]	Name Scott Duncan
	Date 3/12/2019

Internal Research Proposal & Data Access Application

Growing Up in New Zealand

SECTION C – RESEARCH TEAM

Team Member Details & Disclosure *(complete for each team member)*

Project role Secondary supervisor	
Brief biography, role description & justification *(a URL link or attached biography/academic CV is acceptable)* https://unidirectory.auckland.ac.nz/profile/caroline-walker https://orcid.org/0000-0002-9210-7651	
Family name Walker	First name Caroline
University/institution University of Auckland	Department/section GUiNZ
Work phone 923 8592	Mobile
Email caroline.walker@auckland.ac.nz	
Mailing address TAMAKI BUILDING 730 TAMAKI CAMPUS GATE 1, 261 MORRIN RD	

I require access to the data set(s)	☑ Yes	☐ No

Protecting the Principles of the Data Access Protocol

Each team member named in this application must read, understand and agree to uphold the principles of the **Data Access Protocol.** Failure to adhere to the **Data Access Protocol** may result in data access being terminated for this project and all other projects I am named.

Please signal your understanding and acceptance of these principles by checking this box. ☑

Please confirm you have attended a relevant data workshop or familiarised yourself with the workshop materials and technical documents (data dictionaries and data user guides) by checking this box. ☑

Are you a student or research assistant?	☐ Yes	☑ No

*If you selected **"Yes"** above, please sign the **Declaration** below and complete the **Student & Research Assistant Declaration.***

Declaration: I declare that the information provided is timely and accurate to the best of my knowledge.

[redacted]	Name Caroline Walker
	Date

SECTION C – RESEARCH TEAM

Team Member Details & Disclosure *(complete for each team member)*

Project role Tertiary supervisor	
Brief biography, role description & justification *(a URL link or attached biography/academic CV is acceptable)* https://www.aut.ac.nz/profiles?id=tstewart&asset=265031 https://orcid.org/0000-0001-5915-3843	
Family name Stewart	First name Tom
University/institution AUT University	Department/section Human Potential Centre
Work phone 9219999 7855	Mobile
Email tom.stewart@aut.ac.nz	
Mailing address Auckland University of Technology, Private Bag 92006, Auckland 1142, New Zealand	

I require access to the data set(s)	☑ Yes	☐ No

Protecting the Principles of the Data Access Protocol

Each team member named in this application must read, understand and agree to uphold the principles of the **Data Access Protocol.** Failure to adhere to the **Data Access Protocol** may result in data access being terminated for this project and all other projects I am named.

Please signal your understanding and acceptance of these principles by checking this box. ☑

Please confirm you have attended a relevant data workshop or familiarised yourself with the workshop materials and technical documents (data dictionaries and data user guides) by checking this box. ☑

Are you a student or research assistant?	☐ Yes	☑ No

If you selected ***"Yes"*** *above, please sign the* ***Declaration*** *below and complete the* ***Student & Research Assistant Declaration.***

Declaration: I declare that the information provided is timely and accurate to the best of my knowledge.

[redacted]	Name Tom Stewart
	Date 3/12/2019

Internal Research Proposal & Data Access Application

Growing Up in New Zealand

SECTION C – RESEARCH TEAM

Team Member Details & Disclosure *(complete for each team member)*

Project role Project Advisor	
Brief biography, role description & justification *(a URL link or attached biography/academic CV is acceptable)* https://unidirectory.auckland.ac.nz/profile/sj-paine	
Family name Paine	First name Sarah-Jane
University/institution University of Auckland	Department/section Te Kupenga Hauora Maori, FMHS
Work phone 923 4937	Mobile
Email sj.paine@auckland.ac.nz	
Mailing address TAMAKI BUILDING 730 TAMAKI CAMPUS GATE 1, 261 MORRIN RD	

I require access to the data set(s) ☑ Yes ☐ No

Protecting the Principles of the Data Access Protocol

Each team member named in this application must read, understand and agree to uphold the principles of the **Data Access Protocol.** Failure to adhere to the **Data Access Protocol** may result in data access being terminated for this project and all other projects I am named.

Please signal your understanding and acceptance of these principles by checking this box. ☑

Please confirm you have attended a relevant data workshop or familiarised yourself with the workshop materials and technical documents (data dictionaries and data user guides) by checking this box. ☑

Are you a student or research assistant? ☐ Yes ☑ No

*If you selected "Yes" above, please sign the **Declaration** below and complete the **Student & Research Assistant Declaration.***

Declaration: I declare that the information provided is timely and accurate to the best of my knowledge.

[redacted]	Name Sarah-Jane Paine
	Date

Click to Add Member

SECTION C – RESEARCH TEAM

Student/Research Assistant Supervisor/Manager Declaration *(complete for each research assistant/student)*

If you are a **student or research assistant** please fill in, and have your supervisor/manager sign off, the form fields below.	
Student/research assistant name ("the Team Member") Leila Hedayatrad	
Name of student supervisor/manager ("the Supervisor") Scott Duncan	Supervisor/manager role and title Associate Professor
Telephone	Mailing address Auckland University of Technology, Private Bag 92006, Auckland 1142, New Zealand
Email scott.duncan@aut.ac.nz	
Supervisor/Managers Declaration I, the Supervisor declare that I accept all responsibility for the conduct of the Team Member. If the Team Member breaches the principles of the **Data Access Protocol**, I understand that my access to *Growing Up in New Zealand* data for any current and future research projects will be reviewed and may be terminated.	
[redacted]	Name Scott Duncan
	Date 3/12/2019

Click to Add Another

Internal Research Proposal & Data Access Application

Growing Up in New Zealand

SECTION D – PROJECT DECLARATION

Project Declaration

Principal Investigator Declaration

Data Registry of Use

Growing Up in New Zealand maintains a summary of research topics that have been approved to use the *Growing Up in New Zealand* data sets. This is provided on the website as a resource to researchers wishing to utilise the data. Once access to the *Growing Up in New Zealand* data sets has been approved by the **Data Access Committee**, the project summary details will be added to the publically available project summary.

I understand and agree to the public release of project summary details. ✓

Derived Variables and Technical Documentation

I agree to provide copies of the variables derived and corresponding technical documents, as described under **"Derived Variables and Technical Documents" (General Information),** to the **Data Access Coordinator** at the end of the data access period. ✓

Dissemination

I agree to inform the **Data Access Coordinator** of **all forms of published dissemination** as soon as the publication has been confirmed. Publication includes but is not limited to: print, audio, video and online. ✓

Information regarding future data sets ***(optional)***

I would like to receive information regarding future data sets. ✓

Principal Investigator Declaration

I confirm that the information provided in this application is accurate and timely to the best of my knowledge and I will meet all agreed responsibilities and requirements stated in this application.

[redacted]	Name Leila Hedayatrad
	Date 26-Nov-2019

Chief Executive Officer or equivalent (or assigned delegate)

I confirm that my institution,

(Name of institution)

supports this research project (including accepting all liability and associated costs for the research project and will require all researchers to abide by the *Growing Up in New Zealand Data Access Protocol* and the **Data Access Agreement.**

Signature	Name
	Position
Date	Department/section

Email Form to DAC

Appendix C. Supplementary Tables

The results presented in Table S1– S2 and S5 – S7 are from a sensitivity analysis, where the analysis sample required at least three valid days of 24-hour time-use data.

Table S1. Relationship between the activity intensity composition (expressed as isometric log-ratio coordinates) and obesity outcomes.

Obesity outcomes	Isometric log-ratio predictor	Unadjusted model ß– coefficient	P-value	Model R squared	Adjusted model ß– coefficient	P-value	Model R squared
BMI z-score	ilr SB/LPA*MVPA*SLEEP	0.898	**0.023**		0.325	0.362	
	ilr LPA/SB*MVPA*SLEEP	-1.472	**<0.001**		-1.470	**<0.001**	
	ilr MVPA/SB*LPA*SLEEP	0.539	**0.005**	0.04	0.534	0.023	0.09
	ilr SLEEP/SB*LPA*MVPA	0.033	0.935		0.617	0.163	
WC	ilr SB/LPA*MVPA*SLEEP	4.66	**0.029**		1.78	0.440	
	ilr LPA/SB*MVPA*SLEEP	-10.14	**<0.001**		-7.14	**0.003**	
	ilr MVPA/SB*LPA*SLEEP	3.26	**0.008**	0.05	1.76	0.239	0.08
	ilr SLEEP/SB*LPA*MVPA	2.22	0.397		3.59	0.210	
WHtR	ilr SB/LPA*MVPA*SLEEP	0.027	0.069		0.008	0.627	
	ilr LPA/SB*MVPA*SLEEP	-0.04	**0.003**	0.02	-0.040	**0.028**	0.04
	ilr MVPA/SB*LPA*SLEEP	0.015	0.089		0.013	0.193	
	ilr SLEEP/SB*LPA*MVPA	0.003	0.880		0.016	0.419	

ilr = isometric log-ratio, is the first isometric log-ratio coordinate representing each time-use behaviour relative to the remaining behaviours.
BMI z-score = Body mass index z-score; WC = Waist circumference; WHtR= Waist-to-height ratio; SB = Sedentary behaviour; LPA= Light-intensity physical activity; MVPA= Moderate-to-vigorous intensity physical activity.
Models were adjusted for gender, ethnicity, deprivation, mother’s education, fruit intake, vegetable intake, frequency of fizzy drink and fast food consumption, and breakfast consumption.
Bold values represent significant associations.

Table S2. Relationship between the activity type composition (expressed as isometric log-ratio coordinates) and obesity outcomes.

Obesity outcomes	Isometric log-ratio predictor	Unadjusted model ß–coefficient	*P*-value	Model R squared	Adjusted model ß–coefficient	*P*-value	Model R squared
BMI z-score	ilr Sit/Stand*Walk*Run*Lie	0.297	0.168		0.065	0.777	
	ilr Stand/Sit*Walk*Run*Lie	0.187	0.918		0..281	0.183	
	ilr Walk/Sit* Stand*Run*Lie	-0.592	**0.018**	0.023	-0.787	**0.003**	0.014
	ilr Run/Sit* Stand*Walk*Lie	0.126	0.163		0.177	0.064	
	ilr Lie/Sit* Stand*Walk*Run	0.150	0.538		0.262	0.328	
WC	ilr Sit/Stand*Walk*Run*Lie	1.602	0.251		0.837	0.578	
	ilr Stand/Sit*Walk*Run*Lie	-1.759	0.135		0.181	0.893	
	ilr Walk/Sit* Stand*Run*Lie	-2.072	0.198	0.023	-2.796	0.101	0.015
	ilr Run/Sit* Stand*Walk*Lie	0.648	0.267		0.560	0.367	
	ilr Lie/Sit* Stand*Walk*Run	1.580	0.316		1.217	0.484	
WHtR	ilr Sit/Stand*Walk*Run*Lie	0.013	0145		0.006	0.561	
	ilr Stand/Sit*Walk*Run*Lie	0.001	0.897		0.004	0.623	
	ilr Walk/Sit* Stand*Run*Lie	-0.021	0.051	0.018	-0.018	0.115	0.030
	ilr Run/Sit* Stand*Walk*Lie	0.004	0.312		0.003	0.416	
	ilr Lie/Sit* Stand*Walk*Run	0.002	0.795		0.004	0.711	

ilr = isometric log-ratio, is the first isometric log-ratio coordinate representing each time-use behaviour relative to the remaining behaviours; BMI z-score = Body mass index z-score; WC = Waist circumference; WHtR= Waist-to-height ratio.
Models were adjusted for gender, ethnicity, deprivation, mother's education, fruit intake, vegetable intake, frequency of fizzy drink and fast food consumption, and breakfast consumption.
Bold values represent significant associations.

Table S3. Predicted change (95% CI) in obesity outcomes following reallocation of time between behaviours within the activity intensity composition.

Obesity outcomes	Changes in behaviour (%)	SB to/from remaining	LPA to/from remaining	MVPA to/from remaining	Sleep to/from remaining
BMI z-score					
	-15	-0.247 (-0.8 – 0.31)	**1.787 (0.88 – 2.69)**	**0.679 (0.07 – 1.29)**	-0.365 (-0.88 – 0.15)
	-10	-0.149 (-0.48 – 0.19)	**0.964 (0.48 – 1.45)**	**0.679 (0.07 – 1.29)**	-0.235 (-0.57 – 0.1)
	-5	-0.07 (-0.23 – 0.09)	**0.42 (0.21 – 0.63)**	**-0.671 (-1.28 – -0.07)**	-0.114 (-0.28 – 0.05)
	0	0	0	0	0
	5	0.063 (-0.08 – 0.2)	**-0.352 (-0.53 – -0.17)**	**0.278 (0.03 – 0.53)**	0.111 (-0.05 – 0.27)
	10	0.122 (-0.15 – 0.4)	**-0.663 (-1.00 – -0.33)**	**0.465 (0.05 – 0.88)**	0.221 (-0.09 – 0.53)
	15	0.178 (-0.22 – 0.58)	**-0.948 (-1.43 – -0.47)**	**0.611 (0.06 – 1.16)**	0.332 (-0.14 – 0.8)
WC	-15	-1.437 (-5.03 – 2.16)	**8.715 (2.84 – 14.59)**	2.395 (-1.58 – 6.37)	-2.008 (-5.34 – 1.32)
	-10	-0.871 (-3.05 – 1.31)	**4.698 (1.53 – 7.87)**	2.395 (-1.58 – 6.37)	-1.291 (-3.43 – 0.85)
	-5	-0.405 (-1.42 – 0.61)	**2.049 (0.67 – 3.43)**	-2.371 (-6.31 – 1.57)	-0.629 (-1.67 – 0.41)
	0	0	0	0	0
	5	0.367 (-0.55 – 1.28)	**-1.718 (-2.88 – -0.56)**	0.981 (-0.65 – 2.61)	0.61 (-0.4 – 1.62)
	10	0.709 (-1.06 – 2.48)	**-3.235 (-5.42 – -1.05)**	1.640 (-1.08 – 4.36)	1.214 (-0.8 – 3.23)
	15	1.037 (-1.56 – 3.63)	**-4.622 (-7.74 – -1.51)**	2.152 (-1.42 – 5.73)	1.826 (-1.2 – 4.86)
	-15	-0.005 (-0.03 – 0.02)	**0.046 (0 – 0.09)**	0.016 (-0.01 – 0.04)	-0.011 (-0.03 – 0.01)
	-10	-0.003 (-0.02 – 0.01)	**0.025 (0 – 0.05)**	0.016 (-0.01 – 0.04)	-0.007 (-0.02 – 0.01)
WHtR	-5	-0.001 (-0.01 – 0.01)	**0.011 (0 – 0.02)**	-0.016 (-0.04 – 0.01)	-0.004 (-0.01 – 0)
	0	0	0	0	0
	5	0.001 (-0.01 – 0.01)	**-0.009 (-0.02 – 0)**	0.006 (0 – 0.02)	0.003 (0 – 0.01)
	10	0.002 (-0.01 – 0.01)	**-0.017 (-0.03 – 0)**	0.011 (-0.01 – 0.03)	0.007 (-0.01 – 0.02)
	15	0.003 (-0.01 – 0.02)	**-0.024 (-0.05 – 0)**	0.014 (-0.01 – 0.04)	0.01 (-0.01 – 0.03)

BMI z-score = Body mass index z-score, WC = Waist circumference, WHtR =Waist-to-height ratio.
SB = Sedentary behaviour; LPA = Light-intensity physical activity; MVPA= Moderate-to-vigorous intensity physical activity.
Bold values refer to significance values at $p<0.05$.

Table S4. Predicted change (95% CI) in obesity outcomes following reallocation of time between behaviours within the activity type composition.

Obesity outcomes	Changes in behaviour (%)	Sitting to/from remaining	Standing to/from remaining	Walking and running to/from remaining	Lying to/from remaining
BMI z-score	-15	-0.05 (-0.38 – 0.28)	0.163 (-0.12 – 0.45)	**-0.728 (-1.25 – -0.21)**	-0.184 (-0.52 – 0.15)
	-10	-0.031 (-0.24 – 0.17)	-0.617 (-1.7 – 0.47)	**-0.728 (-1.25 – -0.21)**	-0.12 (-0.34 – 0.1)
	-5	-0.015 (-0.11 – 0.08)	-0.148 (-0.41 – 0.11)	**0.697 (0.2 – 1.2)**	-0.059 (-0.17 – 0.05)
	0	0	0	0	0
	5	0.014 (-0.08 – 0.1)	0.095 (-0.07 – 0.26)	**-0.332 (-0.57 – -0.09)**	0.059 (-0.05 – 0.17)
	10	0.026 (-0.15 – 0.2)	0.168 (-0.13 – 0.46)	**-0.561 (-0.96 – -0.16)**	0.119 (-0.1 – 0.34)
	15	0.039 (-0.22 – 0.3)	0.229 (-0.17 – 0.63)	**-0.743 (-1.27 – -0.21)**	0.181 (-0.15 – 0.51)
WC	-15	-0.418 (-2.56 – 1.72)	-0.066 (-1.91 – 1.78)	**-3.514 (-6.86 – -0.17)**	-1.454 (-3.64 – 0.73)
	-10	-0.259 (-1.59 – 1.07)	0.25 (-6.71 – 7.21)	**-3.514 (-6.86 – -0.17)**	-0.949 (-2.38 – 0.48)
	-5	-0.123 (-0.75 – 0.51)	0.06 (-1.61 – 1.73)	**3.371 (0.16 – 6.58)**	-0.468 (-1.17 – 0.24)
	0	0	0	0	0
	5	0.114 (-0.47 – 0.7)	-0.039 (-1.12 – 1.04)	**-1.601 (-3.13 – -0.08)**	0.466 (-0.24 – 1.17)
	10	0.222 (-0.92 – 1.36)	-0.068 (-1.97 – 1.83)	**-2.708 (-5.29 – -0.13)**	0.938 (-0.47 – 2.35)
	15	0.328 (-1.35 – 2.01)	-0.093 (-2.68 – 2.49)	**-3.583 (-7.00 – -0.17)**	1.428 (-0.72 – 3.58)
WHtR	-15	-0.004 (-0.02 – 0.01)	0.002 (-0.01 – 0.02)	-0.018 (-0.04 – 0.01)	-0.004 (-0.02 – 0.01)
	-10	-0.003 (-0.01 – 0.01)	-0.009 (-0.06 – 0.04)	-0.018 (-0.04 – 0.01)	-0.002 (-0.01 – 0.01)
	-5	-0.001 (-0.01 – 0)	-0.002 (-0.01 – 0.01)	0.018 (0 – 0.04)	-0.001 (-0.01 – 0)
	0	0	0	0	0
	5	0.001 (0 – 0.01)	0.001 (-0.01 – 0.01)	-0.008 (-0.02 – 0)	0.001 (0 – 0.01)
	10	0.002 (-0.01 – 0.01)	0.002 (-0.01 – 0.02)	-0.014 (-0.03 – 0)	0.002 (-0.01 – 0.01)
	15	0.003 (-0.01 – 0.02)	0.003 (-0.01 – 0.02)	-0.019 (-0.04 – 0.01)	0.004 (-0.01 – 0.02)

BMI z-score = Body mass index z-score; WC =Waist circumference; WHtR= Waist-to-height ratio.
Bold values refer to significance values at $p<0.05$.

Table S5. Associations between activity intensity and activity type clusters and obesity outcomes (unadjusted).

	Cluster 1	Cluster 2	Cluster 3
Activity intensity clusters			
BMI z-score	0.22 (0.07 – 0.36) [a]	0.61 (0.41 – 0.82)	0.42 (0.20 – 0.65)
WC	57.7 (56.7 – 58.7)	59.2 (58.0 – 60.5)	58.4 (56.8 – 59.6)
WHtR	0.44 (0.44 – 0.45)	0.45 (0.44 – 0.46)	0.44 (0.43 – 0.45)
Activity type clusters			
BMI z-score	0.41 (0.24 – 0.59) [a]	0.71 (0.51 – 0.92)	0.54 (0.31 – 0.77)
WC	59.2 (58.0 – 60.5)	60.0 (58.7 – 61.3)	59.2 (57.7 – 60.6)
WHtR	0.45 (0.45 – 0.46)	0.46 (0.45 –0.47)	0.45 (0.44 – 0.46)

BMI z-score = Body mass index z-score; WC = Waist circumference; WHtR= Waist-to-height ratio.

Values are estimated means (95% confidence interval).

a: Significant difference from Cluster 2 ($p < 0.05$).

Table S6. Associations between activity intensity and activity type clusters and obesity outcomes after adjusting for gender, ethnicity and household deprivation.

	Cluster 1	Cluster 2	Cluster 3
Activity intensity clusters			
BMI z-score	0.20 (0.05 – 0.35) [a]	0.65 (0.46 – 0.84)	0.41 (0.19 – 0.63)
WC	59.1 (58.0 – 60.3)	60.0 (58.7 – 61.3)	59.2 (57.7 – 60.7)
WHtR	0.45 (0.44 –0.46)	0.46 (0.45 – 0.47)	0.45 (0.44 – 0.46)
Activity type clusters			
BMI z-score	0.40 (0.22 –0.58) [a]	0.76 (0.55 –0.96)	0.53 (0.30 – 0.77)
WC	57.7 (56.8 – 58.4)	59.2 (58.7 – 60.8)	58.4 (57.9 – 60.2)
WHtR	0.46 (0.45 – 0.47)	0.45 (0.44 – 0.46)	0.45 (0.44 – 0.46)

BMI z-score = Body mass index z-score; WC = Waist circumference; WHtR= Waist-to-height ratio.

Values are estimated means (95% confidence interval).

a: Significant difference from Cluster 2 ($p < 0.01$).

Table S7. Results of compositional MANOVA of differences in daily activity intensity and activity type compositions between sociodemographic factors.

	Activity intensity composition					**Activity type composition**				
	Pillai's trace	**F**	**df**	**P-value**	**η_p^2**	**Pillai's trace**	**F**	**df**	**P-value**	**η_p^2**
Gender	0.176	33.25	3 ,464	**<0.001**	0.177	0.220	31.78	4,450	**<0.001**	0.220
Child ethnicity	0.044	1.71	12,1386	0.057	0.014	0.092	2.66	16,1796	**<0.001**	0.231
Mother's age at delivery	0.035	1.12	15,1386	0.334	0.011	0.069	2.13	15,1347	0.107	0.023
Mother's education level	0.019	3.05	3,464	**0.028**	0.019	0.019	2.23	4.450	0.064	0.019
Mother's work hours	0.027	1.28	9,1281	0.240	0.008	0.032	1.53	9,1245	0.130	0.010
Household structure	0.031	2.44	6,922	**0.023**	0.015	0.030	1.72	8,894	0.090	0.015
Household income	0.042	2.04	9,1275	**0.031**	0.014	0.047	1.64	12,1236	0.075	0.015
Household deprivation	0.015	1.17	6,924	0.320	0.007	0.036	2.06	8,896	**0.036**	0.018
Residence location	0.010	1.65	3,462	0.176	0.010	0.008	0.944	4,448	0.438	0.008

Bold values represent significant differences.

Appendix D. R Analysis Code

This appendix contains the main analysis code used throughout the thesis. It does not include the code used to create the datasets used for analysis (from the GUiNZ database), nor does it include all the code used to make the graphs/visualisations used in the thesis.

Chapter 3

Code for the analysis of the validation study

```
library(tidyverse)
library(caret)
library(broom)

setwd("C:/Users/lhedayat/Desktop/Paper 1")
```

Incline/posture results

```
df.child <- read_csv('all_data_merged.csv') %>%
  filter(child == 1)

child_inc <- confusionMatrix(df.child$incline, df.child$observation)
%>%
  tidy() %>%
  mutate(child = 1,
         type = 'incline',
         device = 'actigraph')

child_inc <- rbind(child_inc, confusionMatrix(df.child$axivity_pos,
df.child$observation) %>%
  tidy() %>%
  mutate(child = 1,
         type = 'incline',
         device = 'axivity'))

write_csv(child_inc, 'results/child_incline_results.csv', na = "")
```

Intensity results

```
df <- read_csv('all_data_merged.csv') %>%
  filter(child == 1)


child_int <- confusionMatrix(df.child$actigraph, df.child$MET_cat) %>%
  tidy() %>%
  mutate(child = 1,
         type = 'intensity',
         device = 'actigraph')

child_int <- rbind(child_int, confusionMatrix(df.child$axivity, df.chi
ld$MET_cat) %>%
                     tidy() %>%
                     mutate(child = 1,
                            type = 'intensity',
                            device = 'axivity'))

write_csv(child_int, 'results/child_intensity_results.csv', na = "")
```

Comparing devices (t tests)

```
df <- read_csv('all_data_merged_ttest.csv')

df_intensity <- df %>%
  filter(type == 'intensity')

t.test(bal_accuracy ~ device, data = df_intensity, paired = TRUE)

df_intensity %>%
  group_by(device) %>%
  summarise(mean(bal_accuracy))

df_incline <- df %>%
  filter(type == 'incline')

t.test(bal_accuracy ~ device, data = df_incline, paired = TRUE)

df_incline %>%
  group_by(device) %>%
  summarise(mean(bal_accuracy))
```

Chapter 4

Code for compositional multiple regression. Note that the accelerometer dataset was prepared for compositional analysis by imputing zeros (see Chapter 6 below).

```
#devtools::install_github('tystan/deltacomp')
library(compositions)
library(lubridate)
library(tidyverse)
library(car)
library(performance)
library(deltacomp) # install from github
library(psych)
library(plyr)

setwd ("Z:/RF resources/Leila2/")

df <- read_rds("leila_dataset_manuscript_3_imputed.rds")
```

Recoding variables

```
df_all <- df %>%
  filter(acc_sample == 'acc_sample') %>%
  select(sedentary, light, mvpa, sleep_duration_24h,
# composition (intensity)
         sitting, standing, walking, lying, running,
# composition (type)
         WHtR, zbmi, waist_avg,
# outcomes
         child_gender, child_ethnicity, deprivation, mother_education,
# covariates
         fruit_intake, vegetable_intake, fizzy_drink2, fast_food2, bre
akfast) %>% # covariates

  mutate_at(vars(fruit_intake, vegetable_intake, fizzy_drink2, fast_fo
od2, breakfast), as.factor) %>%

  mutate(fizzy_drink2 = fct_collapse(fizzy_drink2,
                                     '2 or 3' = c('2', '3'),
                                     '4 or 5' = c('4', '5'),
                                     '6+' = c('6','7','9','14'))) %>%

  mutate(fast_food2 = fct_collapse(fast_food2,
                                   '2 or 3' = c('2', '3'),
                                   '4 or 5' = c('4', '5'),
                                   '6+' = c('6','7','10','15'))) %>%

  mutate(fruit_intake = fct_recode(fruit_intake,
                                   'Does not eat' = '0',
                                   '<1 serve' = '1',
                                   '1 serve' = '2',
```

```
                                    '2 serve' = '3',
                                    '3 serve' = '4',
                                    '4 serve' = '5',
                                    NULL = '98',
                                    NULL = '99')) %>%

  mutate(vegetable_intake = fct_collapse(vegetable_intake,
                                        'Does not eat' = '0',
                                        '<1 serve' = '1',
                                        '1 serve' = '2',
                                        '2 serve' = '3',
                                        '3 serve' = '4',
                                        '4 serve' = '5',
                                        NULL = '99')) %>%

  mutate(breakfast = fct_collapse(breakfast,
                              '1 or 2' = c('1', '2'),
                              '3 or 4' = c('3', '4'),
                              '5 or 6' = c('5','6'),
                              NULL = '99'))
```

Descriptive table 1

```
table(df_all$child_gender, exclude = NULL)
table(df_all$child_ethnicity, exclude = NULL)
table(df_all$deprivation, exclude = NULL)
table(df_all$mother_education, exclude = NULL)
table(df_all$fruit_intake, exclude = NULL)
table(df_all$vegetable_intake, exclude = NULL)
table(df_all$fizzy_drink2, exclude = NULL)
table(df_all$fast_food2, exclude = NULL)
table(df_all$breakfast, exclude = NULL)
```

Descriptive table 2

```
# Activity intensity
df_all %>%
  select(sedentary, light, mvpa, sleep_duration_24h) %>%
  describe()


comp <- acomp(cbind(df_all$sedentary, df_all$light, df_all$mvpa, df_al
l$sleep_duration_24h))
round(mean(comp),2)
round(clo(mean(comp), total=1440))
round(var(comp),3)

# Activity type
df_all %>%
  select(sitting, standing, walking, running, lying) %>%
  describe()
```

```
comp <- acomp(cbind(df_all$sitting, df_all$standing, df_all$walking, d
f_all$running, df_all$lying))
round(mean(comp),2)
round(clo(mean(comp), total=1440))
round(var(comp),3)
```

Compositional multiple regression

Building the sequential binary partition matrices

```
               # sed, lpa, mvpa, sleep
sbp_sed <- matrix(c(1, -1, -1, -1,
                    0,  1, -1, -1,
                    0,  0,  1, -1),
                  ncol=4,   byrow=TRUE) # ilr1 = sed/lpa+mvpa+sleep

sbp_lpa <- matrix(c(-1, 1, -1, -1,
                    -1, 0,  1, -1,
                    -1, 0,  0,  1),
                  ncol=4,   byrow=TRUE) # ilr1 = lpa/sed+mvpa+sleep

sbp_mvpa <- matrix(c(-1, -1, 1, -1,
                     -1, -1, 0,  1,
                      1, -1, 0,  0),
                   ncol=4,  byrow=TRUE) # ilr1 = mvpa/sed+lpa+sleep

sbp_sleep <- matrix(c(-1, -1, -1, 1,
                      -1, -1,    1, 0,
                      -1,    1,  0, 0),
                    ncol=4, byrow=TRUE)  # ilr1 = sleep/sed+lpa+mvpa


colnames(sbp_sed)   <- c('Sedentary',   'LPA', 'MVPA', 'Sleep')
rownames(sbp_sed)   <- c('ilr1',    'ilr2', 'ilr3')
sbp_sed
```

Creating isometric log ratios

```
sbp <- gsi.buildilrBase(t(sbp_mvpa)) # Select correct sbp from above (
REPEAT 4 TIMES, 1 FOR EACH)

ilr.comp <- ilr(comp, V = sbp)
```

Fit model (m0 = unadjusted, m1 = adjusted)

```
m0 <- lm(df_all$zbmi ~ ilr.comp)
m1 <- lm(df_all$zbmi ~ ilr.comp + df_all$child_gender + df_all$child_e
thnicity + df_all$deprivation +
           df_all$fruit_intake + df_all$vegetable_intake + df_all$ fas
```

```
t_food2 + df_all$fizzy_drink2 +
           df_all$ breakfast)

Anova(m0)
Anova(m1)
```

Check assumptions (residual normality etc.)

```
check_model(m1)
```

The above workflow is repeated, except for activity type, using a 5-part SBP

```
sbp_sit <- matrix(c(1, -1, -1, -1, -1,
                    0,  1, -1, -1, -1,
                    0,  0,  1, -1, -1,
                    0, 0, 0, 1, -1),
                 ncol=5,   byrow=TRUE) # ilr1 = Sit/Stand*Walk*Run*Lie

sbp_stand <- matrix(c(-1, 1, -1, -1, -1,
                      1, 0,  -1, -1,-1,
                      0,   0,  1,  -1, -1,
                      0, 0, 0, 1, -1),
                 ncol=5,   byrow=TRUE) # ilr1 = Stand/Sit*Walk*Run*Lie

sbp_walk <- matrix(c(-1, -1, 1, -1, -1,
                     1, -1, 0, -1, -1,
                     0, 1, 0,  -1, -1,
                     0, 0, 0, 1, -1),
                 ncol=5,  byrow=TRUE) # ilr1 = Walk/Sit* Stand*Run*Lie

sbp_run <- matrix(c(-1, -1, -1, 1, -1,
                    1, -1, -1, 0, -1,
                    0, 1, -1,  0, -1,
                    0, 0,  1,  0, -1),
                 ncol=5, byrow=TRUE)  # ilr1 = Run/Sit* Stand*Walk*Lie


sbp_lie <- matrix(c(-1, -1, -1, -1, 1,
                    1, -1, -1, -1, 0,
                    0,  1, -1,-1, 0,
                    0, 0, 1, -1, 0 ),
               ncol=5,   byrow=TRUE)  # ilr1 = Lie/Sit* Stand*Walk*Run
```

Compositional isotemporal substitution

Increment (mins)

```
RA = 15
```

Substitution for zbmi

```
df_pred <- predict_delta_comps(data = df_all,
                               y = "zbmi",
comps = c("sedentary", "light", "mvpa", "sleep_duration_24h"),

covars = c('child_gender','child_ethnicity','deprivation',
                                         'fruit_intake','vegetable_in
take','fast_food2','fizzy_drink2','breakfast'),
                               comparisons = "prop-realloc",
                               deltas = seq(-60, 60,by=RA)/(24*60),
                               alpha = 0.05)

df_pred %>%
  as_tibble() %>%
  mutate(realloc = rep(seq(-60, 60,by=RA), each = 4)) %>%
  select(1:3, 9, 4:8) %>%
  write_csv('reallocations_intensity_zbmi.csv')
```

And this is repeated for each outcome

Chapter 5

Code for compositional cluster analysis

```
library(compositions)
library(tidyverse)
library(cluster)
library(dendextend)
library(factoextra)
library(psych)

library(missForest) # Need for imputation of diet + screen_time
library(jmv)
library(emmeans)
library(parameters) # To check factor analysis assumptions
library(car)

setwd ("Z:/RF resources/Leila2/")

df <- read_rds("leila_dataset_manuscript_4_imputed.rds") # 623 partici
pants with accelerometer data
```

Factor analysis for nutrition variables

```
df_fact <- df %>%
  select(fruit_intake, vegetable_intake, fizzy_drink2, fast_food2, bre
akfast) %>%
  as.data.frame() %>%
  mutate_all(as.numeric)

# Impute missing values in nutrition data
imputed <- missForest::missForest(df_fact, ntree = 1000)$x %>% round()

fa_model <- factanal(imputed, 2, rotation="varimax", scores = 'Bartlet
t') # perform factor analysis

fa_model

parameters::check_factorstructure(imputed) # Assumptions: okay for fac
tor analysis

# Imputing missing screen time
imputed$screen_time <- df$screen_time
imputed$screen_time <- ifelse(imputed$screen_time > 600, NA, imputed$s
creen_time)
imputed <- missForest::missForest(imputed, ntree = 1000)$x # Impute sc
reen time data

#Adding new variables to main dataset
df <- df %>%
  mutate(unhealthy_food = fa_model$scores[,1],
         healthy_food = fa_model$scores[,2],
         screen_time = imputed$screen_time) %>%
```

```
  mutate(z_screen_time = scale(screen_time)) %>%
  mutate(pid = row_number())
```

Composition

Just for intensity (everything below this is then repeated for type)

```
df1 <- df %>%
  select(pid, sedentary, light, mvpa, sleep_duration_24h, z_screen_tim
e,
         healthy_food, unhealthy_food) %>%
  filter(complete.cases(.))

comp <- acomp(cbind(df1$sedentary, df1$light, df1$mvpa, df1$sleep_dura
tion_24h))

ilr_comp <- cbind(ilr(comp), df1$z_screen_time, df1$healthy_food, df1$
unhealthy_food)
```

Heirarchical clustering

```
clust <- agnes(x = ilr_comp,
               diss = FALSE,
               metric = "euclidean",
               method = "ward")

p <- clust %>%
  as.dendrogram %>%
  set("labels", "") %>%
  set("branches_lwd", 0.2) %>%
  set("branches_k_color", k = 3)

ggplot(p)

ggplot(p) +
  scale_y_reverse(expand = c(0.3, 0)) +
  coord_polar(theta="x")
```

K-means clustering

```
distance <- get_dist(ilr_comp)

fviz_dist(distance, gradient = list(low = "#00AFBB", mid = "white", hi
gh = "#FC4E07"))


fviz_nbclust(ilr_comp, kmeans, method = "wss")
fviz_nbclust(ilr_comp, kmeans, method = "silhouette")
clusGap(ilr_comp, FUN = kmeans, nstart = 25, K.max = 10, B = 75) %>% f
```

```
viz_gap_stat()

k_clust <- kmeans(as.data.frame(ilr_comp), centers = 3, nstart = 25)
fviz_cluster(k_clust, data = ilr_comp)
k_clust

result <- df %>%
  filter(pid %in% df1$pid) %>%
  mutate(cluster = factor(k_clust$cluster))
```

Cluster descriptives

```
result %>%
  descriptives(vars = c('zbmi', 'WHtR', 'waist_avg',
                        'healthy_food', 'unhealthy_food',
                         'z_screen_time'),
               splitBy = 'cluster',
               median = F,
               max = F,
               min = F,
               sd = T,
               freq = T)
```

Comparing clusters

Just for zbmi, repeated for each outcome

```
# ANOVA
m <- lm(zbmi ~ cluster, data = result) # change the outcome zbmi/WHtR/
waist_avg
Anova(m, type = 'III') # anova results

em <- emmeans(m, specs = 'cluster') # estimated means per cluster
em

pairs(em, adjust = 'holm') # pairwise contrasts between cluster estima
ted means

# ANCOVA
m1 <- lm(zbmi  ~ cluster + child_gender + child_ethnicity + deprivatio
n, data = result)
Anova(m1, type = 'III')

em1 <- emmeans(m1, specs = 'cluster')
em1
pairs(em1, adjust = 'holm')

# Comparing guideline adherance
contTables(result, rows = 'PA_guideline', cols = 'cluster', pcCol = T,
phiCra = T)
contTables(result, rows = 'SL_guideline', cols = 'cluster', pcCol = T,
```

```
phiCra = T)
contTables(result, rows = 'ST_guideline', cols = 'cluster', pcCol = T,
phiCra = T)
contTables(result, rows = 'guidelines', cols = 'cluster', pcCol = T, p
hiCra = T)
contTables(result, rows = 'zbmi_c', cols = 'cluster', pcCol = T, phiCr
a = T)
```

Chapter 6

Dataset preparation

Imputation of zeros

```
library(zCompositions)
library(tidyverse)
library(compositions)
library(visdat)

setwd ("Z:/RF resources/Leila2/")

df <- read_rds("leila_dataset_paper1.rds")

# Imputation of zeros and missing via log-ratio expectation-maximisati
on
# For references see: https://rdrr.io/cran/zCompositions/man/lrEM.html

# Activity Type -----------------------------------------------------
-----

df_type <- df %>%
  select(cid, sitting, standing, walking, running, lying) %>%
  group_by(cid) %>%
  mutate(n_missing = sum(ifelse(is.na(c_across()), 1, 0))) %>%
  ungroup() %>%
  filter(n_missing < 4) %>% # Cannot impute if 4/5 parts are missing
  select(-n_missing)

# Visualise NAs and 0s
vis_miss(df_type)
zPatterns(df_type[,2:6], label = NA)
zPatterns(df_type[,2:6], label = 0) # Only 1 person has '0' running

# Firstly, impute the NA values
df_type[df_type == 0] <- 0.0001 # Placeholder for actual actual zeros
df_type[,2:6] <- lrEM(X = df_type[,2:6], label = NA, imp.missing = TRU
E)

# Secondly, impute the zeros
df_type[df_type == 0.0001] <- 0 # Replacing the actual zeros (detectio
n limit = 5 seconds)
df_type[,2:6] <- lrEM(X = df_type[,2:6], label = 0, dl = rep((5/60), 5
))

vis_miss(df_type) # Looks good

# Activity Intensity ------------------------------------------------
-----

df_intensity <- df %>%
  select(cid, sedentary, light, moderate, vigorous, sleep_time) %>%
```

```
  group_by(cid) %>%
  mutate(n_missing = sum(ifelse(is.na(c_across()), 1, 0))) %>%
  ungroup() %>%
  filter(n_missing < 4) %>%
  select(-n_missing)

visdat::vis_miss(df_intensity) # A couple of people missing sleep_time
zPatterns(df_intensity[,2:6], label = NA)
zPatterns(df_intensity[,2:6], label = 0) # No body has any zeros

# Impute the NA values
df_intensity[,2:6] <- lrEM(X = df_intensity[,2:6], label = NA, imp.mis
sing = TRUE)

# Joining imputed compositions back to original dataset --------------
-----

df <- df %>%
  select(-c(sitting, standing, walking, running, lying, # Remove origi
nal
            sedentary, light, moderate, vigorous, sleep_time)) %>%
  left_join(df_type, by = 'cid') %>%
  left_join(df_intensity, by = 'cid')


df <- write_rds(df, "leila_dataset_paper1_imputed.rds")
```

Main analysis

```
#devtools::install_github('TheTS/CodaContrast')
library(zCompositions)
library(tidyverse)
library(compositions)
library(RVAideMemoire)
library(psych)
library(CodaContrast)
library(jmv)
library(lubridate)
library(broom)
library(heplots)

setwd ("Z:/RF resources/Leila2/")
```

Recoding variables

```
df <- read_rds("leila_dataset_paper1_imputed.rds") %>% # 6853
  filter(birth_order == 'First') %>% # 6751 remove twins
  filter(participated == T) %>% # 5479 remove not particpate at 8

  # If 'n_days' is missing, no accelerometer
```

```
  mutate (acc_sample = ifelse(!is.na(n_days), "acc_sample", "no_acc_sa
mple")) %>%



  # Age                                                        # 1st Jun
e 2017) %>%
  mutate(child_age = as.duration(as.Date('2017-06-01') - child_dob) /
dyears()) %>%

  # Mothers age & work hours

  mutate(mother_age_cat = case_when(mother_age_am <= 20 ~ '< 20',
                                    mother_age_am<= 25 ~ '< 25',
                                    mother_age_am <= 30 ~ '< 30',
                                    mother_age_am <=35 ~ '< 35',
                                    mother_age_am <= 40 ~ '< 40',
                                    is.na(mother_age_am) ~ NA_characte
r_, # Fix for missings
                                    TRUE ~ '40+')) %>%



  mutate(mother_work_cat = case_when(mother_work_hours <= 15 ~ '< 15',
                                     mother_work_hours <= 30 ~ '< 30',
                                     mother_work_hours <= 40 ~ '< 40',
                                     is.na(mother_work_hours_am) ~ NA_
character_,
                                     TRUE ~ '40+')) %>%

  # collapsing ethnicity ---------------------------------------------
-------
  mutate (child_ethnicity = fct_collapse(child_ethnicity, "Other" = c(
"Other",

"I don't think about it",

"MELAA")),
         ethnicity_am = fct_collapse(ethnicity_am, Other = c('Other',
                                        'New Zealander','MELAA'))) %>%

  # Collapsing NZDEP
 mutate(deprivation = as.factor(deprivation)) %>%
 mutate(deprivation = fct_collapse(deprivation, 'low' = c('1','2','3')
, 'med' = c('4','5','6','7'), 'high' = c('8','9','10'))) %>%

  # Assigning labels to income
  mutate(house_income = factor(house_income, levels = 1:7,
         labels = c('<20k', '20-30k', '30-50k', '50-70k', '70-100k',
                                        '100-150k', '>150k'))) %>%
  mutate(house_income = fct_collapse(house_income, '<70K' = c('<20k',
'20-30k', '30-50k', '50-70k'))) %>%
```

```
   # Assigning labels to education
  mutate(mother_education = factor(mother_education, levels = 0:4,
         labels = c('Without school qualification',
                    'School or NCEA 1-4', 'Diploma',
               'Bachelor degree', 'Higher degree'))) %>%


  mutate(mother_education = fct_collapse(mother_education, 'lower than
bachelor' = c('Without school qualification',
              'School or NCEA 1-4', 'Diploma'),
              'bachelors or higher' = c('Bachelor degree',
                                        'Higher degree'))) %>%

  # Assigning labels to household structure
  mutate(household_structure = factor(household_structure, levels = 1:
4,
         labels = c('Single parent', 'Both parents',
                    'Parents with extended family',
                   'Parents living with nonkin'))) %>%


  mutate(household_structure = fct_collapse(household_structure, 'with
extendedfamily' = c('Parents with extended family',
                    'Parents living with nonkin'))) %>%

  # Screen time + Meeting Guidelines (yes/no)
  mutate(screen_time_wd = (tv_wd + electronic_wd)*60, # hours to minut
es
         screen_time_we = (tv_we + electronic_we)*60) %>%
  rowwise() %>%
  mutate(screen_time = mean(c_across(screen_time_wd:screen_time_we), n
a.rm = TRUE)) %>%
  ungroup() %>%
  mutate(screen_time = ifelse(is.na(screen_time_wd) & is.na(screen_tim
e_we), NA, screen_time),
         PA_guideline = as.numeric(mvpa >= 60),
         SL_guideline = as.numeric((sleep_time >= 540) & (sleep_time <
= 660)),
         ST_guideline = as.numeric(screen_time < 120),
         guidelines = as.numeric(PA_guideline & SL_guideline & ST_guid
eline),
         guidelines = ifelse(is.na(PA_guideline) | is.na(SL_guideline)
| is.na(ST_guideline), NA, guidelines))
```

Descriptive tables

```
table(df$child_ethnicity, df$acc_sample, exclude = NULL)
table(df$deprivation, df$acc_sample, exclude = NULL)
table(df$house_income, df$acc_sample, exclude = NULL)
table(df$mother_education, df$acc_sample, exclude = NULL)
table(df$household_structure, df$acc_sample, exclude = NULL)
table(df$rurality,df$acc_sample,exclude = NULL)
table(df$mother_age_cat,df$acc_sample,exclude = NULL)
```

```
table(df$screen_time,df$acc_sample,exclude = NULL)
table(df$mother_age,df$acc_sample,exclude = NULL)
table(df$mother_work_cat,df$acc_sample,exclude = NULL)
table(df$guidelines,df$acc_sample, exclude = NULL)
table(df$ST_guideline,df$acc_sample, exclude = NULL)

table(df$ethnicity_am,df$acc_sample)
table(df$acc_sample)
table(df$mother_age_cat,df$acc_sample, exclude = NULL)
table(df$mother_work_cat,df$acc_sample, exclude = NULL)
```

Comparing with and without accelerometer

```
 # gender
contTables(df, rows = 'child_gender', cols = 'acc_sample', pcCol = T,
exp = T)
# ethnicity
contTables(df, rows = 'child_ethnicity', cols = 'acc_sample', pcCol =
T)
 # education
contTables(df, rows = 'mother_education', cols = 'acc_sample', pcCol =
T )
# income
contTables(df, rows = 'house_income', cols = 'acc_sample', pcCol = T)
# deprivation
contTables(df, rows = 'deprivation', cols = 'acc_sample', pcCol = T)
# household_structure
contTables(df, rows = 'household_structure', cols = 'acc_sample', pcCo
l = T)
# residence location
contTables(df, rows = 'rurality', cols = 'acc_sample', pcCol = T)
# mother age
contTables(df, rows = 'mother_age_cat', cols = 'acc_sample', pcCol = T
)
# mother work hours
contTables(df, rows = 'mother_work_cat', cols = 'acc_sample', pcCol =
T)
# mother ethnicity
contTables(df, rows = 'ethnicity_am', cols = 'acc_sample', pcCol = T)

# Contiinuous variables
ttestIS(data = df, vars = 'child_age', group = 'acc_sample', meanDiff
= T, welchs = T)
ttestIS(data = df, vars = 'mother_age', group = 'acc_sample', meanDiff
= T, welchs = T)
ttestIS(data = df, vars = 'mother_work_hours', group = 'acc_sample', m
eanDiff = T, welchs = F)
ttestIS(data = df, vars = 'screen_time', group = 'acc_sample', meanDif
f = T, welchs = F )
```

Guideline adherence

```
#PA Guidelines
contTables(filter(df, acc_sample == 'acc_sample'),
           rows = 'PA_guideline',
           cols = 'child_gender', pcCol = T, exp = T, phiCra = T)

t <- table(df_acc$PA_guideline, df_acc$ethnicity_am)
fisher.test(t)

# Repeated for other variables and guidelines
```

Compositional descriptive

```
# Overall
df_all <- df %>%
  select(sedentary,light,mvpa,sleep_time) %>%
  filter(complete.cases(.))

comp <- acomp(df_all)

round(mean(comp),2)

round(clo(mean(comp), total=1440))

# By gender

dfboy <- df %>%
  select(sleep_time, sedentary, light, mvpa, child_gender) %>%
  filter(child_gender == 'Boy') %>%
  select(-child_gender) %>%
  filter(complete.cases(.))

dfgirl <- df %>%
  select(sleep_time, sedentary, light, mvpa, child_gender) %>%
  filter(child_gender == 'Girl') %>%
  select(-child_gender) %>%
  filter(complete.cases(.))

comp_boy <- acomp(dfboy)
mean(aplus(dfboy))
round(mean(comp_boy), 2)
round (clo(mean(comp_boy), total = 1440))

comp_girl <- acomp(dfgirl)
mean(aplus(dfgirl))
round(mean(comp_girl), 2)
round (clo(mean(comp_girl), total = 1440))

# Repeated for other sociodemographics
```

Compositional MANOVA

```
#intensity ~ gender

df_all <- df %>%
  select(sedentary, light, mvpa, sleep_time, child_gender) %>%
  filter(complete.cases(.))

comp <- acomp(df_all[,1:4])


mean(comp)
round (clo(mean(comp), total = 1440))


round(variation(comp), 2)

m1 <- manova(ilr(comp) ~ df_all$child_gender)
summary(m1)

etasq(m1)

# Geomeric mean plot
plot_geo_means(composition = comp, group = df_all$child_gender, type =
'component')


# Contrasts
lr <- log_ratio_difference(composition = comp,
                           group = df_all$child_gender)

print(lr)
plot_log_ratio_difference(lr)

# type ~ household structure

df_Household_structure <- df %>%
  select(sitting, standing, walking, running ,lying, household_structu
re) %>%
  filter (complete.cases(.))

comp <- acomp( df_Household_structure[,1:5])


m1 <- manova(ilr(comp) ~  df_Household_structure$household_structure)
summary(m1)
etasq(m1)

pairwise_hotelling_test(comp = ilr(comp), groups =  df_Household_struc
ture$household_structure)
```