Sedentary behaviour, work, and health-related outcomes: the application of empirically derived accelerometer cut-points to data from the Health Survey for England

Alexandra Marie Clarke-Cornwell

School of Health & Society,

The University of Salford

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In memory of Lindsey, who always encouraged

me to question the accepted

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Declaration

I declare that this thesis has been composed by myself and that the work has not been submitted for any other degree or professional qualification. I confirm that the work submitted is my own, except where work that has formed part of jointly-authored publications has been included. My contribution and those of the other authors to this work have been explicitly indicated below. I confirm that appropriate credit has been given within this thesis where reference has been made to the work of others.

Results from thesis objectives one and two (Section 1.4.1) are presented within Chapter Three and have been published in *Physiological Measurement* as "*Empirically derived cut-points for sedentary behaviour: Are we sitting differently?*" by Alex Clarke-Cornwell (ACC: PhD candidate), Tracey Farragher (TF), Penny Cook (PC: supervisor), and Malcolm Granat (MG: supervisor). The study was conceived by ACC, MG, PC, and Professor Lindsey Dugdill[1]; data analysis was carried out by ACC; data interpretation was carried out by all authors; ACC wrote the first draft and all authors edited and contributed to the final submission. Chapter Three provides further specifics on data cleaning, data processing, data reduction rules, and the statistical analysis, alongside detailed results for objectives one, two and three.

The data cleaning processes for the Health Survey for England accelerometer data that are described within Chapter Four have been used in a published study in *Sports Medicine* as "*Sedentary Time and Physical Activity Surveillance Through Accelerometer Pooling in Four European Countries*" by Anne Loyen (AL), Alex Clarke-Cornwell (ACC: PhD candidate), Sigmund Anderssen (SA), Maria Hagströmer (MH), Luis Sardinha (LS), Kristina Sundquist (KS), Ulf Ekelund (UE), Jostein Steene-Johannessen (JSJ), Fatima Baptista (FB), Bjorge Hansen (BH), Katrien Wijndaele (KW), Soren Brage (SB), Jeroen Lakerveld (JL), Johannes Brug (JB), and Hidde van der Ploeg (HVDP). The study was conceived by AL and HVDP; data processing and cleaning for the English data was carried out by ACC (Stata programs were validated and transferred to AL); data processing and analysis was carried out by AL; data interpretation was carried out by all authors; AL wrote the first draft and all authors edited and contributed to the final submission. Anne Loyen included this paper as part of her PhD by publication (2017), submitted to VU University Medical Center, Amsterdam, The

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Netherlands; however, only the processing and the cleaning of the Health Survey for England 2008 accelerometer data from this publication have been used within this thesis.

Published papers

Clarke-Cornwell, A. M., Farragher, T. M., Cook, P. A., & Granat, M. H. (2016). Empirically derived cut-points for sedentary behaviour: Are we sitting differently? Physiological Measurement, 37(10). doi: 10.1088/0967-3334/37/10/1669

Loyen, A., Clarke-Cornwell, A. M., Anderssen, S. A., Hagströmer, M., Sardinha, L. B., Sundquist, K., … van der Ploeg, H. P. (2017). Sedentary Time and Physical Activity Surveillance Through Accelerometer Pooling in Four European Countries. Sports Medicine, 47(7). doi: 10.1007/s40279-016-0658-y

Book chapters

Cooper-Ryan, A. M., Clarke-Cornwell, A. M., & Condie, J. (2019). Collaborative work of early career researchers: does the impact agenda transcend continents? In K. Fenby-Hulse, E. Heywood, & K. Walker (Eds.), Research Impact and the Early Career Researcher: Lived Experiences, New Perspectives (1st edition, p. 238). London: Routledge.

Cooper, A. M., & Clarke-Cornwell, A. M. (2015). The Built Environment, Active Design and Public Health: the Impact of Office Design on Activity. In J. Condie & A. M. Cooper (Eds.), Dialogues of Sustainable Urbanisation: Social Science Research and Transitions to Urban Contexts. Penrith: University of Western Sydney.

Manuscripts in preparation

Clarke-Cornwell, A. M., Cook, P. A., Edwardson, C. L., & Granat, M. H. The distribution of activPAL postural and stepping classifications with ActiGraph activity classifications activity – to be submitted to The Journal for the Measurement of Physical Behaviour

Lambert, S. H., Gbadamosi, A. R., Cook, P. A., Granat, M. H., & Clarke-Cornwell, A. M. Occupational sedentary time and measures of wellbeing – to be submitted to BMC Public Health

Clarke-Cornwell, A. M., Cook, P. A., & Granat, M. H. Associations between occupational sedentary time and cardiometabolic markers: the case for an occupational sedentary behaviour paradox? – to be submitted to PLOS One

Clarke-Cornwell, A. M., Rowlands, A., Cook, P. A., Edwardson, C. L., & Granat, M. H. A sequence analysis to examine the transition process between physical behaviours in the workplace: how are these processes linked to cardiometabolic risk factors? – to be submitted to Medicine and Science in Sports and Exercise

Published conference abstracts

Clarke-Cornwell, A. M. Review of wearable technologies. Annals of the Rheumatic Diseases 2017;76(7):SP0023 - European Congress of Rheumatology 2017, Madrid; Invited talk, presented by Alex Clarke-Cornwell

Clarke-Cornwell, A. M., Cook, P.A., & Granat, M. H. Occupational sedentary time and associations with adiposity markers: a quantile regression analysis. Journal of Physical Activity & Health 2018;15(10):S187 - International Society for Physical Activity and Health 2018, London; Accepted as a poster presentation; presented by Alex Clarke-Cornwell

Other conference abstracts

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Loyen, A., Clarke-Cornwell, A. M., Anderssen, S. A., Hagströmer, M., Sardinha, L. B., Sundquist, K., … van der Ploeg, H. P. (2017). Sedentary time and physical activity surveillance through accelerometer pooling in four European countries. - International Society of Behavioral Nutrition and Physical Activity 2017, Victoria; Accepted as a poster presentation; presented by Anne Loyen

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Clarke-Cornwell, A. M., Granat, M. H., & Cook, P. A. Classification of occupations by accelerometer –derived variables for physical behaviour: Health Survey for England 2008. - International Conference on Ambulatory Monitoring of Physical Activity and Movement 2017, Bethesda; Accepted as a poster presentation; presented by Alex Clarke-Cornwell

Clarke-Cornwell, A. M., Cook, P. A., & Granat, M. H. Associations between occupational sedentary time with adiposity markers, and the influence of moderate to vigorous physical activity: does domain matter? - International Society of Behavioral Nutrition and Physical Activity 2019, Prague; Accepted as a short concurrent oral presentation, presented by Alex Clarke-Cornwell

Clarke-Cornwell, A. M., Cook, P. A., Edwardson, C. L., & Granat, M. H. A sequence analysis to examine the transition process between physical behaviours in the workplace: how are these processes linked to cardiometabolic risk factors? - International Conference on Ambulatory Monitoring of Physical Activity and Movement 2019, Maastricht; Accepted as a concurrent oral presentation; presented by Alex Clarke-Cornwell

Invited talks

2018   British Society for Rheumatology and Lilly UK Expert Webinar. *Sedentary behaviour, Work and Health-Related Outcomes -* https://www.lillyrheumatology.co.uk/educationcentre/webinar

2018   Health and Wellbeing at Work Conference, Birmingham. *Designing your work environment to encourage physical activity*

2017   Annual European Congress of Rheumatology (EULAR), Madrid. *Review of wearable technologies*. Annals of the Rheumatic Diseases 2017;76(7) DOI:10.1136/annrheumdis-2017-eular.7177

2016   Work, Health and Wellbeing Conference, The University of Salford. *Strategies for reducing sedentary behaviour in the workplace*

2016   Library of Ideas, Manchester Science Festival. *Digital public health & is sitting the new smoking?*

Abbreviations

agd	ActiGraph data file
AIC	Akaike information criterion
ANOVA	Analysis of variance
AUC	Area under the curve
BHF	British Heart Foundation
BMI	Body mass index
CAPI	Computer-assisted personal interviewing
CDSR	Cochrane Database of Systematic Reviews
CENTRAL	Cochrane Central Register of Controlled Trials
CI	Confidence interval
CINAHL	Cumulative Index to Nursing and Allied Health Literature
cm	Centimetre
cpm	Counts per minute
csv	Comma-separated values
dat	Generic data file
DEDIPAC	Determinants of Diet and Physical Activity
DLW	Doubly labelled water
DNA	Deoxyribonucleic acid
EQ-5D	EuroQol 5 dimensions
GBD	Global Burden of Disease
GEE	Generalised estimating equations
GHQ	General health questionnaire
HbA1c	Haemoglobin A1c (glycated haemoglobin)
HDL	High-density lipoprotein
HMIC	Health Management Information Consortium
HR	Heart rate
IPAQ	International Physical Activity Questionnaire
IQR	Interquartile range
kg	Kilogram
LDL	Low-density lipoprotein
LoA	Limits of agreement
m	Metre

MEDLINE	Medical Literature Analysis and Retrieval System Online
MeSH	Medical subject heading
MET	Metabolic equivalent
mfp	Multivariable fractional polynomial
mg/dl	Milligrams per decilitre
ml	Millilitre
mmHG	Millimetre of mercury
mmol/L	Millimoles per litre
MOSPA-Q	MONICA[2] Optional Study on Physical Activity Questionnaire
mph	Miles per hour
MVPA	Moderate to vigorous physical activity
n.d.	No date[3]
NatCen	National Centre for Social Research
NHANES	National Health and Nutrition Examination Survey
NS-SEC	National Statistics Socio-Economic Classification
OLS	Ordinary least squares
QIC	Quasi-likelihood under the independence model criterion
ROC	Receiver operating characteristic
ROC-AUC	Area under the receiver operating characteristic curve
SAS	Statistical Analysis System
SD	Standard deviation
UK	United Kingdom
US/USA	United States of America
vif	Variance inflation factor
WHO	World Health Organization

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[2] MONItoring of trends and determinants in CArdiovascular disease Project (https://thl.fi/monica/)
[3] Applicable to references with no date (American Psychological Association 6th edition)

Abstract

Background: During the last century, the technological revolution has contributed to changes in physical behaviour in the workplace. The number of moderate physical activity intensity occupations has decreased significantly over this period, and the introduction of desk dependent, computer-based jobs has resulted in an increase in the number of sedentary occupations.

Sedentary behaviour is associated with several health-related outcomes, independent of physical activity; however, the role of occupational sedentary time with health-related outcomes is less clear. Sedentary time in different domains may represent differing associations with health; therefore, there is a need for studies to use more objective, reliable and valid measurements of sitting time in the occupational domain to fully understand the effects of sitting at work and health.

Methods: This thesis comprises two main studies: the first study recruited a sample of university employees/postgraduate students (n=30), whose day was spent mostly sedentary. Participants were asked to wear two types of accelerometer (ActiGraph GT3X+ and activPAL3™) during waking hours for seven days: generalised estimating equations were used to derive a counts per minute threshold for sedentary behaviour for the ActiGraph GT3X+, based on the activPAL™ sedentary classification.

The derived accelerometer cut-points from the first study were used to complete a secondary analysis using data from the Health Survey for England. In 2008, a sub-sample of participants wore an ActiGraph GT1M accelerometer for seven-days, and these data were used to examine the relationship between occupational sedentary time and health-related outcomes.

Results: The derived cut-points from the generalised estimating equations were significantly higher on a Saturday (97 cpm) compared to weekdays (60 cpm) and Sunday (57 cpm). Derived counts per minute for sedentary time during working time were significantly lower compared to non-working time (35 versus 73). Compared to the 100 cpm and 150 cpm thresholds, the empirically derived cut-points were not significantly different in terms of area-under-the-curve, but had lower mean bias for working and non-working times. The amount of sedentary time from the derived and previously proposed cut-points differed significantly; however, this did not affect the beta coefficients and the conclusions drawn from the regression models. In contrast to studies that have found associations with both total sedentary time and leisure-time sedentary behaviour and detrimental health outcomes, there was no evidence that occupational sedentary time is associated with health-related outcomes in the same way. Time spent in moderate to vigorous physical activity was a significant predictor for waist circumference and BMI for occupational sedentary time; furthermore, BMI was a significant predictor of cardiometabolic markers.

Conclusions: Accelerometer cut-points for sedentary behaviour can depend on day and also domain, suggesting that the nature of sitting differs depending on the context in which sedentary time is accrued. It is not known if there are underlying mechanisms of sedentary behaviour in different domains that can explain these differences, and the effect that occupational sedentary time has on health.

"...those who sit at their work and are therefore called 'chair workers,' such as cobblers and tailors, suffer from their own particular diseases ... [T]hese workers ... suffer from general ill-health and an excessive accumulation of unwholesome humors caused by their sedentary life ... so to some extent counteract the harm done by many days of sedentary life."

— Bernardino Ramazzini (1633-1714)

Chapter 1 - Introduction

"Sitting too much is not the same as exercising too little"

— Dr Marc Hamilton

1.1   Introduction

The first chapter of this thesis outlines the rationale and the aims of the research studies. It discusses how sedentary behaviour is defined and measured in the literature, the role of sedentary behaviour in the workplace, the associations between sedentary behaviour and health-related outcomes, and the physiological hypotheses for these associations. Chapter One also reviews the conceptual framework that underpins the research studies contained within this thesis. The chapter concludes with an overall structure of the thesis.

1.1.1   *Defining sedentary behaviour*

The use of the terms 'sedentary' and 'sedentary behaviour' in research has evolved over the last two decades (Pate, O'Neill, & Lobelo, 2008; Sedentary Behavior Research Network, 2012; Tremblay et al., 2017; Yates, Wilmot, Davies, et al., 2011), and the number of research articles published using the term 'sedentary behaviour' has increased exponentially over this same period (Saunders, 2017). The term 'sedentary' comes from the Latin 'to sit', *sedere*, whilst 'sedentary behaviour' encompasses the practice of continued sitting or resting, and cannot be defined merely as a lack of physical activity (Pate et al., 2008). Sedentary behaviour occurs in different environments and domains: **work** can involve long periods of sitting; **commuting** can include sitting when travelling by car or public transport; **household** sedentary time can include activities such as television viewing[4], screen time (i.e. mobile phones and tablets) and personal computer use; and

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[4] Although electronic entertainment is included within the household domain within the ecological model for sedentary behaviour (Owen et al., 2011), many studies classify television viewing as a leisure-time sedentary behaviour (Pinto Pereira et al., 2012; Stamatakis, Hillsdon, Mishra, Hamer, & Marmot, 2009; Sugiyama et al., 2008).

leisure-time sedentary behaviour encompasses activities such as reading, listening to music, eating, and socialising (Owen et al., 2011; Sugiyama, Healy, Dunstan, Salmon, & Owen, 2008).

Pate et al. (2008) defined sedentary behaviour as behaviour that generates low energy expenditure:

> *Sedentary behavior refers to activities that do not increase energy expenditure substantially above the resting level and includes activities such as sleeping, sitting, lying down, and watching television, and other forms of screen-based entertainment. (p.174)*

Conversely, physical activity is defined as "any bodily movement produced by skeletal muscles that requires energy expenditure" (Caspersen, Powell, & Christenson, 1985, p. 126; World Health Organization [WHO], n.d., para. 1). These definitions of sedentary behaviour and physical activity both use the term 'energy expenditure', which refers to the amount of energy required to carry out all physical functions, such as basal metabolic rate[5], food digestion (thermic effect of food), and all physical activity (activity thermogenesis) (Caspersen et al., 1985; Levine, 2004). Energy expenditure can be quantified using metabolic equivalents (METs), with one MET representing the average, resting metabolic rate while seated at rest; for adults, this is equivalent to 3.5ml of oxygen consumption per kilogram of body weight per minute (Plowman & Smith, 2010).

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[5] The energy required for processes such as, breathing, blood circulation, temperature control, muscle contraction, which are needed for the body to function at rest.

The intensity of human movements (including sedentary behaviour and physical activity) can be described in terms of energy expenditure (expressed in METs), with categories of physical behaviour differentiated in terms of energy expenditure on the movement continuum (Figure 1.1) (British Heart Foundation [BHF], 2012; Tremblay, Colley, Saunders, Healy, & Owen, 2010).
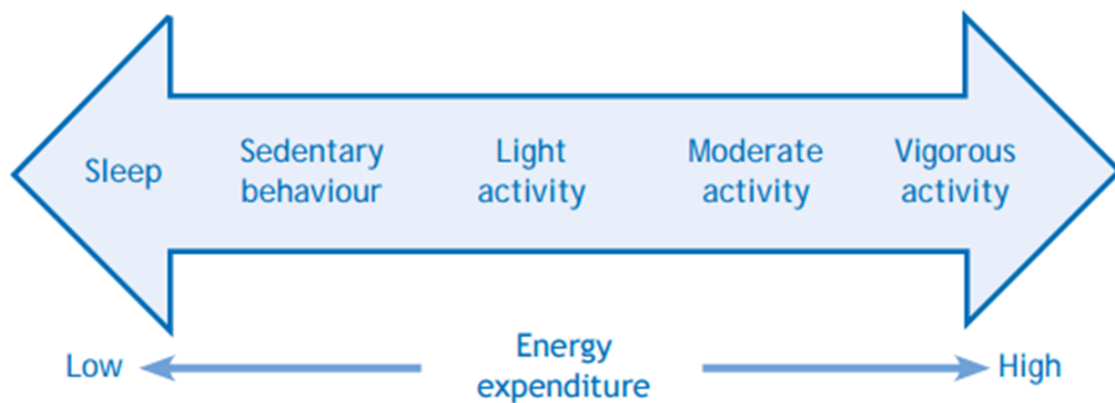
Figure 1.1   Movement continuum in terms of energy expenditure (BHF, 2012, p. 2; adapted from Tremblay et al., 2010)

The energy expenditure of physical behaviours increases along the movement continuum (from left to right), with sedentary behaviour shown as a distinct component to sleep and light physical activity (Figure 1.1). Pate et al. (2008) defined 'light physical activity' independently from sedentary behaviour:

> *Light physical activity, which often is grouped with sedentary behavior but is in fact a distinct activity construct, involves energy expenditure at the level of 1.6-2.9 METs. It includes activities such as slow walking, sitting and writing, cooking food, and washing dishes. (p.174)*

In a letter to the editor of the journal of *Applied Physiology Nutrition and Metabolism,* the Sedentary Behavior Research Network (2012), proposed the following definitions of

'sedentary behaviour' and 'inactive', to avoid further inconsistencies and confusion in research related to sedentary behaviour:

> We suggest that journals formally define sedentary behavior as any waking behaviour characterized by an energy expenditure ≤1.5 METs while in a sitting or reclining posture. In contrast, we suggest that authors use the term "inactive" to describe those who are performing insufficient amounts of MVPA [moderate to vigorous physical activity] (i.e. not meeting specified physical activity guidelines). (p.540)

As a result of a Terminology Consensus Project from the Sedentary Behavior Research Network, the definition of sedentary behaviour has recently been updated to include the term 'lying', alongside 'sitting' and 'reclining' (Tremblay et al., 2017). The two definitions of sedentary behaviour by the Sedentary Behavior Research Network (2012 and 2017) include components of both energy expenditure (≤1.5 METs) and posture (sitting, reclining or lying). The physical behaviours on the movement continuum (Figure 1.1), can be quantified in terms of energy expenditure, with moderate intensity physical activity characterised as energy expenditure between 3 and 5.9 METs, and vigorous intensity as activities with an energy expenditure ≥6 METs (Ainsworth et al., 2011) (Table 1.1); however, there are currently no standardised threshold values (based on energy expenditure) for sedentary behaviour.

Table 1.1   **Energy expenditure (METs) for behaviours on the movement continuum**

Behaviour	Energy expenditure (METs)	Examples	Source
Sleep	0.9	-	(Ainsworth et al., 2011)
Sedentary behaviour	1.0-1.5 or ≤1.5	Sitting, lying down, watching television	(Mansoubi et al., 2015; Pate et al., 2008; Sedentary Behavior Research Network, 2012; Tremblay et al., 2017)
Light activity	1.6-2.9	Slow walking, sitting and writing, cooking food, standing	(Pate et al., 2008; Tremblay et al., 2010)
Moderate activity	3.0-5.9	Swimming, walking (>3 mph), lifting weights	(Ainsworth et al., 2011; Freedson, Melanson, & Sirard, 1998; Pate et al., 1995; The U.S. Department of Health and Human Services, 2008)
Vigorous activity	≥6	Running (>4 mph), bicycling (>10 mph), swimming (front crawl)	(Ainsworth et al., 2011; Freedson et al., 1998; Pate et al., 1995; The U.S. Department of Health and Human Services, 2008)

The recent definitions of sedentary behaviour from the Sedentary Behavior Research Network do not have a lower limit in terms of energy expenditure, compared to the previous definition from Pate et al. (2008), which used a range of 1.0-1.5 METs (Table 1.1). Defining sedentary behaviour in terms of energy expenditure alone can result in misclassification if contextual information is not also provided: for example, some non-sedentary activities are known to produce low energy expenditure, such as standing (Ainsworth et al., 2011; Crouter, Clowers, & Bassett, 2006), and sitting whilst carrying out activities such as typing or note-taking can produce energy expenditure greater than 1.5 METs (Ainsworth et al., 2011; Mansoubi et al., 2015). As part of the Terminology Consensus Project, Tremblay et al. (2017) defined two categories of sitting based on the MET threshold of 1.5: sitting characterised by an energy expenditure ≤1.5 METs is referred to as

passive sitting, and sitting characterised by an energy expenditure >1.5 METs is referred to as *active* sitting. These classifications are illustrated in the conceptual model in Figure 1.2, which shows the physical behaviours of sleep, sedentary behaviour and physical activity in terms of energy expenditure, and also provides postural information, represented within the outer ring (Tremblay et al., 2017). The model shows that sleep, sedentary behaviour and physical activity may all happen while a person is sitting, but at different intensities in terms of energy expenditure.
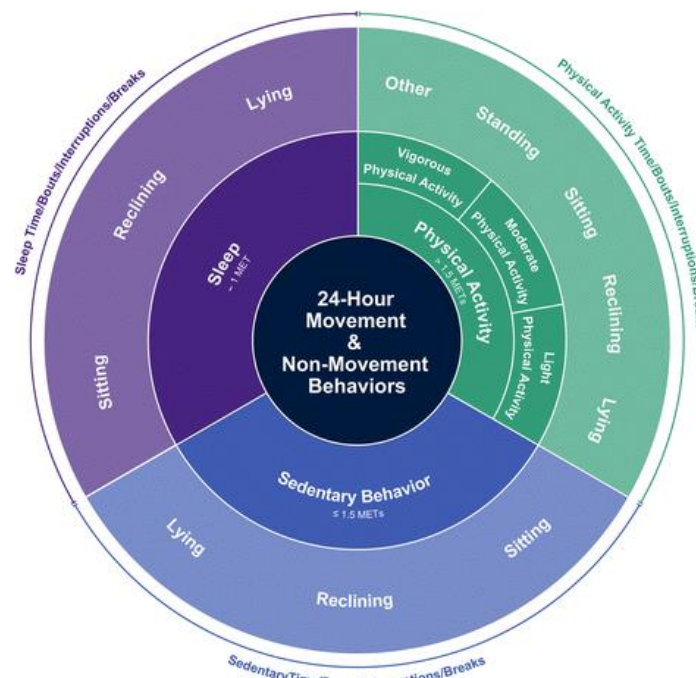
Figure 1.2   Conceptual model of movement-based terminology (Tremblay et al., 2017, p. 11). Reproduced with permission (originally published by Biomed Central).

The term 'inactivity' is not defined in the conceptual model in terms of energy expenditure (Figure 1.2; Tremblay et al., 2017), but has been debated in the literature as a different construct to sedentary behaviour (van der Ploeg & Hillsdon, 2017). Many previous studies (especially in literature from the field of sports and exercise) have combined sedentary behaviour and light physical activity into one category to describe inactivity, or have used

the term 'inactivity' to indicate not meeting a specified/recommended level of moderate to vigorous physical activity (Church et al., 2009; Lowry, Wechsler, Galuska, Fulton, & Kann, 2002; Melanson et al., 2009; Sedentary Behavior Research Network, 2012; Tremblay et al., 2017).

The current physical activity guidelines in the UK, from the Chief Medical Officer, for adults (aged 19-64 years) state:

> *Adults should aim to be active daily. Over a week, activity should add up to at least 150 minutes (2½ hours) of moderate intensity activity in bouts of 10 minutes or more – one way to approach this is to do 30 minutes on at least 5 days a week. (Department of Health, 2011, p. 7)*

The UK physical activity guidelines also state that "comparable benefits can be achieved through 75 minutes of vigorous intensity activity …" (Department of Health, 2011, p. 7). In the Health Survey for England 2016, 66% of men and 58% of women were reported to meet the UK recommended physical activity levels of at least 150 minutes of moderate physical activity, or 75 minutes of vigorous physical activity (or an equivalent combination of both) (Scholes, 2017). Overall, 38% of adults (19 years or older) in England were physically inactive in 2016, which is higher than the weighted global average of 31% for adults (15 years or older) (Hallal et al., 2012; Scholes, 2017). Furthermore, using the definition of inactivity to denote not meeting a recommended level of physical activity, infers that people can be both physically inactive and also accrue a large amount of sedentary time across a day; conversely, people can also meet physical activity recommendations and be highly sedentary (Bakrania et al., 2016; Owen, Healy, Howard, & Dunstan, 2012; Owen, Healy, Matthews, & Dunstan, 2010).

Defining sedentary behaviour as not meeting recommended physical activity guidelines does not consider time spent in light physical activity. There are currently no UK guidelines that quantify recommended amounts of time for light physical activity or sedentary behaviour for adults; however, the UK physical activity guidelines recommend that adults should limit their sedentary behaviour by, "reducing total sedentary time and breaking up extended periods of sitting" (Department of Health, 2011, p. 34). Similarly, Australian physical activity and sedentary behaviour guidelines state that adults should, "Minimise the amount of time spent sitting in prolonged sitting", and, "Break up long periods of sitting as often as possible" (Department of Health: Australian Government, 2014, p. 8). Sedentary behaviour recommendations for adults have yet to be quantified in the UK or Australia; however, daily screen time recommendations for children of no more than two hours have been proposed alongside limiting prolonged periods of sitting, in Canadian and Australian guidelines (Canadian Society for Exercise Physiology, 2017; Department of Health: Australian Government, 2014b). Although some national physical activity guidelines include recommendations to sit less, evidence-based data are not currently available to quantify a recommended daily sedentary time that is not detrimental to health (Biddle et al., 2010).

In addition to defining sedentary behaviour using both energy expenditure and posture, or as not meeting a certain threshold of physical activity, several other definitions have also been used in the literature. A review by Bennett, Winters-Stone, Nail, and Scherer (2006) described the definitions of *sedentary* within physical activity intervention trials between the years 2000 and 2005. The majority of trials (32 out of 42) from this review paper defined *sedentary* in terms of falling below a specified cut-point of minutes (or days per

week) of physical activity; the thresholds for the definition of *sedentary* ranged from <20 minutes per week up to <150 minutes per week of physical activity (the latter being the equivalent of the UK guidelines). Trials that used the definition of a number of days per week of physical activity, used thresholds of <1, <2, or <3 days per week. Further definitions of *sedentary* reported in the review by Bennett et al. (2006) used energy expenditure, calculated subjectively from the 7-Day Physical Activity Recall scale (Blair et al., 1985); one study objectively measured energy expenditure using a Caltrac™ accelerometer, to confirm self-reported sedentary time (Cooper, Moore, McKenna, & Riddoch, 2000); whilst a further study categorised occupation as either *physical* or *sedentary*, when examining activity in both the occupational and leisure-time domains (Williams et al., 2004). Likewise, occupational studies have classified occupations into either sedentary or not, based on the main categoric measure of occupational activity reported (Paffenbarger, Wing, & Hyde, 1978; van Uffelen et al., 2010).

To summarise, sedentary behaviour has been defined as being in a sitting, reclining or a lying position, whilst producing low energy expenditure. Many previous studies that have examined sedentary behaviour have described cohorts as 'sedentary' or 'physically inactive', without any definitive measure or assessment. Sedentary behaviour is a distinct entity to insufficient physical activity and is differentiated from other behaviours on the movement continuum. People meeting the recommended levels of moderate to vigorous physical activity can also be engaged in sedentary behaviours for long periods.

1.1.2   *Measuring sedentary behaviour*

There are a number of available methods to quantify physical behaviour, which can be categorised as either subjective (i.e. self-reported questionnaires and diaries) or objective (i.e. pedometers and accelerometers) (Tudor-Locke & Myers, 2001); however, there is no gold standard method that can measure the multifaceted components of physical behaviour such as, posture, energy expenditure, frequency, intensity and contextual information (Silfee et al., 2018; Welk, 2002). The balance between practicality (i.e. convenience) and validity (i.e. precision) need to be considered when choosing a physical behaviour measure for a study: this usually depends on what information is required to answer the research question(s) (Dugdill & Stratton, 2007). Physical activity is proposed to be purposive in nature, as opposed to sedentary behaviour that tends to be unstructured, occurring at multiple time-points throughout the day, with varying bout lengths and within different domains (i.e. home, transport, work and leisure) (Kang & Rowe, 2015; Owen et al., 2011; Sugiyama et al., 2008). There is currently no measure that can quantify free-living sedentary behaviour that includes both posture and energy expenditure as defined by the Sedentary Behavior Research Network (Granat, 2012; Kang & Rowe, 2015; Sedentary Behavior Research Network, 2012; Tremblay et al., 2017).

1.1.2.1   *Subjective measures*

Subjective measures comprise self-reported methods such as activity diaries and questionnaires: they are practical in terms of cost and low participant burden (Tudor-Locke & Myers, 2001; Welk, 2002). Self-reported physical behaviour measures can also be quick to administer, which can be advantageous for large samples, and can be used alongside

compendiums of physical activities to estimate energy expenditure (Ainsworth et al., 2011). Furthermore, self-reported methods allow for the measurement of domain-specific sedentary behaviours by collecting contextual information on where the behaviour occurred and within which domain (Ainsworth, Cahalin, Buman, & Ross, 2015; Atkin et al., 2012; Tudor-Locke & Myers, 2001; Welk, 2002). Subjective measures of sedentary behaviour are limited by: reported underestimates of sedentary time; the variability in the wording of questions and recall limitations; are subject to social desirability bias; and they tend to have 'low-to-moderate' validity compared to objective measures (Atkin et al., 2012; Bowling, 2009; Clemes, David, Zhao, Han, & Brown, 2012; Rosenberg et al., 2010; Timperio, Salmon, & Crawford, 2003).

1.1.2.2   *Objective measures*

Objective measures of sedentary behaviour include body-worn instruments such as accelerometer-based devices[6], pedometers and heart rate monitors (Dunstan, Howard, Healy, & Owen, 2012; Matthews et al., 2008). In physical behaviour research, the accelerometer is the predominant objective method used in studies that measure sedentary behaviour (Atkin et al., 2012; Edwardson, Winkler, et al., 2016; Owen et al., 2010). Accelerometers are used to quantify human movement by measuring the acceleration of body segments in one or more axes and they are able to measure the frequency and intensity of movement (Tryon & Williams, 1996).

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[6] Throughout this thesis accelerometer-based devices are referred to as accelerometers as is commonly seen in the literature for the measurement of physical behaviour.

The strengths of accelerometers include: their ability to collect a large amount of data and measure frequency, intensity, and duration of sedentary behaviour; they can look at temporal patterns across the day; they can be used to estimate energy expenditure; they can be unobtrusive; and they can be used to record activity over a long period (Ainsworth et al., 2015; Atkin et al., 2012; Kang & Rowe, 2015). Accelerometer limitations include: their expense; it can be difficult to measure some activities that involve upper body movement; they can be a burden to the user if worn for long periods; and it may be difficult to determine between standing that generates low energy expenditure and sitting (Ainsworth et al., 2015; Atkin et al., 2012; Kang & Rowe, 2015; Owen et al., 2010).

Although accelerometers are objective measures of physical behaviour, they require subjective decisions regarding data collection and data processing that may introduce measurement error. Key issues to consider at each stage of a study include: pre-data collection (e.g. number of days of data to collect, which sampling frequency to use), data collection (e.g. attachment location, instructions to participants), and data processing (e.g. technical expertise to process and analyse data, decisions on what a valid day is, how to deal with non-wear and sleep time) (Edwardson, Winkler, et al., 2016; Sirard & Petrucci Jr., 2019). There are currently no standard guidelines for processing accelerometer data (Sirard & Petrucci Jr., 2019).

Objective body-worn measures of sedentary behaviour can be categorised into those that classify posture and those that estimate energy expenditure (Granat, 2012). An accelerometer-based device that uses postural classifications is the activPAL™ (PAL Technologies Ltd, Glasgow, Scotland). It is worn on the anterior aspect of the thigh, and

the sensing element is used to determine the inclination of the thigh. Using proprietary algorithms, data from the activPAL™ are classified into sedentary (sitting/lying), standing, stepping events, and sit-to-stand transitions. The output from the activPAL™ has been validated for these postural classifications in adult populations (Grant, Dall, Mitchell, & Granat, 2008; Grant, Ryan, Tigbe, & Granat, 2006).

Accelerometers that estimate energy expenditure are usually worn on the hip or on the wrist: using proprietary algorithms, the raw acceleration data from either the vertical axis (or the vector magnitude from the vertical, anteroposterior and medio-lateral axes) are integrated as an activity count over a specified epoch. Calibration studies have used statistical modelling between energy expenditure and accelerometer counts to generate regression equations to derive cut-points for different physical activity intensities in the ActiGraph accelerometer (ActiGraph LLC, Pensacola, Florida) (Crouter et al., 2006; Freedson et al., 1998; Troiano et al., 2008). Many studies that have used the ActiGraph to define sedentary behaviour have used a cut-point of less than 100 counts per minute: although this cut-point is generally accepted in sedentary behaviour research, it was not empirically derived for adults (Matthews et al., 2008). This cut-point can under- or over-estimate sedentary time depending on the context or population in which sedentary behaviour is measured (Aguilar-Farías, Brown, & Peeters, 2013; Crouter et al., 2006; Kozey-Keadle, Libertine, Lyden, Staudenmayer, & Freedson, 2011; Lopes, Magalhães, Bragada, & Vasques, 2009).

It is important to have accurate measures of sedentary behaviour to determine the associations with health-related outcomes (Section 1.1.4), and for planning public health

messages. Therefore, a combination of a subjective measure (to collect contextual data on sleep/wake times and domain) and an objective measure (to collect data on duration, frequency and patterns of sedentary behaviour) is recommended for sedentary behaviour research studies (Healy et al., 2011). A more comprehensive overview of subjective and objective measures of physical behaviour is provided as part of the literature review in Section 2.1.

1.1.3   *Historical context of sedentary behaviour in the workplace*

In recent years there has been an increase in research studies that have focussed primarily on sedentary behaviour levels (Biswas et al., 2015; Owen et al., 2010; Prince, Reed, McFetridge, Tremblay, & Reid, 2017; van Uffelen et al., 2010; Wilmot et al., 2012), which has coincided with technological advancements in modern day society (Albrechtsen, 2001; Rind, Jones, & Southall, 2014).

During the last century, jobs and the workplace have changed considerably; we are comparatively more sedentary than our ancestors (Power & Schulkin, 2013). The technological revolution has made us more productive and efficient in our domestic, leisure, transport, and working environments (Albrechtsen, 2001; Brownson, Boehmer, & Luke, 2005; Rind et al., 2014). Labour saving devices have made our lives easier at home, access to televisions and personal computers have changed the way we spend our leisure time, and the automation of some job roles and technology have removed the need for many traditional, physically intensive jobs, such as those in the agricultural and manufacturing industries (Albrechtsen, 2001; Church et al., 2011). The proportion of moderate physical activity intensity occupations has decreased from 48% in 1960 to 20%

in 2008; during this same period, the proportion of sedentary and light physical activity occupations has increased (Figure 1.3; Church et al., 2011).
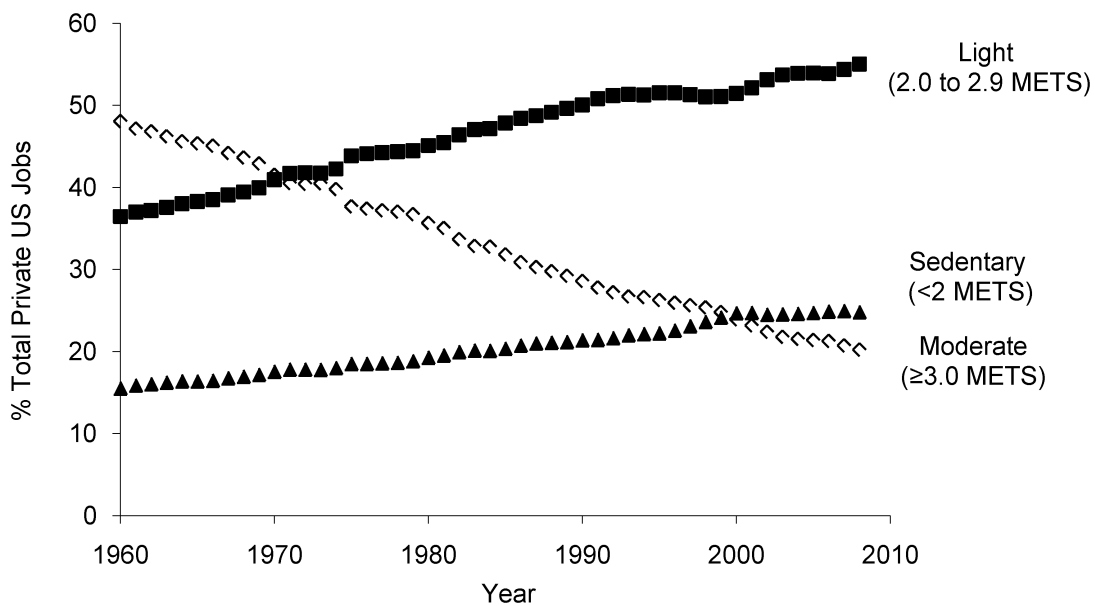
Figure 1.3   **Changes in the proportion of sedentary, light and moderate physical activity occupations in the United States (1960-2008) (Church et al., 2011, p. 4). Reproduced with permission.[7]**

Consequently, levels of physical activity in the occupation and transport domains have decreased, whilst there has been an increase in occupational and leisure-time sedentary time (Brownson et al., 2005). It has been reported that adults spend 55% of their waking time in sedentary behaviours across all domains (Matthews et al., 2008). More specifically, levels of occupational physical activity decreased significantly from 43% to 39% ($p < 0.001$) between 1991 to 2004 in England (Stamatakis, Ekelund, & Wareham, 2007). In the UK, between 1961 and 2005, the number of hours spent in sedentary behaviours per week increased by 50% (28.4 hours per week to 41.7 hours per week) (Ng & Popkin, 2012).

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[7] https://creativecommons.org/licenses/by/4.0/

Similarly, in Denmark between 1990 and 2010, the proportion of the Danish workforce who engaged in high levels of occupational sedentary time (at least three-quarters of work time) increased from 33% to 39% (van der Ploeg, Møller, Hannerz, van der Beek, & Holtermann, 2015). The decrease over time of occupational physical activity and an increase in workplace sedentary time is related to deindustrialisation and a growth in computer based jobs (Owen et al., 2010; Rind et al., 2014; Straker & Mathiassen, 2009).

Studies in Australia and Northern Ireland have reported that, on average, time spent sitting at work accounts for over 60% and 50% of total daily sitting time respectively (Clemes et al., 2015; Miller & Brown, 2004). The study by Miller and Brown (2004) assessed sitting time in different occupational groups: these occupational groups were broadly categorised into *white-collar* workers (managerial and professional workers who tend to work in offices) (Collins, n.d.; United States Department of Labor, 1999), and *blue-collar* workers (those working in industry, generally undertaking physical work) (Collins, n.d.; United States Department of Labor, n.d.). White-collar workers, comprised managerial and administrative staff, sat for over 75 % of their working day, equating to 6.2 and 5.7 hours respectively: in comparison, blue-collar workers, which included cleaners and maintenance staff, only sat for 22 % of their working day (equivalent to 1.6 hours) (Miller & Brown, 2004). Other studies have also reported that a high proportion of working time in office workers is spent sedentary in both England (71%) and Australia (67%) (Clemes, O'Connell, & Edwardson, 2014; Ryde, Brown, Gilson, & Brown, 2014). A study of a Dutch working population also found significant differences in time spent sitting between different occupational sectors (Jans, Proper, & Hildebrandt, 2007). Minutes spent sitting at work each day ranged from 50 minutes for blue-collar workers in the catering industry to 207

minutes for those white-collar workers, working in computerisation. Additionally, research has shown that office workers who spend a high proportion of their working day sitting, are also more likely to be sedentary outside of work (Clemes, O'Connell, et al., 2014).

A consequence of this decrease in physically active occupations has been a decline in daily energy expenditure (Brownson et al., 2005; Church et al., 2011; Katzmarzyk & Mason, 2009). During the last two decades of the 20th Century there was an average reduction of 800 kilocalories per day in terms of energy expenditure from activity, and also a decrease in consumption of approximately 750 kilocalories per day, resulting in a net gain of 50 calories per day (James, 1995). The reduction in calorie consumption was confirmed in a study from the Institute of Fiscal Studies, which reported that households in the UK purchased between 15-30% fewer calories between 1980 and 2009 (Griffith, Lluberas, & Luhrmann, 2013). Consequently, this has resulted in an imbalance between energy consumed in the form of calories compared to the energy we expend through activity and the body's energy needs to maintain function: this energy imbalance has resulted in a positive difference between intake and energy expenditure (James, 1995; Ladabaum, Mannalithara, Myer, & Singh, 2014).

1.1.4   *Sedentary behaviour and health-related outcomes*

Declining energy expenditure from activity over recent decades has coincided with the global obesity pandemic (James, 2004; Prentice & Jebb, 1995). Obesity is a complex disorder that is associated with excess fat: it is diagnosed based on a body mass index (BMI) (kg/m^2) of greater or equal to 30 kg/m^2 (Mayo Clinic, n.d.; WHO, n.d.-a). Obesity has a multifactorial aetiology, including genetic and health conditions; however, the key drivers

are inactivity and eating habits (Mayo Clinic, n.d.; Power & Schulkin, 2013; Prentice & Jebb, 1995). In 2015, the estimated global prevalence of obesity was 12% amongst adults (The GBD 2015 Obesity Collaborators, 2017); more specifically in England, obesity prevalence has risen over 10% between 1993 and 2017 (Figure 1.4; Public Health England, 2019).

Adult (aged 16+) obesity: BMI ≥ 30kg/m^2
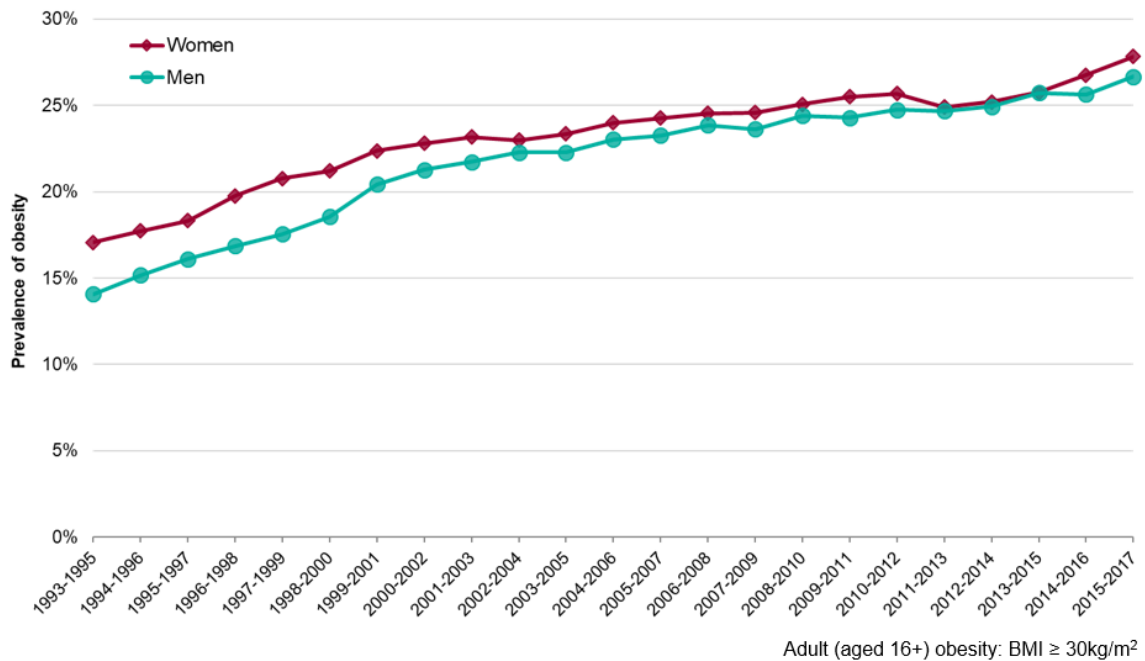
Figure 1.4 **Trends in obesity prevalence among adults in England (Public Health England, 2019); data from Health Survey for England 1993-2017 (three-year averages). Reproduced with permission.[8]**

The obesity pandemic is a major global public health challenge, given that obesity is known to be associated with an increased risk of developing a number of health-related outcomes including, type 2 diabetes, cardiometabolic syndrome, cardiovascular disease, cancer and musculoskeletal disorders (The GBD 2015 Obesity Collaborators, 2017). Sedentary behaviour is an important influence of the obesity pandemic, which is considered to be as

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[8] Contains public sector information licensed under the Open Government Licence v3.0. http://www.nationalarchives.gov.uk/doc/open-government-licence/version/3/

a result of the displacement of light physical activity for sedentary behaviour over recent years (Mansoubi, Pearson, Biddle, & Clemes, 2014; Yates, Wilmot, Khunti, et al., 2011). It is recognised that changes in dietary habits and a decrease in sleep duration are also fundamental factors that have contributed to the obesity pandemic (Cappuccio et al., 2008; Drewnowski, 2007; Patel & Hu, 2008); however, the complex interaction between sedentary behaviour, diet, and sleep with obesity is still not fully understood (Wright & Aronne, 2012).

Associations between sedentary behaviour and obesity have been well established in both children and adults (Biddle et al., 2010; Hu, Li, Colditz, Willett, & Manson, 2003), and remain after taking into account physical activity levels alongside other confounders (Bullock, Griffiths, Sherar, & Clemes, 2017). In addition to being associated with increased levels of sedentary behaviour, obesity is also a risk factor (and in some instances a pathway variable) between sedentary behaviour and several health-related outcomes (de Rezende, Lopes, Rey-López, Matsudo, & do Carmo Luiz, 2014; Stokes & Preston, 2016; Thorp, Owen, Neuhaus, & Dunstan, 2011). There is mounting evidence that increased levels of sedentary time are independently associated with a number of health-related outcomes; mainly cardiovascular disease, cardiometabolic risk factors, type 2 diabetes and mortality (Biswas et al., 2015; Edwardson et al., 2012; Ford & Caspersen, 2012; Garcia, Cox, & Rice, 2017). Despite this wealth of research, recent studies using subjective measures of physical behaviours have suggested that high levels of moderate physical activity may be protective against high levels of self-reported sitting time with respect to mortality (Ekelund et al., 2016; Stamatakis et al., 2019). However, many studies that have found associations between sedentary behaviours and health-related outcomes have primarily measured

leisure-time sedentary behaviour (i.e. television viewing) or total sedentary time (Dunstan et al., 2007; Keadle, Arem, Moore, Sampson, & Matthews, 2015; Thorp et al., 2010; Wijndaele et al., 2011).

The pattern of accumulation of sedentary time can also be important when considering associations with health; for example, two people could amass the same volume of sedentary time across a day, but with different behavioural patterns (Figure 1.5). The 'prolonger' will accumulate sedentary time in long bouts, compared to the 'breaker', who accumulates sedentary time in shorter bouts with a high frequency of sit-to-stand transitions (Dunstan, Healy, Sugiyama, & Owen, 2010).
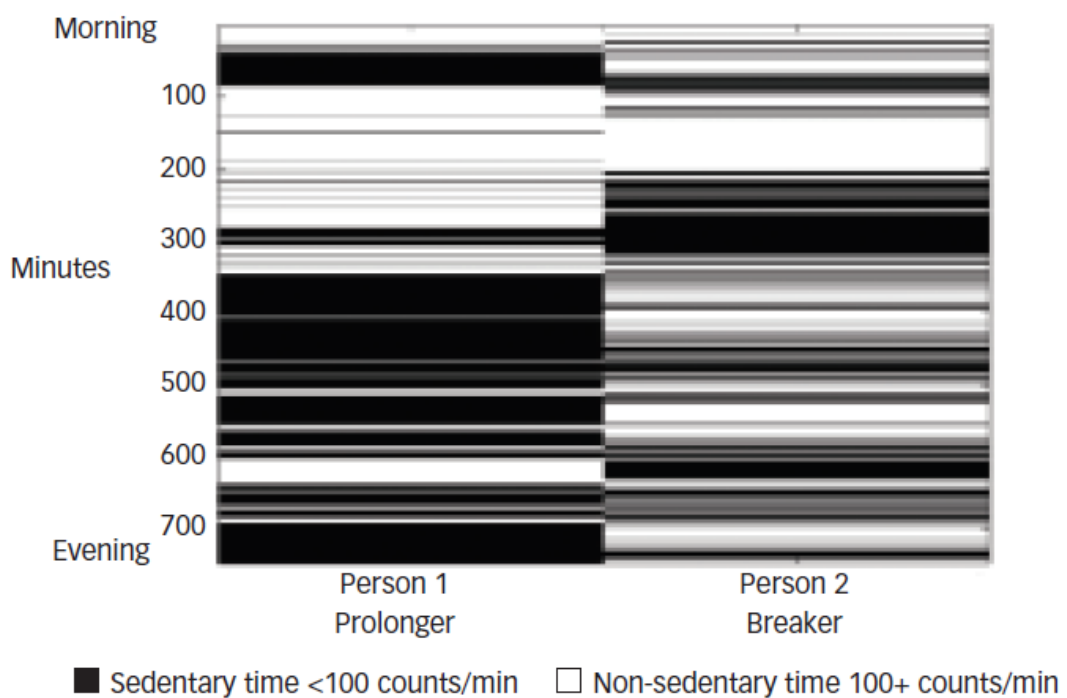
Figure 1.5   **Identical daily sedentary time accumulation in two adults: the prolonger vs. the breaker (Dunstan, Healy, Sugiyama, & Owen, 2010, p. 21). Reproduced with permission.**

Breaking up sedentary time with short and frequent movements is known to have beneficial associations with cardiometabolic markers, blood pressure and levels of fatigue

(Healy et al., 2008; Henson et al., 2016; Larsen, Shaw, Healy, & Dunstan, 2015; McCarthy et al., 2017; Thorp, Kingwell, Owen, & Dunstan, 2014; Wennberg et al., 2016). However, it is not known if there is an advantageous pattern of sedentary time accumulation in terms of bouts and breaks from sitting, which can improve the health risks that are associated with sedentary behaviour (Kim, Welk, Braun, & Kang, 2015).

There is limited evidence to support the same associations for occupational sedentary behaviour and health-related outcomes that have been found between *total* and *leisure-time* sedentary behaviour and health-related outcomes. For example, studies that have examined associations between occupational sedentary time and cardiometabolic risk factors have found more consistent associations for leisure-time sedentary behaviour compared to occupational sedentary behaviour (Pinto Pereira, Ki, & Power, 2012; Saidj, Jørgensen, Jacobsen, Linneberg, & Aadahl, 2013). The concept of sedentary behaviour, health-related outcomes, and the workplace in itself is not new: the seminal work by Morris, Heady, Raffle, Roberts, and Parks (1953) reported lower rates of coronary heart disease in more *physically active* workers (bus conductors, postmen) compared to their more *sedentary* colleagues (bus drivers, office-based employees). Similarly, Paffenbarger, Laughlin, Gima, and Black (1970), found that longshoremen who were more active (cargo handlers) at work compared to their colleagues with more sedentary jobs (clerks and supervisors) were at a lower risk of death from coronary heart disease. Much of this early work on associations between occupational sedentary behaviour and health-related outcomes focussed on the sedentariness of occupational role (Paffenbarger, Blair, & Lee, 2001). More recent studies have also used categories of occupational activity or self-

reported methods to measure sitting time (van Uffelen et al., 2010). However, few studies have used objective and reliable measures of sedentary time in the occupational domain.

In the UK in April 2019, 50% (32.7 million) of the population were economically active with many working in sedentary or light physical activity occupations (Office for National Statistics, 2019). Additionally, for many 'modern' computer- and desk-based occupations, the majority of work time is known to be spent in sedentary behaviours (Clemes, O'Connell, et al., 2014; Jans et al., 2007; Miller & Brown, 2004; Ryde et al., 2014) (Section 1.1.3). With access to a large population, the workplace is therefore an ideal environment to promote a healthy lifestyle and to explore the effects of high levels of occupational sedentary time on health (Black, 2008). In particular, studies that have examined associations between sedentary behaviour and stress, depression, anxiety, and musculoskeletal disorders in the workplace are limited, even though these two conditions are responsible for the majority of work-related ill health and days absent from work (Health and Safety Executive, 2018).

To recap, sedentary behaviour has an important influence on the obesity pandemic and is also associated with several health-related outcomes, independent of physical activity; however, the extent to which physical activity attenuates or eliminates these associations is still unclear. The accumulation and patterning of sedentary time across the day may also have an important impact on health outcomes. The role of occupational sedentary time with health-related outcomes is less clear (BHF, 2012). Sedentary time in different domains may represent differing associations with health; therefore, there is a need for studies to use more objective, reliable and valid measurements of sitting time in the occupational domain, to fully understand the effects of sitting at work and health.

1.1.5   Inactivity physiology

The physiological link between the effect of sedentary behaviour (in particular prolonged sitting) and subsequent health-related outcomes is not yet fully understood. The term *inactivity physiology* has been coined by a research group from the USA who have carried out studies to investigate the underlying biology and possible physiological explanation of sedentary behaviour and its consequent health risks, independent of physical activity levels (Bey & Hamilton, 2003; Hamilton, Hamilton, & Zderic, 2004; Hamilton, Hamilton, & Zderic, 2007; Levine et al., 2005).

The field of inactivity physiology and its underlying cellular processes focuses on a protein enzyme, lipoprotein lipase, found in the blood vessels of muscles. Lipoprotein lipase plays a key role in metabolising fat and sugar; it regulates triglycerides[9], breaks up low-density lipoprotein (LDL, *bad* cholesterol) and produces high-density lipoprotein (HDL, *good* cholesterol) (Bey & Hamilton, 2003; Hamilton et al., 2004).

A laboratory study has demonstrated a 90-95% reduction in lipoprotein lipase in rats after a day of inactivity; triglycerides and HDL were also dramatically reduced (Bey & Hamilton, 2003). Inactivity physiology theorises that sitting induces muscular inactivity; lipoprotein lipase and HDL levels are reduced, and instead of fat being metabolised, it is carried around the body and deposited in adipose tissue, which can lead to obesity and other metabolic conditions (Hamilton et al., 2007; Hamilton, Healy, Dunstan, Theodore, & Owen, 2008).

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[9] Triglyceride is a blood lipid, which helps in the transfer of adipose fat and blood glucose; the enzyme lipoprotein lipase breaks down the triglycerides into other compounds that aid metabolism

The studies from this research group have suggested that sedentary behaviour results in physiological responses that are distinct from those that are a result of physical activity (Ekblom-Bak, Hellénius, & Ekblom, 2010; Hamilton et al., 2004). A study in adults (aged 19 to 32) found that insulin-mediated glucose uptake was reduced significantly after one day of sitting compared to 24-hours without sitting (Stephens, Granados, Zderic, Hamilton, & Braun, 2011). It has been proposed that movement, including activation of postural muscles, stimulates activity of lipoprotein lipase, which in turn helps to improve cholesterol and regulate blood sugars: in addition, the activation of lipoprotein lipase is not significantly different during sit-to-stand transitions from that of higher levels of physical activity (Ekblom-Bak et al., 2010; Hamilton et al., 2004). Therefore, since breaks in sedentary time are known to be beneficial for some cardiometabolic markers, it is important to understand the accumulation and patterning of sedentary time across the day with respect to influences on health (Dunstan, Kingwell, et al., 2012).

1.2   A conceptual framework for determinants of sedentary behaviour

The World Health Organisation define the social determinants of health as "the conditions in which people are born, grow, live, work and age" (WHO, 2013, para. 1). The importance of social factors and their influence on health have been well established (Marmot, 2010); and consequently the traditional epidemiological triangle (the agent, the host and the environment) has been superseded by an ecological framework that examines the multi-faceted influences of health (Mausner & Kramer, 1984).

An ecological model can illustrate the multiple determinants on health, relating to the individual and interactions with their social and physical environments in which behaviours take place. The well-cited determinants of health model by Dahlgren and Whitehead

(1991), demonstrates how health is influenced by multiple factors (Figure 1.6). At the centre of the model are the fixed determinants relating to the individual (i.e. demographic and hereditary factors). The series of layers around the individual show determinants that can vary; they are influenced by individual behaviour, society, our living and working conditions and the environment. Each layer has a subsequent impact on the next, demonstrating the inter-relationships between the individual, their surrounding environment and health.
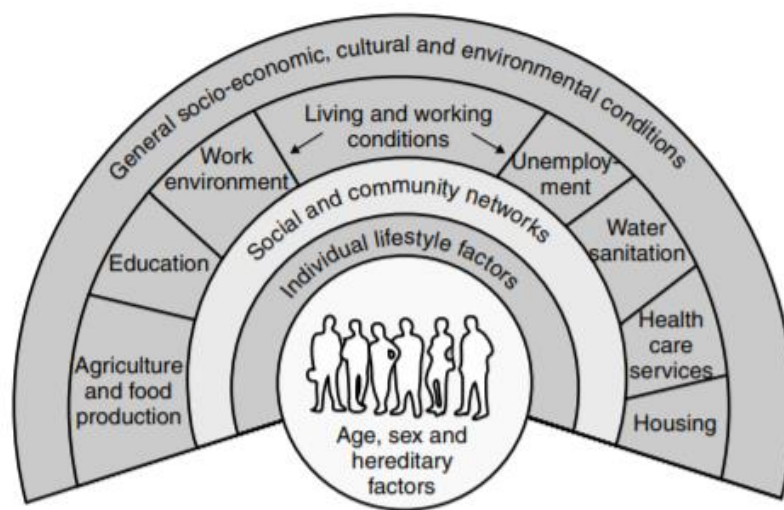
Figure 1.6   **The social determinants of health by Dahlgren and Whitehead (1991); figure reproduced with permission from Dugdill, Crone, and Murphy (2009, p. 7)**

An ecological model of sedentary behaviours has been proposed by Owen et al. (2011) to examine the individual, the environmental setting, and their subsequent influences on sedentary behaviour. This model is based on a similar ecological model for physical activity by Sallis et al. (2006, p. 299), who stated that "Ecological models are particularly well suited for studying physical activity, because physical activity is done in specific places". Likewise, sedentary behaviour occurs in particular settings; the ecological model by Owen et al. (2011) categorised four sedentary behaviour domains (leisure time, household, transport and occupation) (Figure 1.7).
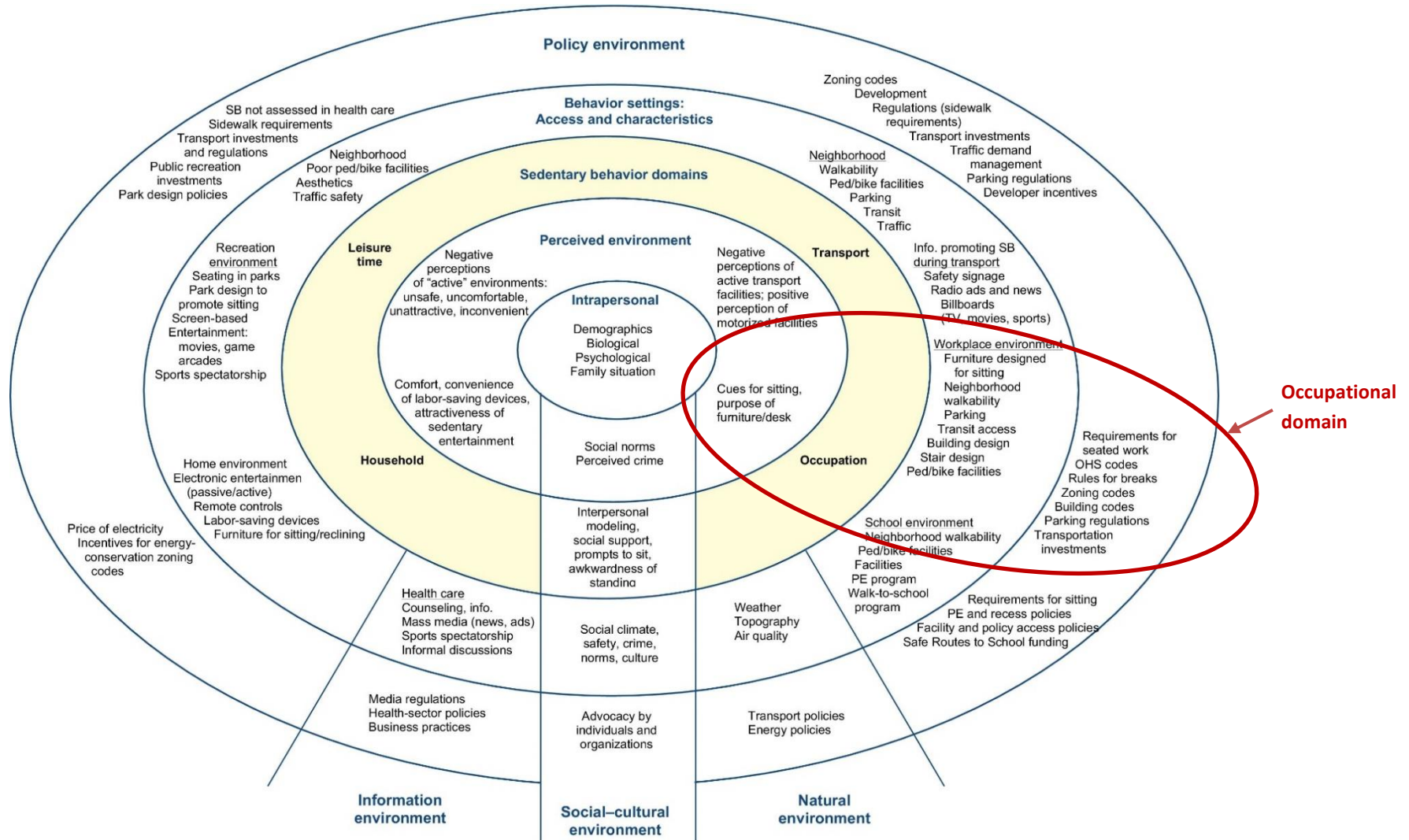
Figure 1.7   Ecological model of four domains of sedentary behaviour (adpated from Owen et al., 2011, p.191). Reproduced with permission. OHS, occupational health and safety; PE, physical education; Ped, pedestrian; SB, sedentary behaviour

The centre of the ecological model for sedentary behaviour represents individual lifestyle factors, with subsequent layers reflecting the interaction of sedentary behaviour with the perceived environment, behaviour settings, and the policy environment: the four sedentary behaviour domains of leisure time, household, transport and occupation, are illustrated in yellow.

Many studies of sedentary behaviour have been focussed on sedentary time accumulated within the leisure-time domain, or total sedentary time across all domains; however, there has been limited research that has looked at correlates of sedentary behaviour in the occupational domain (Figure 1.7), and the impact of the workplace environment on sedentary behaviour. The workplace and policy environments in the ecological model are influenced by societal norms and policies within workplaces. For example, the workplace environment can limit options of behaviour change for sedentary behaviour: people may be required to sit for prolonged periods to use a computer and it is considered the 'norm' to sit in meetings. Within the policy environment there may be limited opportunities to have a break due to productivity expectations, which will impact on occupational sedentary time.

Alternative models include the Systems of Sedentary behaviours framework, which is a systems-based approach: it consists of six clusters of determinants that influence sedentary behaviour without assuming a hierarchy of determinants (Chastin et al., 2016). The Behavioural Epidemiology Framework for sedentary behaviour is used to understand the different types of research needed to understand how sedentary behaviour influences health-related outcomes (Biddle, 2015; Welk, 2002). Nonetheless, the technological revolution has increased the number of sedentary occupations that involve desk-based

work, which are best represented by the layers of the socio-ecological model as fundamental determinants of sedentary behaviour. Furthermore, the quantification of free-living sedentary behaviour is important to help to understand the association between sedentary behaviour and health-related outcomes (Granat, 2012).

1.3 Summary of key findings

- Sedentary behaviour is a distinct entity on the movement continuum, and it is frequently defined in the literature as any waking behaviour characterised by an energy expenditure of ≤1.5 metabolic equivalents, while in a sitting, reclining, (or lying) posture.

- There is currently no method that can quantify free-living sedentary behaviour that includes both posture and energy expenditure as defined above.

- For waist-worn accelerometers there is no empirically derived counts per minute cut-point for adults.

- A combination of a subjective measure and an objective measure is recommended for sedentary behaviour research studies, to collect both contextual and accurate data.

- People can meet recommended levels of moderate to vigorous physical activity and can also be highly sedentary.

- In industrialised countries, technological developments have meant there is less need for people to be active in the workplace. The introduction of desk dependent, computer-based jobs has resulted in an increase in the number of sedentary occupations.

- For those who are economically active, the highest proportion of daily sitting time is accumulated at work, and for desk-based occupations, the majority of work time is known to be spent in sedentary behaviours.

- There is now substantive evidence of the associations between sedentary behaviour and health-related outcomes; the role of occupational sedentary time with health-related outcomes is less clear.

- The extent to which physical activity attenuates or eliminates associations between sedentary behaviour and health-related outcomes requires further investigation.

- It is important to understand the accumulation and patterning of sedentary time across the day and the impact this has on health-related outcomes.

- Sedentary behaviour results in physiological responses that are distinct from those that are a result of physical activity.

1.4   Aims and objectives

This thesis comprises two main sections: the first aim was to empirically derive a new ActiGraph accelerometer cut-point to define sedentary behaviour in adults; the second aim was to apply the cut-point from the first study to a large population survey (Health Survey for England 2008), which collected accelerometer data using an ActiGraph device on a sub-sample of participants, in order to investigate the associations between sedentary behaviour, work, and health-related outcomes.

1.4.1   Study One objectives

1. To empirically derive an optimal threshold for classifying sedentary behaviour, using the counts per minute output from the ActiGraph GT3X+ accelerometer, when compared to the sedentary classification from the activPAL™ accelerometer in a free-living environment.

2. To ascertain whether thresholds for sedentary behaviour cut-points vary by day of the week and in working time versus non-working time.

3. To derive optimal cut-points for different classifications of sedentary behaviour using contextual data from a 24-hour activity log, and to examine if there are differences between them.

1.4.2   Study Two objectives

4. To identify associations between workplace sedentary behaviour and health-related outcomes using the derived cut-point from *Study One.*

5. To examine if associations between workplace sedentary behaviour and health-related outcomes differ between occupational groups.

6. To determine if there are associations between workplace sedentary behaviour and mental ill-health and musculoskeletal disorders.

7. To explore the patterning and sequences of sedentary bouts across the day, and the relationship with measures of adiposity and other health-related outcomes.

1.5   Structure of the thesis

This thesis is divided into seven chapters: **Chapter One** outlined the rationale and the aims of the included research studies, with respect to the changing role of sedentary behaviour in the workplace, and its associations with health-related outcomes.

Chapter Two describes a literature review conducted to explore and critique the current evidence of sedentary behaviour and work, focussing on the prevalence of sedentary behaviour at work, and its association with health-related outcomes. This chapter also provides an overview of the various methods that can be used to measure sedentary behaviour.

Chapter Three addresses the first aim of this thesis: to empirically derive a new ActiGraph accelerometer cut-point to define sedentary behaviour in adults in a free-living environment, in a sample of 30 office-based university workers and postgraduate students. Using generalised estimating equations, accelerometer cut-points for sedentary behaviour were derived for each day of the week, working time and non-working time, and for classifications of sedentary behaviour within different domains. Results from thesis objectives one and two (Section 1.4.1) have already been published (Clarke-Cornwell, Farragher, Cook, & Granat, 2016); however, Chapter Three provides further specifics on data cleaning, data processing, data reduction rules, and the statistical analysis, alongside detailed results for objectives one, two and three.

Chapter Four introduces the Health Survey for England 2008 and its suitability to examine sedentary behaviour, work, and health-related outcomes. This chapter describes the methodology for how the data from the Health Survey for England 2008 were collected, the data cleaning processes, and a critique of the strengths and limitations of using secondary analysis. It also details the variables that were used in the regression models to answer objectives four, five and six (Section 1.4.1). Furthermore, Chapter Four describes the statistical methodologies that were used to address objectives four to seven.

Chapter Five provides the main findings from the regression analyses that were used to answer objectives four, five and six (Section 1.4.1). More specifically, it examines the associations between workplace sedentary behaviour and health-related outcomes using the derived cut-point from *Study One* to classify sedentary time.

Chapter Six details the findings from the analyses used to answer objective seven (Section 1.4.1). This chapter describes a sequence analysis that was carried out to explore the patterning of sedentary time, using data from the Health Survey for England 2008, and the relationship with measures of adiposity and other health-related outcomes.

Chapter Seven discusses the findings from the studies within this thesis. It critically appraises the strengths and weaknesses of the methodologies used and outlines implications for policy and future research.

Throughout this thesis, Table 1.2 is used to illustrate the research aims and objectives, and methods, which are addressed within each chapter.

Table 1.2 Overview of studies: aims, objectives, and methods

Chapter	Aims, objectives and research questions	Methods
Chapter 2	**Aim:** To provide an overview of the literature and to critique the current evidence of sedentary behaviour and work, focussing on the prevalence of sedentary behaviour at work, and its association with health-related outcomes	Structured literature review using six electronic databases
Chapter 3	**Aim:** To empirically derive a new accelerometer cut-point to define sedentary behaviour in adults **Objective 1:** To empirically derive an optimal threshold for classifying sedentary behaviour, using the counts per minute output from the ActiGraph GT3X+ accelerometer, when compared to the sedentary classification from the activPAL™ accelerometer in a free-living environment **Objective 2:** To ascertain whether thresholds for sedentary behaviour cut-points vary by day of the week and in working time versus non-working time **Objective 3:** To derive optimal cut-points for different classifications of sedentary behaviour using contextual data from a 24-hour activity log, and to examine if there are differences between them	Observational study in university workers and postgraduate students (n=30) Application of generalised estimating equations to 1-minute epoch data for the ActiGraph GT3X+ and the activPAL™ data
Chapter 4	**Aim:** To describe the methodology for the Health Survey for England 2008, and a critique of the strengths and limitations of using secondary analysis	Description of data collection and processing
Chapter 5	**Aim:** To apply the cut-point from *Study One* to data from the Health Survey for England (2008), in order to investigate the associations between sedentary behaviour, work, and health-related outcomes **Objective 4:** To identify associations between workplace sedentary behaviour and health-related outcomes using the derived cut-point from *Study One* **Objective 5:** To examine if associations between workplace sedentary behaviour and health-related outcomes differ between occupational groups **Objective 6:** To determine if there are associations between workplace sedentary behaviour and mental ill-health and musculoskeletal disorders	A secondary data analysis of the Health Survey for England 2008 Application of hierarchical regression models – type of regression model dependent on distribution of each dependent variable (health-related outcome)
Chapter 6	**Aim:** To apply the cut-point from *Study One* to data from the Health Survey for England (2008), in order to investigate the associations between sedentary behaviour, work, and health-related outcomes **Objective 7:** To explore the patterning and sequences of sedentary bouts across the day, and the relationship with measures of adiposity and other health-related outcomes	Sequence analysis to describe the characteristics of time-related sequences of sedentary behaviour
Chapter 7	**Aim:** To discuss and critically appraise the studies within this thesis and to outline implications for policy and future research	Discussion and conclusions

Chapter 2 - Literature Review

"The answers you get from the literature depend on the questions you pose"

— Margaret Atwood

Table 2.1   Overview of Chapter 2

Chapter	Aims, objectives and research questions	Methods
Chapter 2	**Aim:** To provide an overview of the literature and to critique the current evidence of sedentary behaviour and work, focussing on the prevalence of sedentary behaviour at work, and its association with health-related outcomes	Structured literature review using six electronic databases
Chapter 3	**Aim:** To empirically derive a new accelerometer cut-point to define sedentary behaviour in adults **Objective 1:** To empirically derive an optimal threshold for classifying sedentary behaviour, using the counts per minute output from the ActiGraph GT3X+ accelerometer, when compared to the sedentary classification from the activPAL™ accelerometer in a free-living environment **Objective 2:** To ascertain whether thresholds for sedentary behaviour cut-points vary by day of the week and in working time versus non-working time **Objective 3:** To derive optimal cut-points for different classifications of sedentary behaviour using contextual data from a 24-hour activity log, and to examine if there are differences between them	Observational study in university workers and postgraduate students (n=30) Application of generalised estimating equations to 1-minute epoch data for the ActiGraph GT3X+ and the activPAL™ data
Chapter 4	**Aim:** To describe the methodology for the Health Survey for England 2008, and a critique of the strengths and limitations of using secondary analysis	Description of data collection and processing
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Chapter 6	**Aim:** To apply the cut-point from *Study One* to data from the Health Survey for England (2008), in order to investigate the associations between sedentary behaviour, work, and health-related outcomes **Objective 7:** To explore the patterning and sequences of sedentary bouts across the day, and the relationship with measures of adiposity and other health-related outcomes	Sequence analysis to describe the characteristics of time-related sequences of sedentary behaviour
Chapter 7	**Aim:** To discuss and critically appraise the studies within this thesis and to outline implications for policy and future research	Discussion and conclusions

The first section of this chapter provides an overview of subjective and objective methods that are used to measure sedentary behaviour. The second section describes a literature review to explore and critique studies of sedentary behaviour, work, and health-related outcomes: more specifically, it focuses on the prevalence of sedentary behaviour at work, and the relationship between occupational sedentary time and health-related outcomes.

2.1   Measurement of sedentary behaviour and physical activity

The reliability[10] and validity[11] of subjective and objective techniques to measure sedentary behaviour and physical activity have been widely reported (Dugdill et al., 2009; Healy et al., 2011; McKenna & Riddoch, 2002; Welk, 2002); however, there is no accepted gold standard method that can measure the complex characteristics of physical behaviour (Welk, 2002). Physical behaviour characteristics include, posture, frequency, intensity, duration, and contextual information of each activity: in addition, the information that is required in order to answer the research question(s) should be considered when choosing a measurement method (Dugdill & Stratton, 2007). There are several methods that are used in research studies to measure physical behaviour, each with advantages and disadvantages that need to be considered, in conjunction with how valid, accurate, reliable and practical the instrument is (Welk, 2002).

Figure 2.1 shows the comparison of the practicality and the validity of a range of physical behaviour measures. Measures that generally have low validity have high practicality in terms of cost and ease of use: conversely, measures with high validity and accuracy can

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[10] The degree to which a question produces consistent results (Atkin et al., 2012; Bowling, 2009)
[11] The degree to which a question measures what it purports to measure (Atkin et al., 2012; Bowling, 2009)

have low practicality in terms of cost and burden to participants (Dugdill & Stratton, 2007). These measures of physical behaviour can be categorised as either subjective (diaries, logs and self-reported methods) or objective (pedometers, heart rate monitors, accelerometers, direct observation, indirect calorimetry, doubly labelled water).
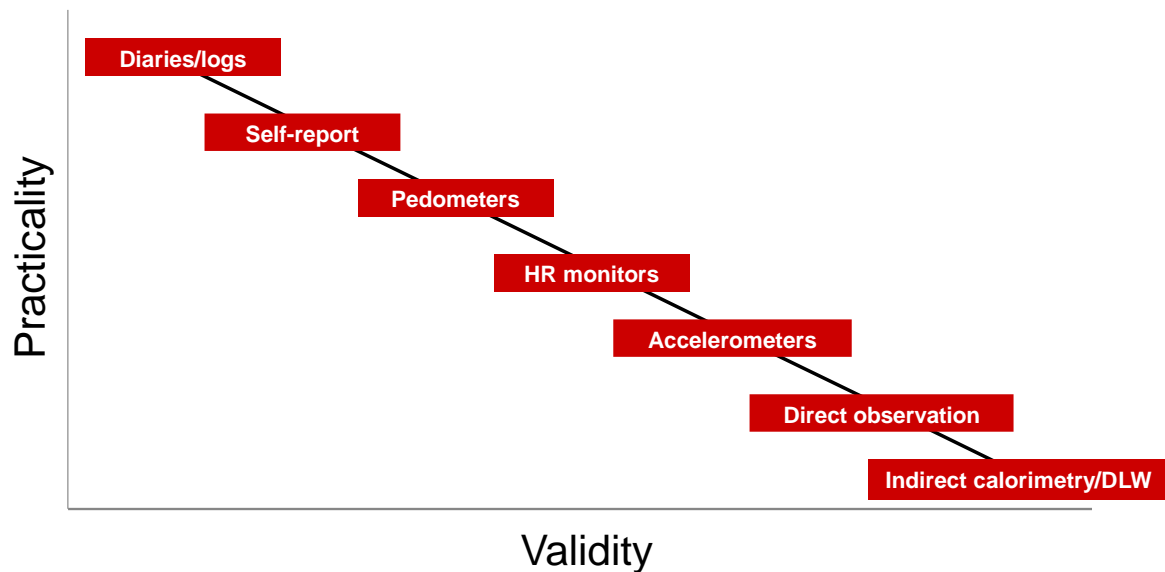
Figure 2.1   **Practicality and validity of physical activity measures (adapted from Dugdill & Stratton, 2007). HR: Heart rate; DLW: Doubly labelled water**

Many methods used to measure sedentary behaviour have been adapted and tailored from those for physical activity; however, sedentary behaviour is more likely to be unstructured compared to the more purposive behaviour of moderate to vigorous physical activity (Kang & Rowe, 2015). Sedentary behaviour is also considered to be a distinct entity to physical activity in terms of differences in energy expenditure and underlying physiology (Sections 1.1.1 and 1.1.4) (Hamilton et al., 2008; Pate et al., 2008), and techniques used for measuring physical activity may not be appropriate for measuring sedentary behaviour (Atkin et al., 2012). Therefore, there is a need to consider the validity and practicality of different methods for measuring sedentary behaviour.

2.1.1 Subjective measures

Subjective measures of physical behaviour require participants to recall time spent in different types of behaviours and include diaries, logs, and self-reported questionnaires: for sedentary behaviour, they can capture contextual data and mode of sitting (such as television viewing, sitting at work, computer use, commuting) (Chau et al., 2011; Clark et al., 2009; Healy et al., 2011; van Uffelen et al., 2010).

2.1.1.1 Diaries and logs

Activity diaries/logs can be used to obtain detailed, time-dependent information of physical behaviours (Ainsworth et al., 2015; Atkin et al., 2012). They can collect data on types of activities and the domain in which they take place: for the ubiquitous nature of sedentary behaviour, this information may be easier to record in an activity diary as it occurs. An example of an activity diary that asks participants to recall the main physical behaviour for a specified period of time is the Bouchard Activity Record (Bouchard et al., 1983). The Bouchard Activity Record is a three-day (including one weekend day) activity diary that asks participants to record the *main* activity performed in each 15-minute period (96 periods in total), based on nine behaviours along the movement continuum, with "1" representing sleeping and "9" for vigorous activity: each of the nine behaviours is given an approximate energy expenditure (Bouchard et al., 1983; Hart, Ainsworth, & Tudor-Locke, 2011). The Bouchard Activity Record has been shown to be valid in estimating time in sedentary behaviour and walking compared to the activPAL™ accelerometer (Hart, Ainsworth, et al., 2011).

The Bouchard activity diary is an example of an ecological momentary assessment method, which intends for activities to be recorded at the time of occurrence within free-living

environments, with the intention of reducing recall limitations (Shiffman, Stone, & Hufford, 2008). The use of ecological momentary assessment methods for physical behaviour research may be improved with the increase in the use of smart-phones and desktop applications (Dunton, Liao, Kawabata, & Intille, 2012; King et al., 2016). Activity diaries are inexpensive to implement and those using ecological momentary assessment methods can increase accuracy; however, they can be subject to recall limitations if they are not filled out regularly throughout the day, and may be a burden with respect to the time needed to complete (Ainsworth et al., 2015; Atkin et al., 2012).

Studies that use objective measures of physical behaviour may also use a type of daily activity log to provide contextual information. Activity logs can be used to record information that cannot be inferred from the objective data; for example, sleep time, waking hours, commuting periods, work start and finish times, and accelerometer wear time (Edwardson, Winkler, et al., 2016).

2.1.1.2 *Self-reported questionnaires*

Many questionnaires to estimate sedentary behaviour were initially designed to measure physical activity and may not distinguish between light physical activity and sedentary behaviour (Atkin et al., 2012; Bennett et al., 2006): for example, the International Physical Activity Questionnaire (IPAQ) (Chastin, Culhane, & Dall, 2014; Rosenberg, Bull, Marshall, Sallis, & Bauman, 2008) and the MONICA Optional Study on Physical Activity Questionnaire (MOSPA-Q) (Chau, van der Ploeg, Dunn, Kurko, & Bauman, 2012).

Advances in sedentary behaviour research have led to the development of sitting and sedentary behaviour focussed questionnaires: the reliability and validity of these self-report measures have been discussed in detail over the last decade (Atkin et al., 2012; Clark

et al., 2009; Dall et al., 2017; Healy et al., 2011). A recent review by Prince, LeBlanc, Colley, and Saunders (2017) examined the sedentary behaviour modules included in national- and international-population surveys, alongside English language sedentary behaviour questionnaires for adults that included psychometric properties. The data from the review by Prince et al. (2017) have been added to the Sedentary Behavior Research Network webpage and are open to editing, such that new questionnaires and any available psychometric properties can be added as they become available (Sedentary Behavior Research Network, 2017). Prince et al. (2017) found that adult sedentary behaviour questions used in health surveys tend not to have been evaluated with respect to reliability and validity (based on 18 surveys); conversely, those questions/questionnaires that have been evaluated are less likely to be used in health surveys (based on 35 questionnaires). Studies that have assessed the reliability and validity of subjective measures of sedentary behaviour have examined varying attributes of the measures and study designs, including the type of assessment (single-item versus composite), type of measure (direct versus proxy), recall period (day, week, usual/typical), type of administration (self-report versus interviewer), and type of criterion measure (Chastin et al., 2018; Dall et al., 2017; Prince, LeBlanc, et al., 2017).

Types of assessment

Single item measures have demonstrated low to moderate validity with accelerometer-derived sedentary time. The IPAQ question on time spent sitting asks about time usually spent sitting on both weekdays and weekend days; Chastin et al. (2014) found that the IPAQ sitting question underestimated sedentary time by an average of 206 minutes on weekdays and 278 minutes on weekend days compared to the activPAL™ accelerometer

assessed sitting time, and that sitting was less accurately reported on weekend days compared to weekdays. Similarly, a single item question that asked participants to record how long they had been sitting for that day underestimated sitting time on average by 173 minutes on weekdays and 219 minutes on weekend days compared to the ActiGraph accelerometer (Clemes et al., 2012); it was noted that some of the variability observed between the subjective and objective measures may be due to the misclassification of standing still as sitting time by the ActiGraph accelerometer (Section 2.1.3.1).

Composite measures of sedentary behaviour calculate the total sedentary time by summing the estimated sedentary times across multiple domains, such as transport, work, television viewing, nonwork computer use and other leisure activities (Clark et al., 2013; Clemes et al., 2012; Marshall, Miller, Burton, & Brown, 2010). In a study of the validity of a range of self-report measures of sedentary behaviour, the composite measures that summed across *domains* produced the lowest bias when compared to an accelerometer (Chastin et al., 2018). Conversely, composite measures that sum *behaviours* tend to overestimate sedentary time due to the high number of categories compared to composite measures of *domain*, which can lead to issues with recall and measurement error (Chastin et al., 2018). Composite measures of behaviour do not take into account concurrent behaviours; for example, people could be engaged in sitting whilst reading on public transport, which are two separate behaviours from the nine behaviours included in the Sedentary Behavior Questionnaire (Rosenberg et al., 2008). Individuals are increasingly involved in sitting behaviours that involve multiple screens, such as television viewing whilst using a laptop or tablet, which are difficult to capture using composite measures (Jago, Sebire, Gorely, Cillero, & Biddle, 2011; Prince, LeBlanc, et al., 2017; Stiglic & Viner,

2019). Domain-specific sitting time questionnaires have shown good reliability and acceptable validity, in particular for sedentary time accumulated on weekdays compared to weekend days, which is likely to be more routine and easier to recall (Chau, van der Ploeg, Dunn, et al., 2012; Clemes et al., 2012; Marshall et al., 2010).

Types of measure

Measures of sedentary behaviour can include direct measures, such as total sedentary time and sedentary time accrued within a domain (Chau, van der Ploeg, Dunn, et al., 2012; Clark et al., 2013), or a proxy of sedentary time can be used to measure sedentary behaviour duration, such as television viewing (Clark et al., 2009; Sugiyama et al., 2008). Clemes et al. (2012) reported that workplace sedentary behaviour was the greatest contribution to sedentary time on a weekday and television viewing was the greatest contribution to sedentary time on a weekend day; therefore, television viewing may not be the most appropriate proxy measure for sedentary behaviour for those who are economically active.

Recall period

Self-reported sedentary behaviour measures can vary in terms of recall period: for example, current day or previous day recall (Clark et al., 2013; Clemes et al., 2012; Matthews et al., 2013); previous week recall (Chau, van der Ploeg, Dunn, et al., 2012; Clark, Thorp, et al., 2011); or usual behaviour for a 'typical' period (Rosenberg et al., 2010). Nonetheless, recall period has been found to have little influence on validity outcome measures for self-reported sedentary time when compared to the activPAL™ accelerometer (Chastin et al., 2018).

Type of administration

Self-reported measures of sedentary behaviour tend to underestimate sedentary time compared to objective measures that have been used as criterion measures, irrespective if they have been administered by an interviewer (Clark, Thorp, et al., 2011; Matthews et al., 2013), in the presence of an interviewer (Clemes et al., 2012), or self-reported by participants (Chau et al., 2011; Marshall et al., 2010). However, different modes of questionnaire administration may present bias with respect to the data collected (Bowling, 2005). Self-reported measures may be subject to social desirability bias, with participants wanting to present themselves at their best by underestimating their daily sitting times (Bowling, 2009); similarly, people tend to overestimate their physical activity time when using self-report methods (Sallis & Saelens, 2000).

Type of criterion measure

The accelerometer is the preferred criterion measure for studies that have carried out psychometric testing of self-reported measures for sedentary behaviour (Dall et al., 2017). Accelerometers are small electronic devices that measure acceleration of the body or part(s) of the body (Tryon & Williams, 1996), and can be categorised into those that classify posture and those that estimate energy expenditure (Granat, 2012). Many studies that have used the ActiGraph, an accelerometer that estimates energy expenditure, have used an arbitrary cut-point of less than 100 counts per minute to define sedentary behaviour (Kozey-Keadle et al., 2011; Matthews et al., 2008; Owen et al., 2010). Psychometric testing studies of self-reported measures for sedentary behaviour recognise that the ActiGraph is not the criterion standard for assessing sitting, standing and walking (Chau, van der Ploeg, Dunn, et al., 2012; Clark, Thorp, et al., 2011; Marshall et al., 2010), as "there are no widely

agreed upon cutoffs for measuring sedentary behaviors with accelerometers" (Rosenberg et al., 2010. p. 702). The activPAL™ accelerometer, a thigh-worn device, is considered to be the gold standard criterion measure for reliability and validity studies that measure sitting time, as it can distinguish robustly between postures (Baumgartner, Mahar, Jackson, & Rowe, 2015; Clemes et al., 2012; Dowd, Harrington, & Donnelly, 2012; Prince, LeBlanc, et al., 2017).

Other attributes of self-reported questionnaires that should be taken into consideration are the populations that they have been tested in and the wording of time-related questions. Many reliability and validity studies have been carried out in university populations (using convenience samples) (Healy et al., 2011), or specific subsets of the population: for example, overweight, young adults (Rosenberg et al., 2010), and breast cancer survivors (Clark et al., 2013). Questionnaires may give people a range of categorical answers for time-related questions: for example, the Sedentary Behaviour Questionnaire asks about time spent in different behaviours and gives response options of, 0 minutes, 15 minutes or less, 30 minutes, 1 hour, 2 hours, 3 hours, 4 hours, 5 hours, or 6 hours or more (Rosenberg et al., 2010). These types of responses can complicate data analysis as people tend to round time to the nearest *part*-hour (Calitri, Lowe, Eves, & Bennett, 2009; van der Henst, Carles, & Sperber, 2002), and by having an unanchored upper category, the precise time in different behaviours is not known and it is not practical to calculate average times (Prince, LeBlanc, et al., 2017).

A validation study of self-reported measures by Chastin et al. (2018) found that the majority of methods underestimated sedentary time with poor accuracy, compared with the activPAL™ accelerometer. The 100 counts per minute cut-point to define sedentary

behaviour from the ActiGraph accelerometer has not been empirically defined in an adult population, and therefore the postural output of the activPAL™ is the preferred criterion measure for sedentary behaviour (Atkin et al., 2012; Prince, LeBlanc, et al., 2017).

2.1.1.3   Strengths and limitations of subjective methods

Subjective methods of physical behaviour measurement (either using activity diaries or questionnaires) are practical in terms of cost and low participant burden (Figure 2.1) (Welk, 2002). Many have been found to have acceptable reliability, and they can collect information on frequency, duration, intensity and type of activity (Atkin et al., 2012; Dall et al., 2017; Healy et al., 2011; Prince, LeBlanc, et al., 2017). They are advantageous for large samples and national/international surveillance surveys as they can be quick to administer, and for those that measure physical activity, they can be used alongside compendiums of activities to estimate energy expenditure (Ainsworth et al., 2000). One of the main advantages of self-reported methods over objective methods is their ability to capture contextual information on mode and domain-specific physical behaviours (Healy et al., 2011; Welk, 2002).

Reliability and validity in self-reported measures of physical activity tend to be adequate due to a wide variety of criterion measurements used across studies (Sallis & Saelens, 2000; Welk, 2002). Reliability of self-reported measures of sedentary behaviour is reported as good to excellent, but validity is only poor to adequate (Prince, LeBlanc, et al., 2017). Self-reported measures are subject to recall limitations with respect to certain characteristics of physical behaviour in terms of frequency, type, intensity, duration: participants are known to overestimate their time in physical activities and underestimate their sedentary time (Healy et al., 2011; Sallis & Saelens, 2000; Timperio et al., 2003; Welk, 2002). Activity

diaries and logs can increase participant burden with expectations of frequent data entry, and are subject to recall limitations if they are not completed as expected (Ainsworth et al., 2015; Atkin et al., 2012).

2.1.2   Objective measures

Advancements in technology have allowed more practical measurements of activity behaviours to be developed that have the potential to overcome the current limitations in subjective physical behaviour measures (Schatzkin et al., 2009).

Healy et al. (2011, p. 220) stated that the ideal objective measure of sedentary time would:

- *be accurate and reliable across different population groups;*
- *distinguish among sleeping, reclining, sitting and standing;*
- *distinguish among different domains and specific behaviors;*
- *be low-cost, have low participant burden, and be able to be worn continuously for extended periods of time;*
- *produce data that are easily analyzed and interpreted and be provided in real time.*

With the exception of accelerometers, few other objective techniques have been used to measure sedentary behaviour (Tremblay et al., 2010). The objective measures shown in Figure 2.1 are briefly discussed below: an overview of the advantages and disadvantages of accelerometers in sedentary behaviour research is presented in Section 2.1.3.

2.1.2.1   Pedometers

Pedometers are small motion sensors that are placed on the hip and measure the number of steps: they respond to the vertical acceleration of the hip, which activates a mechanical lever in the device to move vertically and record a step (Ainsworth et al., 2015; Freedson & Miller, 2000; Sirard & Petrucci Jr., 2019). They are usually attached to the waist strap of

clothing using a clip/elastic belt, have low participant burden, are relatively cheap compared to other activity devices, and their data are easy to process and interpret (Freedson & Miller, 2000; Tudor-Locke & Lutes, 2009; Welk, 2002). Some pedometers allow stride length to be inputted in order to estimate distance; however, they are subject to measurement error at faster speeds and are most appropriate for measuring walking (Tudor-Locke & Myers, 2001; Welk, 2002). Pedometers can offer behavioural feedback via a digital display of number of steps completed: however, they can be sensitive to behaviour change with short-term use, with habitual activity returning in the second week of wear (Clemes & Deans, 2012; Clemes & Parker, 2009).

Although pedometers cannot distinguish between sitting or standing (Tudor-Locke, Hatano, Pangrazi, & Kang, 2008), or determine frequency, intensity and duration of walking (Freedson & Miller, 2000), fewer than 5000 steps per day has been used as a proxy for a sedentary lifestyle (Tudor-Locke & Bassett, 2004; Tudor-Locke, Craig, Thyfault, & Spence, 2013).

2.1.2.2   *Heart rate monitors*

Heart rate monitors are fitted to a belt and worn around the chest; they measure a physiological response to physical activity by detecting electrical impulses from the heart and converting them to beats per minute (Dugdill & Stratton, 2007). They have low participant burden when worn for short periods, and can be easy and quick in terms of data collection and data analysis (Welk, 2002). Heart rate monitors can be used to estimate energy expenditure, and they can be used to analyse the intensity, frequency and duration of activity (Strath et al., 2000; Welk, 2002). There is a strong relationship between heart rate and energy expenditure for higher intensity physical activities; however, this

relationship is not as strong for lower intensity activities and can lead to errors in estimating total energy expenditure (Ainslie, Reilly, & Westerterp, 2003; Rowlands, Eston, & Ingledew, 1997; Welk, 2002).

2.1.2.3   Direct observation

Direct observation is used to measure physical behaviours by trained observers in real-time and is a popular method used to study children's physical activity (McKenzie, 2002). Physical behaviour categories are established prior to observation; this technique can provide information on type, intensity (based on the physical behaviour categories), frequency, and duration of physical behaviours (Welk, 2002). Direct observation provides a method for researchers to collect both quantitative and qualitative data to evaluate contextual and environmental information, such as location, domain, interactions, and expectations of behaviour based on social norms (McCormack, Rock, Toohey, & Hignell, 2010; McKenzie, 2010; Welk, 2002). However, it can be time intensive with respect to observer training, data collection and data analysis: between- and within-observer agreement need to be taken into account, and participants may be subject to the 'Hawthorne effect' where they may alter their behaviour in response to being observed (Bowling, 2009; Welk, 2002).

A study by Kozey-Keadle et al. (2011) validated the sedentary behaviour classifications from the activPAL™ and ActiGraph GT3X accelerometers with direct observation as the criterion measure, in 20 overweight office workers. Each participant was observed for two periods of six hours: both accelerometers underestimated sedentary time with a bias of 7.7 and 16.9 minutes respectively (equivalent to 2.8% and 4.9%). Accurate measures of

sedentary behaviour using direct observation could be used to examine the pattern and accumulation of sedentary time in different populations (Atkin et al., 2012).

2.1.2.4   *Indirect calorimetry*

Indirect calorimetry measures oxygen consumption and carbon dioxide production to assess energy expenditure (Welk, 2002). This can be carried out within a metabolic chamber (closed-circuit method), but more commonly, participants are required to wear a mouthpiece or facemask that is connected to a gas collection device (open-circuit method); the respiratory gases can then be analysed to measure energy expenditure (Bassett, 2000; Dishman, Washburn, & Schoeller, 2001; Valanou, Bamia, & Trichopoulou, 2006). Indirect calorimetry can be a precise method to measure energy expenditure, with high levels of validity and accuracy (Bassett, 2000; Wells & Fuller, 1998; Yates, Cullum, & Pittsley, 2004); nevertheless, it can be expensive, invasive for participants, and it is difficult to assess the patterns of physical behaviour using this technique.

Portable indirect calorimetry systems are available for free-living assessment of physical behaviours (Andre & Wolf, 2007; Valanou et al., 2006). These portable devices have been used in studies that have measured sedentary behaviour as part of a set of specific conditions for short periods (20 minutes) (Levine & Miller, 2007; McAlpine, Manohar, McCrady, Hensrud, & Levine, 2007); however, they can have high participant burden and are not practical in free-living environments where sedentary behaviours naturally occur over long periods (Andre & Wolf, 2007; Welk, 2002).

2.1.2.5   Doubly labelled water

The doubly labelled water method is used to assess total energy expenditure from biological markers that are associated with the rate of metabolism in the body (Welk, 2002). Participants are asked to ingest water with a known concentration of two isotopes of oxygen and hydrogen (Schoeller & van Santen, 1982). After a set period (usually one to three weeks) (Ainslie et al., 2003; Andre & Wolf, 2007; Vanhees et al., 2005), the difference in the rate of loss of the two isotopes is assessed (usually from participants' urine samples collected at the start and end of the data collection period) (Andre & Wolf, 2007; Schoeller, 2008), and the results are used to measure carbon dioxide production; from this, total energy expenditure can be calculated (Schoeller, 2008; Vanhees et al., 2005).

Doubly labelled water is a precise method to measure total energy expenditure and is used as a criterion measure for validating other physical behaviour measures (Ainslie et al., 2003; Andre & Wolf, 2007; Valanou et al., 2006); however, the cost of the isotopes and equipment needed for isotope analysis is high (Vanhees et al., 2005), and it cannot be used to measure frequency or duration of physical behaviours (Bassett, 2000; Vanhees et al., 2005; Welk, 2002). This method would not allow for physical activity intensity to be studied as only total energy expenditure is calculated, and is therefore not a suitable method to measure sedentary behaviour (Welk, 2002).

2.1.3   Accelerometers

Objective measures that have high validity and can accurately measure energy expenditure (direct observation, indirect calorimetry and doubly labelled water) are not suitable for measuring lower intensity behaviours on the movement continuum, including sedentary behaviour (Section 2.1.2). The use of accelerometer-based devices is the main objective

measure used in studies that assess sedentary behaviour (Atkin et al., 2012; Edwardson, Winkler, et al., 2016).

Accelerometer-based devices are generally worn on either the hip, thigh or wrist (Montoye, Pivarnik, Mudd, Biswas, & Pfeiffer, 2016; Sievänen & Kujala, 2017; Welk, 2002); and they measure the acceleration of body movements in one (vertical axis) to three axes (vertical, anteroposterior and medio-lateral axes) (Chen & Bassett, 2005). Most devices use piezoelectric accelerometers; the output of these sensors are voltages that are proportional to the acceleration experienced by the body to which they are attached (Chen & Bassett, 2005; John & Freedson, 2012; Yang & Hsu, 2010). Manufacturers of these devices use proprietary integration algorithms to convert the raw accelerations into activity counts, which can then be summed over pre-defined epochs (Chen & Bassett, 2005; Edwardson, Winkler, et al., 2016; Esliger, Copeland, Barnes, & Tremblay, 2005).

Accelerometers can be categorised into those that estimate energy expenditure and those that classify posture (Granat, 2012; Kang & Rowe, 2015); data can be processed into meaningful variables for analysis, such as energy expenditure, time spent in different postures and number of sit-to-stand transitions, depending on the device that is used (Crouter et al., 2006; Grant et al., 2006; Tryon & Williams, 1996).

2.1.3.1   *Strengths and limitations of accelerometers*

Accelerometers are able to accurately measure frequency, intensity and duration of physical behaviours and can examine temporal patterns of behaviour across the day (Atkin et al., 2012; Welk, 2002). Other strengths of accelerometers include: the ability to capture a large amount of data over long periods; the devices are small so have minimal participant burden (depending on location); they can collect data on time spent at predetermined

levels of activity; and they can be used to estimate energy expenditure or posture (Ainsworth et al., 2015; Atkin et al., 2012; Kang & Rowe, 2015).

Accelerometer limitations include: their expense, particularly for studies with a large number of participants (Healy et al., 2011; Welk, 2002); non-compliance may be difficult to ascertain over long periods of data collection (Trost, McIver, & Pate, 2005; Welk, 2002); they are not able to provide contextual data on where activities occur and sleep/wake times for example (Healy et al., 2011; Kang & Rowe, 2015); and it may be difficult to distinguish between sitting and standing with low energy expenditure (Ainsworth et al., 2015; Dowd, Harrington, & Donnelly, 2012; Welk, 2002). Accelerometers may not be able to measure activities that are not step-based; for example, cycling and use of cardio equipment (e.g. rowing machine), and they may have to be removed for swimming and water-based activities (Colley et al., 2011; Edwardson et al., 2012; O'Connell et al., 2017; Sirard & Petrucci Jr., 2019). Depending on placement, accelerometers may not capture energy expenditure related with movement of the upper body, such as weight-lifting and the use of strength training equipment (Colley et al., 2011). However, some new-generation accelerometers are water-proof (Doherty et al., 2017; Troiano, McClain, Brychta, & Chen, 2014), and advancements in analysis methods have led to the development of algorithms that are able to distinguish between sitting and lying (Lyden, Dinesh, Dall, & Granat, 2016), and classify periods of cycling in posture based devices (Speirs, Loudon, Maxwell, Savelberg, & Granat, 2019).

Neither type of accelerometer (those that estimate energy expenditure and those that classify posture) is able to quantify free-living sedentary behaviour using both energy expenditure and posture in accordance with the definition of sedentary behaviour by the

Sedentary Behavior Research Network (Granat, 2012; Kang & Rowe, 2015; Sedentary Behavior Research Network, 2012; Tremblay et al., 2017) (Section 1.1.2). Two types of accelerometer-based devices have been used in the studies within this thesis; one that is predominantly used to estimate energy expenditure (ActiGraph) and one that is used to classify posture (activPAL™). Each type of accelerometer is discussed below alongside how sedentary behaviour is derived from each type of device.

2.1.3.2   *Energy expenditure devices*

Accelerometers that estimate energy expenditure are generally worn on the hip or on the wrist. The proprietary activity counts from the vertical axis[12] of these accelerometers are summed over pre-defined epochs: in physical behaviour research, the majority of studies have used a one-minute bout (Colley et al., 2011; Freedson et al., 1998; Matthews et al., 2008; Owen et al., 2010; Troiano et al., 2008). These counts per minute are arbitrary numbers and are not comparable between accelerometers due to different manufacturer proprietary algorithms that are used to compute them (Straker & Campbell, 2012). Therefore, calibration studies have derived thresholds of counts per minute that correspond to different intensities of physical activity using regression equations (Crouter et al., 2006; Freedson et al., 1998; Troiano et al., 2008); however, there is no empirically derived cut-point for sedentary behaviour for the ActiGraph using these methods.

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[12] Earlier versions of the ActiGraph only had the capability to measure activity counts from the vertical axis: new-generation ActiGraph devices are tri-axial accelerometers and activity counts can be calculated as a composite measure of the vector magnitude of these three axes (vertical, anteroposterior, medio-lateral) (Sasaki et al., 2011). Cut-points within this thesis refer to those measured on the vertical axis, unless otherwise stated.

The ActiGraph accelerometer range (ActiGraph LLC, Pensacola, Florida) is widely used in physical activity and sedentary behaviour research. National health studies in both the UK (Health Survey for England) and the USA (The National Health and Nutrition Examination Survey [NHANES]) have used a version of the ActiGraph on sub-samples of participants (Craig, Mindell, & Hirani, 2009a; Matthews et al., 2008). The ActiGraph is usually attached to a belt and worn just above the hip (Figure 2.2). NHANES, a continuous health survey, have recently switched to wrist-worn ActiGraph devices, which has increased compliance amongst participants (Kang & Rowe, 2015; Troiano et al., 2014); however, it is difficult to compare outputs from the two types of device, as there is greater misclassification for the estimation of energy expenditure and time spent in sedentary behaviour from a wrist-worn ActiGraph compared to a hip-worn ActiGraph (Rosenberger et al., 2013).

Figure 2.2 **Photograph of a hip-worn ActiGraph attached to a belt (ActiGraph LLC., 2019. [Online]. Available from: www.actigraphcorp.com/ actigraph-wgt3x-bt/)**

In 2008, the Health Survey for England asked a sub-sample of participants to wear an ActiGraph GT1M for seven days: the accelerometer cut-point to define sedentary behaviour in the Health Survey for England analysis was ≤199 counts per minute, which was taken from a children's study that used an ActiGraph accelerometer (Mattocks et al., 2008). This is in contrast to a cut-point of <100 counts per minute that was proposed using

accelerometer data from the NHANES (Matthews et al., 2008; Troiano et al., 2008). Matthews et al. (2008) were the first to describe time spent in sedentary behaviours for participants in the NHANES in the USA. The accelerometer originally used in NHANES was the ActiGraph 7164 model; the cut-point for sedentary behaviour of <100 counts per minute was not empirically derived from this study, but from a controlled calibration study that defined sedentary behaviour thresholds in a sample of adolescent girls (Treuth, Schmitz, et al., 2004). Although this cut-point is often used in adult studies, it should be highlighted that it was derived from an adolescent female population whose activity behaviour may be different to adults, with children tending to carry out activities in more short and sporadic bursts (Carson, Cliff, Janssen, & Okely, 2013). Accelerometer data from the Treuth et al. (2004) study were recorded in 30-second epochs, with a sedentary behaviour threshold defined as 50 counts per 30-second epoch; this was doubled to 100 counts per minute for the study by Matthews et al. (2008). The relationship between epoch length and cut-point is not linear, and therefore it is recommended that cut-points should not be converted to different length epochs as it is thought that this would lead to "considerable error in total estimates" (Aguilar-Farías, Brown, & Peeters, 2013, p. 5).

The cut-point of <100 counts per minute may under- or over-estimate sedentary time based on the context or population in which the sedentary time is accrued; for example, higher cut-points of 150 and 200 counts per minute have been suggested in studies with overweight participants (Kozey-Keadle et al., 2011; Lopes et al., 2009), and lower cut-points of <25 and <22 counts per minute have been suggested in older populations (Aguilar-Farías

et al., 2013; Koster et al., 2016).[13] In addition, it can be difficult to determine sitting and standing with low energy expenditure using the cut-point of <100 counts per minute (Crouter et al., 2006; Dowd, Harrington, & Donnelly, 2012). ActiGraph physical activity cut-points have been shown to be valid in different populations (Berendsen et al., 2014; Santos-Lozano et al., 2013; Sasaki, John, & Freedson, 2011); however, validation studies for the sedentary behaviour cut-point of <100 counts per minute have found wide confidence intervals for percentage bias for estimated sedentary times, indicating random errors at the individual level (Kim, Barry, & Kang, 2015; Kozey-Keadle et al., 2011). It is not known how much misclassification is introduced to studies that aim to calculate time in different physical behaviour activity classifications (Hart, Ainsworth, et al., 2011; Marshall et al., 2010).

2.1.3.3   Posture classification devices

Accelerometers that classify body posture are generally worn on the thigh and can be attached directly onto the skin (Chastin & Granat, 2010; Edwardson, Rowlands, et al., 2016; Godfrey, Conway, Meagher, & ÓLaighin, 2008). The thigh's acceleration along the three axes (vertical, anteroposterior, medio-lateral) is used to determine the inclination of the thigh, and body posture is classified using proprietary algorithms (Edwardson, Winkler, et al., 2016; Kang & Rowe, 2015).

The activPAL™ (PAL Technologies Ltd, Glasgow, Scotland) is a thigh-worn accelerometer-based device that classifies posture into sedentary (sitting/lying), standing, and stepping

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[13] The use of the <100 counts per minute cut-point in different contexts and populations is discussed further in Section 3.2.

events; in addition, it also measures cadence (stepping speed), and the number of sit-to-stand and stand-to-sit transitions (Figure 2.3) (Edwardson, Winkler, et al., 2016; Grant et al., 2006). Energy expenditure for sitting/lying, standing, and stepping based on different cadences can also be inferred from estimates of energy expenditure for each activity (PAL Technologies Ltd, 2010).

Figure 2.3   Photograph of a thigh-worn activPAL™ (Author's personal collection)

The postural outputs from the activPAL™ have been validated in pre-school children (Davies et al., 2012), adolescents (Dowd, Harrington, & Donnelly, 2012), adults (Grant et al., 2006; Kozey-Keadle et al., 2011; Lyden, Kozey-Keadle, Staudenmayer, & Freedson, 2012), and older adults (Grant et al., 2008). It has been found to be a reliable and valid measure of step count and stepping time in adults, for a range of walking speeds (0.90, 1.12, 1.33, 1.56, and 1.78 m/s) (Ryan, Grant, Tigbe, & Granat, 2006); but is less accurate for slower walking speeds (<0.5 m/s) (Stansfield, Hajarnis, & Sudarshan, 2015). Furthermore, algorithms have recently been developed that are highly accurate in being able to distinguish between sitting and lying (Lyden et al., 2016), and periods of cycling (Speirs et al., 2019). The activPAL™ is often used as the criterion measure in sedentary behaviour

studies (Gill et al., 2018; Kozey-Keadle et al., 2011; Prince, LeBlanc, et al., 2017), and is increasingly referred to as the 'gold standard' accelerometer-based device in measuring sedentary time (Baumgartner et al., 2015; Chastin et al., 2018; Koster et al., 2016; Prince, LeBlanc, et al., 2017).

2.1.4 *Considerations when using accelerometers in research*

The use of accelerometers to measure sedentary behaviour in free-living environments has many advantages over subjective measures; however, subjective decisions need to be considered with respect to data collection and data processing in order to minimise measurement error (Sirard & Petrucci Jr., 2019). These decisions can be divided into: pre-data collection; data collection; and data processing.

2.1.4.1 *Pre-data collection considerations*

Prior to collecting data, a number of decisions need to be made with respect to the research questions and proposed study outcomes. Hart, Swartz, Cashin, and Strath (2011)[14] and Aguilar-Farias, Martino-Fuentealba, Salom-Diaz, and Brown (2019)[15] both found that five days of accelerometer data are needed to accurately predict time spent in sedentary behaviours, and that including one weekend day improves the accuracy of these estimates. This is particularly relevant to those who are economically active who report different sedentary behaviour patterns on weekdays compared to weekend days (Clemes et al., 2015). Accelerometers can be worn during waking hours, working hours or for 24-hours per day. In conjunction with the research question(s), wear location of the device may

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[14] ActiGraph 7164
[15] ActivPAL3™μ

influence when the accelerometers are worn; for example, a wrist- or thigh-worn device may have lower participant burden when worn overnight compared to a hip-worn device (Janssen & Cliff, 2015). When the NHANES changed its physical behaviour data collection method in 2011 from a hip to a wrist-worn ActiGraph, compliance, defined as at least six days of valid wear, increased from 40%–70% in the 2003–2004 survey to 70%–80% in the 2011–2012 survey (Troiano et al., 2014). Researchers may also decide on wear location based on the population or physical behaviour of interest; for example, postural data will be more accurate from a thigh-worn device compared to a wrist-worn device, which may be affected by arm movements (Migueles et al., 2017; Sievänen & Kujala, 2017).

Accelerometers can be charged and initialised using manufacturer approved software. The choice of sampling frequency (number of data samples per second) can depend on type of data (postural, count or acceleration signal), length of wear, and activity level of the population (Edwardson, Winkler, et al., 2016; Sievänen & Kujala, 2017). Researchers need to decide if participants will be instructed on how and when to wear the accelerometer (verbal, written and/or other media) and whether it should be removed for any water-based activities or contact sports. A number of newer generation accelerometers are waterproof or water-resistant (Sliepen, Brandes, & Rosenbaum, 2017); however, some accelerometers, such as the activPAL™ will need waterproofing by covering it with a small nitrile sleeve and wrapping it in a waterproof medical dressing (Edwardson, Winkler, et al., 2016) (Figure 2.4).

Figure 2.4   **activPAL™ in nitrile sleeve and waterproof medical dressing (Author's personal collection)**

2.1.4.2   Data collection considerations

Data collection decisions include how to distribute the accelerometer to participants: an activity diary/log will also need to be issued if contextual information is required (Section 2.1.1.1), such as sleep time, waking hours, commute time, work start and finish times, and times when the accelerometer was removed. It is recommended that devices are distributed face-to-face, in order that participants can be shown how to wear/attach the accelerometer, change any waterproof dressing, and fill in the activity diary/log if required; however, this may not be practical for large studies (Trost et al., 2005).

Researchers rely on participants to wear accelerometers as stated and worn correctly each day; compliance (i.e. higher wear time) is increased for continuous 24-hour wear compared to waking-hour protocols (Migueles et al., 2017). To improve compliance, researchers may make reminder calls, texts or emails; depending on costs, an electronic diary could help with compliance and save time by reducing data entry (Edwardson, Winkler, et al., 2016; Trost et al., 2005). Devices and activity diary/logs can be returned via mail, face-to-face

pick up, or central deposit locations for workplace studies. Device distribution, reminders, and collection all have time and costs implications, which depend on the size, time, and funds allocated to a study.

2.1.4.3 Data processing considerations

The extent to which manufacturer software packages can process and analyse the raw accelerometer data varies; for example, the activPAL™ software[16] uses proprietary algorithms to classify postural data (sitting/lying, standing and stepping) (PAL Technologies Ltd, Glasgow, Scotland), which is shown as charts within the software and can be downloaded into *csv*[17] files for further analysis (Edwardson, Winkler, et al., 2016). The raw ActiGraph data can be downloaded and processed in the ActiLife[18] software and allows users to make decisions using a selection of algorithms to derive physical behaviour outcomes such as, cut-points to classify physical activity intensities, energy expenditure estimates, and non-wear periods (ActiGraph LLC, Pensacola, Florida). To carry out further processing and analysis, raw accelerometer data files can be transferred to statistical software, which requires technical expertise (Winkler et al., 2016).

The epoch length used to analyse processed accelerometer data can vary, usually between 1-second and 60-seconds; consequently, different epoch lengths will result in different times spent in physical behaviour categories (Edwardson & Gorely, 2010; Sievänen & Kujala, 2017). Within the physical behaviour literature, a 60-second epoch is generally

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[16] Available from http://www.palt.com/software/
[17] Comma-separated values file: used to store tabular data, and can be opened using spreadsheet software, such as Excel
[18] Licenses for this data analysis software platform can be purchased from https://www.actigraphcorp.com/actilife/

reported for adults (Matthews et al., 2008; Migueles et al., 2017). The use of the 60-second epoch in physical activity and sedentary behaviour studies is most likely a consequence of early accelerometers used in the NHANES that were initialised to collect data in 60-second epochs (Kang & Rowe, 2015), and calibration studies that have used accelerometer counts from 60-second epochs to predict energy expenditure for different intensities of physical activity using regression equations (Crouter et al., 2006; Freedson et al., 1998; Troiano et al., 2008).

Non-wear time is often described as a pre-defined number of zero counts per minute, generally from an energy expenditure based accelerometer (Atkin et al., 2012). Identifying non-wear time is an important part of the data processing stage, as it can be difficult to distinguish between true periods of still sitting or lying that can result in zero counts, and periods when an accelerometer is removed (Atkin et al., 2012; Evenson & Terry, 2009). Studies using the ActiGraph accelerometer have used fixed windows of zero counts ranging from 10- to 60-minutes to define non-wear time, which may result in different estimates of time in physical behaviours (Evenson & Terry, 2009). Furthermore, using NHANES 2003-2004 accelerometer data, Chen and Troiano (2017) observed a higher than expected percentage of non-wear episodes for a shorter non-wear definition of 20-minutes of zero counts compared to 60-minutes. Similarly, a non-wear definition of 60-minutes of zero counts was the most accurate in estimating sedentary time compared to 20-, 40-, and 180-minute periods using the Actical accelerometer (Phillips Respironics, Bend, Oregon) (Oliver, Badland, Schofield, & Shepherd, 2013). The most commonly used algorithm for detecting and deleting non-wear time for ActiGraph data uses a 60-minute moving time window of zero counts, which allows for up to two consecutive minutes of counts between 1 and 100

(Troiano et al., 2008). An algorithm with a 90-minute moving window, which allows for an interval of up to two non-zero counts if there are 30-minutes of zero counts upstream and downstream from the non-zero count interval, was found to be more accurate during a 24-hour period when compared to the Troiano (2008) 60-minute algorithm (Choi, Liu, Matthews, & Buchowski, 2011); however, the 60-minute algorithm performed well during waking hours. For postural classification accelerometers, non-wear time can be removed manually using daily activity logs that ask to record any removal periods (Edwardson, Winkler, et al., 2016), or by removing long periods (i.e. >3 hours) of sedentary time (Barreira et al., 2016). An automated algorithm has recently been developed for the activPAL™ to isolate waking hours from 'sleep' (time in bed) and prolonged non-wear periods (≥ 2 hours) (Winkler et al., 2016).

Decision rules for data processing could introduce possible sources of error that can result in variability of outcome measures, particularly with respect to deciding on the number of hours that constitute a valid day, and the number of days of valid data (Kang & Rowe, 2015; Katapally & Muhajarine, 2014). It is generally accepted that a minimum of 10-hours of wear time per day implies a valid day (Atkin et al., 2012; Colley, Connor Gorber, & Tremblay, 2010; Migueles et al., 2017), and a minimum of four valid days is recommended to constitute reliable and valid data (Migueles et al., 2017; Trost et al., 2005); nonetheless, Edwardson et al. (2016) found that many studies that use the activPAL™ report an average of over 15-hours of wear time during waking hours per day.

These processing considerations may have a significant impact on outcome variables in physical behaviour studies (Mâsse et al., 2005); however, there are currently no standard guidelines for processing accelerometer data (Sirard & Petrucci Jr., 2019).

2.2 Literature review search strategy

A structured literature review was carried out in two stages based on the key concepts of 'sedentary behaviour', 'work' and 'health-related outcomes' (Figure 2.5). The primary purpose was to retrieve studies that examined and measured sedentary behaviour in the workplace (A): a secondary purpose was to identify studies that investigated associations between sedentary behaviour, work, and health-related outcomes (B).
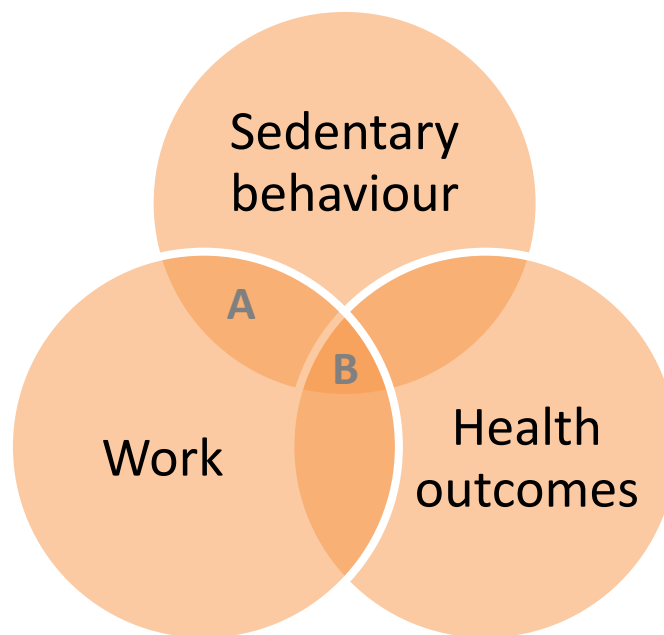
Figure 2.5   Venn diagram of literature review strategy

The subject coverage information and descriptions of all electronic library databases that were available from the University of Salford[19] were initially searched for relevant keywords that related to health sciences, health care, public health, or medicine; databases that had been used in a systematic review of workplace physical activity interventions were also checked for relevance (Dugdill, Brettle, Hulme, McCluskey, & Long, 2008). Information

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[19] http://www.salford.ac.uk/library/access-to-e-resources

(subject coverage, keywords, website descriptions) from each database were entered into an Excel spreadsheet, and a basic search for 'sedentary behaviour' and 'work' was carried out in each database. Databases that returned relevant results were included in the literature review: a total of six electronic library databases were selected to reflect the breadth of the concepts of 'sedentary behaviour', 'work' and 'health-related outcomes'.[20]

In order to identify studies to be included in the literature review, synonyms for the three concepts in Figure 2.5. were discussed with a librarian, and detailed search strategies were developed for each database. Medical subject headings (MeSH)[21] or subject areas, free terms, and synonyms for 'sedentary behaviour', 'work' and 'health-related outcomes' were combined using Boolean operators (AND and OR) (Aveyard, 2014). The search terms and search strategies for each database can be seen in Appendix 1.

To further identify references, a "snowballing" technique was also employed: "snowballing" is a secondary search method that explores references within articles that were retrieved in the initial search and is "especially powerful for identifying high quality sources in obscure locations" (Greenhalgh & Peacock, 2005, p. 1065). This method can identify articles that were not picked up in the original search, which may be due to

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[20] CINAHL (Cumulative Index to Nursing and Allied Health Literature); The Cochrane Library [included CDSR (Cochrane Database of Systematic Reviews) and CENTRAL (Cochrane Central Register of Controlled Trials)]; HMIC (Health Management Information Consortium) via Ovid [no longer available from the University of Salford]; MEDLINE (Medical Literature Analysis and Retrieval System Online) via Ovid; PsycINFO via Ovid; Web of Science

[21] A vocabulary developed by the National Library of Medicine, which is used to index journal articles in MEDLINE

limitations with keyword searches within library databases (Choong, Galgani, Dunn, & Tsafnat, 2014; Greenhalgh & Peacock, 2005). For example, the medical subject heading for *Sedentary lifestyle* within the MEDLINE database is described as: "Usual level of physical activity that is less than 30 minutes of moderate-intensity activity on most days of the week." (Lynch, Matthews, Wijndaele, & Health, 2019, p. 305), which may not pick up articles that use the term 'sedentary behaviour' that is defined using energy expenditure and/or posture (Section 1.1.2).[22] Relevant literature was also retrieved from other sources, including academic conferences in the field of physical behaviour and via social media sources used by academics (Miah, 2017). Twitter is increasingly being used to evidence the impact of academic literature (Haustein et al., 2014; Mohammadi, Thelwall, Kwasny, & Holmes, 2018), and also plays a significant role in the dissemination of real-time information before content is picked up via library databases (Mohammadi et al., 2018; Priem & Costello, 2010). The literature review was an ongoing process that was continuously updated (via database automatic updates) throughout the course of the studies included in this thesis, to ensure that significant papers were consequently added to relevant sections.

2.3   Total sedentary time

Population surveys can be a convenient resource in which to measure sedentary behaviours. Matthews et al. (2008) were the first to describe the amount of time that people spend in sedentary behaviours using the well-established NHANES. The study by

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[22] A medical subject heading for *Sedentary behaviour,* defined as "behaviors during waking hours that have low energy expenditure and are often performed in a sitting or reclining posture" was only recently added to MEDLINE in January 2019 (Lynch, Matthews, Wijndaele, & Health, 2019, p. 305).

Matthews et al. (2008) used data from the 2003-2004 NHANES survey (n=6329); participants were asked to wear the ActiGraph 7164 accelerometer on the hip for seven-days during all waking hours, and sedentary time was defined when counts per minute were less than 100 (Section 2.1.3.2). On average, adults of working age (those aged between 20 and 69 years old) spent between 7.48 (age 20-29) and 8.41 (age 60-69) hours of their waking time in sedentary behaviours each day. For all participants (age ≥6 years) the average time spent in sedentary behaviours was 7.7 hours, which was equivalent to 54.9% of their waking time. In contrast, a study using the Canadian Health Measures Survey in 2007-2009 (n=2832), found that adults (aged 20-79 years old) were on average sedentary for 69% of waking hours, which was equivalent to 9.5 hours (Colley et al., 2011). This survey also collected sedentary data objectively, using an Actical accelerometer, and defined sedentary time as less than 100 counts per minute; however, a recent study found that the Actical can overestimate time spent in sedentary behaviours by over 20% compared to the ActiGraph, and that this may explain some of the differences in observed sedentary time between the Canadian and American surveys (Duncan et al., 2018).

Trends in sedentary behaviours from NHANES were analysed by Yang et al. (2019) between 2001 and 2016; however, this study used the self-reported data from questions that asked about the number of hours people sat watching television or videos, or using a computer outside of work, and total time usually spent sitting each day. Data were available for 31,898 adults (aged ≥20 years) between 2003 and 2016. The percentage of adults who sat watching television or videos for greater than two hours per day remained stable at approximately 65% across the data collection period, while the percentage of adults using a computer for more than one hour outside of work increased from 29% to 50% (Figure

2.6). There was a significant increase in the number of total hours sitting each day from 5.5 hours in the 2007-2008 survey to 6.4 hours in the 2015-2016 survey (Figure 2.6), which the authors conclude is most likely a consequence of the increase in computer use outside of work; however, there was a decrease of 0.6 hours between the two most recent surveys (2013-2014 and 2015-2016).
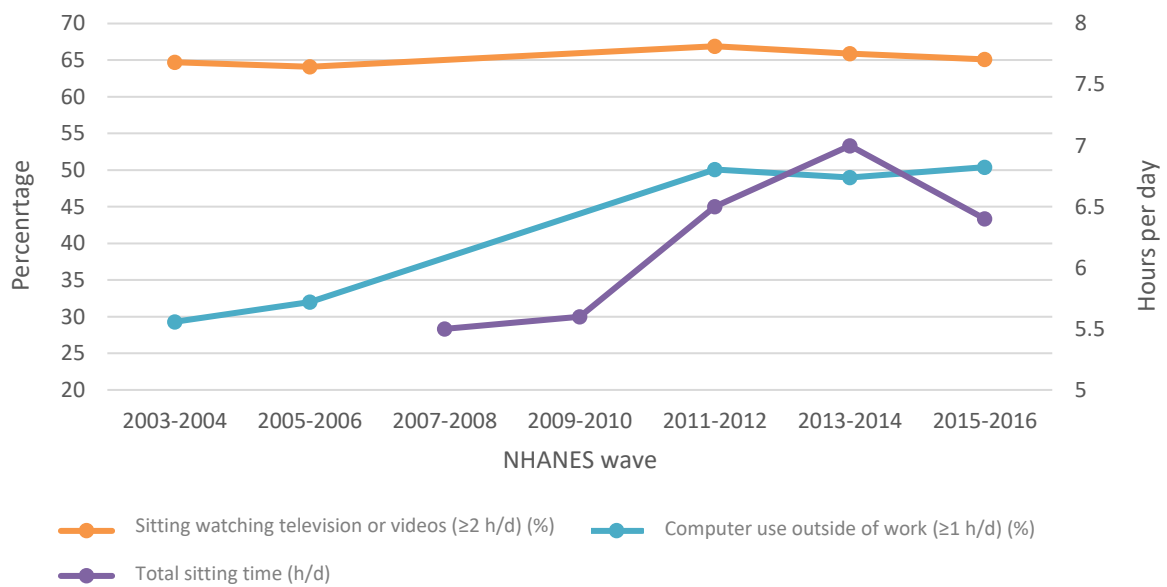
Figure 2.6   Trends in self-reported sedentary behaviours from NHANES (2003-2016) (data from Yang et al., 2019)

The Health Survey for England (a nationally representative annual survey) has also reported trends in self-reported sedentary time (Scholes, 2017). In 2008, 2012, and 2016, the same set of questions were asked about time spent sitting during leisure time and work on weekdays and weekend days. Time spent in sedentary behaviours between 2008 and 2016 decreased for both men and women, with higher average times spent sitting on a weekend day compared to a weekday; however, the average time spent sitting between 2012 and 2016 was similar for both men and women on weekdays and weekend days (Figure 2.7).
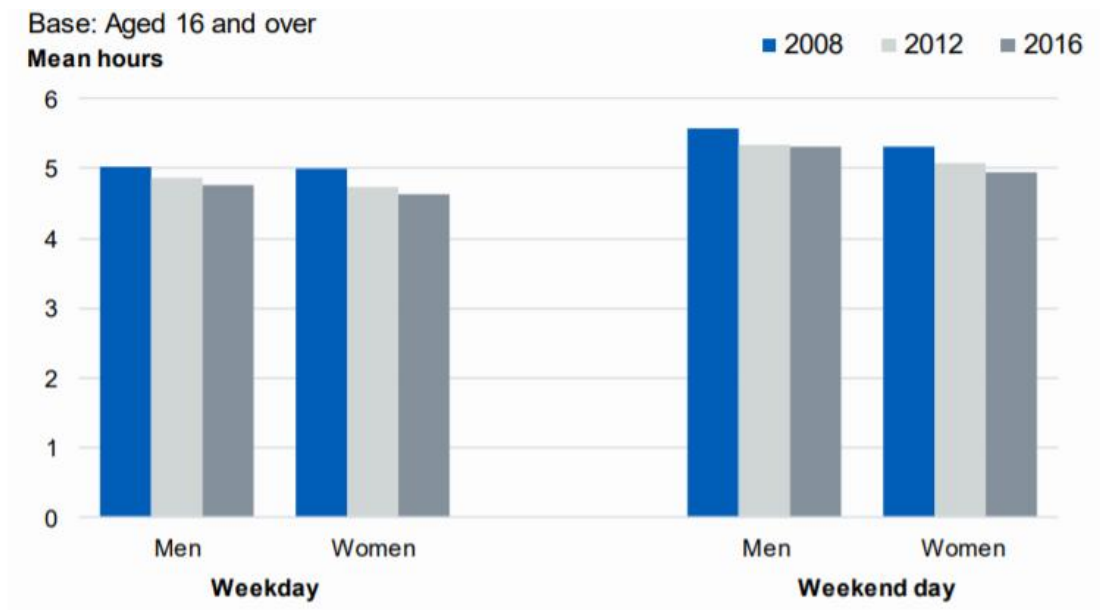
Figure 2.7   Average total sedentary time for adults in 2008, 2012, and 2016. Data from the Health Survey for England (Scholes, 2017, p. 31)

Chau et al. (2012) examined trends in non-occupational sedentary behaviours using data from the Australian Time Use Survey. This survey used ecological momentary assessment methods to assess the primary activity for each five-minute period over two days. The mean non-occupational sedentary time remained high and stable between 1997 (447 minutes per day [7.45 hours]) and 2006 (453 minutes per day [7.55 hours]); however, the composition of sedentary time changed over this same period, with an increase in leisure-time computer use and time spent in sedentary transport, compared to a decrease in other leisure-time sedentary behaviours, such as reading, listening to music and other hobbies (Chau, Merom, et al., 2012). The mean non-occupational sedentary times from the Australian Time Use Surveys were higher than those seen for total sedentary time in the NHANES and Health Survey for England surveys (Scholes, 2017; Yang et al., 2019), which suggests differences in the accuracy of the self-reported methods used in national surveys (Atkin et al., 2012; Shiffman et al., 2008).

There are differences in both objective and subjective estimates of sedentary time from population surveys. The variations in choice of accelerometer or questions used to assess sedentary time, alongside differences in study designs, prevents the ability to compare results from population surveys. For example, it is not clear if there has been a genuine temporal decrease in total sedentary time in the underlying populations as indicated by recent data from Health Survey for England and NHANES (Scholes, 2017; Yang et al., 2019), or if variations in methodologies are more likely to have influenced the reported sedentary times (Prince, LeBlanc, et al., 2017; Strain, Milton, Dall, Standage, & Mutrie, 2019).

With self-reported methods of sedentary behaviour subject to recall limitations and social desirability bias (Bowling, 2009), the use of objective measures may be beneficial in the surveillance and harmonisation of sedentary behaviour data (Loyen et al., 2017; Strain et al., 2019). Many population surveys present data on total sedentary time or leisure-time sedentary time, with few presenting data on sedentary time in other contexts: it has been reported that occupational sedentary time data in national and time use surveys may not provide sufficient detail compared to leisure-time sedentary behaviours (Chau, Merom, et al., 2012; Loyen, Chau, Jelsma, van Nassau, & van der Ploeg, 2019). For example, the Health Survey for England collects data on activities while at work, but includes both sitting down and standing up in the same category (Scholes, 2017). A recent study using self-reported data from the Australian Health Survey has reported temporal trends for both occupational- and leisure-time sedentary behaviour, using the 2007-2008, 2011-2012, and 2014-2015 surveys (Loyen et al., 2018). High levels of sedentary time were observed in both domains on workdays and these remained stable across the three data collection

points: mean occupational sedentary time was 227, 233, 228[23] minutes per day and mean leisure-time sedentary time was 205, 187, 206[24] minutes per day respectively, with no significant trends observed in either domain. Measuring sedentary behaviour in different settings is important: with few population surveys measuring sedentary behaviour within the occupational domain, it is important to add to this literature-base "to guide research strategy and to identify the most-relevant target groups" [for interventions] (Owen et al., 2011, p. 194).

2.4   Sedentary behaviour and health-related outcomes

2.4.1   *Obesity*

Increased levels of sedentary behaviour are known to be associated with obesity (Biddle et al., 2010; Brown, Miller, & Miller, 2003; Hu et al., 2003; Mummery, Schofield, Steele, Eakin, & Brown, 2005). Obesity is also known to be a risk factor for health-related outcomes that have independent associations with sedentary behaviour (de Rezende et al., 2014; Stokes & Preston, 2016; Thorp et al., 2011); however, the complex nature of obesity and its association with sedentary behaviour is still not fully understood (Wright & Aronne, 2012). For example, Hu et al., (2003) found that associations between television viewing and obesity were attenuated when dietary habits were considered.

2.4.2   *Cardiometabolic risk factors*

Metabolic syndrome is a multifaceted disorder that comprises a number of interconnected risk factors for cardiovascular disease and type 2 diabetes (Kassi et al., 2011). There are no

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[23] Equivalent to 3.8, 3.8, 3.8 hours per day
[24] Equivalent to 3.4, 3.1, 3.4 hours per day

standardised criteria to define metabolic syndrome, and it is usually diagnosed if a patient has three or more risk factors from the specific criteria being applied (Kassi et al., 2011); however, the following risk factors (also referred to as cardiometabolic markers) are generally included in studies that examine associations with sedentary behaviour:

- obesity (BMI and/or waist circumference)

- HDL-cholesterol

- triglycerides

- blood pressure

- fasting glucose

A meta-analysis by Edwardson et al. (2012) found that the odds of having metabolic syndrome were nearly doubled for those who spent a high amount of time in sedentary behaviours compared to low levels: metabolic syndrome was defined using the International Diabetes Federation criteria, as central obesity (measured using waist circumference), and two out of four other risk factors (raised blood pressure, raised triglycerides, reduced HDL cholesterol, or raised fasting glucose). Out of the 10 studies included in the Edwardson (2012) review, nine of the studies used self-reported measures of either television viewing time, leisure-time sedentary behaviour or total sedentary time: only one study used an ActiGraph accelerometer, and sedentary behaviour was defined using the <100 counts per minute cut-point. Associations between sedentary time and cardiometabolic markers have also been found to be attenuated by adjustment for total physical activity (Maher, Olds, Mire, & Katzmarzyk, 2014), and measures of adiposity (Stamatakis & Hamer, 2012). Using mutually exclusive categories of high/low sedentary behaviour and high/low physical activity, Bakrania et al. (2016) found that people with both

low and high levels of sedentary time, in conjunction with high levels of physical activity had more favourable cardiometabolic markers, compared to those who had high sedentary time and low levels of physical activity.

2.4.3 Diabetes, cardiovascular disease, and cancer

A number of systematic reviews have been published that have found associations between sedentary time and both diabetes and cardiovascular disease, independent of physical activity (Biswas et al., 2015; Ford & Caspersen, 2012; Wijndaele et al., 2011; Wilmot et al., 2012); however, these associations may be attenuated by BMI (Stamatakis et al., 2017). The meta-analysis by Biswas et al. (2015) also found significant associations between self-reported sitting time and cancer incidence and cancer mortality; this is in line with other reviews that have found that high levels of sitting are associated with some cancers (endometrial, colorectal, and lung), but not with other types (ovarian, rectum, prostate, stomach, oesophagus, testes renal cell carcinoma or non-Hodgkin lymphoid neoplasms) (Schmid & Leitzmann, 2014; Shen et al., 2014). There are conflicting findings as to whether there is an association between sedentary behaviour and breast cancer (Lynch, Courneya, & Friedenreich, 2013; Schmid & Leitzmann, 2014; Shen et al., 2014).

2.4.4 Mortality

It is also known that high levels of self-reported sitting time are associated with all-cause mortality and cardiovascular mortality, independent of physical activity levels (Biswas et al., 2015). A review of reviews found that these associations are likely to be causal for all-cause mortality (Biddle et al., 2016); however, two recent studies have proposed that high levels of physical activity may be protective against high levels of self-reported sitting time with respect to associations with mortality (Ekelund et al., 2016; Stamatakis et al., 2019)

(Figure 2.8). Nonetheless, the study by Stamatakis et al. (2019) reported that for those meeting the physical activity guidelines of 150 minutes of moderate to vigorous physical activity per week and who sit for ≥8 hours a day, are still at increased risk of mortality, which suggests that high levels of physical activity are needed to eliminate this effect in those who also sit for long periods each day (Figure 2.8).
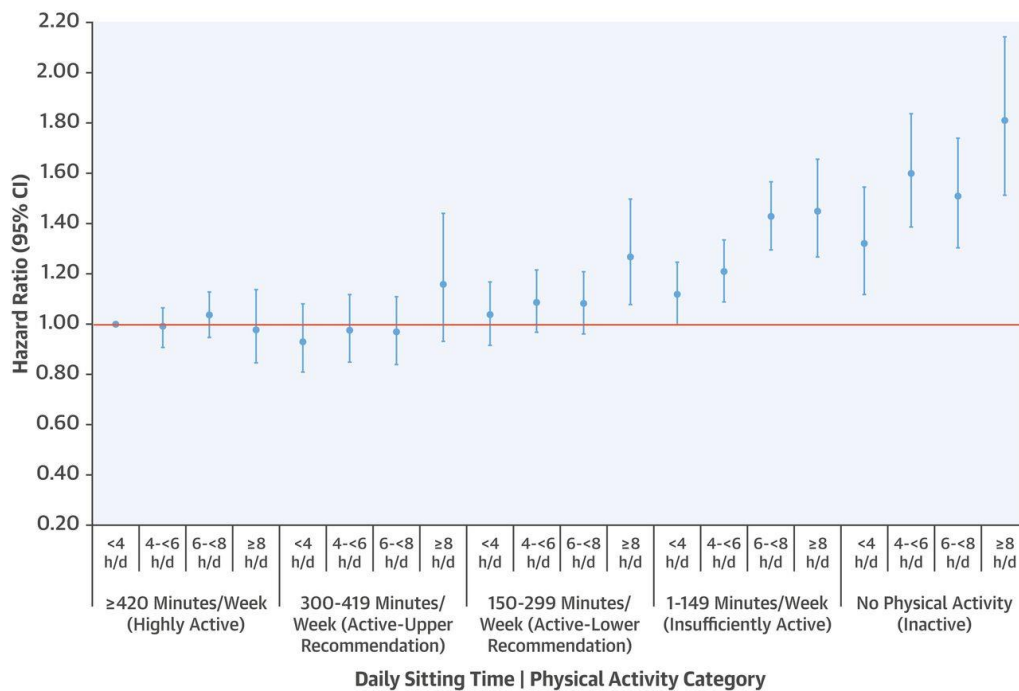
Figure 2.8   **Mortality risk for different levels of sitting time and physical activity (Stamatakis et al., 2019, p. 2066)**

2.4.5   *Mental ill-health*

Evidence of associations between sedentary time and mental ill-health, and sedentary time and musculoskeletal disorders are limited, despite the fact that these are the most commonly reported reasons for being absent from work (Chen, Liu, Cook, Bass, & Lo, 2009; Health and Safety Executive, 2018). Teychenne and colleagues (2010 and 2015) conducted two systematic reviews to look at the association between sedentary behaviour and anxiety, and sedentary behaviour and depression; although associations were reported between high levels of sedentary time and an increased risk of anxiety and depression,

many of the included studies had methodological weaknesses that related to not addressing sources of bias. For example, sedentary time was mainly measured by self-reported hours of television viewing, with only a few studies using validated subjective or objective methods (Teychenne, Ball, & Salmon, 2010; Teychenne, Costigan, & Parker, 2015).

2.4.6   Is there an independent effect of sedentary behaviour and health?

An overview of systematic reviews of sedentary behaviour and health-related outcomes found strong evidence in adults of associations between sedentary behaviour and mortality, cardiovascular disease, type 2 diabetes and metabolic syndrome (de Rezende et al., 2014). However, associations between other health-related outcomes (mental ill-health and musculoskeletal conditions) is still unclear; the complex relationship between sedentary behaviour and health-related outcomes is dependent on the methodological quality of studies, how sedentary behaviour is measured in terms of accuracy and reliability, and how potential confounders are measured and accounted for (de Rezende et al., 2014; Healy et al., 2011; Page, Peeters, & Merom, 2015). Recent studies have found that associations between sedentary behaviour and health-related outcomes may be attenuated by higher amounts of physical activity, and therefore the reciprocity between these two behaviours should be considered (Bakrania et al., 2016; Ekelund et al., 2016; Stamatakis et al., 2019).

Furthermore, it is also important to consider the pattern of accumulation of sedentary behaviour and moderate to vigorous physical activity throughout the day, and whether specific patterns are not detrimental to health (Chinapaw, Altenburg, & Brug, 2015; Chinapaw, Wang, Andersen, & Altenburg, 2019; Colley et al., 2013). For example, breaking

up prolonged periods of sitting has been found to be beneficial for cardiometabolic and diabetic physiological markers, and levels of fatigue (Dunstan, Kingwell, et al., 2012; Healy et al., 2008; Henson et al., 2016; McCarthy et al., 2017; Wennberg et al., 2016); however, there is no consensus on what constitutes a prolonged sedentary period, with definitions of greater than 20-, 30-, 40- and 55-minutes found in the literature (Dowd, Harrington, Bourke, Nelson, & Donnelly, 2012; Ryan, Dall, Granat, & Grant, 2011; Thorp et al., 2012). It remains unclear as to the independent effect of sedentary behaviour and health, specifically for different domains of sedentary behaviour. The next section discusses the literature on the prevalence of sedentary behaviour within the occupational domain.

2.5 Sedentary behaviour in the workplace

2.5.1 Methods to assess sedentary behaviour in the workplace

An early review paper in the field of sedentary behaviour and work identified 11 studies that measured either physical activity and/or sedentary behaviour in the workplace; the included papers were published between 1990 and 2009 (Castillo-Retamal & Hinckson, 2011). Five of the included studies used subjective methods, with only two of these measuring occupational sedentary behaviour (Kruger, Yore, Ainsworth, & Macera, 2006; Mummery et al., 2005); three used objective measurement techniques (two used a pedometer (Gilson, McKenna, Puig-Ribera, Brown, & Burton, 2008; Schofield, Badlands, & Oliver, 2005), and one an accelerometer (Ruiz-Tendero, Salinero-Martin, Webster, & Aznar-Lain, 2006)); the remaining three studies used indirect calorimetry to measure energy expenditure in sedentary workers under laboratory conditions (Beers, Roemmich, Epstein, & Horvath, 2008; Levine & Miller, 2007; McAlpine et al., 2007).

The two studies that measured occupational sedentary behaviour using subjective methods in the review by Castillo-Retamal and Hinckson (2011) both carried out telephone surveys; one in Australian workers based in Queensland (Mummery et al., 2005), and the other in a national sample of American workers (Kruger et al., 2006). The study by Mummery et al. (2005) asked 1579 workers in full-time employment to estimate the number of hours and minutes they sat during a normal work day. The overall mean occupational sitting time was 200 minutes per day, with professional workers (managers and administrators) sitting significantly longer compared to both white-collar (clerical sales and service workers) and blue-collar workers (tradespeople and laborers) (249, 207, and 136 minutes per day respectively; p<0.001). The aim of the American study was to examine the associations between occupational physical activity and leisure-time physical activity, with occupational sedentary behaviour defined as sitting *or* standing; however, a high proportion of the working population were described as sedentary during workdays (54.7% of men and 67.8% of women).

The studies in the Castillo-Retamal and Hinckson (2011) review that used a pedometer to record occupational activity differed in study design: a convenience sample of university employees (from Spain, Australia and England: n=216) were found to take an average of 9165 steps on a working day (Gilson et al., 2008). The study by Schofield et al. (2005) also employed a convenience sample (n=181), but included office, retail, university, health and blue-collar workers: by using two pedometers for work and non-work, steps accrued during work hours were calculated. The average daily step count per working day was 9765 for men and 9943 for women, which is similar to the study by Gilson et al. (2008). Blue collar workers (mechanics, green keepers, dry cleaners) reported an average of 10,334 working

steps each day (n=9), compared to 4623 working steps per day by university workers (n=88); furthermore, blue-collar workers accumulated the majority of their daily steps in the workplace (71%) and university workers the least (49%) (Schofield et al., 2005). A study by Steele and Mummery (2003) was classified as using a subjective measure to examine physical activity during working hours, but also used a pedometer to record steps at work in the Castillo-Retamal and Hinckson review. The study by Steele and Mummery (2003) randomly selected university employees in the professional, white-collar, and blue-collar occupational categories.[25] The average number of steps during working hours was 5069, with professional, white-collar, and blue-collar workers recording an average of 2835, 3616, and 8757 working steps per day respectively. The results by occupational category are much lower than those seen in the study by Schofield et al. (2005), but may be explained by differences in sampling methods (convenience compared to random) that could have introduced selection bias in the Schofield study (Bowling, 2009), and the differences in the sector in which blue-collar workers were sampled. Only one study in the Castillo-Retamal and Hinckson (2011) review used an accelerometer (MTI ActiGraph) to measure physical activity in Spanish university workers (n=47) (Ruiz-Tendero et al., 2006). The average daily step count on weekdays from the hip-worn accelerometer was 14,327, with cleaning staff recording a higher number of daily steps (19,925; n=9), compared to administrative (13,392; n=14) and research staff (13,310; n=24). These average daily steps on working days were much higher compared to studies of university staff that also included a pedometer (Gilson et al., 2008; Schofield et al., 2005): Ruiz-Tendero et al. (2006)

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[25] Professional workers (managers and administrators); white-collar workers (clerical sales and service workers); blue-collar workers (tradespeople and laborers)

proposed that these differences may be environmental with respect to campus designs that may or may not be conducive to walking, or differences could relate to variations in step outputs between pedometers and accelerometers (Barreira et al., 2013; Lee, Williams, Brown, & Laurson, 2015).

The studies included in the review by Castillo-Retamal and Hinckson (2011) evidence differences in the amount of sedentary time accrued in the workplace; these difference may be as a consequence of how sedentary time is measured or occupational sedentary time may vary by different occupational classifications. Therefore, the following section will discuss evidence from more recent studies that have assessed sedentary time in the workplace.

2.5.2 Sedentary time at work

There have been a number of cross-sectional studies that have reported the prevalence of sedentary time in the workplace using both subjective and objective measures; the majority of these studies have been carried out in Australia, the UK, and other European countries.

2.5.2.1 Subjective measures

Studies that have used a domain-specific questionnaire have reported that workers spend between five and seven hours of the workday sedentary (Bennie et al., 2015; Clemes et al., 2015; Kazi et al., 2014). The study by Bennie et al. (2015) recruited a convenience sample of companies with office-based employees in Australia (n=801), who reported a median daily sitting time of 540 minutes, and 300 minutes of occupational sitting time (54% of total sitting time) using the Domain-Specific Sitting Time Questionnaire: this questionnaire

assesses time spent sitting on weekdays and weekend days in the domains of transport, work, watching television, using a computer at home, and leisure (Marshall et al., 2010). A survey of UK employees in the education, government, retail, telecommunications, and services sectors (n=504), also used the Domain-Specific Sitting Time Questionnaire to assess occupational sitting time (Kazi et al., 2014): they found a median occupational sitting time of 390 minutes, which was 90 minutes longer compared to the study by Bennie et al. (2015); however, the percentage of occupational sitting time compared to total sitting time was similar between the two studies (54% in the Australian study (Bennie et al., 2015), 56% in the UK study (Kazi et al., 2014)). The difference may be explained by the high occupational and total sitting times reported by those in the telecommunications and service sectors in the study by Kazi et al. (2014): occupational sitting time was 480 minutes and total sitting time was 750 minutes for telecommunication workers, and 405 and 660 minutes for service sector workers respectively (see also Section 2.5.3). For all of the occupational sectors in this study, participants who sat for long periods in the workplace also sat for long periods outside of work, which has also been reported in other occupational sedentary behaviour studies (Clemes et al., 2015; Clemes, O'Connell, et al., 2014; Jans et al., 2007). The study by Clemes et al. (2015) also used the Domain-Specific Sitting Time Questionnaire in a large sample of civil servants in Northern Ireland (n=4436); mean occupational sitting time was 376 minutes, which accounted for 60% of total sitting time of 625 minutes (Figure 2.9).
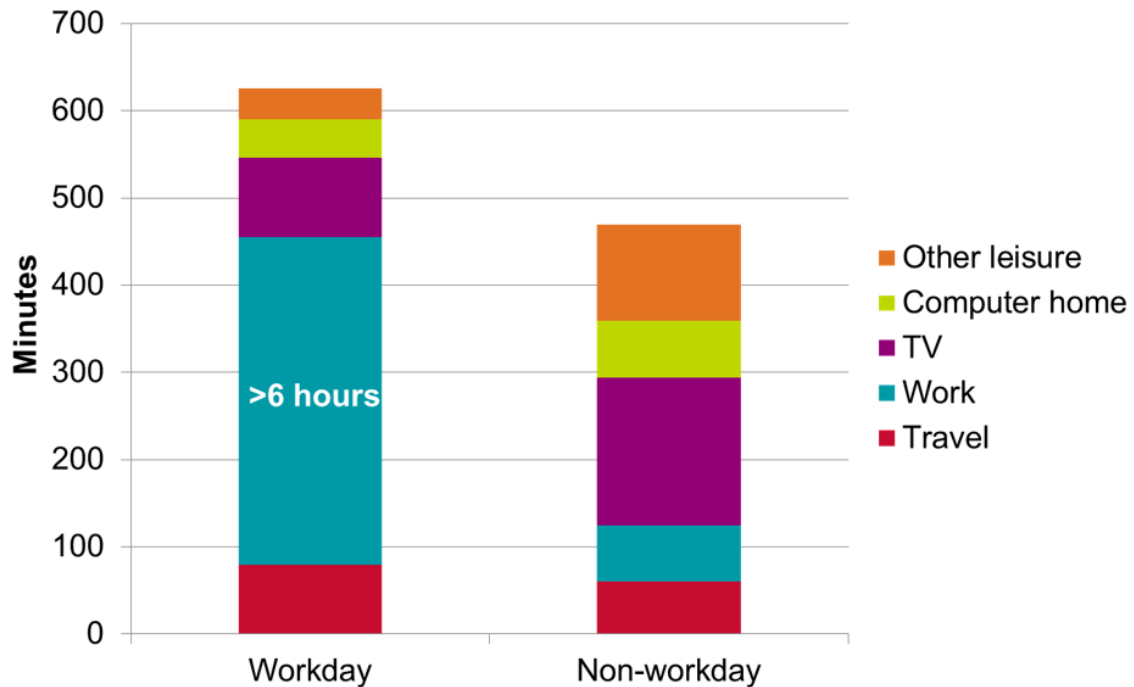
Figure 2.9   **Domain specific sitting-time (data extracted from Clemes et al., 2015)**

Figure 2.9 shows that on workdays, participants sat for over 10 hours, with the majority of this time accumulated in the workplace: there was a significant difference in sitting times on workdays compared to non-workdays (625 vs. 469 minutes per day; $p<0.001$). This finding is supported by other studies that have examined the prevalence of occupational sitting time in office workers (Hadgraft et al., 2015; Kirk et al., 2016; Parry & Straker, 2013).

The Workforce Sitting Questionnaire has also been used to measure the prevalence of occupational sedentary time (Chau et al., 2011), with daily occupational sitting times of 281 minutes per day reported in NHS workers in the UK (Mackenzie, Till, & Basu, 2017), and 225 minutes per day in participants from a health survey in Australia (De Cocker, Duncan, Short, van Uffelen, & Vandelanotte, 2014). The lower occupational sedentary times reported in these two studies compared to studies that used the Domain-Specific Sitting Time Questionnaire, maybe explained by the inclusion of blue-collar workers, who reported significantly lower sitting times at work compared to desk-based colleagues: for

example, the mean minutes per day of occupational sitting time ranged from 126 minutes for estates staff, compared to 358 minutes in desk-based workers in the NHS study (Mackenzie et al., 2017), and from 130 minutes per day for blue-collar workers compared to 252 minutes for professional workers in the Australian survey (De Cocker et al., 2014).

2.5.2.2   Objective measures

The majority of studies that have examined the prevalence of occupational sedentary time have been in office-based workers, which have included government and university-based employees. Two studies that examined occupational sedentary time objectively in UK university office-based workers, found similar mean occupational sitting times of 318 minutes per day (Ryan et al., 2011), and 306 minutes (Kirk et al., 2016), when measured by an activPAL™ accelerometer; a study using an ActiGraph accelerometer with sedentary behaviour defined using the <100 counts per minute cut-point, found a slightly higher mean occupational sitting time of 333 minutes per day in office workers (Clemes, O'Connell, et al., 2014).

Many studies have reported approximately six hours of occupational sedentary time for desk-based workers, with the percentage of occupational time spent sitting ranging from 65% (Clemes, Patel, Mahon, & Griffiths, 2014; Ryan et al., 2011), to 82% (Parry & Straker, 2013); compared to blue-collar workers who have been reported to sit for only 38% of their working day (Gupta, Heiden, Mathiassen, & Holtermann, 2016).

2.5.3   Sedentary time in different occupational groups

A study in an Australian government workplace, assessed sitting time and number of steps of workers in different occupational groups (Miller & Brown, 2004). Sitting time at work

was self-reported and steps per day were recorded using a pedometer. Managerial and administrative staff sat on average for 300 minutes each day at work; in comparison, blue-collar workers sat for only 96 minutes each day. Furthermore, a study of 7724 Australian women found that those in professional and skilled occupations sat for 60 minutes more each day compared to blue collar workers (419 vs. 461 vs. 358 minutes respectively), although self-reported sitting time was not specific to working hours, but included all daily activities (van Uffelen, Heesch, & Brown, 2012).

A study of a Dutch working population also found significant differences in time spent sitting between different occupational sectors (n=7720) (Jans et al., 2007). Time spent sitting at work and in leisure time on the previous day was determined by self-report. On average, workers sat for 117 minutes at work, which accounted for 28% of daily sitting time. Time sitting at work varied greatly between work sectors, with workers in the catering industry sitting for only 50 minutes per day compared to 207 minutes for those working in computerisation. These occupational sedentary times are much lower compared to groups of office workers in the studies carried out in the UK and Australia described in Section 2.5.2. Differences may be explained by the measurement of sedentary time (using a telephone survey with 50% response rate, which may have been subject to selection bias), variations in sedentary time between European countries has been reported previously (Loyen et al., 2017), and cultural differences may exist in the workplace between European countries (Sagiv & Schwartz, 2007).

A study in the USA assessed occupational sedentary time in university workers (n=625) in four occupational classifications (administration, faculty, facilities, other staff) (Fountaine, Piacentini, & Liguori, 2014), using the Occupational Sitting and Physical Activity

Questionnaire (Chau, van der Ploeg, Dunn, et al., 2012). The mean minutes of occupational sitting time ranged from 158 minutes for facilities staff to 394 minutes per day for both administration and faculty staff.

For those who are economically active, a large proportion of their occupational time is spent sitting, and those who sit for long periods at work, may also sit for long periods outside of work; however, occupational sedentary time varies significantly by occupational category, with the majority of studies carried out in desk-based office workers.

2.6   Occupational sedentary time and health-related outcomes

It is not known if similar associations exist between occupational sedentary time and health-related outcomes as those that have been widely reported for total and leisure-time sedentary behaviour (Section 2.4). There are limited studies that have used objective and reliable measures of occupational sedentary time to examine health-related outcomes. Many of these studies have used a categoric measure of the primary occupational activity to define *sedentary* and *mainly sitting* occupations for example: this has led to conflicting findings for many health-related outcomes, including obesity (Chau, van der Ploeg, Merom, Chey, & Bauman, 2012; van Uffelen et al., 2010), cancer (Johnsson, Broberg, Johnsson, Tornberg, & Olsson, 2017; Ma, Yao, Sun, Dai, & Zhou, 2017), type 2 diabetes (van Uffelen et al., 2010), and mortality (Brown et al., 2010; Chau et al., 2015; Stamatakis et al., 2013).

2.6.1   Obesity

The study of Australian adults by Mummery et al. (2005) also examined the relationship between sitting time at work and overweight and obesity. Self-reported occupational sitting time, physical activity and BMI were obtained from the 1579 participants via a telephone interview. Participants were asked to estimate the number of hours and minutes

of sedentary time during a normal working day and occupational group was defined as blue-collar workers, white-collar workers and professionals. After adjusting for occupational classification and leisure-time physical activity, those who sat for more than six hours at work per day were more likely to be overweight or obese compared to those who sat for less than 45 minutes. Although this study used self-reported measures, it was the first to report the relationship between occupational sitting time and overweight and obesity, independent of leisure-time physical activity.

There is no clear association between obesity risk and categoric measures of occupational activity (Chau, van der Ploeg, Merom, et al., 2012; van Uffelen et al., 2010). In a systematic review of occupational sitting and health-related outcomes by van Uffelen et al. (2010), the 13 studies that measured obesity used self-reported measures to define occupational sitting, with ten of these studies using a categorical measure that expressed the primary activity of their workday, as *sitting* or *sedentary.* Six out of these 13 studies found a positive association between occupational sitting and BMI, six studies found no association, and one study found a negative association. Furthermore, a study by Chau et al. (2012) found that workers whose work was 'mostly sitting' were significantly more likely to be overweight or obese compared to those with 'mostly standing' jobs, independent of leisure-time sedentary time *and* leisure-time physical activity.

Studies that have examined correlates of occupational sedentary time have consistently found that high BMI values are associated with high levels of occupational sedentary time, using both domain specific questionnaires (Clemes et al., 2015; De Cocker et al., 2014), and objective measures (Hadgraft et al., 2015). A study of blue-collar workers in Denmark who had their sedentary time measured objectively using an ActiGraph GT3X+ accelerometer,

found that sitting in prolonged bouts (>30 minutes) was associated with increased levels of BMI and waist circumference (Gupta, Hallman, et al., 2016); however, the same association was not seen for leisure-time sedentary behaviour, suggesting that the domain in which sedentary time is accrued may have different effects on health.

2.6.2   *Cardiometabolic risk factors*

Following on from findings from Gupta et al. (2016), which found that associations of BMI varied between different measures of sedentary time, there is increasing evidence that associations with cardiometabolic markers also differ between measures of occupational sedentary time and leisure-time sedentary behaviour (Pinto Pereira et al., 2012; Saidj et al., 2013). Pinto Pereira et al. (2012) used data from the 1958 British Birth Cohort, using a biomedical survey when participants were 44 to 45 years old, to examine associations of leisure time sitting and occupational sitting with biomarkers for cardiovascular disease. The measurement for all biomarkers was obtained on home visits by a nurse; biomarkers included cholesterol, triglycerides, blood pressure, glycated haemoglobin[26], blood pressure and hypertension, fibrinogen[27], C-reactive protein[28], and metabolic syndrome[29]. Television viewing time per day was used as a proxy for leisure-time sedentary time, and sitting at work was obtained from the question, "How many h/week do you sit doing light work": both were categorised into 0–1, 1– 2, 2–3, and ≥3 hours per day. The authors found that

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[26] Glycated haemoglobin is used to indicate if blood glucose levels from the previous month were above average

[27] Fibrinogen can indicate a person's ability to form and break down blood clots

[28] C-reactive protein is a measure of inflammation throughout the body

[29] Defined as the co-occurrence of 3 out of 5 risk factors; abdominal obesity, elevated blood pressure, elevated fasting glucose, elevated triglycerides, reduced HDL cholesterol

higher levels of television viewing were associated with unfavourable health outcomes for all biomarkers, although these were mediated by BMI. Occupational sedentary time was associated with increased triglycerides and decreased HDL cholesterol in men only, and these associations were also attenuated when adjusted for BMI (Figure 2.10).
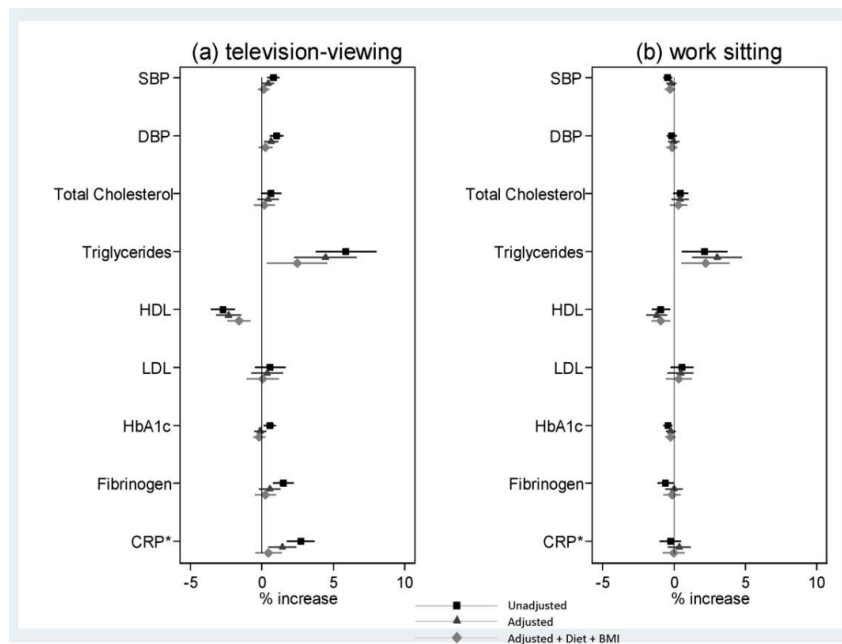
Figure 2.10   **Change in biomarkers per category increase in television viewing and occupational sedentary time in men (Pinto Pereira et al., 2012, p. 7)**

A study by Saidj, et al. (2013) also found fewer associations between occupational sitting and cardiometabolic risk factors compared to leisure time sitting. This study used data from Health2006, a population-based survey in Denmark; 2544 working adults were asked about the number of hours they spent sitting each day in leisure time and in work. Leisure time sitting was derived from, "In your leisure time, how many hours and minutes per day do you spend watching television, sitting quietly, reading, and listening to music or the like?", and occupational sitting was derived from, "During work, how many hours and minutes per day do you engage in sedentary work?". Leisure time sitting was adversely associated with, markers of adiposity, total- HDL- and LDL-cholesterol, triglycerides, and insulin, whereas occupational sitting was only associated with HDL cholesterol, triglycerides and insulin.

Similar to the study by Pereira et al. (2012), all associations were attenuated by adjusting for a measure of adiposity (waist circumference). This adds to the literature that associations of sitting time and health may function differently, depending on the domain in which sitting is measured.

The Health Survey for England 2008 contained self-reported questions on sedentary time, and objectively measured sedentary time from an ActiGraph GT1M accelerometer in a sub-sample of participants. In 2012, Stamatakis et al. published two papers using the Health Survey for England 2008 to examine the associations between sedentary time and cardiometabolic risk factors. The first study used only the self-reported sedentary time questions, and in agreement with Pereira et al. (2012), found that associations between sedentary behaviour and cardiometabolic risk factors were mediated by BMI or waist circumference. The second study examined associations between sedentary time and cardiometabolic risk factors, using both subjective and objective measures from the Health Survey for England 2008, in working age adults (Stamatakis et al., 2012b). The authors found associations between self-reported sedentary time and BMI, waist circumference, blood pressure and total cholesterol; sedentary time measured using an accelerometer was only found to be associated with total cholesterol. This was the first study to look at the association with objectively measured sedentary time and cardiometabolic risk factors in working adults; however, it should be noted that the sedentary times reported in this study were across the whole day and not limited to the working day. Although the Health Survey for England 2008 did not record working day times for those in employment, other studies have used set time frames to represent time at work in specific occupations (Kirk et al., 2016; Ryan et al., 2011; van Dommelen et al., 2016).

2.6.3   *Cardiovascular disease*

In the systematic review of occupational sitting and health risks by van Uffelen et al. (2010), no papers were retrieved for cardiometabolic risk factors. There were eight papers that described the association between cardiovascular disease and occupational sitting; however, the focus of all eight papers was physical activity and sedentary occupations, not necessarily sedentary time at work. As per the obesity studies included in this review, occupational activity was mainly categorised using definitions such as, *sedentary*, or *mainly sitting*; only one study collected information on self-reported occupational sitting time. The eight studies gave inconsistent results, with four reporting an increased risk of cardiovascular disease with occupational sitting, one found a negative association between occupational activity and cardiovascular risk, and three found no association.

2.6.4   *Mortality*

Studies that have examined occupational sitting and mortality have found inconsistent results (Brown et al., 2010; Chau et al., 2015; Stamatakis et al., 2013). The systematic review of occupational sitting and health risks by van Uffelen et al. (2010) retrieved six studies that looked at associations between mortality (including cardiovascular and cancer mortality) and sedentary behaviour at work; all used categories of occupational activity to define sedentary occupations. Four of these studies reported associations between sedentary occupations and increased all-cause or cardiovascular mortality risk; one found an inverse association, for all-cause mortality and another study, which looked at working posture, found no association with sitting posture and mortality. Similarly, a study by Stamatakis et al. (2013) used data from seven British health surveys to study the association between occupational sitting, defined by main occupational activity, and all-

cause, cardiovascular and cancer mortality. Occupational activity was assessed from the question, "When you're at work are you mainly sitting down, standing up, or walking about?". Women in sedentary occupations were found to be at increased risk of all-cause and cancer mortality, compared to women in standing or walking occupations; however, no associations were found for all-cause, or cardiovascular mortality in men. Data from a large prospective study in Norway (n=50,817), also found inconsistent results for occupational sedentary behaviour and mortality (all-cause and cardiometabolic diseases) (Chau et al., 2015). Although total sedentary time was associated with all-cause and cardiometabolic disease-related mortality, these associations were not seen for television viewing time and occupational sedentary behaviour. However, compared to jobs that mainly involved sitting, other occupational categories had lower risks of all-cause mortality; although this was only significant for occupations that were defined as mainly walking and lifting (hazard ratio 0.65, 95% CI (0.11 to 0.97)).

2.6.5   Mental ill-health

The relationship between sitting at work and mental ill-health is also unclear (Kilpatrick, Sanderson, Blizzard, Teale, & Venn, 2013; Proper, Picavet, Bemelmans, Verschuren, & Wendel-Vos, 2012; Puig-Ribera et al., 2015). A study by Proper et al. (2012) found no association between sitting at work and mental ill-health, whilst Kilpatrick et al. (2013) found that sitting time at work was associated with increased levels of psychological distress. There are a number of differences between these two studies that may account for the differing conclusions. Firstly, the Proper et al. (2012) study used data from a Dutch cohort study that was designed to examine lifestyle factors and ageing, and Kilpatrick et al. (2013) used data from an Australian survey that was designed to examine health at work

in state government employees: the difference in mean age between the two studies was nearly 14 years, with the mean age of the Dutch participants 59 (±9), and the Australian participants 46.2 (±10.3). Although both used self-reported measures of occupational sedentary time, Proper et al. (2012) asked participants to record their *weekly* sitting time at work, compared to employees in the study by Kilpatrick et al. (2013), who were asked about their *daily* occupational sedentary time. Lastly, the scale used to assess mental ill-health differed; although both asked questions relating to depression, the Mental Health Inventory was used to assess *general* mental ill-health during the last month in the Dutch cohort, compared to the Kessler Psychological Distress Scale, which assesses the *severity* of distress in the last four weeks.

2.6.6   *Musculoskeletal conditions*

There has been a dearth of research that has looked at associations between occupational sitting and musculoskeletal disorders, despite the fact that work-related musculoskeletal disorders are the most common cause for being absent from work in the UK (Health and Safety Executive, 2018).

Since the year 2000, there have been four systematic reviews that have examined associations between sitting at work and low back pain. A review by Hartvigsen et al. (2000) retrieved 35 articles; 21 of these examined sedentary occupations and low back pain, and 14 examined categories of sitting at work. Only one low quality study found an association between sitting at work and low back pain; however, this study looked at *sitting in a poor posture* over a prolonged period. A study by Skov et al. (1996) investigated the risk of low back pain and the amount of time spent sitting at work (25%, 50%, 75% and 100%); although risk of low back pain increased with time sitting, none of the risks were

statistically significant. Similar to the Hartvigsen review, Lis et al. (2007) found no significant associations between low back pain and sitting at work for more than half of the working day. This review also reported on the risk of low back pain in occupations that were exposed to whole body vibration (e.g. driving) and awkward postures (e.g. pilots). For occupations that involved whole body vibration and awkward postures, the risk of low back pain increased significantly. Two further reviews in 2009 (Chen et al.) and 2010 (Roffey et al.) also found no consistent evidence of an association between occupational sitting and risk of low back pain. These four papers reviewed studies that used a variety of definitions for occupational sitting; the majority of studies looked at sedentary occupations or the predominant categorical activity at work (i.e. *mostly sitting/standing*), some examined self-reported sedentary time, but the definitions of low and high differed greatly (e.g. <2 hours vs. ≥2 hours, and <6 hours vs. ≥6 hours). None of the studies used an objective measure of occupational sedentary behaviour. The aetiology of low back pain is complex (Frymoyer et al., 1983) and therefore it may be difficult to isolate sitting at work as one risk factor. The results from the Lis review (2007) suggest that it is those jobs that *don't* involve desk-related sedentary time that may be associated with an increased risk of low back pain; for example, a recent study found a non-significant association between objectively measured occupational sedentary time and low back pain in blue-collar workers (odds ratio 1.34, 95% CI (0.99 to 1.82); p=0.06) (Gupta et al., 2015). Conversely, results from studies that have looked at occupational sedentary time and neck pain have found that occupations that report low sitting during work have reduced neck and shoulder pain, compared to jobs with moderate sitting (Hallman, Gupta, Mathiassen, & Holtermann, 2015).

2.7 Summary of key findings

- There is currently no method that can quantify free-living sedentary behaviour that includes both posture and energy expenditure.

- For waist-worn accelerometers there is no empirically derived counts per minute cut-point for adults.

- It is important to have accurate measures of sedentary behaviour to determine the associations with health-related outcomes and for planning public health messages.

- A combination of a subjective measure and an objective measure is recommended for sedentary behaviour research studies, to collect both contextual and accurate data.

- For those who are economically active, the majority of daily sedentary time is accrued in the workplace, with higher levels of sedentary behaviour observed on weekdays compared to weekend days.

- It remains unclear as to the independent effects of sedentary behaviour and health, and the extent to which physical activity attenuates these.

- It has been suggested that sedentary time in the leisure and work domains may represent differing associations with health-related outcomes.

- There is limited evidence of a link between sedentary behaviour in the occupational domain and many health-related outcomes, despite the fact that occupational sedentary time makes up the majority of total daily sedentary time for those who are economically active.

- Associations that have been reported between occupational sedentary time and health-related outcomes are attenuated by markers of adiposity.

- It is important to look at domain specific sedentary behaviour to further our understanding of associations between sedentary behaviour and health-related outcomes.

Chapter 3 - Study to empirically derive accelerometer cut-points for sedentary behaviour: are we sitting differently?

"The important thing is not to stop questioning. Curiosity has its own reason for existing"

— Albert Einstein

Table 3.1   Overview of Chapter 3

Chapter	Aims, objectives and research questions	Methods
Chapter 2	**Aim:** To provide an overview of the literature and to critique the current evidence of sedentary behaviour and work, focussing on the prevalence of sedentary behaviour at work, and its association with health-related outcomes	Structured literature review using six electronic databases
Chapter 3	**Aim:** To empirically derive a new accelerometer cut-point to define sedentary behaviour in adults **Objective 1:** To empirically derive an optimal threshold for classifying sedentary behaviour, using the counts per minute output from the ActiGraph GT3X+ accelerometer, when compared to the sedentary classification from the activPAL™ accelerometer in a free-living environment **Objective 2:** To ascertain whether thresholds for sedentary behaviour cut-points vary by day of the week and in working time versus non-working time **Objective 3:** To derive optimal cut-points for different classifications of sedentary behaviour using contextual data from a 24-hour activity log, and to examine if there are differences between them	Observational study in university workers and postgraduate students (n=30) Application of generalised estimating equations to 1-minute epoch data for the ActiGraph GT3X+ and the activPAL™ data
Chapter 4	**Aim:** To describe the methodology for the Health Survey for England 2008, and a critique of the strengths and limitations of using secondary analysis	Description of data collection and processing
Chapter 5	**Aim:** To apply the cut-point from *Study One* to data from the Health Survey for England (2008), in order to investigate the associations between sedentary behaviour, work, and health-related outcomes **Objective 4:** To identify associations between workplace sedentary behaviour and health-related outcomes using the derived cut-point from *Study One* **Objective 5:** To examine if associations between workplace sedentary behaviour and health-related outcomes differ between occupational groups **Objective 6:** To determine if there are associations between workplace sedentary behaviour and mental ill-health and musculoskeletal disorders	A secondary data analysis of the Health Survey for England 2008 Application of hierarchical regression models – type of regression model dependent on distribution of each dependent variable (health-related outcome)
Chapter 6	**Aim:** To apply the cut-point from *Study One* to data from the Health Survey for England (2008), in order to investigate the associations between sedentary behaviour, work, and health-related outcomes **Objective 7:** To explore the patterning and sequences of sedentary bouts across the day, and the relationship with measures of adiposity and other health-related outcomes	Sequence analysis to describe the characteristics of time-related sequences of sedentary behaviour
Chapter 7	**Aim:** To discuss and critically appraise the studies within this thesis and to outline implications for policy and future research	Discussion and conclusions

3.1   Chapter Three overview

Chapter Three describes the rationale, methodology, and the results of a study to empirically derive a new ActiGraph accelerometer cut-point to define sedentary behaviour in adults, which addresses the first aim of this thesis.

This chapter firstly discusses the background and rationale for this study; secondly, it details the methodology with respect to the study design, data processing, and statistical analyses; comparisons are made to alternative statistical methods that have been previously used to derive or test accelerometer cut points for physical activity and sedentary behaviour. Thirdly, the results that address objectives one, two, and three are described (Table 3.1):

1. To empirically derive an optimal threshold for classifying sedentary behaviour, using the counts per minute output from the ActiGraph GT3X+ accelerometer, when compared to the sedentary classification from the activPAL™ accelerometer in a free-living environment.

2. To ascertain whether thresholds for sedentary behaviour cut-points vary by day of the week and in working time versus non-working time.

3. To derive optimal cut-points for different classifications of sedentary behaviour using contextual data from a 24-hour activity log, and to examine if there are differences between them.

This first study has been written up as one complete chapter, due to the unique methodology and statistical processes used. Part of the text in the background and

rationale, methodology, and results[30] sections of this chapter have been published in *Physiological Measurement* as "*Empirically derived cut-points for sedentary behaviour: Are we sitting differently?*" (Clarke-Cornwell et al., 2016); however, further specifics on data cleaning, data processing, data reduction rules, and statistical methods are included within this chapter. Permission to use this work as part of this thesis has been obtained from *Physiological Measurement* (Appendix 2).

3.2　　　**Study background and rationale**

3.2.1　　Sedentary behaviour and health-related outcomes

Sedentary behaviour (defined as any waking behaviour in a sitting or reclining position, with energy expenditure ≤1.5 METs (Sedentary Behaviour Research Network, 2012)) is associated with a number of health-related outcomes (Owen et al., 2010), including: metabolic syndrome risk factors (Hamilton, Hamilton, & Zderic, 2007; Stamatakis, Hamer, Tilling, & Lawlor, 2012); obesity (Hu et al., 2003); type 2 diabetes (Hu et al., 2003); back pain (Chen, Liu, Cook, Bass, & Lo, 2009); and mortality (in particular from cardiovascular disease and cancer) (Katzmarzyk et al., 2009; van der Ploeg et al., 2012). Many of these correlates of sedentary behaviour and health-related outcomes have been shown to be independent of moderate to vigorous physical activity levels (Owen et al., 2010). The extent to which this apparent effect of sedentary behaviour is an artefact of the way physical activity is incorporated into the analysis models is unclear, since a recent study that adjusted for total physical activity (including light physical activity) showed that sedentary behaviour was not an independent risk factor for cardiometabolic biomarkers

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[30] For objectives 1 and 2

(Maher et al., 2014). A compositional analysis by Chastin et al. (2015) showed that the distribution of time spent in sedentary behaviour, co-dependent with time spent sleeping, and in light- and moderate to vigorous physical activity, was associated with some, but not all cardiometabolic biomarkers. There is a need to improve how we measure sedentary behaviour and light physical activity.

3.2.2 Measuring sedentary behaviour

Many studies that have found associations between sedentary behaviours and health-related outcomes have primarily measured self-reported sedentary time based on leisure time (i.e. television time) (Thorp et al., 2010), or self-reported total sedentary time (Proper, Cerin, Brown, & Owen, 2007). Subjective measures of sedentary behaviour are limited by: underestimates of sedentary time (Clemes et al., 2012; Rosenberg et al., 2010); recall limitations in questionnaires; and tend to have 'low-to-moderate' validity compared to objective measures (Atkin et al., 2012). Objective measures of sedentary behaviour, such as those obtained from the use of accelerometer-based devices, including the ActiGraph and activPAL™ monitors (Dunstan, Kingwell, et al., 2012; Healy et al., 2016; Matthews et al., 2008), are able to examine duration, frequency and intensity of activities, including how much time is spent at a predetermined level of activity using different thresholds.

3.2.3 Describing sedentary behaviour objectively in populations

Matthews et al. (2008) were the first to describe time spent in sedentary behaviours using an objective measure of sedentary time for participants in the 2003-2004 wave of NHANES. The accelerometer-based device used in NHANES in the 2003-3004 survey was the ActiGraph 7164, with sedentary behaviour defined as less than 100 counts per minute. This cut-point was based on a study that defined sedentary behaviour thresholds in a sample of

adolescent girls (age 13-14 years old) (Treuth, Schmitz, et al., 2004). The aim of the study by Treuth et al. (2004) was to define a regression equation to estimate energy expenditure from ActiGraph counts using the ActiGraph 7164 device, and to define thresholds of these counts for different activity levels (including sedentary behaviour). Although the 100 counts per minute cut-point has been widely used in adult sedentary behaviour studies it should be noted that:

i. It was derived from an adolescent female population; it is known that activity behaviour differs between children and adults, with children and adolescents tending to carry out activity in short and sporadic bursts compared to adults (Carson et al., 2013; Welk, Corbin, & Dale, 2000), and total sitting time is known to increase as we get older (Matthews et al., 2008).

ii. It was derived from two screen-based leisure activities (TV viewing and playing computer games), which may not be representative of sedentary time in adults (Clark, Healy, et al., 2011).

iii. The counts from the study by Treuth et al. (2004) were recorded in 30 second epochs; the relationship between epoch length and cut-point is not linear, and it has been suggested that doubling count thresholds from 30 second to 60 second epochs, would lead to "considerable error in total estimates" (Aguilar-Farías et al. 2013, p. 297).

3.2.4   *Validity of the 100 counts per minute cut-point*

There are no widely agreed thresholds for sedentary behaviour, with limited evidence on the validity of the <100 cut-point (Rosenberg et al., 2010); the true extent of the misclassification of periods of physical behaviours (i.e. standing still) as sedentary time is

unclear (Clemes et al., 2012; Marshall et al., 2010). In a study of 20 overweight office workers (mean BMI 33.7 kg/m^2), Kozey-Keadle et al. (2011) suggested that 150 counts per minute may be a more appropriate cut-point to define sedentary behaviour, when compared to direct observation. This is comparable to an ActiGraph calibration study, by Lopes et al. (2009), which also found a higher threshold (200 counts per minute) for sedentary behaviour in obese and overweight patients (mean BMI 31.0 kg/m^2) (Lopes et al., 2009). In contrast, studies of older adults have found that a much lower threshold (<22 and <25 counts per minute respectively, based on the activPAL™ sedentary behaviour classification) may be more appropriate to define sedentary behaviour in older populations (Aguilar-Farías et al., 2013; Koster et al., 2016) (Figure 3.1). In addition, Crouter et al. (2006) proposed an arbitrary cut-point of 50 counts per minute to distinguish sedentary behaviour from light physical activity in a cohort of working-age adults (mean BMI 24.2 kg/m^2). These studies suggest that it may be appropriate to have different cut-points dependent on the contextual information of the population being studied, such as age, BMI and occupational group (Owen et al., 2010).
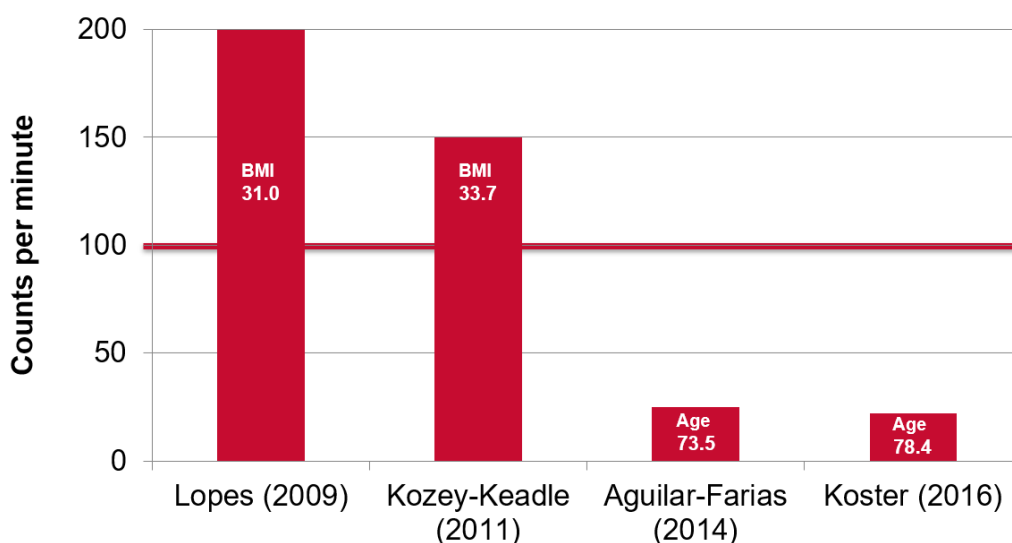
Figure 3.1   **Comparison of accelerometer cut-points for different sub-populations**

3.2.5 *Sedentary behaviour in different domains*

It has been suggested that sedentary time in the work and leisure domains may represent differing associations with health-related outcomes (Pinto Pereira et al., 2012; Saidj et al., 2013). Given that there is so much variation between the ActiGraph cut points derived for different populations, it is reasonable to assume that different contexts may also lead to different thresholds. There have been no empirically derived ActiGraph cut-points for sedentary behaviour in adults, and therefore the primary aim of this study was to empirically derive an optimal threshold for correctly classifying sedentary behaviour, using the counts per minute output from the ActiGraph GT3X+ accelerometer, when compared to the sedentary classification from the activPAL™ accelerometer in a free-living environment. It is important to be able to accurately measure sedentary behaviour on different days (i.e. work and non-work) (Proper et al., 2007), and also in different domains (i.e. working and non-working hours) (Clemes, O'Connell, et al., 2014; Thorp et al., 2012) in order that we can fully understand the consequences of how sedentary time is accrued and its correlates with health-related outcomes. Consequently, a subsequent aim was to ascertain whether thresholds for sedentary behaviour cut-points varied by day of the week, in working hours versus non-working hours, and within different sitting contexts.

3.3 Study methodology

3.3.1 *Methods*

A convenience sample of 30 employees/postgraduate students (healthy volunteers that spent most of their 'working day' sitting) from the University of Salford was asked to participate in the study. Volunteers self-reported that their work role was 100% office-based work, mostly on a computer. Prior to study commencement, ethical approval was

granted by the College of Health and Social Care Ethical Approval Panel, the University of Salford; application number HSCR14/10 (Appendix 3).

Accelerometers

This study involved participants wearing two accelerometer-based devices simultaneously for seven days:

- The ActiGraph GT3X+ accelerometer is a small (4.6x3.3x1.5cm), light-weight (19g) instrument that records acceleration in the vertical, anteroposterior and medio-lateral axes, worn at the waist (ActiGraph LLC, Pensacola, Florida) (Figure 3.2). To ensure the outcomes of this study were analogous with other generations of ActiGraph devices, only the accelerations on the vertical axis were analysed (Matthews et al., 2008; Stamatakis, Hamer, et al., 2012; Thorp et al., 2012).

Figure 3.2 **Photographs of a hip-worn ActiGraph GT3X+ attached to a belt (ActiGraph LLC., 2019. [Online]. Available from: www.actigraphcorp.com/ actigraph-wgt3x-bt/)**

The activPAL3™ is a small, light-weight (15g) accelerometer-based device that is attached to the anterior aspect of the thigh (PAL Technologies Ltd, Glasgow, Scotland). Data from this instrument classifies activities into sedentary (sitting/lying), standing and stride events, using proprietary algorithms (Chastin & Granat, 2010; Edwardson, Winkler, et al., 2016) (Figure 3.3).

Figure 3.3 **Photographs of a thigh-worn activPAL3™ (Author's personal collection)**

Procedure

Participants were asked to wear the ActiGraph GT3X+ and the activPAL3™ devices, simultaneously for seven days. The ActiGraph GT3X+ was worn during all waking hours and removed overnight; the activPAL3™ was worn continuously for 24 hours a day and was only removed for bathing or swimming. The ActiGraph GT3X+ was worn on the right hip (on the midaxillary line), attached with an adjustable belt; the activPAL3™ was attached to the front (middle-anterior line) of the right thigh (with a hypoallergenic double-sided adhesive pad). Height and weight were self-reported and used to calculate body mass index.

Participants were asked to fill in a detailed activity diary with designated fields to record their sleeping hours; they were also asked to record their working hours, and if either accelerometer was removed, the time it was removed and the reason it was removed. The diary was printed in booklet form with a separate page for each day of the study: a page from the activity diary is shown in Figure 3.4.

Date: _____

Time woke up: _____

Time started work/university: _____

Time finished work/university: _____

Time went to sleep: _____

Please provide details here of any times that you have been swimming or cycled today:

activPAL™ (thigh placed accelerometer)	ActiGraph (waist placed accelerometer)
Time removed: _____ Time put back on: _____ Reason: _____	Time removed: _____ Time put back on: _____ Reason: _____
Time removed: _____ Time put back on: _____ Reason: _____	Time removed: _____ Time put back on: _____ Reason: _____
Time removed: _____ Time put back on: _____ Reason: _____	Time removed: _____ Time put back on: _____ Reason: _____

Figure 3.4   Example page from the activity diary

The information from the diary was used to determine sleep time (and conversely waking time), wear time, and non-wear time, as these factors are important when describing sedentary behaviour alongside the time-stamped data from the accelerometers (Healy et al., 2008, 2011; McCrady & Levine, 2009; Owen et al., 2010). Instructions on how to complete the diary were included at the front of the activity diary (Appendix 4).

For one work day, each participant was asked to fill out a detailed activity diary; this was adapted from the Bouchard Activity Record (Bouchard et al., 1983) (see Section 2.1.1.1 for further details). In brief, the Bouchard Activity Record is a self-reported activity log that

consists of a table with each cell representing 15-minute intervals over a 24-hour period: each behaviour is given a numeric assignment from 1 to 9, ranging from less intensive behaviours (e.g. lying, sleeping) to more moderate and vigorous behaviours (e.g. running). The sitting category was sub-divided to record sitting in different contexts[31]. Participants were asked to record the *primary* activity performed during each 15-minute interval of the day (see Appendix 4 for the detailed activity log and accompanying activity codes).

A participant information sheet was sent to each participant at least 24-hours before receiving the accelerometers (Appendix 6): participants were also asked to complete a consent form (Appendix 7). The accelerometers were initialised and set to record for seven days, to start at midnight on the day that they were given out; the participants were shown how to wear both accelerometers and were given verbal instructions on how to fill out the activity diary.

3.3.2   Accelerometer accuracy

The manufacturers of both accelerometers state that calibration is not required; however, the devices used for the study were checked for accuracy before the study commenced, i.e. that they recorded what they intended to record, and in the case of the ActiGraph GT3X+ devices, that the counts per minute were consistent between the devices.

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[31] Watching television, cinema etc.; Sitting at work whilst using a computer; Sitting at work, not using a computer (i.e. sitting at a desk, in a meeting); Sitting at home whilst using a computer, playing a video game etc.; Relaxing but in a sitting position e.g. listening to music, reading; Driving a car; Sitting on public transport or in a car (not as the driver); Eating, social sitting (e.g. eating at home/work/restaurant, having coffee, chatting); Cycling; Sitting other

3.3.2.1   ActivPAL3™ accuracy

The 15 activPAL3™ devices available for this study were checked for accuracy in terms of the postural output according to the manufacturer's manual; firstly, they were all kept upright (vertical) for 24 hours and the output checked for any spurious data; secondly, they were kept flat (horizontal) for one hour, then turned upright (vertical) for one hour. Both tests showed 100% accuracy in terms of the correct postural output (either *sedentary* or *upright*).[32] A sports laboratory-based test was also established to check the accuracy of the three main outputs from the activPAL3™ of sedentary, standing, and stepping. Up to six activPAL3™ devices were attached to the front (middle-anterior line) of both thighs of a PhD student at the University of Salford (with hypoallergenic double-sided adhesive pad) (Figure 3.5).

Figure 3.5   **Photograph of accelerometer accuracy testing placement for the activPAL3™ device (Author's personal collection)**

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[32] Although the reliability and validity of the activPAL™ has been widely documented (Grant et al., 2006; Ryan et al., 2006), the tests here are specific to the accuracy of the devices in this study.

The student was asked to perform two minutes of walking, two minutes of sitting, and two minutes of standing, and then asked to repeat these activities, resulting in 12 minutes of data for each device (Dahlgren, Carlsson, Moorhead, Häger-Ross, & McDonough, 2010): the start and end time of each activity was noted. The "Events" file that can be downloaded from the activPAL3™ software contains precise information on each sedentary bout, standing bout, and each step, including start time and duration of the event. The "Events" file was checked for each activPAL3™ device to confirm the activities recorded within the 12 minutes of testing. All 15 activPAL3™ devices had 100% accuracy in recording the correct activity for each two-minute period.

3.3.2.2   ActiGraph GT3X+ accuracy

The ActiGraph GT3X+ devices were checked for accuracy using the Kin-Com isokinetic dynamometer main lever in the sports laboratory at the University of Salford. The output from the ActiGraph GT3X+ of counts per minute, relates directly to the acceleration of the device in the vertical axis through proprietary algorithms. It was not possible to check the accuracy of the raw acceleration counts for this study using standard methods[33]; however, accuracy was checked in terms of each accelerometer recording the same counts per minute, when placed under the same conditions. The Kin-Com isokinetic dynamometer is primarily used for measuring force, whilst simultaneously measuring (or controlling)

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[33] The reliability of counts from ActiGraph devices can be tested on a hydraulic shaker plate (Esliger & Tremblay, 2006), set at specified accelerations; however, the University of Salford did not have access to a hydraulic shaker plate.

velocity: the main lever can be set to move through angles at a pre-specified speed (degrees per second).

The six ActiGraph GT3X+ devices available for this study were tested on three separate occasions in the sports laboratory. For each test the lever arm on the Kin-Com was set to move through 90 degrees (downwards, from a horizontal to a vertical position) in three seconds, and back to the horizontal in three seconds; this was repeated 200 times over 20 minutes for each device. Each device was attached to the Kin-Com main lever, with the USB connector facing upwards, 27 centimetres from the top of the lever (Figure 3.6).
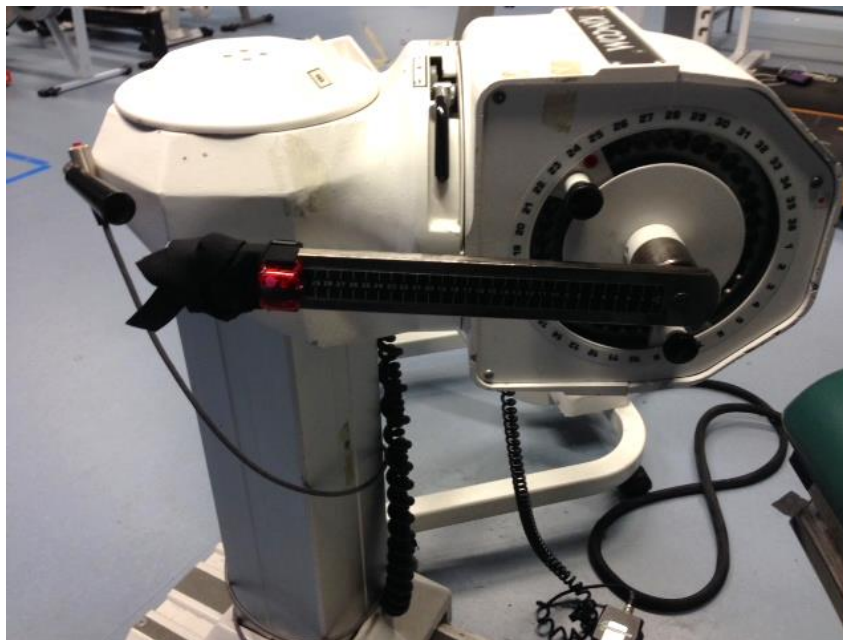
Figure 3.6   **Accuracy testing of the ActiGraph GT3X+ accelerometer, using the Kin-Com dynamometer**

The first and last minute of data were removed from the analysis, and the percentage difference in average counts per minute was compared between each accelerometer. Some variation was expected due to the angle setting precision of the Kin-Com dynamometer; the angle is set to *whole* degrees only, and therefore the angle set for each test could range from 89.5° to 90.4°. The results from the first testing period showed that

the average counts per minute for five of the ActiGraph devices were comparable to within 5% of one another; however, one device had an average count that was 20% lower than the other five devices. The second and third testing periods found that all six devices had very good between-device reliability with differences of less than 5% seen; there was no obvious explanation as to why differences were seen in one of the devices during the first testing period. It was decided not to include this device for this study, in case there was an intermittent fault. Differences within each device across the three testing periods were also compared; there were no differences in the average counts per minute for each device between the three testing periods, with the exception of the device that had shown differences in the between-device tests.

3.3.3   Data cleaning and data reduction

Despite the increasing use of accelerometers in sedentary behaviour research, there is a lack of consensus as to the most appropriate way to process, clean and remove non-wear time, commonly referred to as data reduction (Atkin et al., 2012; Edwardson, Winkler, et al., 2016; Mâsse et al., 2005) (Section 2.1.4).

3.3.3.1   Data processing

The data from both accelerometers were downloaded from each manufacturer's software programs, and imported into Stata, where all data cleaning, reduction and analysis was carried out (StataCorp. 2013. *Stata Statistical Software: Release 13.* College Station, TX: StataCorp LP).

The data from the ActiGraph GT3X+ device were downloaded using the ActiLife v5.10.0 software by ActiGraph, using the low filter extension for 60 second epochs. Using the low

filter extension allows greater comparability to older models of the ActiGraph (Cain, Conway, Adams, Husak, & Sallis, 2013).[34] The data from the proprietary *agd*[35] files were exported as a *csv* file and viewed in Excel. Figure 3.7 shows an extract of the data from the ActiGraph GT3X+, for one participant over 10 minutes. The file is date and time-stamped (*Date* and *Time* columns), in one-minute epochs and the counts per minute are contained in the *Axis1, Axis2,* and *Axis3* columns; the other variables are immaterial for this study and have not been used in the analysis. Only the counts per minute from the vertical axis (*Axis1*) were transferred to Stata along with the *Date* and *Time* variables.

	A	B	C	D	E	F	G	H	I
1	Date	Time	Axis1	Axis2	Axis3	Steps	Lux	Inclinometer	Vector Magnitude
655	12/04/2014	10:52:00	2	2	11	3	0	3	11.36
656	12/04/2014	10:53:00	21	55	30	8	0	3	66.08
657	12/04/2014	10:54:00	57	120	33	0	0	3	136.89
658	12/04/2014	10:55:00	117	247	35	5	0	3	275.54
659	12/04/2014	10:56:00	77	70	53	5	0	3	116.78
660	12/04/2014	10:57:00	151	209	88	6	0	3	272.44
661	12/04/2014	10:58:00	7	6	2	10	0	3	9.43
662	12/04/2014	10:59:00	167	251	78	10	0	3	311.41
663	12/04/2014	11:00:00	6	2	0	7	0	3	6.32
664	12/04/2014	11:01:00	199	151	136	14	0	3	284.43

Figure 3.7   Extract of ActiGraph GT3X+ counts per minute data

The data from the activPAL3™ device were downloaded using the activPAL3™ v7.2.29 software by PAL Technologies. Figure 3.8 shows an extract of the data from the "Events" file (as a *csv* file) from the activPAL3™, for one participant for ten bouts of behaviour. The *ActivityCode* variable is coded as 0 for sedentary, 1 for standing, and 2 for stepping. For example, line 2 shows that the device became active at 23:59:48.0 and for the following 32829.8 seconds the activity was coded as sedentary (most likely the participant was

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[34] This includes the GT1M model that was used in the Health Survey for England 2008; the data from the Health Survey for England 2008 are used in subsequent chapters of this thesis.
[35] ActiGraph data file: file type compatible with ActiLife software

sleeping); at 09:06:57.8 the device recorded a standing activity for 47.1 seconds. The variables of *Time*, *Interval (s)* and *ActivityCode* were transferred to Stata for data cleaning. The "Events" file data were used in preference to the summary *csv* data files available from the activPAL software, as these provide more precise information with respect to the chronological order in which the activity events occurred.

	A	B	C	D	E	F	G
1	Time	DataCount (samples)	Interval (s)	ActivityCode	CumulativeStepCount	Activity Score (MET.h)	Abs(sumDiff)
2	11/04/2014 23:59:48.0	0	32829.8	0	0	11.39924	4986
3	12/04/2014 09:06:57.8	328298	47.1	1	0	1.83E-02	1510
4	12/04/2014 09:07:44.9	328769	4	2	1	2.28E-03	183
5	12/04/2014 09:07:48.9	328809	5.9	2	2	3.02E-03	274
6	12/04/2014 09:07:54.8	328868	9.6	1	2	3.73E-03	535
7	12/04/2014 09:08:04.4	328964	5	2	3	2.67E-03	275
8	12/04/2014 09:08:09.4	329014	8.4	1	3	3.27E-03	569
9	12/04/2014 09:08:17.8	329098	4.4	2	4	2.43E-03	406
10	12/04/2014 09:08:22.2	329142	22.5	1	4	0.00875	685

Figure 3.8   **Extract of activPAL™ raw data**

3.3.3.2   Data cleaning

The data from the activPAL3™ were in a different format to the ActiGraph GT3X+ data in terms of the time variable. The activPAL3™ records data in tenths of seconds, and therefore the data from the "Events" file needed to be expanded (in tenths of seconds), before being collapsed (to minutes), so that it could be matched to the ActiGraph GT3X+ data. In brief, the following cleaning process was written and executed in a Stata command file:

i.   Starting with the activPAL3™ data: the activPAL3™ device starts and finishes a few seconds before the initialised time, and these times were removed from the file

ii. The file was expanded to 604,800,000 rows of data for each participant (corresponding to the number of milliseconds in one week, since Stata records time in milliseconds)

iii. The file was collapsed so that each row of data was the equivalent of one minute (10,080 minutes in one week)

iv.   The seconds of activity (sedentary, standing, active) were summed from the milliseconds that made up each minute

v.   Lastly, the minute by minute data from the ActiGraph GT3X+ files were matched to the activPAL3™ file using the *Time* variables downloaded from each device

3.3.3.3   *Removal of non-wear time*

Mâsse et al. (2005) reviewed decision rules for accelerometer reduction, for four reduction algorithms used in physical activity research. They concluded that;

> *... the decision rules employed to process accelerometer data have a significant impact on important outcome variables. Until guidelines are developed, it will remain difficult to compare findings across studies. (p. S544)*

Five questions relating to data processing were proposed that should be considered in accelerometer data reduction. Some of these questions are not relevant to this study as they relate to studies where the monitoring period is important in relation to predicting an *average* sedentary time, or where *habituation* of sedentary behaviour should be considered. This study was concerned with deriving a cut-point for sedentary behaviour from the ActiGraph GT3X+ device, and therefore the data used in the analysis were not subject to some of these data processing rules; it was more important that the data were as *clean* as possible in terms of true wear time. Therefore, the issue of identifying wearing periods and the subsequent questions are considered in this section. Mâsse et al. (2005, p. S545) proposed the following two questions in relation to identifying wearing periods for accelerometers in physical activity research, which also apply to sedentary behaviour research:

1. *How do we measure or estimate interruption in wearing time during the day?*

2. *If diary information is collected, what algorithm should be used to identify when the accelerometer is assumed to be removed, given that time stamped in a diary does not always match the accelerometer time?*

Identifying non-wear times from participants needs to be considered as it can be difficult to distinguish between true periods of inactivity and periods when an accelerometer was removed (Edwardson, Winkler, et al., 2016; Mâsse et al., 2005). For this study, participants were asked to fill in an activity diary and state what times either accelerometer was removed for sleeping, shower/bathing, swimming, contact sports, and also periods of cycling, as accelerometers may not accurately measure this type of behaviour (Colley et al., 2011). The accuracy of the times in activity diaries is not known, and therefore current algorithms used for sedentary behaviour data reduction with respect to removing non-wear time have been considered alongside the data from the activity diaries.

The most commonly used algorithm for detecting and deleting non-wear time for ActiGraph data was designed to detect non-wear time during waking hours in NHANES (Troiano et al., 2008). Non-wear time was defined for one-minute epochs, where 60 consecutive minutes of zero counts on the vertical axis were recorded; allowing for up to two consecutive minutes of counts ranging from 1 to 100. Other studies have defined non-wear time using bouts of zero counts of as little as 10 minutes in children (Brage et al., 2004; Eiberg et al., 2005; Ekelund, Yngve, Brage, Westerterp, & Sjostrom, 2004; Riddoch et al., 2004), 15 minutes in pregnant women (Rousham, Clarke, & Gross, 2006), 20 minutes in women and adolescent girls (Evenson & Terry, 2009; Treuth, Sherwood, et al., 2004), 60 and 90-minutes in adults (Choi et al., 2011; Matthews et al., 2008; Troiano et al., 2008),

and up to 180 minutes in adolescents (Van Coevering et al., 2005). However, Chen and Troiano (2017) found that a 60-minute bout of zero counts was more accurate compared to shorter bouts of zeros that produced a higher than expected number of non-wear episodes using NHANES accelerometer data.

There are no commonly used non-wear algorithms for activPAL3™ data. Some studies have classified long periods of sedentary time (i.e. >3 hours) as non-wear time (Barreira et al., 2016), and a newly developed algorithm has been developed to isolate waking time from 'sleep' (time in bed), which incorporates the exclusion of long periods of sedentary time (≥ 2-hours) (Winkler et al., 2016). In studies that have reported the frequency of bouts of different lengths, the proportion of sedentary bouts greater than 120-minutes is rare (Ryan, Dall, Granat, & Grant, 2011; Smith et al., 2015).

3.3.3.4   Data reduction rules

A number of decision rules were devised to ensure that the data used in the analysis of this study were as *clean* as possible. This led to some *aggressive* decision rules compared to previously published non-wear time algorithms; however, because the aim of this study was to derive a new counts per minute threshold for sedentary behaviour derived from the ActiGraph GT3X+ accelerometer, and not to assess sedentary time across the day, it was the quality of the data that was deemed to be important and not the number of minutes included. The following data reduction rules for removing non-wear time were written into the Stata command file as part of the data cleaning process.

The rules for deleting non-wear time were as follows:

i. Firstly, each participant's data were manually checked alongside their activity diaries and data were deleted for the following reasons:

    a. Participants did not always state at what time they began wearing both[36] devices each day, and therefore the first movement of each device each was considered as a participant attaching the device in the morning and the converse in the evening. When the devices were attached in the morning, the first five minutes after the second device was attached were deleted. Two examples are shown in Figure 3.9 and Figure 3.10. The variables *sedentary, standing,* and *active* contain the number of seconds recorded as such from the activPAL3™, and the variable *axis1* are the counts per minute from the ActiGraph GT3X+.

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[36] The participant information sheet for this study stated for the activPAL™ to be worn for 24 hours; however, many participants chose to wear it during waking hours when they were also wearing the ActiGraph GT3X+.

	time	sedentary	standing	active	axis1
567	29may2014 09:26:00	60	0	0	0
568	29may2014 09:27:00	60	0	0	0
569	29may2014 09:28:00	60	0	0	0
570	29may2014 09:29:00	60	0	0	0
571	29may2014 09:30:00	60	0	0	0
572	29may2014 09:31:00	60	0	0	0
573	29may2014 09:32:00	60	0	0	0
574	29may2014 09:33:00	60	0	0	0
575	29may2014 09:34:00	60	0	0	0
576	29may2014 09:35:00	60	0	0	0
577	29may2014 09:36:00	60	0	0	993
578	29may2014 09:37:00	44	16	0	128
579	29may2014 09:38:00	0	52.7	7.3	0
580	29may2014 09:39:00	0	57.2	2.8	1178
581	29may2014 09:40:00	0	60	0	492
582	29may2014 09:41:00	26.3	32.5	1.2	140
583	29may2014 09:42:00	60	0	0	0
584	29may2014 09:43:00	60	0	0	1
585	29may2014 09:44:00	60	0	0	0
586	29may2014 09:45:00	60	0	0	0

Figure 3.9   **Deletion of epochs in the morning (a)**

For the participant in Figure 3.9, the activity diary stated a wake-up time of 09:15, but the ActiGraph GT3X+ had zero counts until 09:36, and the activPAL3™ had full sedentary minutes until 09:37. Because the activPAL3™ was the second device to be attached, the first five minutes were deleted, and therefore epochs before 09:42 were deleted from this day's data.

Figure 3.10 shows an example of when the activPAL3™ was attached before the ActiGraph GT3X+ device. There was some movement of the activPAL3™ at 08:09, and the first non-zero count from the ActiGraph GT3X+ was at 08:11. The first five minutes of wearing, with both accelerometers attached were deleted, and therefore epochs before 08:16 were excluded from the analysis.

	time	sedentary	standing	active	axis1
1922	30may2014 08:01:00	60	0	0	0
1923	30may2014 08:02:00	60	0	0	0
1924	30may2014 08:03:00	60	0	0	0
1925	30may2014 08:04:00	60	0	0	0
1926	30may2014 08:05:00	60	0	0	0
1927	30may2014 08:06:00	60	0	0	0
1928	30may2014 08:07:00	60	0	0	0
1929	30may2014 08:08:00	60	0	0	0
1930	30may2014 08:09:00	50.7	7.7	1.6	0
1931	30may2014 08:10:00	18.3	41.7	0	0
1932	30may2014 08:11:00	0	38.1	21.9	932
1933	30may2014 08:12:00	54.9	2.8	2.3	422
1934	30may2014 08:13:00	27.8	32.2	0	141
1935	30may2014 08:14:00	0	52	8	293
1936	30may2014 08:15:00	0	41.9	18.1	540
1937	30may2014 08:16:00	0	52.1	7.9	211
1938	30may2014 08:17:00	0	55.8	4.2	206
1939	30may2014 08:18:00	0	29.3	30.7	632
1940	30may2014 08:19:00	14.4	21.6	24	486
1941	30may2014 08:20:00	60	0	0	0

Figure 3.10   Deletion of epochs in the morning (b)

This was repeated for each participant each morning and evening; some participants put the devices on quite soon after waking up, some stated they put it on after showering, and other participants chose to write the time they attached both devices and not what time they woke up. Figure 3.11 shows the data of a participant who recorded in their activity diary that they went to bed at 21:00. From the data, it appears that the ActiGraph GT3X+ was removed at 20:59, and the activPAL3™ one minute later. Since the ActiGraph GT3X+ was removed first, the five minutes *before* the time it was seen to be taken off were deleted; in this example, the time from 20:54 until the participant put both devices on the next day was removed.

	time	sedentary	standing	active	axis1
1251	04jun2014 20:50:00	60	0	0	0
1252	04jun2014 20:51:00	60	0	0	0
1253	04jun2014 20:52:00	60	0	0	162
1254	04jun2014 20:53:00	54.2	5.8	0	411
1255	04jun2014 20:54:00	0	38.7	21.3	500
1256	04jun2014 20:55:00	0	14.5	45.5	1006
1257	04jun2014 20:56:00	0	60	0	387
1258	04jun2014 20:57:00	31.2	28.8	0	273
1259	04jun2014 20:58:00	0	51.4	8.6	715
1260	04jun2014 20:59:00	0	44.8	15.2	1405
1261	04jun2014 21:00:00	50.6	1	8.4	0
1262	04jun2014 21:01:00	60	0	0	0
1263	04jun2014 21:02:00	60	0	0	0
1264	04jun2014 21:03:00	60	0	0	0
1265	04jun2014 21:04:00	60	0	0	0
1266	04jun2014 21:05:00	60	0	0	0

Figure 3.11   Deletion of epochs in the evening

b. The process described in part (a) above was repeated for each instance that the accelerometers were removed and recorded in the activity diary. As well as sleeping, people recorded times when they took the accelerometers off for showering/bathing, swimming, private appointments, or going out for the evening socially.

c. There were also a number of instances when the accelerometers were worn, but the results could likely bias the outcomes of this study. For example, accelerometers do not currently, accurately measure the activity levels of cycling, but it was difficult to see cycling periods from the clean data. Figure 3.12 shows an example of a cycling period with both accelerometers being worn.

	time	sedentary	standing	active	axis1
5381	15apr2014 17:40:00	0	0	60	5448
5382	15apr2014 17:41:00	0	0	60	5483
5383	15apr2014 17:42:00	0	0	60	4707
5384	15apr2014 17:43:00	0	19.4	40.6	1836
5385	15apr2014 17:44:00	0	34.3	25.7	526
5386	15apr2014 17:45:00	0	40.2	19.8	516
5387	15apr2014 17:46:00	0	46.1	13.9	368
5388	15apr2014 17:47:00	0	26.4	33.6	385
5389	15apr2014 17:48:00	0	0	60	539
5390	15apr2014 17:49:00	0	0	60	502
5391	15apr2014 17:50:00	31.9	15.2	12.9	78
5392	15apr2014 17:51:00	25.1	8.1	26.8	171
5393	15apr2014 17:52:00	0	0	60	682
5394	15apr2014 17:53:00	0	4	56	625
5395	15apr2014 17:54:00	36.9	19	4.1	91
5396	15apr2014 17:55:00	0	37	23	308
5397	15apr2014 17:56:00	0	20	40	238
5398	15apr2014 17:57:00	0	41.3	18.7	82
5399	15apr2014 17:58:00	0	45.9	14.1	455
5400	15apr2014 17:59:00	0	8.2	51.8	746
5401	15apr2014 18:00:00	0	35.7	24.3	288
5402	15apr2014 18:01:00	0	54.7	5.3	235
5403	15apr2014 18:02:00	0	45.3	14.7	848
5404	15apr2014 18:03:00	0	37.3	22.7	797
5405	15apr2014 18:04:00	0	45.4	14.6	812
5406	15apr2014 18:05:00	38.5	9.6	11.9	891
5407	15apr2014 18:06:00	0	46.9	13.1	137
5408	15apr2014 18:07:00	0	48.9	11.1	331
5409	15apr2014 18:08:00	0	47.9	12.1	298
5410	15apr2014 18:09:00	0	60	0	285
5411	15apr2014 18:10:00	0	60	0	678

Figure 3.12   Cycling wear time deletion (self-reported cycling time highlighted)

The activity diary stated that there was a period of cycling (home from work) from 17:50-18:00 (see highlighted rows in Figure 3.12). It is difficult to gauge from the data when the period of cycling began and ended; therefore, for any periods of cycling, the 10 minutes before and the 10 minutes after the stated period were also deleted. For this example of a cycling period, data from 17:41 to 18:10 inclusive were removed.

d. The process described in part (c) was repeated for times in the activity diary that were recorded for times when the activPAL3™ had fallen off, readjusting either accelerometer, going to the gym, or being at a theme park.

ii. Secondly, the Troiano algorithm was used to determine further non-wear time from the ActiGraph GT3X+ data (Troiano et al., 2008); non-wear time was defined as 60 consecutive minutes of zero counts, allowing for up to two consecutive minutes of counts ranging from 1 to 100. The ActiLife software has the Troiano algorithm as one of its data reduction options; however, this is available for use on the *agd* files and could not be used on the data after the reduction methods in part (i) had been processed due to the different formats of the data. Therefore, an automated programme was written in Stata based on the SAS[37] code available from NHANES (National Cancer Institute, n.d.), in order to replicate the Troiano algorithm (see Methods, Section 4.3.3).

iii. Thirdly, activPAL3™ non-wear time was considered. It was imperative for this study that both accelerometers were worn at the same time. Part (ii) above, deleted non-wear time derived from the ActiGraph GT3X+ device by looking at consecutive zero counts. For the activPAL3™, consecutive minutes of sedentary time (equal to 60 seconds defined as sedentary for each epoch) were considered. Figure 3.13 shows the distribution of the lengths of sedentary bouts in this study; the number of bouts greater than 120 minutes was extremely low, similar to previous studies (Ryan et al., 2011; Smith et al., 2015; Winkler et al., 2016); therefore, sedentary bouts longer than 120

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[37] Statistical Analysis System (SAS) is a statistics and analytics software suite https://www.sas.com/en_us/home.html

minutes were also assumed to be non-wear time, and removed within the Stata command file used throughout the data cleaning process. It is not known (without direct observation) whether these bouts were prolonged periods of sedentary time or non-compliance; however, for this study, the aggressive method of data reduction did not impact on the interpretation of the results.
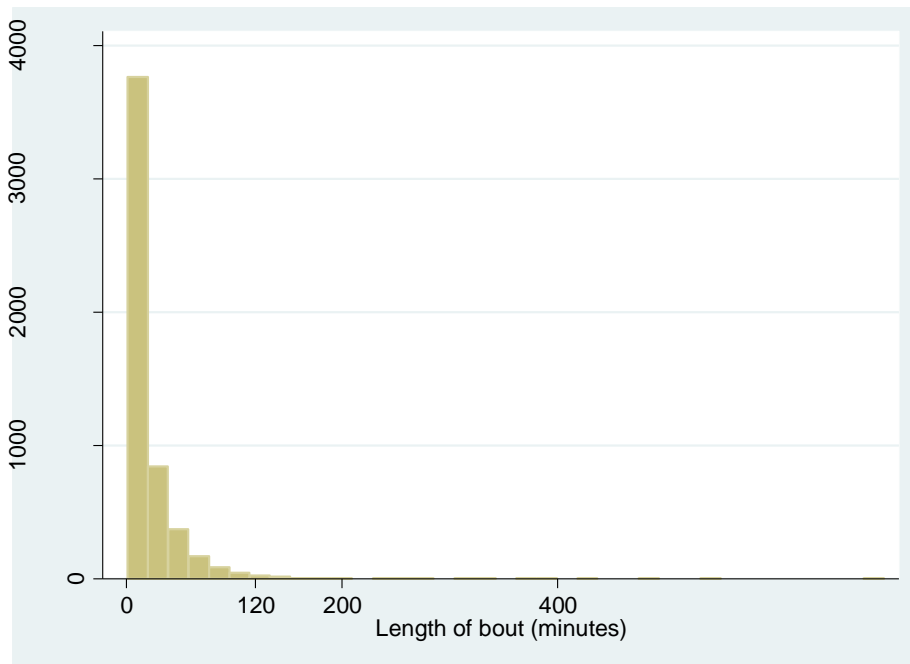
Figure 3.13   Distribution of length of sedentary bouts

iv.   Lastly, spurious data of over 15,000 counts per minute from the ActiGraph GT3X+ device were considered (Esliger et al., 2005).

An example of the distribution of the counts per minute data, after data cleaning and reduction is shown in Figure 3.14. These data show the counts per minute from the ActiGraph GT3X+ accelerometer across the waking hours for one participant, on one working day. There are four periods of non-wear time that are marked with an **X**; from the corresponding diary entries the first and second periods of non-wear are cycling to and from work, the third is when the activPAL3™ fell off for a few minutes, and the fourth corresponds to the participant having a shower. The high spike in counts after returning

home from work is consistent with a period of physical activity (running) that the participant had also recorded.
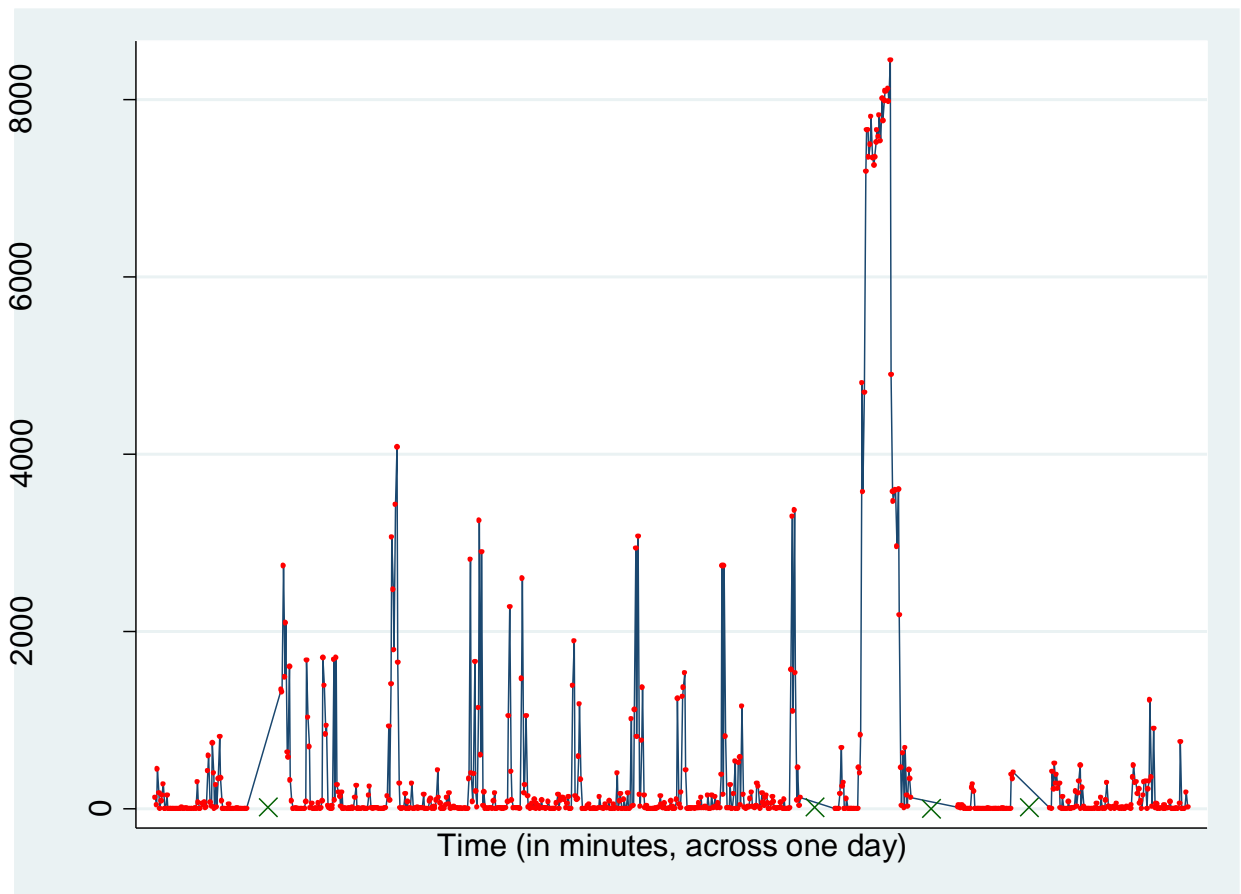
Figure 3.14   **Example of distribution of counts per minute across time (minutes), after data reduction**

3.3.4   Statistical analysis methodology

This section introduces the statistical methods used in this study, which first presents some of the basic concepts of regression; Sections 3.3.4.2 to 3.3.4.5 outline the more complex regression models used.

3.3.4.1   Linear regression

The relationship between two linear variables, for a sample size n, can be described mathematically as:

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i , \qquad\qquad i = 1, \ldots., n$$

where the following component parts equate to:

- y_i is the dependent (outcome) variable

- x_i is the independent (exposure) variable

- β_0 is the intercept term

- β_1 is an unknown constant (i.e. the coefficient of the independent variable)

- ε_i is the error term

A simple linear regression model predicts the value of the dependent variable from the independent variable and assumes that this relationship is linear. When there is more than one independent variable, the linear regression model can be expressed as:

$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots \beta_p x_{ip} + \varepsilon_i$, for p independent variables. This equation can also be written in vector form:

$$\begin{pmatrix} y_1 \\ y_2 \\ \vdots \\ y_n \end{pmatrix} = \begin{pmatrix} \beta_0 \\ \beta_0 \\ \vdots \\ \beta_0 \end{pmatrix} + \begin{pmatrix} x_{11} & \cdots & x_{1p} \\ x_{21} & \cdots & x_{2p} \\ \vdots & \ddots & \vdots \\ x_{n1} & \cdots & x_{np} \end{pmatrix} \begin{pmatrix} \beta_1 \\ \beta_2 \\ \vdots \\ \beta_p \end{pmatrix} + \begin{pmatrix} \varepsilon_1 \\ \varepsilon_2 \\ \vdots \\ \varepsilon_n \end{pmatrix}$$

The shorthand for this vector form is $\boldsymbol{y} = \mathbf{X}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$, (Konishi, 2014).

3.3.4.2   Non-linear regression

When the relationship between two variables is not linear, a parametric non-linear regression is used to model the dependent variable as a *function* of the independent variables. When there is more than one independent variable, the relationship can be described as:

$\boldsymbol{y} = F(\mathbf{X}\boldsymbol{\beta}) + \boldsymbol{\varepsilon}$, where F can take the form of any nonlinear function; for example, exponential functions, logarithmic functions, trigonometric functions, and power functions (Konishi, 2014).

3.3.4.3 Choosing a regression model

For this study, the dependent variable of counts per minute from the ActiGraph GT3X+ accelerometer, can be modelled by the independent variable of time (in one-minute epochs) and whether that epoch is defined as sedentary or not, classified as 60-seconds of sedentary time from the activPAL3™ accelerometer.

The numerous data points of counts per minute for each participant (a maximum of 10,080 across a week) are likely to be autocorrelated (Nelson-Wong, Howarth, Winter, & Callaghan, 2009; Tryon, 2011); for example, the counts per minute from time t, are likely to be closely related with the counts per minute from times $t - 1$ and $t + 1$, especially for sedentary bouts. In other words, if any given minute is sedentary, the minute before and the minute after are also likely to be sedentary: this hypothesis is consistent with a study by Dowd et al. (2012), which found that less than 1% of daily sedentary time was accumulated in bouts of less than one minute, with 96% of sedentary time accumulated in periods of greater than six minutes. Similarly, in a study of 83 office workers, 20% of sitting events, equating to 67% of sedentary time, were accumulated in sitting bouts of 20 minutes or greater (Ryan et al., 2011).

To account for this correlation of counts per minute and time, generalised estimating equations (GEEs) were considered the most appropriate regression method. GEEs extend standard regression techniques (Liang & Zeger, 1986), and are readily being applied to epidemiological studies (Hanley, 2003). One of the assumptions of GEEs is that of linearity

of the outcome variable over time; however, the outcome variable (counts per minute) in this study is not linear with time (see Figure 3.14). These changes over time can be accounted for using multivariable fractional polynomials with the GEEs (Royston & Sauerbrei, 2005). Therefore, the following two sections will describe the methodology of GEEs and multivariable fractional polynomials, with respect to this study.

3.3.4.4   *Generalised estimating equations*

Generalised estimating equations were first introduced by Liang and Zeger (1986), and are an extension of generalised linear models. They are used to model correlated data and expect successive measurements to be correlated. GEEs take into account the within-subject correlation between measurements, whilst also making use of all available data. An advantage of GEE analysis over standard regression techniques is that they are designed specifically for analysis of repeated measures. GEEs are flexible models that don't hold any assumptions about the distribution of the dependent variable, compared to methods based on likelihood that require the distribution of the outcome variable to be specified (Liang & Zeger, 1986; Zeger & Liang, 1986).

The generalised estimating equation can be described mathematically, for a sample size n, over n_i time points:

$$g\{E(\boldsymbol{y}_{ij})\} = \mathbf{X}_{ij}\boldsymbol{\beta}, \qquad y \sim \text{F}, i = 1, \ldots., n \text{ and } j = 1, \ldots., n_i$$

where the following component parts equate to:

- $\boldsymbol{y}_{ij}$ is the response for subject i at time j, and $E(\boldsymbol{y}_{ij})$ is the response mean

- F is the distributional family of the outcome variable, $\boldsymbol{y}_{ij}$

- $\mathbf{X}_{ij}$ is the vector of covariates

- $\boldsymbol{\beta}$ is the vector of unknown regression coefficients

- $g(\cdot)$ is the link function

The distribution of $\boldsymbol{y}_{ij}$ is assumed to be a member of an *exponential family,* such as Gaussian (normal), inverse Gaussian, gamma, binomial or Poisson. Each *exponential family* has a natural transformation, known as the link function; it is a non-linear function that is used to predict the mean of the distribution function.

GEE takes into account the correlation of the repeated measurements of the outcome variable, by specifying a 'working correlation structure' for the within-subject correlations (Zeger & Liang, 1986). In order to obtain correct estimations using GEE analysis, a number of working correlation structures have been defined (Hardin & Hilbe, 2002; Liang & Zeger, 1986). The chosen correlation structure for each GEE analysis should ideally have the simplest structure and fit the data well; however, GEE analysis can produce robust outcome variables even with the wrong choice of correlation structure, particularly with large sample sizes and dichotomous outcome variables (Burton, Gurrin, & Sly, 1998; Liang & Zeger, 1986; Twisk, 2013). There are six types of working correlation structures available in Stata for GEE analysis:

i. Independence – assumes that the correlation of each measurement between time points is independent; for example, for times, t_1, t_2, t_3, t_4 , the matrix of the correlation structure is defined as:

$$\begin{bmatrix} 1 & 0 & 0 & 0 \\ 0 & 1 & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix}$$

ii. Exchangeable – assumes that the correlation between each measurement is equal; useful for clustered data, where ρ (rho) is Spearman's correlation coefficient (a non-

parametric method to assess the relationship between two variables, range -1 to +1) (Dancey, Reidy, & Rowe, 2012):

$$\begin{bmatrix} 1 & \rho & \rho & \rho \\ \rho & 1 & \rho & \rho \\ \rho & \rho & 1 & \rho \\ \rho & \rho & \rho & 1 \end{bmatrix}$$

iii. Autoregressive – assumes that the correlation depends on the distance between measurements, with decreasing correlation over time:

$$\begin{bmatrix} 1 & \rho & \rho^2 & \rho^3 \\ \rho & 1 & \rho & \rho^2 \\ \rho^2 & \rho & 1 & \rho \\ \rho^3 & \rho^2 & \rho & 1 \end{bmatrix}$$

iv. Stationary, M-dependent – assumes that correlations exist for a number of defined time periods (M). For example, a stationary matrix, M-dependent, assumes equal correlations t measurements apart, equal correlations $t + 1$ measurements apart etc. up to $t = M$, while thereafter (for $t > M$), assumes no correlation. A *2-dependent* stationary correlation structure would be defined as:

$$\begin{bmatrix} 1 & \rho_1 & \rho_2 & 0 \\ \rho_1 & 1 & \rho_1 & \rho_2 \\ \rho_2 & \rho_1 & 1 & \rho_1 \\ 0 & \rho_2 & \rho_1 & 1 \end{bmatrix}$$

v. Non-stationary, M-dependent – assumes that there is a natural order to the data with different correlations between each time point, dependent on M. A *1-dependent* non-stationary correlation structure would be defined as:

$$\begin{bmatrix} 1 & \rho_1 & 0 & 0 \\ \rho_1 & 1 & \rho_2 & 0 \\ 0 & \rho_2 & 1 & \rho_3 \\ 0 & 0 & \rho_3 & 1 \end{bmatrix}$$

vi.　Unstructured – assumes that all correlations between measurements are different. For this type of correlation structure, all correlations would need to be estimated separately:

$$\begin{bmatrix} 1 & \rho_1 & \rho_2 & \rho_3 \\ \rho_1 & 1 & \rho_4 & \rho_5 \\ \rho_2 & \rho_4 & 1 & \rho_6 \\ \rho_3 & \rho_5 & \rho_6 & 1 \end{bmatrix}$$

There are a number of advantages and limitations of GEE analysis compared to traditional regression and generalised linear modelling techniques. Firstly, GEEs can be used to model both dependent and independent variables measured at different time points, whereas in standard regression techniques, measurements are assumed to be independent (Singer & Willett, 2003). Secondly, the repeated measurements are likely to be related, and this correlation can be taken into account in the analysis by specifying an appropriate correlation structure for the data. GEE analysis will still produce unbiased estimates even when the correlation structure is specified incorrectly (Burton et al., 1998). Thirdly, GEE analysis makes use of all the available data for each individual; it allows for missing data, but only if there is a small amount and the missing values are random (Liang & Zeger, 1986). Fourthly, GEE analysis allows the user to specify the *exponential family* and related link function, relevant to the dependent variable. Lastly, although GEE analysis is now more commonly used in epidemiological studies (Hanley, 2003; Merlo, 2003), it is a complicated method to implement in practice with little user-friendly literature on its application in epidemiology and the social sciences (Twisk, 2013).

The decision-making process for choosing the most appropriate exponential family and correlation structure for this study is described in Sections 3.4.2 and 3.4.3.

3.3.4.5 Multivariable fractional polynomials

In order to investigate a non-linear relationship between a dependent variable and a continuous independent variable, a systematic approach is needed. Royston and Sauerbrei (2005, p. 561) demonstrated that using fractional polynomials to model non-linearity can give a "satisfactory practical solution to the problem of simultaneously identifying a subset of 'important' predictors and determining the functional relationship for continuous predictors." Fractional polynomials use simple power transformations for the continuous covariates (x) to improve the fit of the model; for example, the simple model with one continuous covariate would become:

$$y_i = \beta_0 + \beta_1 x_i^p + \varepsilon_i.$$

Royston and Altman (1994) suggested that p be chosen from a restricted set, S, where $S = \{-2, -1, -0.5, 0, 0.5, 1, 2, 3\}$, and x^0 denotes $\log(x)$. The multivariable fractional polynomial procedure selects the best fractional polynomial power transformations for each continuous variable in the model (Sauerbrei & Royston, 1999).

3.3.4.6 Statistics used in other studies that have derived physical behaviour thresholds

A review of the literature (Chapter Two) was unable to locate any empirically derived accelerometer cut-points for sedentary behaviour in adults; however, there are a number of studies that have identified physical activity cut-points in adults (Matthews et al., 2008; Sasaki et al., 2011; Troiano et al., 2008), in children (Butte et al., 2014; Evenson, Catellier, Gill, Ondrak, & McMurray, 2008; Mattocks et al., 2007; Pate, Almeida, McIver, Pfeiffer, & Dowda, 2006; Pulsford et al., 2011; Puyau, Adolph, Vohra, & Butte, 2002; Trost, Fees, Haar,

Murray, & Crowe, 2012), and in adolescents (Treuth, Schmitz, et al., 2004; Trost, Loprinzi, Moore, & Pfeiffer, 2011).

The majority of authors have used regression analysis between oxygen consumption (measured using indirect calorimetry, related to energy expenditure), and counts per minute (from accelerometers) to produce regression equations for different activity intensities. These prediction equations to determine activity intensity cut-points have mainly been carried out on structured activities; for example, in adults, treadmill activities of walking and running have been assessed (Crouter et al., 2006; Sasaki et al., 2011), and in children and adolescents, playground games such as hopscotch, throwing and catching, and computer games have been used as part of the assessment (Pulsford et al., 2011; Trost et al., 2011). Furthermore, validation studies of regression equations to derive accelerometer cut-points for physical activity have generally taken place in laboratory conditions, with each activity being performed for a few minutes, usually 5-10 minutes each (Crouter, Kuffel, Haas, Frongillo, & Bassett, 2010; Pulsford et al., 2011; Trost et al., 2011).

3.3.4.7   *Evaluating agreement and accuracy of physical behaviour thresholds*

Receiver operating characteristic (ROC) analysis has also been used to identify activity cut-points for both physical activity and sedentary behaviour (Dowd, Harrington, & Donnelly, 2012; Kim, Lee, Peters, Gaesser, & Welk, 2014; Mackintosh, Fairclough, Stratton, & Ridgers, 2012). ROC curves are widely used in statistics to identify optimal cut-points for dichotomising continuous measurements. However, it should be noted that these cut-points are not empirically derived through observation and are essentially arbitrary (Lindelow, Hardy, & Rodgers, 1997).

Nevertheless, to evaluate agreement of the optimal cut-points derived from ROC, area under the curve (AUC) has been used to calculate classification accuracy (Aguilar-Farías et al., 2013; Pulsford et al., 2011; Trost et al., 2012, 2011). ROC-AUC analysis can be used to compare the classification of different cut-points, by comparing the sensitivity and specificity of the derived cut-point compared to the *true* outcome. Sensitivity and specificity, and their relationship to ROC-AUC are described below in Section 3.3.4.8.

Bland-Altman plots are used to examine agreement between two measurements from different methods (Bland & Altman, 1986). They have been widely used to assess differences, and demonstrate agreement, in derived physical activity and sedentary behaviour times from two different accelerometers (Aguilar-Farías et al., 2013; Kozey-Keadle et al., 2011; Ridgers et al., 2012; Van Cauwenberghe, Wooller, Mackay, Cardon, & Oliver, 2012).

This study used ROC-AUC methods to analyse the accuracy of the derived ActiGraph GT3X+ cut-points for sedentary behaviour compared to the activPAL3™ sedentary behaviour classification: Bland-Altman plots were also used to assess the agreement between the number of sedentary time minutes calculated from both accelerometers.

3.3.4.8   Sensitivity, specificity and the area under the curve

This section describes how sensitivity and specificity are calculated with respect to this study, using the activPAL3™ as the criterion measure. The sedentary classification from the activPAL3™ has been defined as the 'gold standard' for measuring sedentary time (Baumgartner et al., 2015; Chastin et al., 2018; Koster et al., 2016; Prince, LeBlanc, et al., 2017), where an epoch of one minute, with 60 seconds of sedentary behaviour is termed an *Actual positive*, and any minutes with some upright activity are known as *Actual*

negatives; the derived cut-point from the GEEs will dichotomise the counts per minute from the ActiGraph GT3X+ into *Test positives* and *Test negatives* (Figure 3.15).

		Criterion measure (from activPAL3™)		
		Actual positive (=60 seconds sedentary)	Actual negative (<60 seconds sedentary)	Total
Test outcome (ActiGraph GT3X+)	Test positive	a	b	$a + b$
	Test negative	c	d	$c + d$
	Total	$a + c$	$b + d$	

Figure 3.15   Defining sensitivity and specificity

In Figure 3.15, the shaded terms are referred to as:

a. True positive

b. False positive

c. False negative

d. True negative

Sensitivity is the proportion of all true positives correctly identified from the test outcome and can be defined as $\frac{a}{a+c}$. Specificity is the proportion of all the true negatives correctly identified from the test outcome and can be defined as $\frac{d}{b+d}$.

For this study, sensitivity can be described as the probability of defining a sedentary minute from the ActiGraph GT3X+ cut-point, given that the minute is defined as sedentary from the activPAL3™. Specificity can be described as the probability of defining a non-sedentary

minute from the ActiGraph GT3X+ cut-point, given that the minute is defined as non-sedentary from the activPAL3™. ROC analysis chooses the cut-point with the maximum sensitivity and specificity. ROC-AUC analysis calculates the area under the curve when sensitivity is plotted against (1-specificity) (Silman & Macfarlane, 2002).
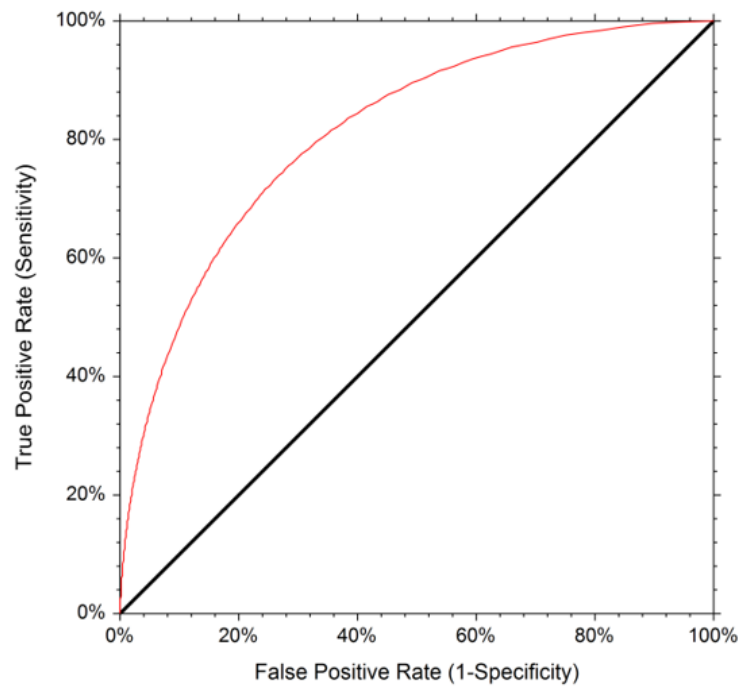
Figure 3.16   **Area under the curve example. (NCSS Data Analysis, 2019. [Online]. Available from: https://www.ncss.com/software/ncss/roc-curves-ncss)**

It is assumed that the area under the curve is equal to one, and that the diagonal black line represents complete randomness from differentiating between positive and negative (AUC=0.5). To maximise the validity of the outcome, choosing the value at the 'peak' of the red curve will be the optimal cut-point; when comparing two different cut-points, the one that gives the bigger area under the curve is seen as the optimum (Silman & Macfarlane, 2002).

3.3.4.9   Resampling techniques

Once a final model has been chosen to predict a new cut-point for ActiGraph GT3X+ counts per minute, the estimates of the model can be resampled to obtain robust estimates of the standard errors and confidence intervals of the predicted values (Bai & Pan, 2008). The three main resampling techniques include:

i.   Split sampling (or cross-validation) – this is where the model is generated using one half (or a predetermined part) of the data for which the model is generated; the results from the model are then tested on the other half of the data set.

ii.   Jackknife resampling –for this resampling method, the model is tested in samples of size $n - 1$.

iii.   Bootstrap resampling – this method generates the model on a number (usually 100+) samples of the data set drawn at random with replacement; the sampling distribution of the statistics of interest can then be ascertained; however, the time it takes to run this type of analysis needs to be taken into account in the study design (Honoré & Hu, 2017).

Bootstrapping is the preferred resampling technique in the literature, and was the chosen technique used in the GEE regression models in this study (Bai & Pan, 2008; Sherman & Cessie, 1997).

3.3.4.10   Statistical analysis summary

The statistical methods used in previous studies to derive physical activity cut-points from accelerometers have used regression analysis (between energy expenditure and counts per minute) to produce regression equations for different activity intensities. It is not

appropriate to use these methods in a free-living environment over a number of days, and therefore the activPAL3™ was used to determine sedentary classification, without being a burden to the participant.

The method of choice, multivariable fractional polynomials models with GEEs, is able to use all available data and make minute by minute comparisons of derived sedentary time from the two accelerometers. Bootstrapping methods were also employed to obtain accurate estimates of standard errors and confidence intervals for the predicted counts per minute cut-points.

3.3.4.11   Statistical analysis plan

The statistical models of choice for this study, GEEs, were used to make minute by minute comparisons of counts per minute from the ActiGraph GT3X+ and the sedentary classification of the activPAL3™. A sedentary minute from the activPAL3™ was defined when all 60-seconds were classified as sitting or lying. Individual GEE models were generated for each day of the week, working days, weekend days, all seven days of the week, work times and non-work times, and each 'type' of sitting recorded in the detailed activity log. For each GEE model, the mean of the predicted distribution was calculated from the reciprocal of μ[38].

The GEE models were limited to the waking hours of between 08:00 and 22:00; working hours were limited between 09:00 and 16:30; and non-working hours were limited between 18:00 and 22:00. GEE models produce asymptotically normal, unbiased standard

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[38] Based on the gamma distribution and the reciprocal link function – see Sections 3.4.2 and 3.4.3

errors when missing data are missing completely at random (Zeger & Liang, 1986); standardising waking and working hours assured that there were sufficient replicates for model convergence.

The accuracy of the standard errors of the derived cut-points from the GEE models was maximized using bootstrapping techniques, by resampling the observations 1000 times for each regression model (Efron, 1979); all models were adjusted for age and sex. The classification accuracy of the derived cut-points was compared to that of the previously proposed cut-points for sedentary behaviour (50, 100 and 150 counts per minute; Crouter et al., 2013, Matthews et al., 2008, Kozey-Keadle et al., 2011), by calculating the sensitivity, specificity, and area under the receiver operating characteristic curve. ROC-AUC analysis calculates the area under the curve when sensitivity (probability a minute is defined as sedentary from the ActiGraph GT3X+ derived cut-point, given that the minute is defined as sedentary from the activPAL3™) is plotted against, 1-specificity (probability a minute is defined as non-sedentary from the ActiGraph GT3X+ derived cut-point, given that the minute is defined as non-sedentary from the activPAL3™) (Figure 3.15). To maximize the validity of the outcome, the outcome that gives the bigger area under the curve was seen as the optimum when comparing cut-points. The amount of sedentary time has been presented as the percentage of sedentary time across each day. Mean bias percentages [(ActiGraph GT3X+ sedentary minutes/activPAL3™ sedentary minutes) – 1 x 100], average difference in sedentary time and limits of agreement (LoA) for sedentary time calculated from the derived cut-points, were compared to sedentary time from the activPAL3™ using the Bland-Altman method.

3.4   Results

Data from all thirty participants (20 females, 10 males) were included in the results. The average age of men in the study was 44.8 ± 11.1 years, and the average age of women was 38.3 ± 10.2 years (there was no statistically significant difference in age, p=0.1574); the range of ages across the sample was 24 to 62 years old. The mean BMI of participants was 23.93 (± 2.46, range: 19.2-28.0 kg/m^2).

3.4.1   *Data cleaning and data reduction*

Accelerometers were reported not to be worn, or worn incorrectly, on only eight of the 210 days of data collection; reasons included going away for the weekend, not being in work on the first day of data collection and incorrect placement of the activPAL3™. After data reduction, participants provided an average of 11 hours 27 minutes of data per day (SD=2 hours 34 minutes) equating to 82% of the waking day between 08:00 and 22:00. Percentage of clean data is not often reported (Aguilar-Farías et al., 2013; Kozey-Keadle et al., 2011); however, despite the fact that the data reduction process was considered to be *aggressive*, 82% of usable data as a percentage of awake time is higher than those previously reported (for example, 65% by Mâsse et al. (2005) and 75% by Matthews et al. (2002)).

Of the data that were removed, the majority of minutes were as a result of information in the activity diaries (main reasons were cycling, showering/bathing and swimming); after these data were removed, only two participants had further data removed after identifying periods of 60 minutes or greater of zero counts from the ActiGraph GT3X+ (allowing for up to two minutes of non-zero counts) (Troiano et al., 2008). In total, 137,515 trimmed minutes of accelerometer data were available. The majority of these minutes (82,020;

59.6%) were classified as sedentary only from the activPAL3™ (equal to all 60 seconds of the minute being sedentary); 30.8% (42,380) were upright only minutes (including standing and stepping), and the remainder 9.5% (13,115) were mixed minutes, containing both sedentary and upright activity.

3.4.2   Choosing the exponential family that best fits the data

Generalised estimating equations analysis allows the user to specify the *exponential family* and related link function, relevant to the dependent variable. For this study, the dependent variable was counts per minute from the ActiGraph GT3X+ accelerometer. The distribution of counts per minute from the ActiGraph GT3X+ accelerometer for all participants can be seen in the simple histogram in Figure 3.17.
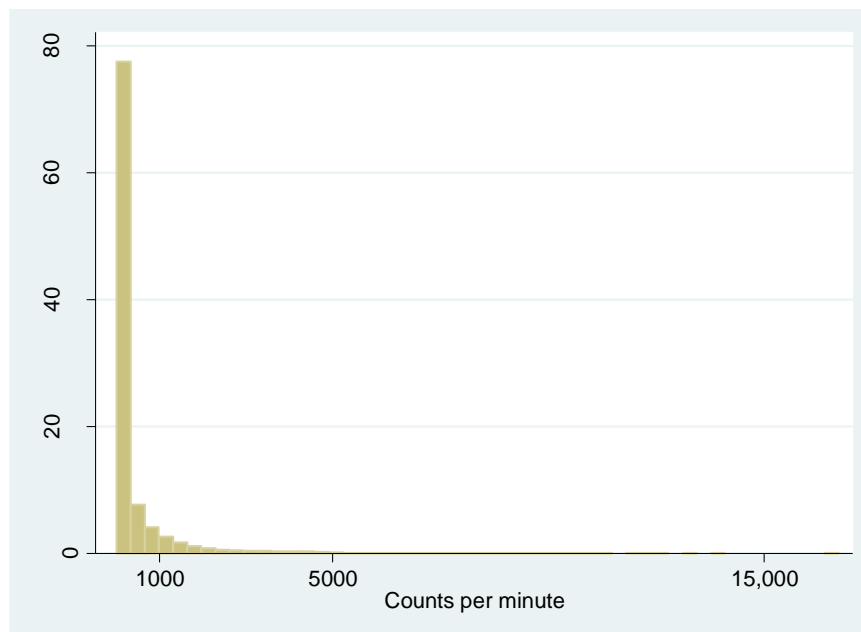
Figure 3.17   Distribution of counts per minute from the ActiGraph GT3X+

The ActiGraph GT3X+ counts per minute data were positively skewed: by summarising the data, the variance of the counts per minute variable was much bigger than the mean indicating that a Poisson distribution would not be a good fit of the data due to

overdispersion. In statistics overdispersion occurs when a variable has a larger variance than expected (Carruthers, Lewis, Mccue, & Westley, 2008).

Compared to the Poisson distribution, the negative binomial distribution or the gamma distribution can be more appropriate in cases of overdispersion. The negative binomial distribution was a much better fit than the Poisson distribution for the counts per minute data with respect to overdispersion; however, the deviance between a negative binomial distribution and a gamma distribution should also be compared (Konishi, 2014). The deviance of a model is a simple goodness of fit test; the smaller the deviance, the better fit the model to the data. After applying a negative binomial model and a gamma model to the counts per minute variable over time, the gamma distribution gave the smallest deviance value. Therefore, the gamma distribution was used as the *exponential family* for the GEE analyses in this study. The next section will describe how the appropriate correlation structure was chosen.

3.4.3   Choosing an appropriate correlation structure

For generalised estimating equations analysis, a simple structure that fits the data well is favourable. In generalised linear models, variable model selection can be optimised using criteria such as the Akaike information criterion (AIC) (Carruthers et al., 2008; Symonds & Moussalli, 2011); however, this method is not applicable to GEE analysis as it makes assumptions about the distribution of the outcome variable, something GEE does not. Cui, (2007, p. 209) developed the quasi-likelihood under the independence model criterion (QIC) that can be, "used to select the best-working correlation structure". The *qic* command has been developed in Stata so that different correlation structures for models (with the same defined *exponential* family) can be compared: the correlation structure

with the smallest QIC is favoured (Cui, 2007). The QIC values were checked for each GEE

model used in the analyses, and the autoregressive correlation structure was consistently

chosen to best fit the data; this correlation structure assumes that the correlation between

each count per minute depends on the distance between each measurement, with decreasing

correlation over time.

3.4.4   *Running the regression models in Stata*

Generalised estimating equations can be used to account for the autocorrelation of the

counts per minute; however, these models assume linearity of the counts per minute over

time (Liang and Zeger 1986). The outcome variable of counts per minute for this study has

a polynomial distribution, and therefore the use of multivariable fractional polynomials

with GEEs takes into account the polynomial nature of the counts (Royston & Sauerbrei,

2005). To run the multivariable fractional polynomial command, *mfp,* alongside the

generalised estimating equations command, *xtgee,* in Stata, the computer memory and the

version of the Stata software need to be considered. Both commands use a large amount

of memory space, and take a long time to run, especially for a large set of time points.

Therefore, the models in this study were run with and without the assumption of linearity:

when the results from these two methods were compared, there was no impact on the

precision of estimates of the derived cut-points and their associated standard errors.

Consequently, only the *xtgee* models were run alongside the bootstrapping techniques.[39]

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[39] The Stata command files (for the *xtgee* models with bootstrapping techniques) for each day of the week took between one and three days to run; files for the work and non-work times took approximately one week; and, files for weekdays and total week took up to six weeks to run (using a desktop computer with an i7-core processor, 8.00GB or random-access memory, and a 64-bit operating system).

3.4.5   *Sedentary time, comparisons between devices*

The prevalence of sedentary time from all included minutes from the activPAL3™ was 65.1%, and the ActiGraph GT3X+ reported a comparable percentage of sedentary time using the 100 counts per minute cut-point (64.4%). Despite the similarity in these percentages of sedentary time, only 82% of sedentary minutes from the activPAL3™ were recorded as sedentary minutes from the ActiGraph GT3X+; using the Freedson (1998) activity cut-points for sedentary, light, and moderate and vigorous physical activity, 17.7% of sedentary time from the activPAL3™ was recorded as light physical activity from the ActiGraph GT3X+ and the remaining 0.1% was recorded as moderate to vigorous physical activity.

In studies of largely office-based workers, sitting time on workdays is known to be much higher compared to non-work days (Clemes, O'Connell, et al., 2014; Parry & Straker, 2013; Thorp et al., 2012). While our study was not designed to measure total sedentary time, we also found higher percentages of sitting time on working days compared to the weekend (61.2% vs. 53.8%); and working hours versus non-working hours, using the activPAL3™ sedentary classification (65.9% vs. 58.6%). The workplace is a key setting for prolonged bouts of sedentary time, defined as ≥20 minutes (Ryan et al., 2011). Although we found this was also true for our study, since 70.2% of sedentary time during working hours was spent in prolonged bouts, this was not statistically significant to non-working hours, (66.7%).

With limited evidence on the validity of the <100 counts per minute cut-point for sedentary behaviour (Kim, Barry, et al., 2015; Kozey-Keadle et al., 2011; Rosenberg et al., 2010), the true extent of the misclassification within different activity classifications from the

ActiGraph accelerometer is unclear (Clemes et al., 2012; Hart, Ainsworth, et al., 2011; Marshall et al., 2010). Therefore, the time-matched data for both the activPAL3™ and the ActiGraph GT3X+ accelerometers in this study enabled a further investigation to evaluate the distribution (and any misclassification) of the activPAL postural and stepping classifications (sitting/lying, standing and stepping) within the physical behaviour classifications from the ActiGraph GT3X+.

The data from the ActiGraph GT3X+ were categorised using the Freedson (1998) activity cut-points for sedentary, light, moderate, and vigorous physical activity (≤99, 100-1951, 1952-5724, ≥5725): for each of these categories, the percentage of activity (sitting/lying, standing and stepping) from the activPAL3™ was calculated. The ActiGraph GT3X+ count distribution, median, interquartile range and the range for activPAL3™ minutes that were wholly classified as sedentary are shown in Table 3.2. Although the median ActiGraph GT3X+ counts within the activPAL3™ sitting/lying and standing classifications were both low (1 and 5 respectively), the range of values were both wide (0-9808 and 0-4452). All the count ranges for the activPAL3™ classifications included zero: interestingly, the sitting/lying classification had a larger range of counts per minute compared to the standing classification.

Table 3.2   **ActiGraph GT3X+ count distribution within each activPAL3™ classification**

activPAL3™ classification	ActiGraph GT3X+ count distribution		
	Median	Interquartile range	Range
Sitting/lying	1	0-30	0-9808
Standing	5	0-39	0-4452
Stepping	3990	2968-4882	0-13,247

The ActiGraph GT3X+ sedentary category contained 83.1% sitting/lying, 16.8% standing and 0.1% stepping; the ActiGraph GT3X+ light physical activity category contained 37.7%

sitting/lying; 91.1% of the ActiGraph GT3X+ moderate and vigorous physical activity categories were accumulated in steps (Figure 3.18).
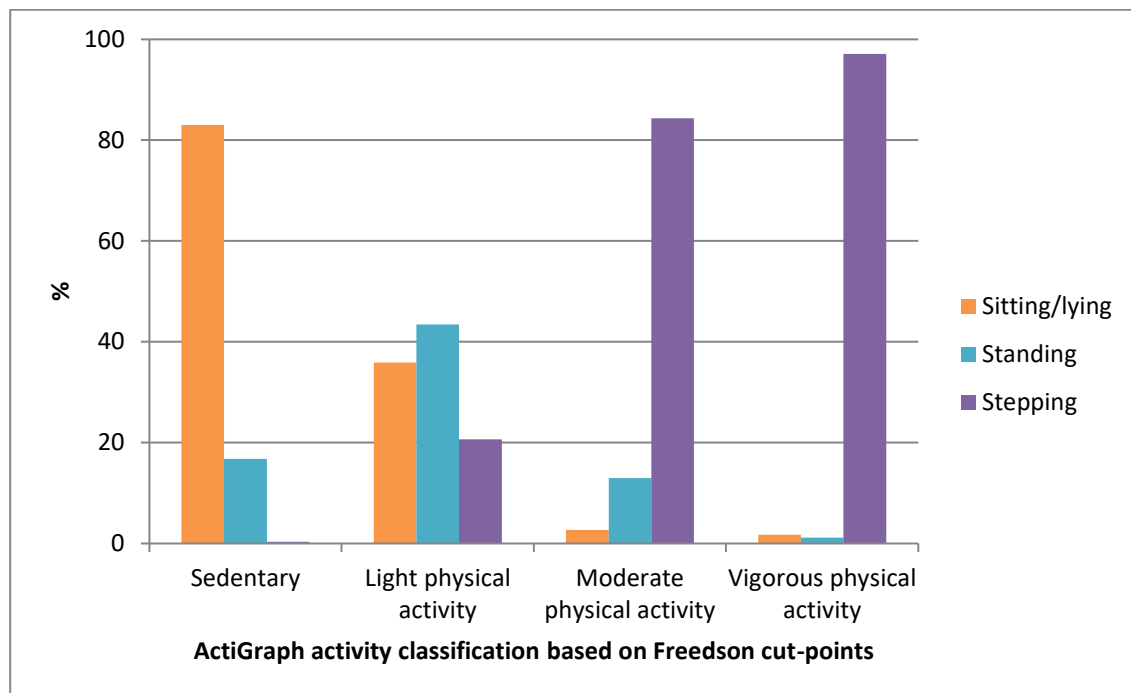
Figure 3.18 **% of activPAL categories accumulated within ActiGraph activity classifications**

In this group of office-based workers, the <100 counts per minute sedentary behaviour cut-point from the ActiGraph GT3X+ misclassified 16.9% of minutes; while the light physical activity cut-point classification contained nearly 40% of sedentary minutes when compared to the activPAL3™ postural sitting/lying category.

3.4.6   *Objective 1 results*

1. *To empirically derive an optimal threshold for classifying sedentary behaviour, using the counts per minute output from the ActiGraph GT3X+ accelerometer, when compared to the sedentary classification from the activPAL™ accelerometer in a free-living environment.*

The empirically derived cut-point from the generalised estimating equation regression models across all days of the week was 65 counts per minute (95% CI 60-71). The derived

sedentary behaviour threshold for week days (Monday to Friday) was lower than that derived for weekend days (60 [95% CI 51-72] vs. 74 [95% CI 67-84] counts per minute); however, this was not significant (Figure 3.19).
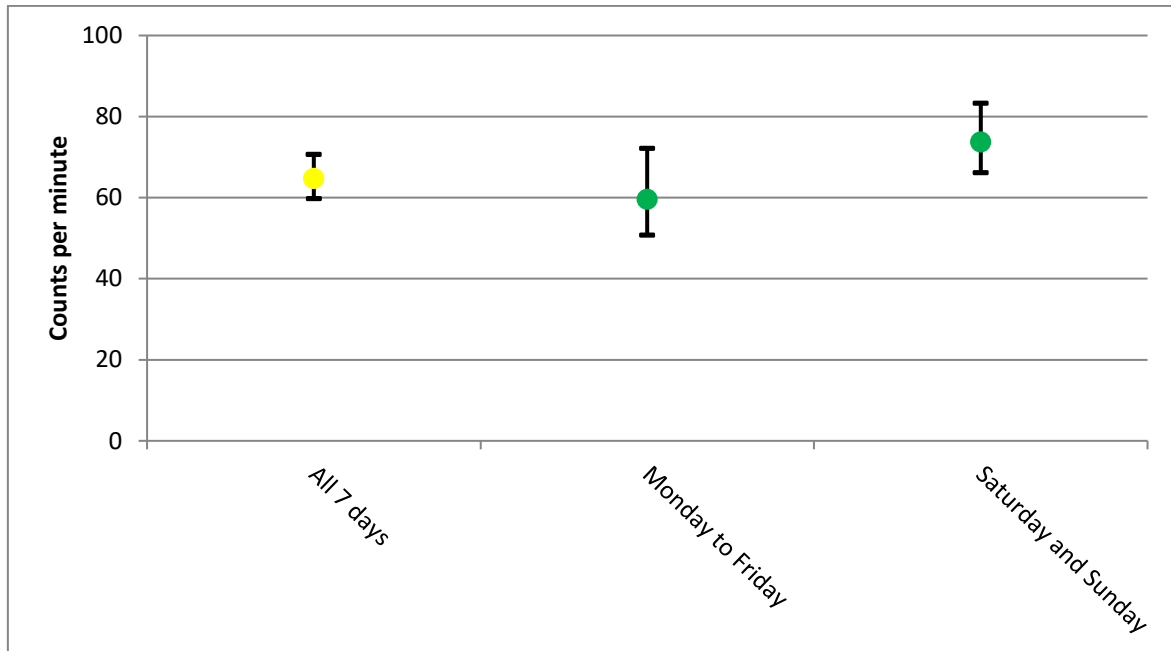
Figure 3.19   **ActiGraph GT3X+ accelerometer-derived cut-points (95% CI) for sedentary behaviour from GEE regression models (week, weekdays, weekend days)**

There were no significant differences between the derived cut-points for sedentary behaviour and the previously proposed cut-points (50, 100, and 150 counts per minute) in terms of ROC-AUC analysis (Table 3.3). As expected, the higher thresholds of 100 and 150 counts per minute resulted in higher sensitivity values, due to the number of true sedentary minutes correctly identified with increasing threshold; this may reflect the high percentage of sedentary minutes seen in the light physical activity category (Figure 3.18). Although the higher cut-points of 100 and 150 counts per minute had high sensitivity values they overestimated sedentary time between 25-49 minutes per day (100 counts per minute) and 55-80 minutes per day (150 counts per minute). Across all 7-days and for weekdays, the lowest mean bias and smallest average differences in sedentary time occurred for the 50 counts per minute cut-point; however, for weekend days, the derived

cut-point of 74 counts per minute produced the lowest mean bias and average difference

in sedentary time (Table 3.3).

Table 3.3   **Accuracy of the derived cut-points compared to cut-points compared to previously derived cut-points (week, weekdays, weekend days)**

	Sedentary time (measured by the activPAL3™)	Sensitivity	Specificity	AUC	Mean bias	Average difference	95% LoA
	(%)	(%)	(%)		% (95% CI)	(mins)	(mins)
All 7 days	56.65						
Derived (65 cpm)		83.65	74.40	0.79	5.35 (-3.89, 14.59)	18.17	(-91.94, 128.27)
50 cpm+		80.69	76.24	0.78	1.01 (-8.37, 10.39)	0.08	(-114.12, 114.29)
100 cpm++		88.24	70.52	0.79	12.90 (3.89, 21.90)	49.22	(-52.67, 151.11)
150 cpm+++		92.21	65.78	0.79	20.45 (11.33, 29.58)	80.11	(-17.09, 177.30)
Monday to Friday	61.22						
Derived (60 cpm)		84.25	73.23	0.79	2.11 (-3.59, 7.82)	3.87	(-111.28, 119.02)
50 cpm+		82.31	74.42	0.78	-0.62 (-6.37, 5.13)	-8.38	(-127.07, 110.32)
100 cpm++		89.36	68.76	0.79	10.27 (4.71, 15.83)	40.18	(-64.31, 144.66)
150 cpm+++		93.09	64.10	0.79	17.24 (11.59, 22.89)	70.83	(-23.38, 170.04)
Saturday and Sunday	53.79						
Derived (74 cpm)		80.51	77.52	0.79	1.63 (-5.83, 9.10)	4.32	(-91.74, 100.37)
50 cpm+		75.19	80.65	0.78	-6.91 (-14.85, 1.02)	-22.11	(-124.04, 79.81)
100 cpm++		84.43	74.78	0.80	8.43 (1.06, 15.80)	24.91	(-68.09, 117.91)
150 cpm+++		89.24	69.82	0.80	18.03 (10.24, 25.82)	54.71	(-41.67, 151.08)

3.4.7 Objective 2 results

2. *To ascertain whether thresholds for sedentary behaviour cut-points vary by day of the week and in working time versus non-working time.*

The derived cut-points for all days of the week were less than 100 counts per minute; cut-points for Monday to Friday ranged from 41-60 counts per minute and were similar to Sunday (57 [95% CI 49-68] counts per minute) (Figure 3.20). The cut-point for Saturday (97 [95% CI 85-111] counts per minute) was significantly higher compared to the other days of the week (with the exception of Thursday).

Figure 3.20 **ActiGraph GT3X+ accelerometer-derived cut-points (95% CI) for sedentary behaviour from GEE regression models (days of the week)**

Notably, cut-points for working hours were substantially lower compared to non-working hours (35 [95% CI 30-41] vs. 73 [95% CI 54-113] counts per minute) (Figure 3.21).

Figure 3.21 **ActiGraph GT3X+ accelerometer-derived cut-points (95% CI) for sedentary behaviour from GEE regression models (working and non-working hours)**

Table 3.4 **Accuracy of the derived cut-points compared to cut-points compared to previously derived cut-points (days of the week; working and non-working**

	Sedentary time (measured by the activPAL3™)	Sensitivity	Specificity	AUC	Mean bias	Average difference	95% LoA
	(%)	(%)	(%)		% (95% CI)	(mins)	(mins)
Monday	54.44						
Derived (54 cpm)		84.56	74.22	0.79	9.27 (-2.56, 21.09)	23.55	(-149.53, 196.63)
50 cpm+		83.95	74.56	0.79	8.20 (-3.58, 20.00)	19.75	(-154.07, 193.57)
100 cpm++		90.11	68.98	0.80	19.96 (7.10, 32.81)	64.45	(-111.10, 242.00)
150 cpm+++		93.37	64.41	0.79	28.18 (14.14, 42.22)	95.25	(-82.84, 273.34)
Tuesday	60.63						
Derived (41 cpm)		83.61	74.94	0.79	2.45 (-5.39, 10.28)	-1.92	(-140.73, 136.89)
50 cpm+		85.59	73.64	0.80	5.45 (-2.38, 13.28)	10.62	(-122.82, 144.05)
100 cpm++		92.22	68.49	0.80	15.95 (7.97, 23.93)	54.96	(-67.06, 176.98)
150 cpm+++		95.32	64.06	0.80	22.48 (13.95, 31.01)	81.46	(-40.05, 202.98)
Wednesday	64.17						
Derived (52 cpm)		82.27	73.95	0.78	-0.99 (-9.13, 7.16)	-17.63	(-194.43, 159.17)
50 cpm+		81.88	74.21	0.78	-1.52 (-9.72, 6.68)	-20.26	(-199.10, 158.58)
100 cpm++		89.17	68.83	0.79	8.67 (1.20, 16.15)	28.63	(-119.61, 176.87)
150 cpm+++		93.00	64.24	0.79	15.35 (7.88, 22.83)	59.85	(-76.99, 196.70)
Thursday	59.98						
Derived (60 cpm)		82.08	70.73	0.76	5.85 (-4.63, 16.34)	11.70	(-161.96, 185.37)
50 cpm+		79.87	72.20	0.76	2.43 (-7.86, 12.73)	-3.07	(-181.58, 175.43)
100 cpm++		87.23	66.14	0.77	14.63 (3.75, 25.50)	49.59	(-111.53, 210.71)
150 cpm+++		91.56	61.30	0.76	22.58 (11.23, 33.93)	83.82	(-68.80, 236.43)
Friday	64.76						
Derived (59 cpm)		83.40	75.38	0.79	-2.09 (-8.59, 4.41)	-12.41	(-138.85, 114.03)
50 cpm+		81.69	76.48	0.79	-4.27 (-10.90, 2.36)	-22.36	(-151.59, 106.86)
100 cpm++		89.14	70.77	0.80	6.15 (0.57, 11.73)	24.55	(-82.52, 131.61)
150 cpm+++		92.93	66.25	0.80	12.63 (7.21, 18.05)	52.77	(-47.13, 152.68)
Saturday	49.91						
Derived (97 cpm)		80.82	77.02	0.79	7.23 (-2.89, 17.35)	11.44	(-121.61, 144.50)
50 cpm+		70.42	82.14	0.76	-9.03 (-19.15, 1.10)	-46.00	(-205.55, 113.55)
100 cpm++		81.30	76.79	0.79	7.99 (-2.11, 18.08)	14.06	(-117.47, 145.58)
150 cpm+++		87.11	71.97	0.80	19.22 (8.30, 30.14)	53.06	(-67.99, 174.10)
Sunday	54.76						
Derived (57 cpm)		80.97	77.96	0.79	2.38 (-8.36, 13.13)	1.16	(-154.32, 156.63)
50 cpm+		79.58	78.93	0.79	-0.02 (-10.63, 10.60)	-7.63	(-163.56, 148.30)
100 cpm++		87.32	72.45	0.80	14.40 (2.85, 25.95)	44.37	(-104.63, 193.36)
150 cpm+++		91.20	67.35	0.79	23.17 (10.69, 35.65)	76.42	(-69.07, 221.91)
Working hours (Monday to Friday)	65.85						
Derived (35 cpm)		83.54	69.34	0.76	0.00 (-7.79, 7.79)	-4.62	(-93.61, 84.37)
50 cpm+		86.72	66.82	0.77	4.77 (-2.77, 12.30)	8.11	(-73.97, 90.20)
100 cpm++		92.57	60.84	0.77	14.11 (6.71, 21.52)	33.16	(-37.65, 103.98)
150 cpm+++		95.35	56.21	0.76	19.56 (11.93, 27.19)	47.51	(-20.52, 115.53)
Non-working hours (Monday to Friday)	58.62						
Derived (73 cpm)		83.54	75.46	0.80	6.04 (-5.83, 17.91)	3.62	(-39.70, 46.94)
50 cpm+		79.34	78.22	0.79	-0.70 (-12.22, 10.81)	-4.19	(-48.58, 40.21)
100 cpm++		86.73	72.29	0.80	12.05 (-0.48, 24.58)	10.34	(-33.05, 53.74)
150 cpm+++		90.77	66.82	0.79	20.75 (6.88, 34.62)	19.96	(-25.04, 64.94)

+ Crouter 2006; ++ Matthews 2008; +++ Kozey-Keadle 2011; sensitivity and specificity (%); AUC, area under the curve; LoA, limits of agreement; mins, minutes; cpm, counts per minute; Sedentary time as measured by the activPAL™

Similar to the ROC-AUC analysis for all days, weekdays and weekend days, there were no significant differences between the derived cut-points and the previously proposed cut-points (50, 100, and 150 counts per minute (Table 3.4). Likewise, the higher thresholds of 100 and 150 counts per minute resulted in higher sensitivity values compared to the 50 counts per minute and the derived cut-points. The 100 and the 150 counts per minute cut-points all overestimated sedentary time for all days (range 14-64 minutes and 53-95 minutes per day respectively), for working hours (33 and 48 minutes), and for non-working hours (10 and 20 minutes). The lowest mean bias and smallest average differences in sedentary time occurred for either the derived cut-point (four days) or the 50 counts per minute cut-point (3 days); however, for working and non-working hours, the derived cut points of 35 and 73 counts per minute produced the lowest average differences in daily sedentary time (Table 3.4).

Figure 3.22 shows the Bland-Altman plots for the mean differences and limits of agreement for sedentary time determined from the activPAL3™ and the derived ActiGraph GT3X+ cut points, for both working and non-working hours. The limits of agreement were narrower for non-working sedentary time compared to working hours; this may be due to fewer non-working hours compared to working hours in this analysis. However, the mean bias percentage was smaller for working hours when compared to non-working hours (<0.01% vs. 6.04%) (Table 3.4).
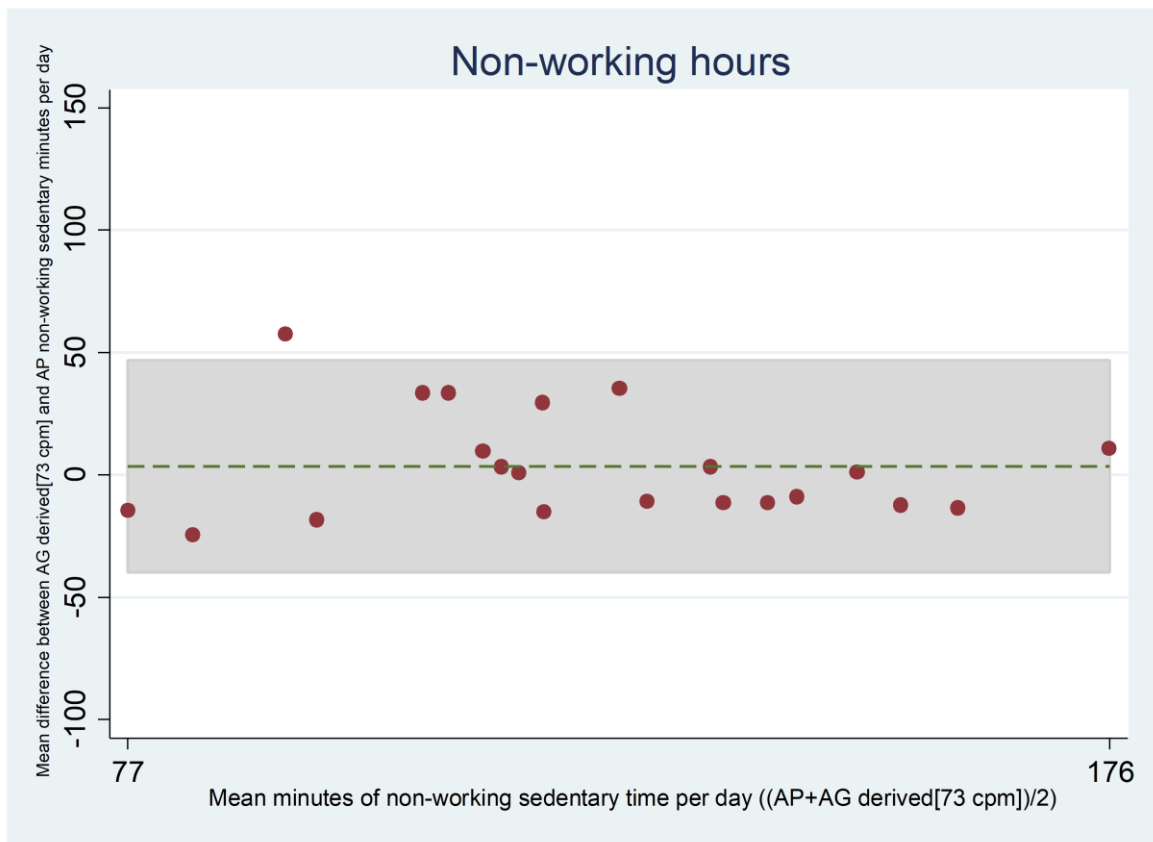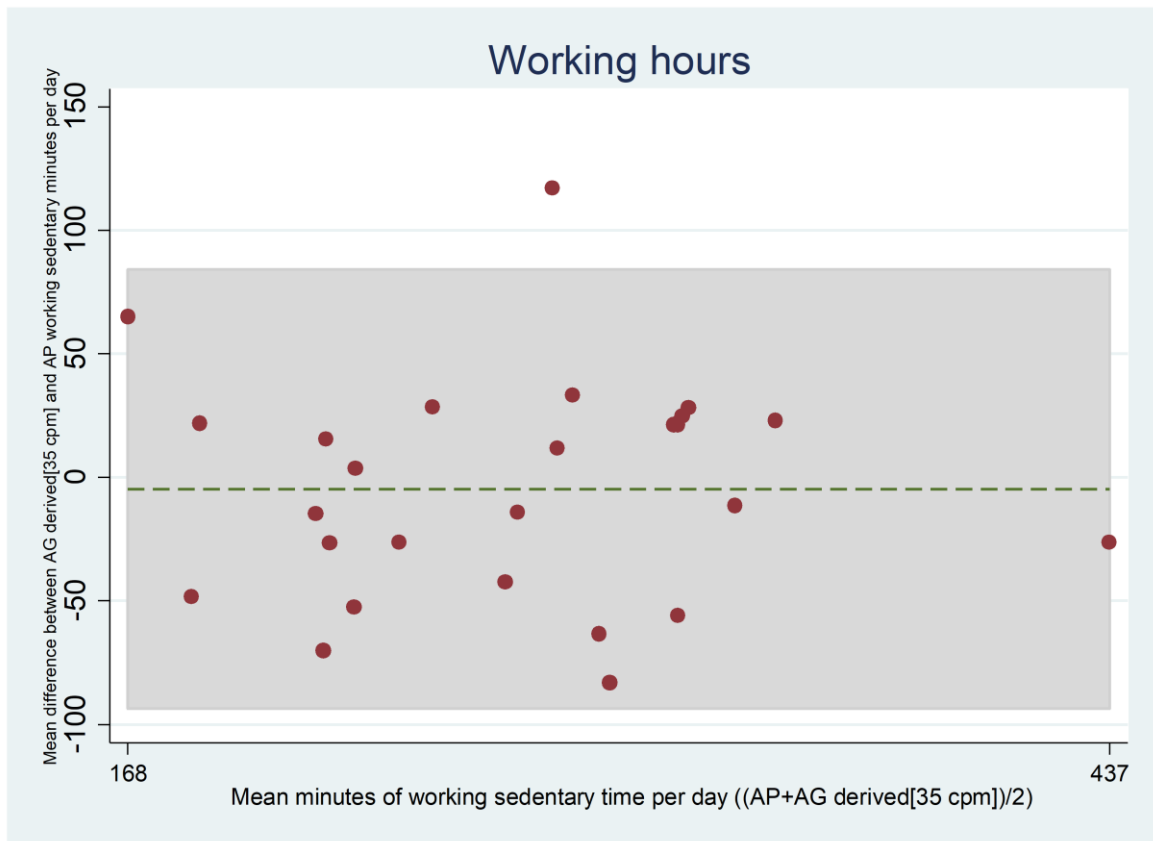
Figure 3.22   Bland-Altman plots of the relationship between activPAL3™ and derived ActiGraph GT3X+ sedentary time, for working and non-working hours

3.4.8   *Objective 3 results*

3. *To derive optimal cut-points for different classifications of sedentary behaviour using contextual data from a 24-hour activity log, and to examine if there are differences between them*.

The data from the detailed activity diary that was completed for one working day for each participant was manually extracted from the diaries; participants had been asked to record the *primary* activity performed during each 15-minute interval of the day (Appendix 4), with the sitting category sub-divided into ten different contexts:

1) Watching television, cinema etc.

2) Sitting at work whilst using a computer

3) Sitting at work, not using a computer (i.e. sitting at a desk, in a meeting)

4) Sitting at home whilst using a computer, playing a video game etc.

5) Relaxing but in a sitting position e.g. listening to music, reading

6) Driving a car

7) Sitting on public transport or in a car (not as the driver)

8) Eating, social sitting (e.g. eating at home/work/restaurant, having coffee, chatting)

9) Cycling

10) Sitting other

For each participant, any sitting periods of 15-minutes for each type of sitting were documented and matched to the time-matched data from the activPAL3™ and the ActiGraph GT3X+ accelerometers. GEE models were then generated for each type of sitting. Table 3.5 details the number of participants, the range of 15-minute periods of data, and the total minutes of matched accelerometer data that were included in each GEE model.

Table 3.5   **Details of sitting data extracted from the detailed activity log**

Sitting context	Participants	Range of 15-minute periods	Sedentary Minutes	Non-sedentary minutes
Watching television	12	2-11	290	435
Sitting at work whilst using a computer	25	5-41	2103	5857
Sitting at work, not using a computer	17	1-20	340	880
Sitting at home whilst using a computer	9	2-12	189	557
Relaxing but in a sitting position	11	1-10	143	516
Driving a car	14	2-12	380	772
Eating, social sitting	22	1-23	425	583
Sitting other	7	1-5	72	127

Between 7 and 25 participants contributed data to the analyses for eight out of the ten sitting contexts. The context that contributed the most data was *Sitting at work whilst using a computer* (5-41 periods, equivalent to 75-615 minutes). The number of minutes of S*itting on public transport or in a car* (111 minutes) was not high enough to be able to run the GEE model. Cycling data were removed as part of the data reduction process; however, four participants recorded having cycled on the day that the detailed activity log was completed. The original data that corresponded to these cycling times were retrieved; however, only 2 of 250 minutes of data were recorded as sedentary by the activPAL3™, and consequently the GEE model could not converge to produce a cut-point estimate. Nonetheless, the bar chart in Figure 3.23 shows the distribution of counts for these *Cycling* minutes; the median (interquartile range) for the counts was 647 (308-1129), with counts ranging from 0-4805, indicating that a derived cut-point for sitting while cycling would be much higher than those previously proposed for sedentary behaviour.
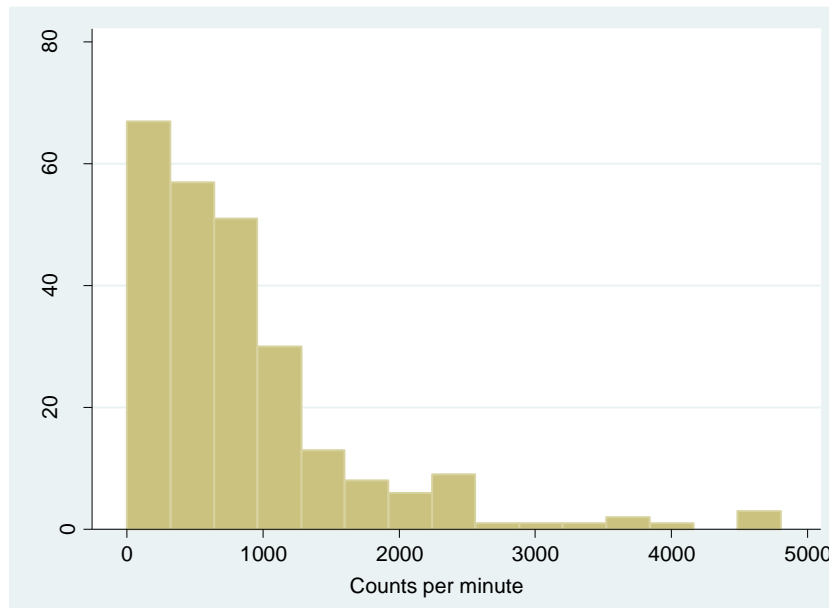
Figure 3.23 **Distribution of ActiGraph GT3X+ counts for *Cycling* minutes**

There were too few participants and minutes of sedentary time for the different sitting types to carry out detailed accuracy and Bland-Altman analyses (Lu et al., 2016); therefore, descriptive statistics for the derived cut-point are provided. The derived cut-points for the different sitting contexts were all less than 100 counts per minute, with the exception of *Driving a car*; the cut-points for sedentary behaviour ranged from 29 (95% CI 23-38) counts per minute for *Sitting at work whilst using a computer*, to 86 (95% CI 54-224) counts per minute for others types of sitting (Figure 3.24). Wide confidence intervals were seen for the three categories that contributed the fewest number of minutes to the analyses: *Watching television, Relaxing but in a sitting position,* and *Sitting other*. The two cut-points for sitting at work (whilst using and not using a computer) were 29 and 42 counts per minute respectively, which are similar to the derived cut-point of 35 counts per minute that was derived for working hours (Section 3.4.7 above). The derived cut-point for sitting while driving was 187 counts per minute (95% CI 154-240), which indicates that the ActiGraph GT3X+ accelerometer may also register accelerations due to other movements of the body caused by the movements of the car (Lyden et al., 2019).
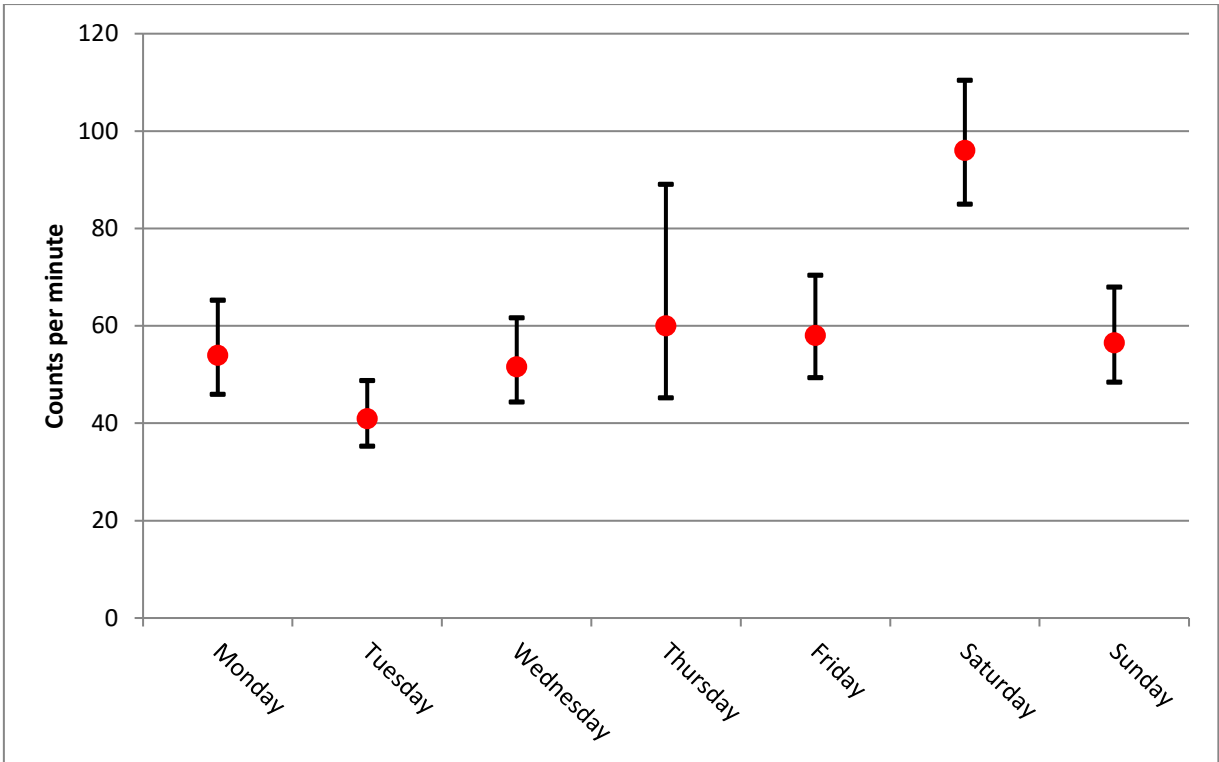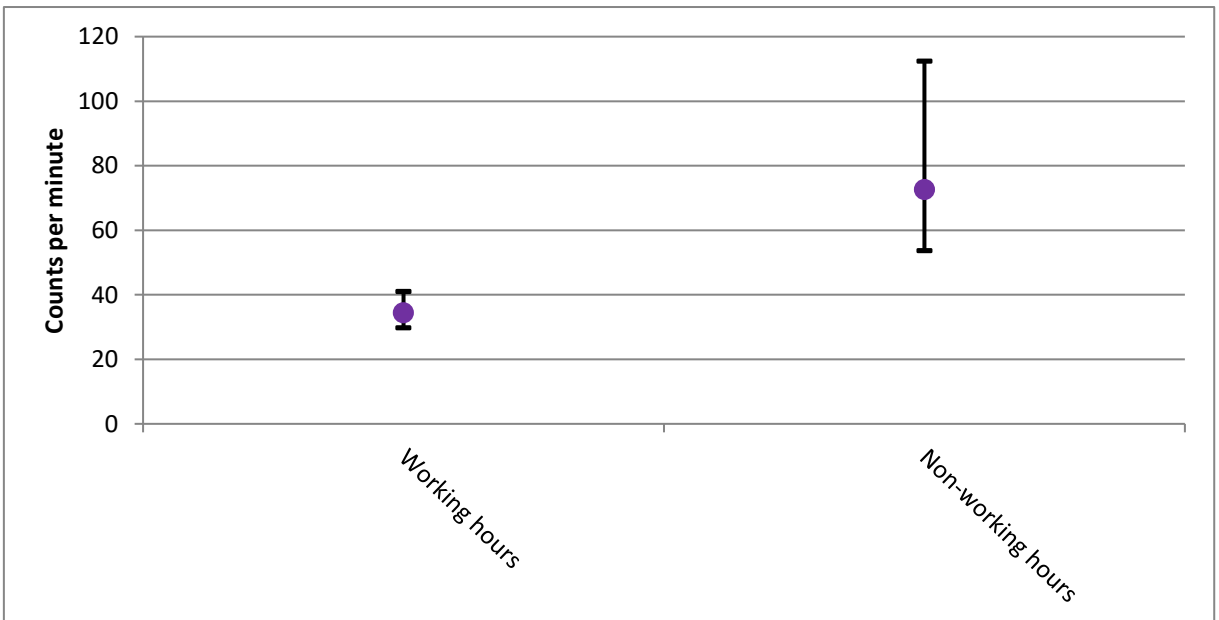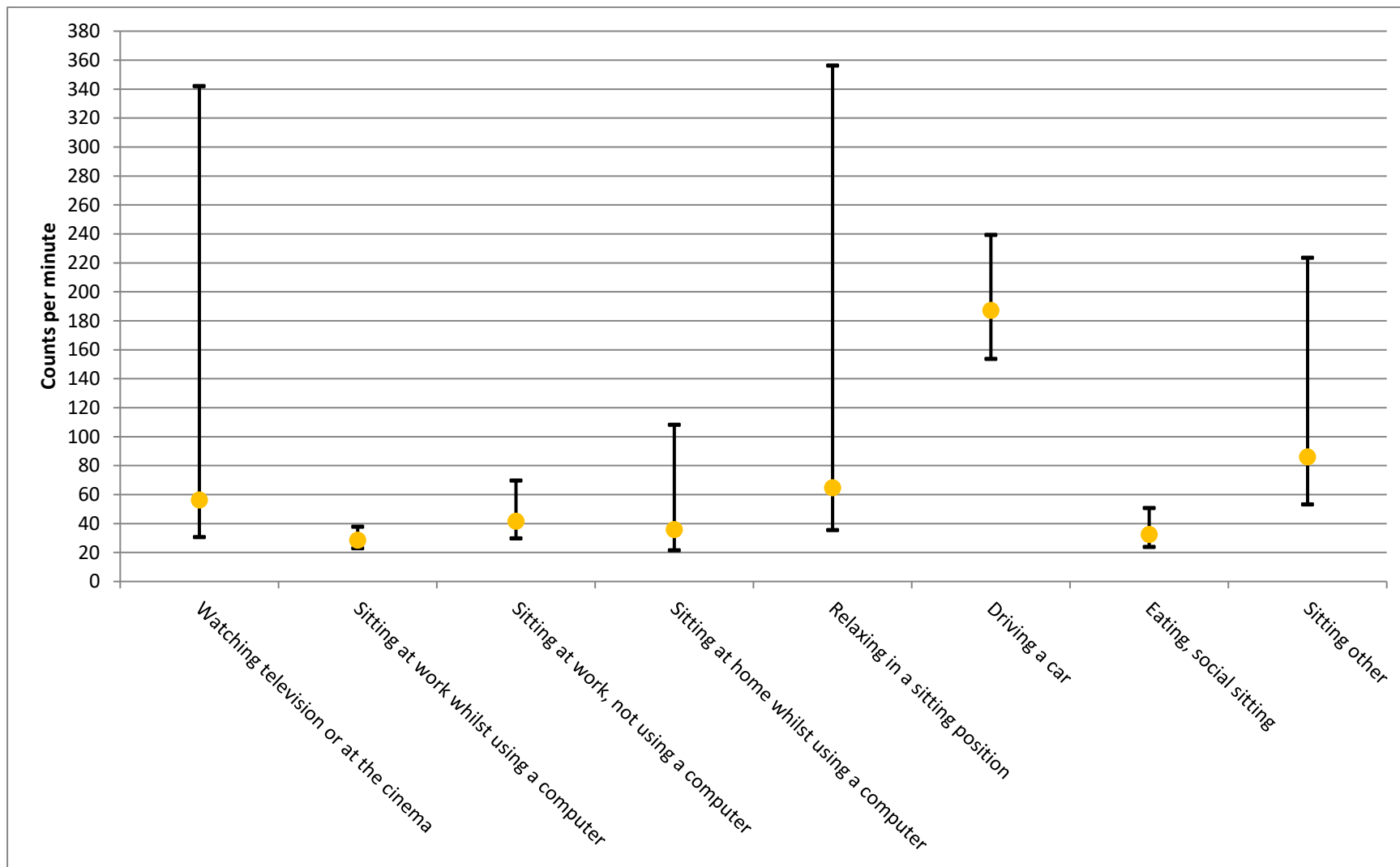
Figure 3.24 **ActiGraph GT3X+ accelerometer-derived cut-points (95% CI) for sedentary behaviour from GEE regression models (sitting types from the detailed activity log)**

3.5 Conclusions

This study is the first to empirically derive accelerometer cut-points for sedentary behaviour in adults, in a free-living environment. The derived cut-points performed better in terms of mean bias and average difference in sedentary time, compared to previously proposed cut-points. Specifically, the 100 counts per minute cut-point over-estimated work time sedentary behaviour by 14.11% compared to an overestimation of <0.01% for the derived cut-point of 35 counts per minute.

The prevalence of sedentary time recorded by the activPAL3™ and the ActiGraph GT3X+ (using the 100 counts per minute cut-point) were similar (65.1% vs. 64.4%). However, this agreement may be due to the way in which the ActiGraph GT3X+ classifies both standing and car travel. Periods of standing still can be classified by the ActiGraph GT3X+ (Section 3.4.5) as sedentary, increasing total sedentary time. Car travel may be classified by the ActiGraph GT3X+ as non-sedentary time, reducing total sedentary time (Section 3.4.8). The overall agreement between the two devices may be explained by the misclassification of standing still (underestimation) and the misclassification of car travel (overestimation) being approximately equal in magnitude.

This derived cut-point in office-based workers suggests that this group is more stationary while sitting: since this study used a hip-worn ActiGraph accelerometer, the differences in stillness while sitting in different contexts must originate from limited hip movement, which suggests that people sit differently depending on the environment where sedentary time is accrued.

Since sedentary behaviour is independently linked to several health-related outcomes, it is imperative to have accurate and reliable measures of sedentary time when using objective

measures. It is not known if sedentary behaviour accrued in different domains and contexts

have different impacts on health, and therefore a more precise definition of accelerometer

thresholds of sedentary behaviour is needed.

3.6   Summary of key findings

- The widely used accelerometer cut-point of 100 counts per minute to define sedentary behaviour was not empirically derived for an adult population (Matthews et al., 2008; Treuth, Schmitz, et al., 2004).

- The 100 counts per minute cut-point has been found to both under- and over-estimate sedentary time dependent on the underlying population being studied (Aguilar-Farías et al., 2013; Koster et al., 2016; Kozey-Keadle et al., 2011; Lopes et al., 2009).

- Sedentary time in different domains may represent differing associations with health-related outcomes (Pinto Pereira et al., 2012; Saidj et al., 2013).

- The use of an activity diary in studies allows for contextual data to be analysed alongside objective data; however, this relies on accurate reporting from participants.

- Decision rules to process accelerometer data may have a significant impact on outcome variables; therefore, it is important that studies detail these processes with respect to harmonisation of accelerometery data (Wijndaele et al., 2015).

- Generalised estimating equations are an extension of standard regression techniques that take into account the autocorrelation of accelerometer counts per minute, making use of all available data (Liang & Zeger, 1986).

- This study found higher percentages of sitting time on week days compared to weekend days, and also for working hours compared to non-working hours: this was consistent with previous studies in office workers (Clemes, O'Connell, et al., 2014; Parry & Straker, 2013; Thorp et al., 2012).

- The ActiGraph GT3X+ cut-point for sedentary behaviour (<100 counts per minute) misclassified 16.9% of minutes as either standing or stepping, and the cut-point for light physical activity (100-1951) contained nearly 40% of sitting or lying.

- The empirically derived cut-points for sedentary behaviour from the generalised estimating equations in this study were consistently less than 100 counts per minute, with the exception of sitting while driving; the cut-point across the week was 65 counts per minute.

- Empirically derived sedentary behaviour cut-points varied by day of the week between 41 and 97 counts per minute; cut-points for working hours were significantly less than non-working hours (35cpm vs. 73cpm).

- The accelerometer data for (both postural and counts per minute, in one-minute epochs), was not able to isolate periods of cycling.

Chapter 4 - Methodology: a secondary analysis method using data from the Health Survey for England 2008

"I think you can have a ridiculously enormous and complex data set, but if you have the right tools and methodology then it's not a problem"

— Aaron Koblin

Table 4.1   Overview of Chapter 4

Chapter	Aims, objectives and research questions	Methods
Chapter 2	**Aim:** To provide an overview of the literature and to critique the current evidence of sedentary behaviour and work, focussing on the prevalence of sedentary behaviour at work, and its association with health-related outcomes	Structured literature review using six electronic databases
Chapter 3	**Aim:** To empirically derive a new accelerometer cut-point to define sedentary behaviour in adults **Objective 1:** To empirically derive an optimal threshold for classifying sedentary behaviour, using the counts per minute output from the ActiGraph GT3X+ accelerometer, when compared to the sedentary classification from the activPAL™ accelerometer in a free-living environment **Objective 2:** To ascertain whether thresholds for sedentary behaviour cut-points vary by day of the week and in working time versus non-working time **Objective 3:** To derive optimal cut-points for different classifications of sedentary behaviour using contextual data from a 24-hour activity log, and to examine if there are differences between them	Observational study in university workers and postgraduate students (n=30) Application of generalised estimating equations to 1-minute epoch data for the ActiGraph GT3X+ and the activPAL™ data
Chapter 4	**Aim:** To describe the methodology for the Health Survey for England 2008, and a critique of the strengths and limitations of using secondary analysis	Description of data collection and processing
Chapter 5	**Aim:** To apply the cut-point from *Study One* to data from the Health Survey for England (2008), in order to investigate the associations between sedentary behaviour, work, and health-related outcomes **Objective 4:** To identify associations between workplace sedentary behaviour and health-related outcomes using the derived cut-point from *Study One* **Objective 5:** To examine if associations between workplace sedentary behaviour and health-related outcomes differ between occupational groups **Objective 6:** To determine if there are associations between workplace sedentary behaviour and mental ill-health and musculoskeletal disorders	A secondary data analysis of the Health Survey for England 2008 Application of hierarchical regression models – type of regression model dependent on distribution of each dependent variable (health-related outcome)
Chapter 6	**Aim:** To apply the cut-point from *Study One* to data from the Health Survey for England (2008), in order to investigate the associations between sedentary behaviour, work, and health-related outcomes **Objective 7:** To explore the patterning and sequences of sedentary bouts across the day, and the relationship with measures of adiposity and other health-related outcomes	Sequence analysis to describe the characteristics of time-related sequences of sedentary behaviour
Chapter 7	**Aim:** To discuss and critically appraise the studies within this thesis and to outline implications for policy and future research	Discussion and conclusions

Chapter Four describes the study design and analysis methods used to address the second aim of this thesis, to investigate the associations between sedentary behaviour, work, and health-related outcomes using the cut-points derived in Chapter Three. A secondary data analysis was chosen as opposed to collecting primary data, given that a large, nationally representative survey with a high-quality dataset already existed: the Health Survey for England 2008 collected data on physical behaviours using both subjective and objective measures.

The first section of this chapter discusses the Health Survey for England and the suitability of a secondary analysis method to address the second aim of this thesis. The second section provides an overview of the research design and data collection methods used for the Health Survey for England 2008, and how these data were obtained from a national data archiving repository; the accelerometer data were not available via this repository, and therefore the methods for obtaining and cleaning the accelerometer data are described. The accelerometer data were provided by the National Centre for Social Research (NatCen), the organisation that carries out the Health Survey for England each year.

The third section of this chapter justifies the regression methods used to model each health-related outcome variable with respect to occupational sedentary time, in order to answer objectives four to six. It also describes the methodology of sequence analysis, which was used to address objective seven.

4.1 Study design

4.1.1 The Health Survey for England

The Health Survey for England is a cross-sectional, nationally representative survey of adults living in private households. It has been conducted on an annual basis since 1991,

and is used to monitor health trends and factors that affect the health of people living in England. All surveys have included adults (aged ≥16), with children aged 2-15 included since 1995, and all ages since 2002 (UK Data Service, 2019b).

The data and results from the Health Survey for England are used by government agencies (including the Department of Health and Public Health England), local authorities, the National Health Service, and other organisations, such as universities and charities to:

– estimate and monitor the prevalence of people in England with specific health-related outcomes

– estimate and monitor the prevalence of lifestyle and other risk factors associated with health-related outcomes

– investigate differences in the prevalence of health-related outcomes and their risk factors amongst specific population subgroups, i.e. gender, age-groups, BMI categories, geographic areas, and categories of economic indicators

– help plan public services

– help develop and evaluate policy (Craig, Mindell, & Hirani, 2009b; NHS Digital, 2019; UK Data Service, 2019b).

The Health Survey for England is also used to monitor the progress of national health targets and campaigns; for example, the "5 a day" campaign that recommends people eat at least five portions of fruit and vegetables each day (Health and Social Care Information Centre, 2018; Public Health England, 2018). Previously, data from the Health Survey for England were used to identify a higher than expected prevalence of untreated hypertension; these data have since been used to inform the practice of regular blood pressure checks in primary care (NatCen, 2019; Public Health England, 2014).

The Health Survey for England comprises a set of core health questions and anthropometric measurements each year including questions on: demographic information, lifestyle factors (smoking, alcohol, diet, physical activity), general health, longstanding illnesses, use of health services, measurements of height, weight and blood pressure, and the analysis of blood and saliva samples (to measure cholesterol, glycated haemoglobin, and cotinine levels) (UK Data Service, 2019b). A specialist module of questions are also asked each year that focus on a particular disease, condition or population group; for example, cardiovascular disease, respiratory disease, children and young people, physical activity, and ethnic minority groups (NatCen, 2019; UK Data Service, 2019b). These modules are revisited periodically in order to monitor trends; for example, physical activity has been the module of special interest in 2008, 2012, and 2016.

Data are collected using a variety of methods: firstly, face-to-face interviews, self-completion questionnaires, and height and weight are measured by an interviewer for each eligible person in a household; secondly, for those who agree, a specially trained nurse will visit to measure blood pressure, waist and hip circumference, and to collect blood and saliva samples.

The Health Survey for England is currently funded by NHS Digital[40] and has been carried out by NatCen and the Health and Social Survey Research group at University College London since 1994 (NHS Digital, 2019). The anonymised dataset from each Health Survey

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[40] The information and technology partner to the health and social care system in the UK https://digital.nhs.uk/

for England is made available from the UK Data Service, which is a national data service that provides access to a range of data collections from the UK (UK Data Service, 2019a).

4.1.2 *Secondary data analysis*

Secondary data analysis can be defined as "… analysis of data that was collected by someone else for another purpose" (Smith et al., 2011, p. 920). The use of secondary data can be time and cost-effective in comparison to primary data studies and can eliminate logistical issues of primary data collection; for example, gaining ethics, accessing a large and representative sample, and obtaining funds and resources to collect the data (Hox & Boeije, 2005; Kiecolt & Nathan, 1985). Many available secondary datasets are from nationally representative surveys and studies, which include standard measures to collect a wide range of data on a large number of people (Kiecolt & Nathan, 1985; Smith et al., 2011). With increasing access to data services and repositories and the ability to access readily available data, secondary data analysis can be a convenient option for researchers (Greenhoot & Dowsett, 2012).

Compared to primary data collection, users of secondary data do not have the contextual knowledge of how the data were collected or control of the questions and measures used. Secondary data may not include all the required variables to answer the objectives of the secondary analysis, which may impact on residual confounding (Hox & Boeije, 2005): this may be due to the original data being collected for a different purpose, or identifying variables being removed in order that available data are anonymised (Cheng & Phillips, 2014). Many large surveys rarely use all the available data that were collected, and therefore a secondary analysis can build on the original objectives of the study by carrying out more detailed analyses (Smith, 2008).

Before carrying out a secondary data analysis, there are a number of things to consider: firstly, the appropriateness of the secondary dataset to answer the new research objectives; secondly, the availability of the data, metadata and study methodologies for the original study. It is important to have this additional and contextual information, in order to clean the data for the purposes of the intended study and to assess the quality of the data. Lastly, a secondary dataset can contain many variables that will need to be checked and cleaned: although a large dataset allows researchers to test complex hypotheses, "getting to know" and cleaning the data can add time to a secondary analysis study (Greenhoot & Dowsett, 2012; Smith et al., 2011).

Many of the research councils that fund and support research now have data sharing policies (Medical Research Council, 2011; National Institure for Health Research, 2019; National Institutes of Health, 2007). Making data available for other researchers can be cost-effective, can help to verify existing results, can expedite the advancement of research, and has benefits to society with respect to informing policy.

4.2 Health Survey for England research design

The Health Survey for England is cross-sectional in design, with data collected continuously throughout the year; however, a different cohort is sampled each year. Cross-sectional studies are used to examine associations between potential risk factors and health-related outcomes. Although they are not able to measure causality, cross-sectional studies are useful for the surveillance of health-related outcomes, and can be used to justify studies with a more robust study design that can establish causality (e.g. cohort studies) (Rothman, 2002; Silman & Macfarlane, 2002).

4.2.1 Selection of participants

The Health Survey for England uses a multi-stage stratified random sample design of private households in England to obtain a nationally representative sample (Craig et al., 2009b). The sampling frame used is the small user Postcode Address File, which is a database that contains all addresses and postcodes in the UK: fewer than 1% of households are not included in the Postcode Address File (Craig et al., 2009b; Royal Mail, 2019). The Postcode Address File can be split into postcode sectors that contain approximately 3000 addresses; for the Health Survey for England, addresses are randomly sampled within a stratified sample of postcode sectors to provide a nationally representative sample.

The complex survey design of the Health Survey for England uses participant weights to account for non-response bias and any unequal probability in participant selection. Prior to 2003, the Health Survey for England did not employ sample weights, as the survey samples were generally well matched to the national population; however, the introduction of weights aimed to reduce any possible biases in the study design when estimating prevalence rates (Craig et al., 2009b).

4.2.2 Ethical considerations

For each chosen address, an advance letter and leaflet is sent out to introduce the Health Survey for England and inform the occupants that an interviewer will be in touch. It is made clear to survey participants throughout the interview and nurse visit that their answers will be used, to provide statistical analyses, and there is no restriction on the kind of research or analyses that are intended. The leaflet that is included with the advance letter gives information about ethical approval; this includes a section entitled, "Is the survey confidential?", which states "The information collected is used for research and statistical

purposes only and is dealt with according to the 1998 Data Protection Act".[41] A second detailed leaflet is provided to those who agree to the nurse visit, setting out what will happen, and again it is made clear that the results are likely to be used for further research (see Appendix 8 for samples of these documents).

Participants are asked to give written consent in a consent booklet at the nurse visit for blood and saliva samples to be collected (to measure cholesterol, glycated haemoglobin, and cotinine levels). Prior to 2014,[42] written consent was also taken for blood samples to be stored and for participant's personal information (name, address and date of birth) to be linked to three national health registers in order that their survey data be linked with mortality data, hospital records and cancer registry.

When ethical approval is obtained for the Health Survey for England, it is confirmed that an anonymised dataset will be made available from the UK Data Service, a national data archiving repository (Section 4.3.1). NatCen takes care to ensure that no variable, or combination of variables, can be used to identify any individuals in the dataset. In 2008, the Health Survey for England was approved by the Oxford A Research Ethics Committee, reference 07/H0604/102.

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[41] The Health Survey for England surveys now comply with updated data protection legislation, including the General Data Protection Regulation (GDPR) and the UK Data Protection Act 2018 (DPA)
https://digital.nhs.uk/services/health-surveys-service
https://www.ucl.ac.uk/epidemiology-health-care/general-data-protection-regulation-gdpr
[42] https://www.statisticsauthority.gov.uk/wp-content/uploads/2019/05/NHS-Digital-data-review-May-2019-update.pdf

4.2.3   Health Survey for England 2008 data collection

As with previous years, the Health Survey for England 2008 used a multi-stage stratified random sample design. The core sample employed in 2008 consisted of 16,056 addresses from the Postcode Address File; a further boost sample of 19,404 addresses were included to increase the number of children (aged 2-15) recruited, in order that detailed analyses could be carried out in this age-group (Craig et al., 2009b). A maximum of two adults and two children were interviewed in households that agreed to take part. The 2008 dataset included a final sample of 9191 households, with 15,102 adults (aged 16 years and over) and 7521 children. The response rate of households with at least one respondent was 64%, and the individual response rate was 58% (Craig et al., 2009b). These response rates were similar to 2007 (64% and 58%) and 2009 (68% and 61%): although response rates had fallen since 1994 (77% and 71%), Mindell et al. (2012) suggested that rates may have started to plateau between 2006 and 2009. Nevertheless, results from the two most recent surveys show that response rates have fallen further; 2016 (59% and 55%) and 2017 (60% and 55%).

4.2.3.1   Interviewer visit

Participants were visited at home by an interviewer, and data were collected using face-to-face interviews and self-completion questionnaires. The face-to-face interviews used a computer-assisted personal interviewing (CAPI) technique that enabled interviewers to record answers directly onto a laptop. Information was collected at both the household and individual level: the household questionnaire collected data on household size, home-ownership, type of residence, household income, and socio-economic status. Each eligible

adult in a household (maximum of two adults) was asked a wide range of questions, including:

- Demographic data on age, gender, and ethnicity

- General health and longstanding illnesses

- Lifestyle factors, including fruit and vegetable consumption, smoking status and alcohol intake

- The specialist module in 2008 focussed on physical activity and fitness levels, and a number of questions were included that asked about physical activities carried out in the previous four weeks

- Adults were asked to complete a self-completion booklet that included questions on general health and wellbeing over the previous few weeks

- Anthropometric measures of weight and height were measured using portable scales and a stadiometer (Craig et al., 2009b, 2009a).

The average length of the household interview ranged from 46 minutes for one adult (aged 65+), and up to 98 minutes for a household with two adults (aged 16+) and two children (aged 0-15) (NatCen and University College London, 2011).

4.2.3.2   Nurse visit

For those participants that agreed, a subsequent visit was arranged with a specially trained nurse, which included the following measures:

- Blood pressure

- Non-fasting blood samples were taken for the analysis of cholesterol (total and HDL) and glycated haemoglobin (haemoglobin A1c [HbA1c])[43]

- Saliva sample to measure cotinine levels

- Waist and hip circumference

- A self-completion booklet that included questions on eating habits

The average length of the nurse visit was between 5 and 13 minutes for each child and between 32 and 53 for each adult (NatCen and University College London, 2011).

4.2.3.3   Accelerometer sub-sample

As part of the specialist module on physical activity and fitness levels in 2008, a sub-sample of participants was randomly selected to wear an accelerometer to collect objective measures of physical behaviour. This was the first time that an objective measure of physical behaviour had been used in a national survey in England; however, objective methods were not used in subsequent surveys that focused on physical activity in 2012 and 2016.

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[43] Average blood glucose levels over the previous 8-12 weeks

Up to two participants in each of the households in the sub-sample were selected and asked to wear an accelerometer for seven days. Participants were not selected to wear an accelerometer if they were younger than four-years, pregnant, confined to bed, had undergone recent abdominal surgery (as the accelerometer was worn on a belt around the waist), or if they had a latex allergy (since the belt contained latex). The interviewer obtained verbal consent from participants who agreed to wear an accelerometer.

There were 7963 people (2435 children, 5528 adults) in the households who were randomly selected for the accelerometer sub-sample; of which 6222 (1656 children, 4566 adults) were selected to wear an accelerometer (Figure 4.1). The physical activity report from the Health Survey for England 2008 states that "… a fault with the device meant that there were unusable data for 18% of men and 20% of women selected for accelerometry" (Craig et al., 2009a, p. 66). This resulted in a sample of 4484 participants (1273 children and 3211 adults) who agreed to wear an accelerometer and provided usable data.
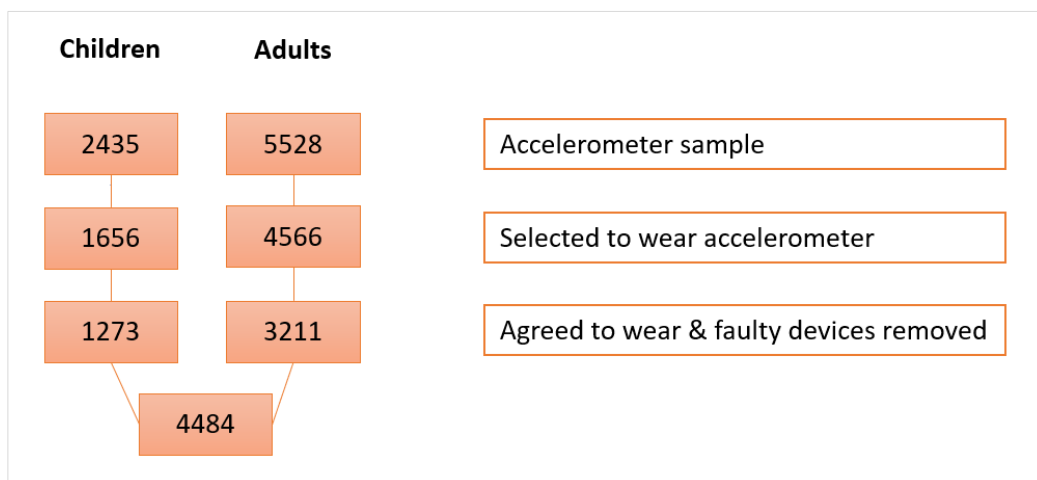
Figure 4.1 **Health Survey for England 2008 accelerometer sample**

These 4484 participants were asked to wear an ActiGraph GT1M accelerometer for seven days: the accelerometer was attached to a belt and worn on the right hip (Figure 4.2). The ActiGraph GT1M is similar to the ActiGraph GT3X+ that was used in the study in Chapter

Three; however, the GT1M is an earlier model of the ActiGraph that collected data from the vertical axis only.

Figure 4.2 **Photograph of an ActiGraph GT1M, and a hip-worn ActiGraph attached to a belt (ActiGraph LLC., 2019. [Online]. Available from: www.actigraphcorp.com/ actigraph-wgt3x-bt/)**

Participants were asked to wear the ActiGraph GT1M accelerometer during waking hours only, and were provided with an activity log and asked to record any times that the accelerometer was removed each day; for example, the time it was taken off each evening and the time it was attached each morning, and any periods of sport such as swimming and contact sports (Colley et al., 2011). An information leaflet was also provided with further details on how to wear the ActiGraph GT1M and frequently asked questions (Appendix 9). Participants received a £20 high street voucher after returning the accelerometer, as a token of appreciation.

The data files from the ActiGraph GT1M accelerometers were processed in KineSoft, an accelerometer data analysis software (KineSoft, Loughborough, UK). This software used the processed counts per minute outcome to calculate time spent in physical behaviours for the Health Survey for England analysis: the main variables of interest that were included in the physical activity report were average minutes per day of sedentary time, light physical activity, and moderate to vigorous physical activity. The Health Survey for England defined sedentary behaviour as counts per minute as <199, which is double the commonly

used <100 counts per minute cut-point (Matthews et al., 2008). The 199 cut-point for sedentary behaviour was taken from a study that examined the practicality of the use of accelerometers in large studies of children (Mattocks et al., 2008): the sedentary behaviour cut-point was arbitrarily set at <199 due to the confines of the software used in the study, which "… derived categories of physical activity intensity in blocks of 200 counts/min, …" (Mattocks et al., 2008, p. S101). The cut-points for physical activity intensities were developed by Troiano et al. (2008), by calculating a weighted average from previous calibration studies: they are one of the cut-point classification options within the ActiLife software and are well-cited in the physical behaviour literature (Evenson & Wen, 2011; Loyen et al., 2017; van Nassau, Chau, Lakerveld, Bauman, & van der Ploeg, 2015) (Figure 4.3).

Physical activity intensity	Counts per minute (cpm)	Metabolic Equivalents (METS)
Sedentary	0-199	0 to below 1.5
Light	200-2,019	1.5 to below 3
Moderate (MPA)	2,020-5,998	3 to below 6
Vigorous (VPA)	More than 5,998	6 or more
Moderate and vigorous (MVPA)	2,020 or more	3 or more

Figure 4.3   Physical activity cut-points used in the Health Survey for England 2008 (Craig et al., 2009a, p. 65)

4.3   Data analysis methods

4.3.1   Obtaining data from the UK Data Service

An anonymised copy of the Health Survey for England dataset is made available each year from a national data archiving repository, the UK Data Service. To access the datasets, researchers need to register with the UK Data Service, provide details of the research project that the data are intended to be used for, and accept the End User Licence. The End User Licence and the project registration details to use the anonymised dataset for the

Health Survey for England 2008 can be seen in Appendix 10 (NatCen and University College London, 2011).

Datasets from the UK Data Service come with documentation and metadata relevant to each dataset, which is supplied by each individual data provider. For the Health Survey for England 2008 dataset, the following data, metadata, and documentation were provided:

– Study information and bibliographic citation

– Anonymised dataset in SPSS and Stata formats

– Data dictionaries, which included information on the variable labels and any relevant coding

– List of variables and derived variables

– User guide

– Published reports on physical activity and methods (Craig et al., 2009a, 2009b)

– Interviewing and supporting documents, including questionnaires, showcards, and interviewer instructions

4.3.2   *Obtaining accelerometer data*

The accelerometer data that were collected in the Health Survey for England 2008 were not deposited with the UK Data Service, as were the data from the interviewer and nurse visits. Therefore, the Research Director at NatCen was contacted, who agreed to provide access to the ActiGraph accelerometer data files. However, NatCen did not have access to the specialist software that was used to analyse the ActiGraph data; therefore, the files could not be released until the files had been converted to a usable format and checked for any data that could not be released under data protection policies. Consequently, two

visits were made to the NatCen offices in London to convert the data files to a useable format.

NatCen had access to the data files from the 4484 participants in the accelerometer sub-sample who agreed to wear an accelerometer and provided usable data (Figure 4.1). These data files were in the format of *dat*[44] files, which were the file types used in previous versions of the ActiLife software: the *dat* files were converted to *agd*[45] files using the ActiLife5 software on a laptop. The ActiLife software was then used to convert the proprietary *agd* files to *csv* files, so that they could be imported into Stata to be checked and cleaned. Out of the 4484 *dat* files, six would not open using the ActiLife software and a further 79 could not be converted into *agd* files; this resulted in 4399 data files with usable data (Figure 4.4).

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[44] Generic data file
[45] ActiGraph data file: file type compatible with ActiLife software; these file formats can be used to view the data in ActiLife version 6.1 and later

Children	Adults	
2435	5528	Accelerometer sample
1656	4566	Selected to wear accelerometer
1273	3211	Agreed to wear & faulty devices removed
	4484	Data files available from NatCen
	4478	6 .dat files would not open
	4399	79 could not convert to .agd format
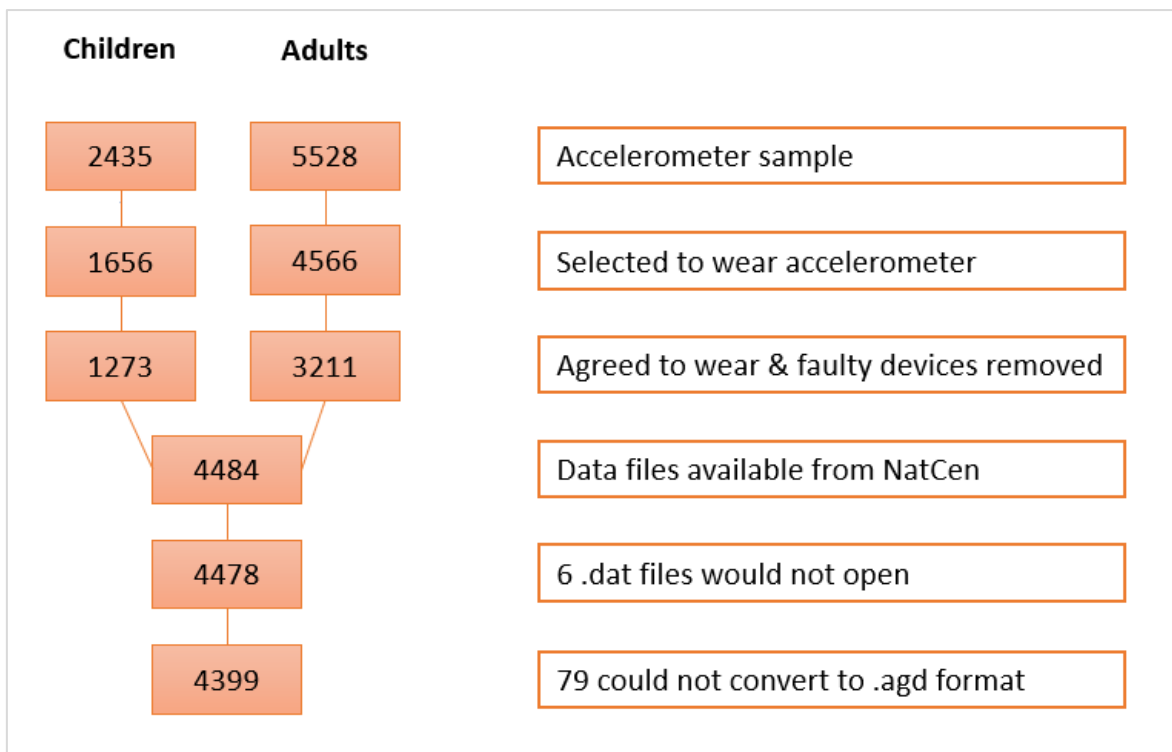
Figure 4.4   Health Survey for England 2008 accelerometer data files

The filename for each of the accelerometer data files contained the participant identification number that could be matched to the anonymised dataset retrieved from the UK Data Service. Furthermore, each participant data file contained three variables: date, time and counts per minute. The date variable was not able to be released due to NatCen data protection policies; therefore, new variables were created for day of the week, month, and day of data collection (to indicate the number of days of data provided).

The day of data collection ranged from one day, up to 146 days, indicating that at least one ActiGraph had recorded data for 146 days. Therefore, the data files needed to be matched to the seven-day period of data collection; this was completed on a second visit to NatCen due to the time it had taken to process the files during the first visit. For the second visit, an Excel sheet was provided by a researcher at NatCen with a list of participant identification numbers and dates of the interview (when the accelerometer was given to participants), and also the start date of data collection that was recorded in the activity log

by the participant. A Stata programme had been written prior to this visit, to match these dates to the previously processed files. The programme was run twice for both the interview dates and also the activity log dates; any days prior to the proposed start date were deleted, as were days that occurred more than seven days after this to isolate the seven days of data collection. This resulted in two new files for each participant; the first contained data with the day after the interview as the first day of data collection, and the second contained data with the day recorded in the log book as the first day of data collection. The matching Excel sheet was deleted from the laptop before leaving the NatCen offices.

4.3.3   Non-wear time algorithm applied to England accelerometer data

A group of researchers from the Determinants of Diet and Physical Activity (DEDIPAC) Knowledge Hub also required the accelerometer data from the Health Survey for England 2008 for a study that aimed to harmonise and analyse accelerometer data from national surveys from four European countries. The ActiGraph data files were no longer in a format that could be processed in the ActiLife software with respect to removing non-wear time. Therefore, as part of this thesis, a programme was written in Stata to replicate the commonly used Troiano non-wear algorithm. This algorithm uses a *moving window* to define non-wear sequences as a minimum of 60 consecutive minutes of zero counts, allowing for up to two consecutive minutes of counts ranging from 1 to 100 (Troiano et al., 2008). The flow chart in Figure 4.5 represents the Stata programme that was written to replicate the Troiano non-wear algorithm: this was based on the SAS code, which is available from NHANES (National Cancer Institute, n.d.). In brief, each minute is coded as *definite* wear time (counts>100, three or more consecutive counts between 1 and 99), or

possible non-wear time: the algorithm then loops through the dataset counting the length of possible non-wear sequences and checking for the number of counts between 1 and 99 within each possible non-wear sequence. The Stata programme can also be seen in Appendix 11. This programme was validated separately by the researchers from DEDIPAC and was consequently used in a study that resulted in the publication by Loyen et al. (2017), which described population levels of sedentary behaviour and physical inactivity from national data in four European countries.
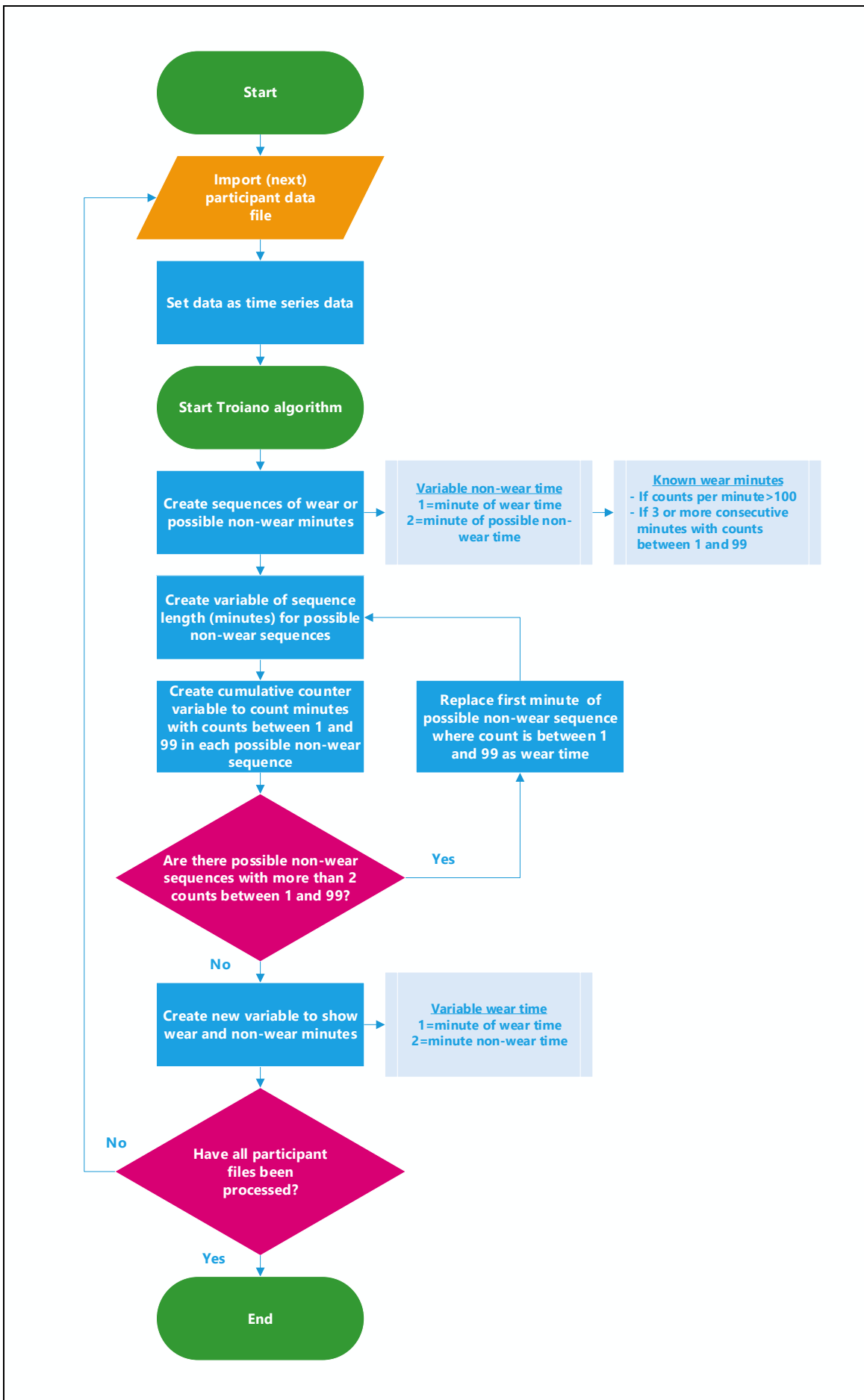
Figure 4.5   Flow chart of Troiano non-wear algorithm (used in Stata program/code)   177

4.3.4   Data cleaning, list of variables, and descriptive analyses

The second aim of this thesis is to investigate the associations between sedentary behaviour, work, and health-related outcomes: this section details the variables chosen for the regression analyses that were used to predict the effect of sedentary behaviour on each chosen health-related outcome. The Health Survey for England 2008 dataset obtained from the UK Data Service contained 2080 variables: the data dictionary and the *List of Variables* document, were used alongside previous articles that had used data from the Health Survey for England 2008 to choose the variables to be used as dependent and independent variables in the regression models (NatCen and University College London, 2011).

Sections 4.3.4.1 and 4.3.4.2 below describe the subjective and objective measures of sedentary behaviour and physical activity that were collected in the Health Survey for England 2008; Section 4.3.4.3 details the health-related outcomes that were chosen as dependent variables (cardiometabolic risk factors of adiposity, total and HDL cholesterol, glycated haemoglobin, and systolic and diastolic blood pressured are first described (Kassi et al., 2011), followed by details of longstanding illness and measures of mental wellbeing); Sections 4.3.4.4 and 4.3.4.5 describe the independent variables that were adjusted for in the regression analyses. A coding schedule of variables can also be seen Appendix 12.

4.3.4.1   Subjective sedentary behaviour and physical activity variables

– Subjective sedentary time was assessed from a set of questions on television viewing and other periods of sedentary behaviour during leisure time, on weekdays and weekend days.

– In 2008, a set of new occupational activity questions were included; previous questions categorised the type of work activity, but the focus of the new questions was on what participants do at work to capture type, frequency and duration of work activities. Occupational activities that lasted ten minutes or more were classified as sitting/standing, walking, climbing stairs or ladders, and lifting, carrying or moving heavy loads; therefore, occupational sedentary time could not be accurately assessed subjectively.

– Physical activity was subjectively assessed from a set of questions that included frequency and duration of a range of activities (that lasted ten minutes or more) during the four weeks prior to being interviewed.

– Variables for **average minutes per day of sedentary time were derived for all week, weekdays, weekend days and at work; a variable for average minutes per day of moderate to vigorous physical activity** was also derived by the Health Survey for England. These derived variables were extracted for comparison with the objective measures of sedentary behaviour and physical activity.

4.3.4.2   Objective sedentary behaviour and physical activity variables

– The accelerometer data files for each participant contained a maximum of 10,080 rows (equating to minutes in a week); after non-wear time was removed using the process described in Section 4.3.3, these files were collapsed to one row of data that included variables for the average minutes per day of **sedentary time for all week, weekdays, weekend days, work time, and non-work time**. Work times were defined between the hours of 9:00am and 5:00pm on weekdays, and non-work time was defined as wear time excluding time between 9:00am and 5:00pm (Hall, 2017; Maxhuni et al., 2016;

Ryan et al., 2011). Four variables were derived for each time period using the relative derived cut-points from Chapter Three, and the previously proposed cut-points of 50, 100, and 150 counts per minute.

– A variable for average minutes of moderate to vigorous **physical activity per day** (based on the Troiano cut-point of ≥2020 counts per minute) was also computed.

4.3.4.3 *Health-related outcomes – dependent variables*

– **BMI** (kg/m^2) was derived from the objective height and weight measures that were taken at the interviewer visit (using standardised protocols). Height was measured, without shoes, using a portable stadiometer to the nearest 0.1cm, and weight was measured, without shoes, using a set of portable scales to the nearest 0.1kg. BMI was treated as a continuous variable, both as a dependent variable, and as an independent covariate for regression models for other health-related outcomes (He, Pombo-Rodrigues, & MacGregor, 2014; O'Donovan, Lee, Hamer, & Stamatakis, 2017).

– **Waist circumference** is increasingly being used as the preferred measure of obesity compared to BMI, which does not distinguish fat from fat-free mass; waist circumference (and not BMI) is used in criteria to define metabolic syndrome (Kassi et al., 2011; Lee, Huxley, Wildman, & Woodward, 2008). Waist circumference was measured by the nurse to the nearest 0.1cm; two measurements were taken, and the mean was used. Waist circumference was treated as a continuous variable (Bakrania et al., 2016).

- Non-fasting blood samples to measure cholesterol (total and HDL) and glycated haemoglobin (HbA1c[46]), were collected during the nurse visit, and blood analytes were assayed at the Royal Victoria Infirmary in Newcastle-upon-Tyne[47]. **Total cholesterol**, **HDL cholesterol**, and **glycated haemoglobin** were treated as continuous variables (Bakrania et al., 2016; Stamatakis & Hamer, 2012; Stamatakis, Hamer, et al., 2012).

- **Blood pressure** was measured during the nurse visit using a portable Omron monitor. A standardised protocol was used that asked participants to sit down for five minutes; three blood pressure measurements were taken using the right arm at one-minute intervals, and the average of the last two readings was used for analysis purposes. Both **systolic** and **diastolic blood pressure** were treated as continuous variables (He et al., 2014; O'Donovan et al., 2017).

- Longstanding illness was assessed by asking participants, "Do you have any long-standing illness, disability or infirmity? By long-standing I mean anything that has troubled you over a period of time, or that is likely to affect you over a period of time?". Participants could list up to six illnesses, which were then grouped using a coding frame into groups using headings from the International Classification of Diseases (Version 10).[48] Data for **musculoskeletal conditions**, **mental and behavioural disorders**, and

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[46] Average blood glucose levels over the previous 8-12 weeks
[47] Analytical methods and equipment are detailed in Craig et al. (2009b)
[48] https://icd.who.int/browse10/2008/en

diseases of the heart and circulatory system were coded as *yes* or *no* (Rind et al., 2014; Ryan, McDonough, Kirwan, Leveille, & Martin, 2014).

- The **GHQ**[49]**-12** was used to assess mental ill-health. The GHQ-12 is a well-established 12-item questionnaire that is used to measure psychological stress or mental ill-health (Goldberg, 1972). It asks 12 questions relating to general health over the last few weeks: for example, the first question asks, "Have you recently been able to concentrate on whatever your' doing", with four possible answers (better than usual, same as usual, less than usual, much less than usual). The GHQ can be scored out of 12, with positive answers scoring '0' (i.e. better than usual, same as usual) and negative answers scoring '1' (i.e. less than usual, much less than usual) (Mullarkey & Wall, 1999). A cut-off of ≥3 can indicate 'minor psychiatric distress' (Goldberg, 1972); however, a more conservative cut-off of ≥4 is used in the literature, which is also associated with anxiety and depression (Aalto, Elovainio, Kivimäki, Uutela, & Pirkola, 2012; Hamer, Coombs, & Stamatakis, 2014). For the analyses in this study, the **GHQ-12** was dichotomised with a cut-off of ≥4.

- The **EQ-5D**[50] is a health-related quality of life measure, which consists of five domains (mobility, self-care, usual activities, pain/discomfort, and anxiety/depression); each domain is scored at three levels (no problems, moderate/some problems, severe/extreme problems) (The EuroQOL Group, 1990). EQ-5D utility scores can be derived by applying a set of tariffs to the responses for each level, within each domain (developed from a UK population) (Dolan, Gudex, Kind, & Williams, 1995): the UK EQ-

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[49] GHQ – general health questionnaire
[50] EQ-5D - EuroQol 5 dimensions

5D scores range from 1 to -0.594, where '1' signifies perfect health, '0' death, and negative values have been described as 'states worse than death' (Harrison et al., 2009; Macran & Kind, 2001). The Health Survey for England 2008 uses a EQ-5D summary value for each participant, derived from the set of tariffs that were applied to each level, within each domain (Dolan et al., 1995; EuroQol Research Foundation, 2018). The **EQ-5D** summary score was treated as continuous variable, with upper and lower censoring at '1' and '-0.594' respectively (Anokye, Trueman, Green, Pavey, & Taylor, 2012; Maheswaran, Petrou, Rees, & Stranges, 2013).

4.3.4.4   Independent variables – demographic related

- In the Health Survey for England 2008, **age** was recorded as age at interview; it was treated as a continuous variable.

- **Gender** was categorised as male or female.

- **Ethnicity** was categorised as white or non-white due to small numbers within some ethnicity categories in the final analysis dataset; other studies that have used Health Survey for England 2008 have also treated ethnicity as a dichotomous variable (Anokye & Stamatakis, 2014; Bakrania et al., 2016; He et al., 2014).

- Person level socio-economic status was defined using **equivalised household income**. A show-card with pre-defined income bands was presented to participants to determine household income; however, equivalised household income is increasingly being used as this takes into account the household composition (Anokye & Stamatakis, 2014; Carney & O'Neill, 2018). The derived equivalised household income was categorised into quintiles (He et al., 2014; Maheswaran et al., 2013).

– Average **fruit and vegetable portions** per day was treated as a continuous variable (taken from the derived Health Survey for England variables) (Coombs & Stamatakis, 2015; He et al., 2014).

– **Smoking status** was categorised as **never, ever,** or **current** (taken from the derived Health Survey for England variables) (Anokye & Stamatakis, 2014; Bakrania et al., 2016; Hamer et al., 2014; Ryan et al., 2014).

– **Alcohol consumption** was categorised as none, ≤4 (men)/≤3 (women), >4 (men)/>3 (women) units per day, from the heaviest drinking day in the previous week (adapted from the derived Health Survey for England variables)[51] (Hamer et al., 2014; Maheswaran et al., 2013; Roth, Mindell, Roth, & Mindell, 2013).

– **General health** was measured using the question, "How is your health in general?", with options of very good/good/fair/bad/very bad. This variable was further categorised into 'very good/good' and 'less than good health' (Roth et al., 2013).

– The **number of longstanding illnesses** given by the participant (maximum of six) were coded as 'none', or 'one or more' (Rind et al., 2014).

– **Blood pressure medication** and **cholesterol medication** was determined from questions at the nurse visit; coded as 'no' or 'yes' (Bakrania et al., 2016).

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[51] The top derived category of >8 (men)/>6 (women) units per day was merged into the >4 (men)/>3 (women) category due to small numbers

- The **National Statistics Socio-economic Classification** (NS-SEC) shows the structure of socio-economic positions in the UK and replaces the previously used Social Class and Socio-economic Groups classifications (Office for National Statistics, 2013). For the purposes of this study the three-class version is used: managerial and professional occupations, intermediate occupations[52], routine and manual occupations. These categories can be further described as professional, white-collar, and blue-collar workers respectively (Goldthorpe & McKnight, 2003), and are similar to categories derived from the Australian Standard Classification of Occupations that have been used to describe occupation sedentary behaviour (Mummery et al., 2005; Steele & Mummery, 2003).[53]

4.3.4.6 *Descriptive analyses*

In order to complete the regression analyses, the dataset was restricted to those with objective measures of sedentary time and physical activity, those who had at least one valid day of data (defined as at least 600 minutes of accelerometer wear time) (Atkin et al., 2012; Colley et al., 2010; Migueles et al., 2017), and those who were in full-time employment (based on >30 hours per week) (Craig et al., 2009b).

Descriptive analyses were carried out: to compare the accelerometer sample to those in full-time employment; to examine differences in subjective and objective physical

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[52] Positions in clerical, sales, service and intermediate technical occupations that do not involve general planning or supervisory powers.

[53] Professionals (managers and administrators, professionals and associate professionals) White-collar workers (elementary clerical sales and service workers, intermediate clerical sales and service workers, and advanced clerical sales and service workers) Blue-collar workers (tradespeople and related workers, intermediate production and transport workers, laborers and related workers).

behaviour measures; and to determine the differences in objectively measured sedentary time using the derived cut-points from Chapter Three and the previously proposed cut-points of 50, 100, and 150 counts per minute. Descriptive statistics for the variables described in the previous sections are presented as means (standard deviations (SD)) or medians (interquartile range (IQR)) for continuous variables, after assessing for normality.[54] Categorial variables are presented as numbers and percentages (n, %). Inferential analyses were undertaken to compare the variables between males and females, and also by occupational group: t-tests were used to examine differences between normally distributed continuous variables with two-groups; the Wilcoxon rank-sum test was used to examine differences between non-normally distributed continuous variables with two-groups; analysis of variance (ANOVA) was used to examine differences between normally distributed continuous variables with more than two-groups; Kruskal-Wallis tests were used to examine differences between non-normally distributed continuous variables with more than two-groups; and, chi-square tests were used to assess for associations between two categorical variables.

4.3.5   *Regression analyses*

Regression analyses were developed to predict the effect of sedentary behaviour on each health-related outcome as the dependent variable. The choice of regression model depends on the type and distribution of the dependent variable, and therefore it was not

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[54] The Shapiro-Wilk test was used to assess continuous variables for normality, alongside visual inspection of the histograms for each variable, due to the large sample size, which can influence the significance of this test (Ghasemi & Zahediasl, 2012)

appropriate to use the same regression model for each health-related outcome. Therefore, the following regression models were chosen based on the different variable types.

4.3.5.1   *Linear regression models – systolic blood pressure, diastolic blood pressure, total cholesterol, HDL cholesterol, and glycated haemoglobin*

Linear regression (also referred to as ordinary least squares (OLS)) has previously been described in Section 3.3.4.1: to recap, a linear regression model predicts the value of the dependent variable from one or more independent variable and assumes that this relationship is linear. The linear regression model with more than one independent variable can be expressed as:

$$y_i = \beta_0 + \beta_1 x_{i1} + \beta_2 x_{i2} + \cdots \beta_p x_{ip} + \varepsilon_i \text{ , for } p \text{ independent variables}$$

The linear regression model can be used to understand the mean change in a dependent variable given a one-unit change in each independent variable, and is best suited to continuous dependent variables that are normally distributed (Alexopoulos, 2010).

4.3.5.2   *Quantile regression models – body mass index and waist circumference*

Linear regression models the mean of the dependent variable and assumes that the relationship between the dependent and independent variable is the same at all levels. Quantile regression models can be used to determine how the effect of the independent variable differs for different quantiles of the dependent variable, and are therefore more appropriate for modelling data that are non-normally distributed (Despa, 2007). The best-known quantile is the median (the 0.5 quantile) and regression models of this quantile are often referred to as median regression.

Quantile regression models are useful in health research, as they can be used to determine the effects of the independent variable for patients at different quantiles of the dependent variable, compared to linear regression methods that provide information about the average patient only (Lê Cook & Manning, 2013). Results of quantile regression models estimate the change in the specified quantile(s) of the dependent variable by a one unit change in the independent variable (Despa, 2007).

4.3.5.3 Tobit regression models – EQ-5D

Health variables, such as the EQ-5D are often measured using a utility score where health status is measured on a scale that is censored at an upper and/or lower limit; this can lead to issues in the interpretation of scores at these limits (Austin, Escobar, & Kopec, 2000). Linear regression of censored data can produce biased estimates of the regression coefficients: although the Tobit model assumes normality, the model has been found to reasonably predict the dependent variable within the censored values range (Austin et al., 2000; Maheswaran et al., 2013). Tobit models are often used in health research to model the EQ-5D variable that is both upper (1.0) and lower (-0.594) censored (Clarke, Gray, & Holman, 2002; Dakin, 2013).

4.3.5.4 Generalised linear models (GLM) – GHQ-12, musculoskeletal conditions, heart and circulatory conditions, and mental disorders

Logistic regression is often used to model dichotomous count data from cross-sectional studies (Barros & Hirakata, 2003); however, the appropriateness of the resulting odds ratios has been widely debated in the epidemiologic literature (Greenland, 1979; skove, Deddens, Petersen, & Endahl, 1998). When the disease prevalence of the dependent variable is low (i.e. <20%) (Davies, Crombie, & Tavakoli, 1998), there is little difference

between the odds ratio and the prevalence rate ratio (Barros & Hirakata, 2003; skove et al., 1998); however, when the prevalence of the dependent variable is more frequent, the odds ratio can overestimate the prevalence rate ratio (Barros & Hirakata, 2003). Therefore, alternative regression models have been suggested that provide more robust estimates of the prevalence rate ratio (Barros & Hirakata, 2003; skove et al., 1998). For the analyses of dichotomous dependent variables in this study (GHQ-12, musculoskeletal conditions, heart and circulatory conditions, and mental disorders), Poisson regressions models with a robust estimator were carried out using the generalised linear model command in Stata: results are presented as prevalence rate ratios.

4.3.5.5   *Hierarchical regression models*

A hierarchy of regression models were developed to predict the effect of sedentary time for each health-related outcome: model 1 adjusted for age, sex, and accelerometer wear time; model 2 was adjusted for ethnicity and lifestyle factors (fruit and vegetable consumption, alcohol consumption, smoking status, equivalised household income); model 3 was adjusted for health factors (general health, longstanding illness, BMI); model 4 was further adjusted for physical activity; model 5 was only used for the sedentary work time models, where a further adjustment for non-work sedentary time was made. This method of incrementally adjusting for covariates is a conventional method within sedentary behaviour research studies (Bellettiere et al., 2017; Coombs & Stamatakis, 2015; Hamer et al., 2014; Stamatakis, Coombs, Rowlands, Shelton, & Hillsdon, 2014).

- **Model 1:** age, sex, accelerometer wear time

- **Model 2:** age, sex, accelerometer wear time, ethnicity, fruit and vegetables, alcohol, smoking, income

- **Model 3:** age, sex, accelerometer wear time, ethnicity, fruit and vegetables, alcohol, smoking, income, general health, [longstanding conditions][55], [BMI][56]

- **Model 4:** age, sex, accelerometer wear time, ethnicity, fruit and vegetables, alcohol, smoking, income, general health, [longstanding conditions], [BMI], physical activity

- **[Model 5:** age, sex, accelerometer wear time, ethnicity, fruit and vegetables, alcohol, smoking, income, general health, [longstanding conditions], [BMI], physical activity, non-occupational sedentary time]

Models for blood pressure and cholesterol levels were also adjusted for either blood pressure medication or cholesterol medication respectively (added to Model 4).

In order to assess the effect of the derived cut-points from Chapter Three, the models were built for each of the objective sedentary time variables (sedentary time for all week, sedentary time for weekdays, occupational sedentary time), using the four sedentary behaviour cut-points (derived, 50, 100, and 150 counts per minute). The effect sizes presented in the regression models represent a 10-minute change in sedentary time.

A number of research studies of sedentary behaviour have found associations with health-related outcomes, independent of physical activity (Section 2.4); however, there is an

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[55] Except in the models where musculoskeletal conditions, heart and circulatory conditions, and mental disorders were the dependent variables
[56] Except in the model with BMI as the dependent variable

emerging debate in the literature as to whether or not adjustment for physical activity is appropriate (Bellettiere et al., 2017; Page et al., 2015). This is based on whether time spent in sedentary behaviour is co-dependent or independent of time spent in physical activity across the day, due to the composition of behaviours across the day, i.e. if one behaviour increases, then inherently, another decreases (Chastin et al., 2015; Page et al., 2015). The regression models in this study were all adjusted for physical activity in Model 4: other behaviours such as light physical activity or sleep were not measured in this study, and therefore the collinearity between sedentary time, and more specifically occupational sedentary time, and physical activity was perceived to be minimal. The collinearity of covariates were checked for each model with variance inflation factors, using the *vif* command in Stata (Coombs & Stamatakis, 2015; Stamatakis, Hamer, et al., 2012); variance inflation factors quantify the severity of multicollinearity in regression models (Mansfield & Helms, 1982).

Accelerometry weights were derived as part of the complex survey design of the Health Survey for England to account for non-response bias; however, the accelerometer sample were more likely to be older, retired and have a longstanding illness (Roth et al., 2013). The participants who were included in the regression analyses were a sub-sample of the accelerometer sample, and only included those people who were in full-time employment; therefore, they were not representative of the accelerometer sample with respect to age, employment status and longstanding illness. Applying the accelerometer weights to a specific sub-sample may not be appropriate and can lead to estimate bias (Levy &

Lemeshow, 2013; West, Berglund, & Heeringa, 2008), and were therefore not used in the subsequent analyses.[57]

To take into account the proposed differences in occupational sedentary time and health-related outcomes within different occupation categories (i.e. blue-collar and white-collar workers) (Hadgraft et al., 2015; Stamatakis, Davis, Stathi, & Hamer, 2012; Varela-Mato et al., 2017), a stratified analysis was carried out for the occupational classifications: managerial and professional occupations, intermediate occupations, routine and manual occupations, using the derived cut-points from Chapter Three.

Finally, due to people accruing large amounts of sedentary time across the day and still meeting the physical activity guidelines, and the recent studies that have found attenuations in health effects relating to high levels of sitting alongside high levels of moderate physical activity (Ekelund et al., 2016; Stamatakis et al., 2019), the way in which people accumulate their sedentary time and physical activity was taken into account (Hadgraft et al., 2015; Saidj et al., 2013). Mutually exclusive categories were created for high/low sedentary time and high/low physical activity: the sedentary time variables (using the derived cut-point from Chapter Three) were dichotomised using the median minutes per day, and physical activity was dichotomised into those meeting or not meeting 150 mins of moderate to vigorous physical activity each week (Bakrania et al., 2016; Loprinzi, Lee, & Cardinal, 2014). The alpha level of 0.05 was used for all analyses.

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[57] In addition, quantile regression and sequence analysis methods do not support weights, which can affect the convergence of the models

4.3.6   Sequence analysis

4.3.6.1   What is sequence analysis?

Social sequences can be defined as "… empirically observed, temporarily ordered regularities." (Stovel, 2010, p. 5). Human behaviours (both social and physical) are connected to each other through ordered 'elements' across time and space (Giddens, 1984): sequence analysis can be used to make more sense of behaviours over time by examining the timing and order of these 'elements' to measure and classify their structure (Cornwell, 2015). Sequence analysis originated in the field of computer science to examine dissimilarities between sequences of code, and is now used extensively in bioinformatics research to assess DNA sequences to help understand their structure, and to study the similarities between sequences (Blanchard, 2011).

The regression analysis techniques described in Section 4.3.5 do not hold assumptions with respect to the order and sequence of events; nevertheless, taking into account what happens at times $t-1$ and $t+1$ for each event is becoming more common in social sciences research, particularly with the increasing availability and access to time-relevant data (Diggle, Heagerty, Liang, & Zeger, 2013). In a similar way to the generalised estimating equations that were used in the study detailed in Chapter Three, sequence analysis uses information from a previous event at time $t-1$ to understand what happens at time t (Cornwell, 2015).

4.3.6.2   Sequence properties

Sequences contain a set of elements that appear in a specific number of positions P_i: the number of positions correspond to the length of the sequence (Figure 4.6). A sequence S_i

is represented as string of adjacent elements in n positions: the letters of *A* and *B* in the sequence in Figure 4.6 represent two observed behaviour/social phenomena that occur at each position (Brzinsky-Fay, Kohler, & Luniak, 2006; Cornwell, 2015). For example, in a study on sedentary behaviour, *A* could indicate a sitting element, and *B*, a non-sitting element. Sets of identical elements are referred to as episodes or spells in sequence analysis (similar to the term 'bouts' that is used in physical behaviour research). For social phenomena, such as life events, each event may only appear once in a sequence; however, in physical behaviour research, these elements are more likely to be recurrent, where the same behaviour can occur multiple times within a time period (Cornwell, 2015).
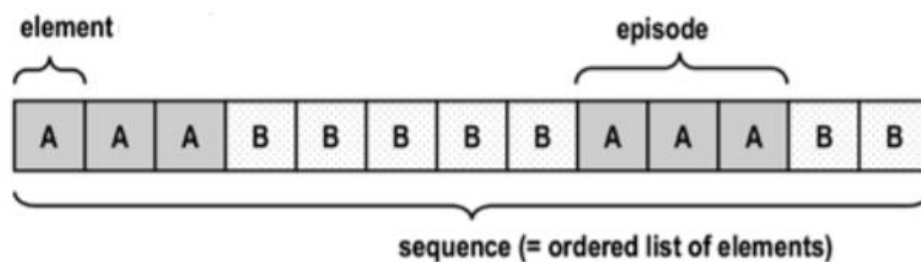
Figure 4.6   Sample sequence (adapted from Brzinsky-Fay, Kohler, & Luniak, 2006, p. 435)

4.3.6.3   Health Survey for England 2008 sequence analysis

Behaviours across the day can be described using elements of time intervals (Bakeman & Quera, 2011). For the sequence analysis of the occupational accelerometer data from the Health Survey for England 2008, the main activity for each five-minute interval was coded as either sedentary behaviour, light physical activity, or moderate to vigorous physical activity across one working day. Five minute intervals have been used extensively in studies of time use (Fisher, Gershuny, Gauthier, & Victorino, 2000), and are an acceptable time interval to capture the prolonged nature of sedentary behaviour (Kim, Welk, et al., 2015). The sequences were bound by the assumed working hours of 9:00am to 5:00pm on

weekdays (Hall, 2017; Maxhuni et al., 2016; Ryan et al., 2011), and therefore, the sequences for each participant were of a fixed length of 96 positions (each position representing five minutes, equivalent to eight hours).

In order to address Objective 7, to explore the patterning and sequences of sedentary bouts across the day, and the relationship with measures of adiposity and other health-related outcomes, a sequence analysis was carried out in Stata, using the *SQ* sequence analysis package (Brzinsky-Fay et al., 2006). For each cardiometabolic risk factor, the *SQ* package was used to compute descriptive statistics for the mean length of episodes (i.e. bouts) for each type of activity across the working day, and the mean number of episodes of each activity type. The sequence patterning for the cardiometabolic risk factors were displayed graphically using state distribution graphs, which display the proportion of participants in each activity at each position.

4.3.6.4   *Optimal matching and hierarchical cluster analysis*

The descriptive sequence analysis described above looks at the relationships *within* the sequences; the method of optimal matching can be used to examine the relationships *between* sequences. Optimal matching can be used to assess the degree of difference, referred to as the 'distance', between each pair of sequences: it is similar to the sequence analysis techniques that are used to analyse DNA sequences (Sankoff & Kruskal, 1983). The distance between each sequence is determined by the number of operations that would be required to transform one sequence into another: for example, in its simplest form, the sequence *AA* can be transformed into the sequence *AB*, by changing the second element of the first sequence from *A* to *B.* Optimal matching algorithms are used to determine the minimum distance between each pair of sequences; the distances between each pair of

sequences are consequently stored in a matrix, **D**, which is referred to as the 'dissimilarity matrix' (Cornwell, 2015; Eriksson, 2018).

Hierarchical cluster analysis methods can then be used to analyse the dissimilarity matrix to generate clusters of participants who have similar behaviour sequence structures. Hierarchical cluster analysis for sequence data detects sequences that are the least distant from one another, and clusters them into homogenous groups of sequences: this process is repeated to form a nested hierarchy of clusters, which can be represented in a dendrogram (Figure 4.7).
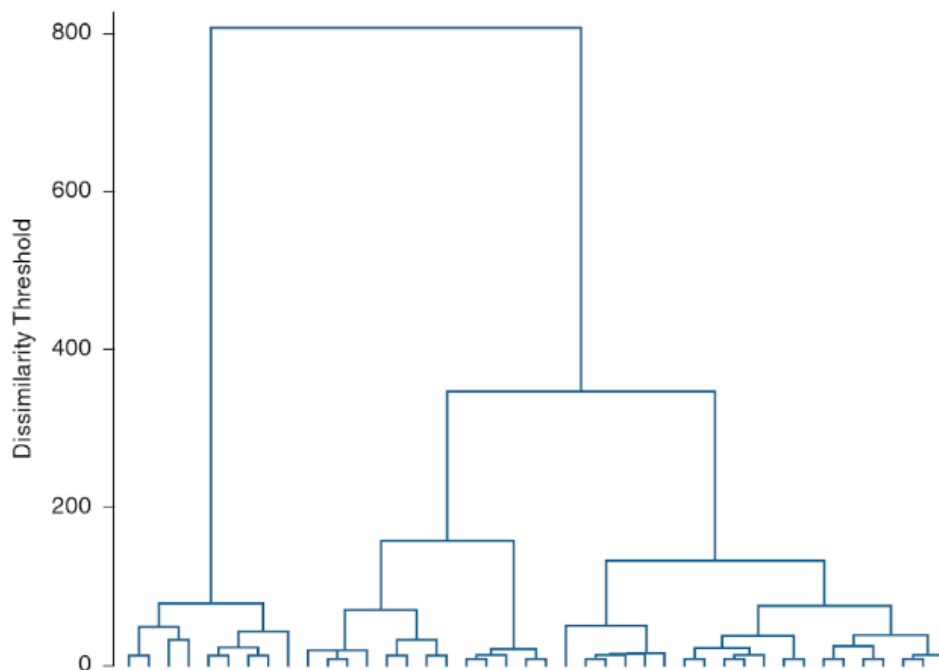
Figure 4.7   **Example of a dendrogram for hierarchical clusters analysis (Cornwell, 2015, p. 133)**

There is no widely agreed method on how to best determine the final cluster solution, i.e. what is a meaningful number of clusters that best represent the data (Eriksson, 2018; Köppe, 2017). Many researchers use heuristic methods that involve visually inspecting the dendrogram to find the optimum number of clusters: once a cluster solution has been decided, the cluster characteristic profiles can be examined for differences. Optimal

matching and a hierarchical cluster analysis were carried out for the occupational accelerometer data from the Health Survey for England 2008.

4.4 Summary of key findings

- Secondary data analysis can be a convenient option for researchers, especially with the ability to access high-quality, and readily available data (Greenhoot & Dowsett, 2012).

- Secondary data analysis can build on the original objectives of the study by carrying out more detailed analyses (Smith, 2008); however, a secondary dataset may not include all the required variables to answer the objectives of the new analysis, which may impact on residual confounding (Hox & Boeije, 2005).

- The Health Survey for England 2008 contains both subjective and objective measures of sedentary time and is therefore an ideal dataset to answer objectives four to seven; however, with a large number of variables to clean, this can add time to a secondary analysis study (Greenhoot & Dowsett, 2012; Smith et al., 2011).

- The format of the processed accelerometer data meant that it was no longer compatible with the ActiLife software; consequently, this provided the opportunity to have the Stata programmes used to clean and derive the accelerometer variables to be validated by another research group.

- The choice of regression model depends on the type and distribution of the dependent variable, and therefore it is not appropriate to use the same regression model for each health-related outcome.

- A sequence analysis with optimal matching, and a hierarchical cluster analysis, was carried out in Stata (using the *SQ* sequence analysis package), to generate clusters of participants who have similar behaviour sequence structures.

Chapter 5 - Main results chapter

"If the universe was scientific and just left to itself, then we'd have statistical probabilities to rely on. But once people are involved it sometimes becomes much more problematic because they're erratic. People do crazy things that don't make sense."

— **Sara Sheridan, Brighton Belle**

Table 5.1   **Overview of Chapter 5**

Chapter	Aims, objectives and research questions	Methods
Chapter 2	**Aim:** To provide an overview of the literature and to critique the current evidence of sedentary behaviour and work, focussing on the prevalence of sedentary behaviour at work, and its association with health-related outcomes	Structured literature review using six electronic databases
Chapter 3	**Aim:** To empirically derive a new accelerometer cut-point to define sedentary behaviour in adults **Objective 1:** To empirically derive an optimal threshold for classifying sedentary behaviour, using the counts per minute output from the ActiGraph GT3X+ accelerometer, when compared to the sedentary classification from the activPAL™ accelerometer in a free-living environment **Objective 2:** To ascertain whether thresholds for sedentary behaviour cut-points vary by day of the week and in working time versus non-working time **Objective 3:** To derive optimal cut-points for different classifications of sedentary behaviour using contextual data from a 24-hour activity log, and to examine if there are differences between them	Observational study in university workers and postgraduate students (n=30) Application of generalised estimating equations to 1-minute epoch data for the ActiGraph GT3X+ and the activPAL™ data
Chapter 4	**Aim:** To describe the methodology for the Health Survey for England 2008, and a critique of the strengths and limitations of using secondary analysis	Description of data collection and processing
Chapter 5	**Aim:** To apply the cut-point from *Study One* to data from the Health Survey for England (2008), in order to investigate the associations between sedentary behaviour, work, and health-related outcomes **Objective 4:** To identify associations between workplace sedentary behaviour and health-related outcomes using the derived cut-point from *Study One* **Objective 5:** To examine if associations between workplace sedentary behaviour and health-related outcomes differ between occupational groups **Objective 6**: To determine if there are associations between workplace sedentary behaviour and mental ill-health and musculoskeletal disorders	A secondary data analysis of the Health Survey for England 2008 Application of hierarchical regression models – type of regression model dependent on distribution of each dependent variable (health-related outcome)
Chapter 6	**Aim:** To apply the cut-point from *Study One* to data from the Health Survey for England (2008), in order to investigate the associations between sedentary behaviour, work, and health-related outcomes **Objective 7:** To explore the patterning and sequences of sedentary bouts across the day, and the relationship with measures of adiposity and other health-related outcomes	Sequence analysis to describe the characteristics of time-related sequences of sedentary behaviour
Chapter 7	**Aim:** To discuss and critically appraise the studies within this thesis and to outline implications for policy and future research	Discussion and conclusions

Chapter Five presents the results from the main regression analyses to address objectives four to six:

4. To identify associations between workplace sedentary behaviour and health-related outcomes using the derived cut-point from *Study One.*

5. To examine if associations between workplace sedentary behaviour and health-related outcomes differ between occupational groups.

6. To determine if there are associations between workplace sedentary behaviour and mental ill-health and musculoskeletal disorders.

This chapter first describes the data from the Health Survey for England 2008 and the participants from the accelerometer sub-sample. The characteristics with respect to the full-time workers with accelerometer data are presented for: demographic data, lifestyle information, health-related outcomes, and accelerometer derived variables. Secondly, the results from the regression analyses developed to predict the effect of sedentary behaviour on each of the health-related outcomes (described in Chapter Four) are presented, in order to address objective 4. The following health-related outcomes are first considered: waist circumference, BMI, systolic blood pressure, diastolic blood pressure, total cholesterol, HDL cholesterol, glycated haemoglobin, heart and circulatory conditions. The stratified analyses are then presented for the occupational classifications of: managerial and professional occupations, intermediate occupations, routine and manual occupations, using the derived cut-points from Chapter Three, to determine if associations between workplace sedentary behaviour and health-related outcomes differ between occupational groups (Objective 5). Lastly, the regression models for the variables that relate to mental

ill-health and musculoskeletal disorders are discussed, in order to address objective 6 (musculoskeletal conditions, mental disorders, GHQ-12, and the EQ-5D).

5.1   Results

In 2008, the Health Survey for England recruited 22,623 participants (Craig et al., 2009a); the mean age of those who took part was 35.9 (SD 23.74), with more female than male participants (53.6% vs. 46.4%).

From the main sample, 6222 (both children [1656] and adults [4566]) were selected to wear an ActiGraph GT1M accelerometer for seven days, and 4399 usable ActiGraph files were obtained from NatCen (Section 4.3.2). Out of these 4399 files, 3146 were from adults (age ≥16): after applying the Troiano non-wear algorithm (Troiano et al., 2008), there were 2356 adult data files with valid data for the seven days of wear time, using the first day of data collection as the day that was recorded in the log book by the participants (Figure 5.1).
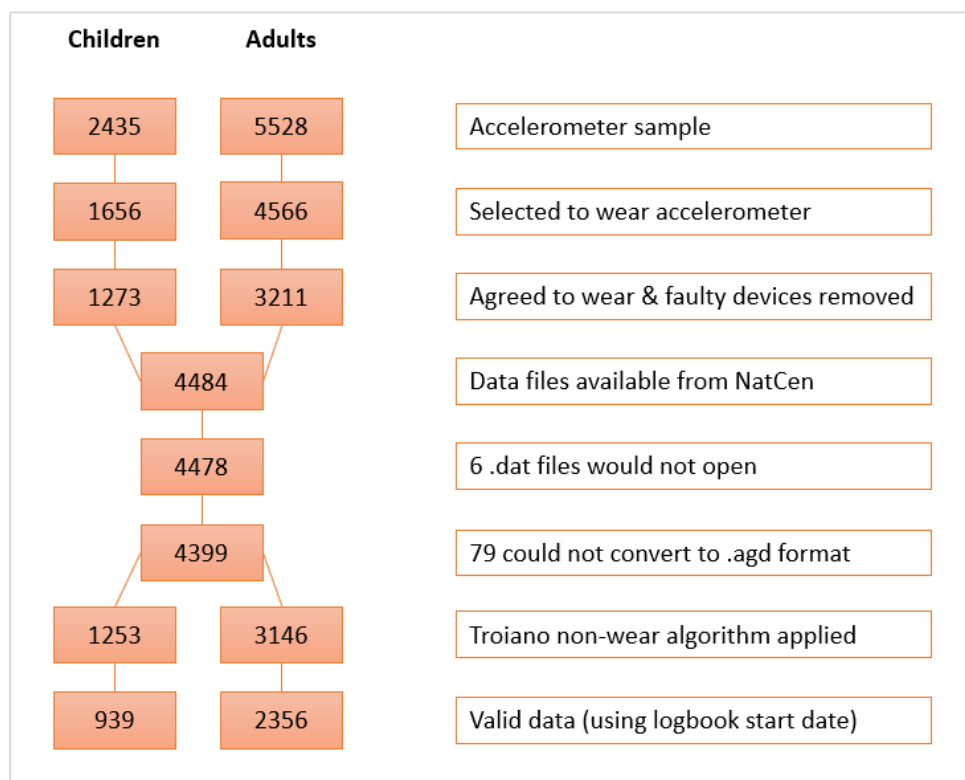
Figure 5.1   Health Survey for England 2008 accelerometer sample

The 2356 participants with accelerometer data had a similar gender profile to the whole sample (54.9% females compared to 45.1%); however, they had a higher mean age of 51.6 (SD 18.5). Roth et al. (2013) reported that those in the accelerometer sample were also more likely to be retired and have a longstanding illness. Therefore, in order to look at the associations between occupational sedentary time and health-related outcomes, the dataset was restricted to those who were in full-time employment in the week prior to the interview (based on >30 hours per week) , and those who had at least one valid day of data (defined as at least 600 minutes of accelerometer wear time) (Atkin et al., 2012; Colley et al., 2010; Migueles et al., 2017). Out of the 2356 adult participants with accelerometer data, 911 were in full-time employment; of these, 18 did not have at least one day of valid accelerometer data, resulting in a final sample size of 893, which were included in the regression models. The mean age of the participants in the full-time workers sample was 43.1 years (SD 12.4), which is similar to an analysis from 2016 that found the average age of workers in the UK was 41.3 years (Greenwood, 2016). More men were in full-time work compared to women (454 males (61.0%) vs. 348 females (39.0%); p<0.001), and 92% of full-time workers had data for at least four days.

Figure 5.2 presents the subjective sedentary time and physical activity data compared to the objectively derived sedentary time and physical activity data for the accelerometer sample (n=2356) (using the derived accelerometer cut-points from Chapter Three). For the sedentary time variables (across the week, weekdays, weekend days, and work time), the objective estimates of mean minutes per day spent in sedentary time were significantly higher compared to the subjective data. The self-reported variable of mean minutes of physical activity per day was significantly higher compared to the accelerometer derived

variable (59.21 (SD 83.44) vs. 28.38 (SD 25.52)). These results are in line with literature that has shown that participants tend to underestimate their sedentary time and overestimate their time in physical activities when measured subjectively (Healy et al., 2011; Sallis & Saelens, 2000; Timperio et al., 2003; Welk, 2002).
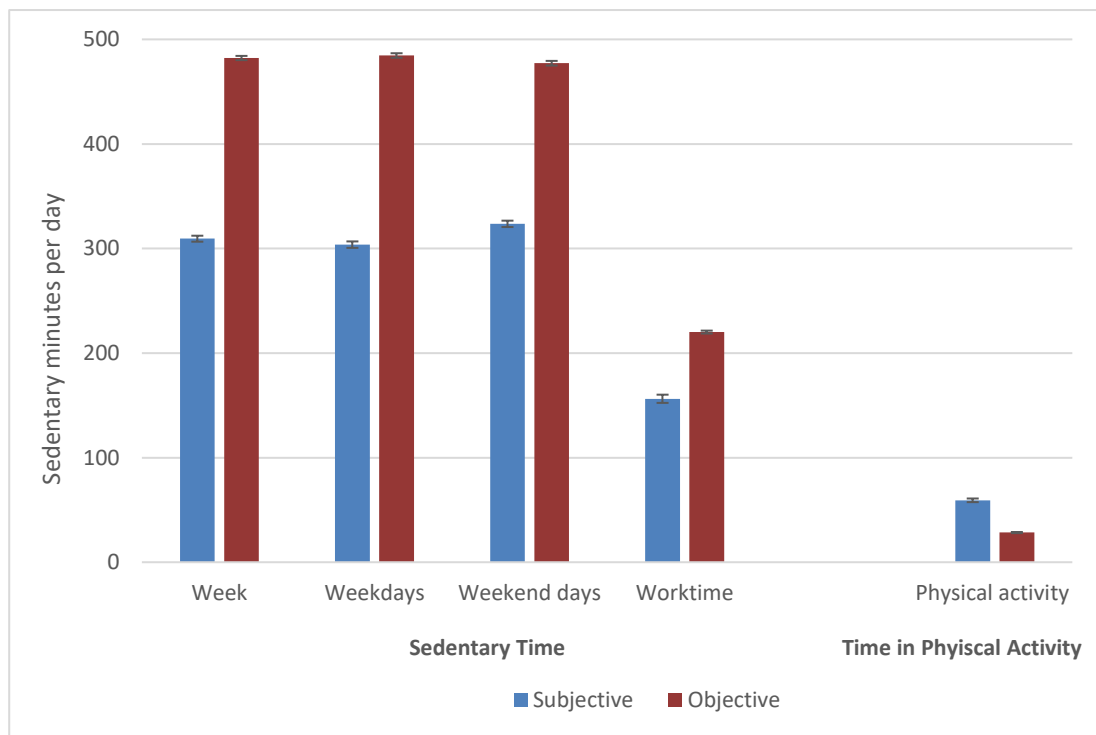
Figure 5.2 **Comparison of subjective and objective physical behaviour variables (mean sedentary time with standard error bars)**

For the subjective measures of daily sedentary time, participants reported lower total daily sitting times on weekdays compared to weekend days; this was consistent for data from the whole sample (n=22,623), the accelerometer sample (n=2356), and the full-time workers sample (n=893) (Figure 5.3). This finding was reversed for the objective measures (using the derived cut-points) of total sitting time: for both the accelerometer and full-time workers sample, participants reported higher amounts of daily sitting time on weekdays compared to weekend days. However, this was only significant for full-time workers (486.3 vs. 461.0 minutes, p<0.001).
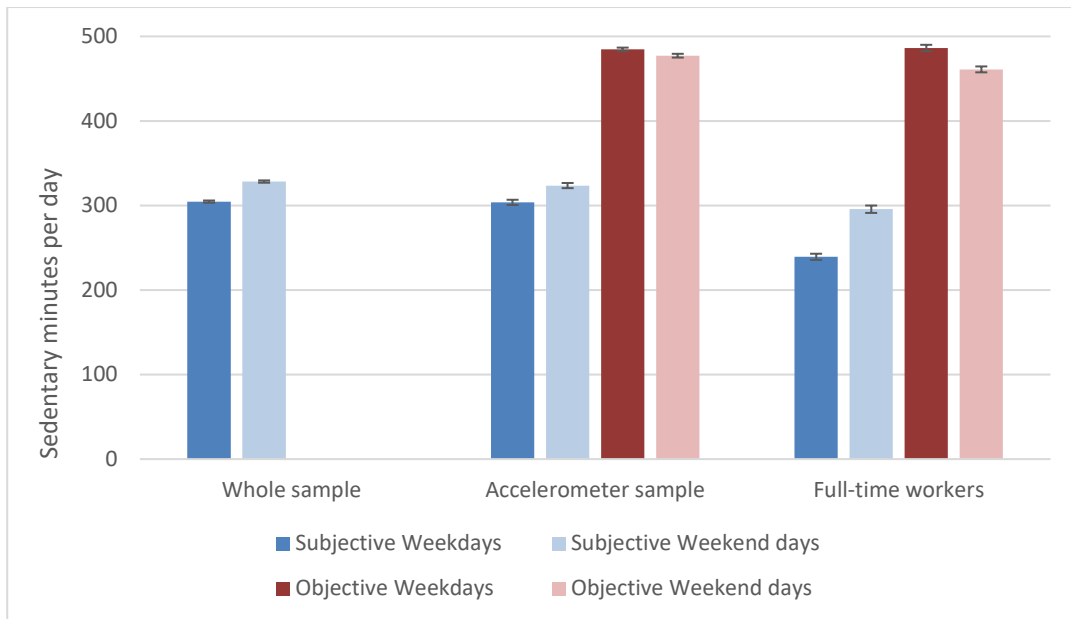
Figure 5.3   Comparison of weekday and weekend total daily sitting times, with standard error bars

Figure 5.4 shows the differences in the mean daily sedentary times (minutes), for the week, weekdays, weekend days, and work times, computed for the relevant derived cut-points from Chapter Three[58], and the previously proposed cut-points from the literature (50, 100, and 150 counts per minute) (Crouter et al., 2006; Kozey-Keadle et al., 2011; Matthews et al., 2008). For each time period shown, the mean daily sedentary times from the four cut-points, were significantly different from each other (p<0.001). The amount of sedentary time increased with increasing cut-point; the difference in cut-points resulted in differences of 91, 92, 87 minutes between the 150- and the 50-counts per minute cut-points for the week, weekdays, weekend days respectively. For work times, sedentary time from the 150 counts per minute cut-point was 51 minutes higher (284 minutes) compared to the time calculated for the 50 counts per minute cut-points (233 minutes), and was over

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[58] Derived cut-points were 65 across the week, 60 for weekdays, 74 for weekends days, and 35 for work times.

an hour different compared to the derived cut-point of 35 counts per minute (284 vs. 220 minutes).
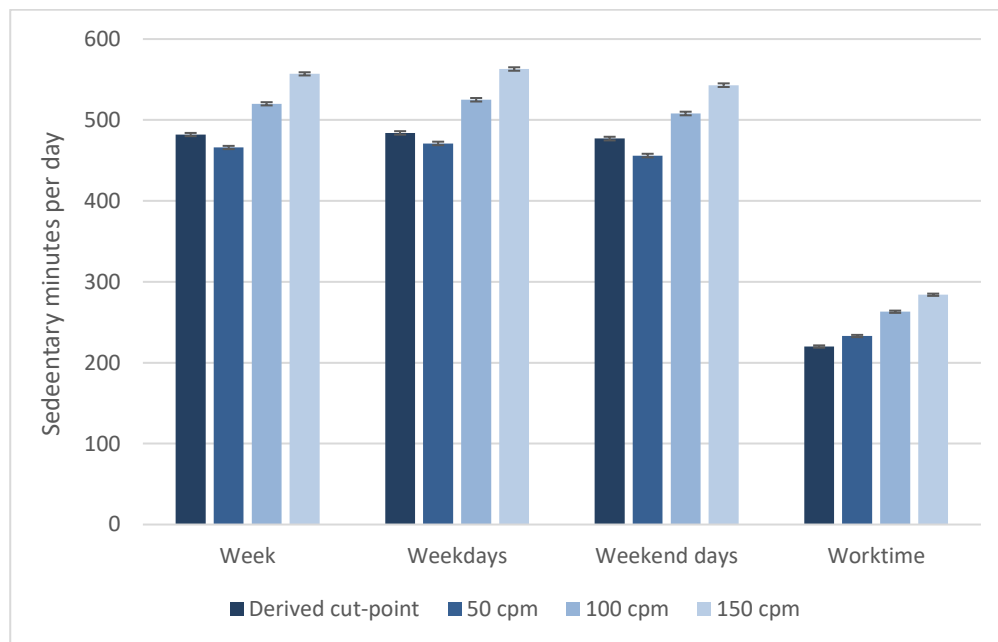
Figure 5.4   **Comparison of mean daily sedentary minutes from the derived and previously proposed cut-points, with standard error bars**

Table 5.2 presents the baseline characteristics for the participants in the full-time workers sample, and also shows any differences by sex and occupational group. Men were slightly older (44.0 vs. 41.7 years), consumed fewer fruit and vegetables each day, were less likely to have never smoked, and were more likely to drink alcohol compared to women. Men were, in general, also more likely to have less favourable health-related outcomes compared to women: higher BMI, lower HDL cholesterol, higher systolic blood pressure, and were more likely to report having a longstanding heart condition. However, women were more likely to be categorised as having GHQ-12 scores of greater than or equal to four, which can indicate probable mental ill-health (Craig et al., 2009a); women also sat significantly longer during working hours (232.7 vs. 214.9 minutes), and participated in lower levels of moderate to vigorous physical activity each day compared to men (22.5 vs.

34.7 minutes) (Table 5.2). Interestingly, women reported lower daily total sitting times compared to men, but these differences were not significant.

Table 5.2 also shows the baseline characteristics for the three occupational classifications: managerial and professional, intermediate, and routine and manual. Men were more likely to have a routine or manual job compared to women (34.1% vs. 25.4%), while women were more likely to have a managerial or professional occupation (50.7% vs. 45.1%). There were no significant differences related to the health-related outcomes between the three occupational categories; however, differences were seen for lifestyle factors. Those in routine and manual jobs were more likely to consume fewer fruit and vegetables each day, and be a current smoker, compared to managers and professionals; conversely, those in managerial and professional occupations were more likely to drink more than the recommended alcoholic units[59] per day compared to those in routine and manual roles (52.7% vs. 43.6%). For all daily sedentary time variables, the greatest mean daily sedentary times were seen in the managerial and professional occupations, followed by intermediate occupations, with routine and manual workers reporting the lowest daily sitting times; more specifically, the mean daily sitting times during working hours were 258.0, 212.4, and 172.2 minutes respectively. A u-shaped association was seen for time in physical activity, with both managerial and professional occupations (30.5 minutes) and those in routine and manual roles (32.1 minutes), undertaking significantly more minutes of moderate to vigorous physical activity each day compared to intermediate occupations (27.2 minutes).

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[59] New drinking guidelines were introduced in the UK in 2016 https://www.drinkaware.co.uk/alcohol-facts/alcoholic-drinks-units/latest-uk-alcohol-unit-guidance/

Table 5.2   Baseline characteristics of the full-time workers sample

Characteristic	Total	Sex		NS-SEC		
		Male (n=545)	Female (n=348)	Managerial and professional (n=422)	Intermediate (n=196)	Routine and manual (n=274)
Demographic data						
Age (in years)[a]	43.1 (12.4)	**44.0 (12.4)**	**41.7 (12.4)**	42.3 (11.6)	44.6 (12.0)	43.2 (13.2)
Sex[b]						
Male	545 (61.0)	-	-	**246 (58.3)**	**113 (57.7)**	**186 (67.9)**
Female	348 (39.0)	-	-	**176 (41.7)**	**83 (42.3)**	**88 (32.1)**
Ethnicity[b]						
White	820 (91.8)	499 (91.6)	321 (92.2)	385 (91.2)	181 (92.4)	254 (92.7)
Non-white	73 (8.2)	46 (8.4)	27 (7.8)	37 (8.8)	15 (7.6)	20 (7.3)
Income quintile[b, d]						
1	25 (3.2)	16 (3.4)	9 (3.0)	**5 (1.3)**	**6 (3.9)**	**14 (5.9)**
2	76 (9.8)	43 (9.1)	33 (10.9)	**16 (4.2)**	**17 (10.9)**	**43 (18.1)**
3	141 (18.2)	91 (19.2)	50 (16.6)	**28 (7.3)**	**39 (25.0)**	**74 (31.2)**
4	242 (31.2)	150 (31.7)	92 (30.5)	**116 (30.4)**	**52 (33.3)**	**74 (31.2)**
5	291 (37.6)	173 (36.6)	118 (39.1)	**217 (56.8)**	**42 (26.9)**	**32 (13.5)**
Lifestyle information						
Fruit and veg. (portions per day)[c]	3.3 (2.0, 5.0)	**3.0 (2.0, 4.7)**	**3.7 (2.0, 5.3)**	**4.0 (1.0, 5.3)**	**3 .0 (1.7, 4.8)**	**3.0 (1.3, 4.5)**
Smoking status[b]						
Never smoked	472 (53.0)	**269 (49.5)**	**203 (58.5)**	**261 (62.0)**	**92 (47.4)**	**118 (43.1)**
Previous smoker	211 (23.7)	**146 (26.9)**	**65 (18.7)**	**84 (20.0)**	**56 (28.9)**	**71 (25.9)**
Current smoker	207 (23.3)	**128 (23.6)**	**79 (22.8)**	**76 (18.0)**	**46 (23.7)**	**85 (31.0)**
Alcohol consumption[b]						
None	201 (22.6)	**99 (18.3)**	**102 (29.3)**	**75 (17.8)**	**43 (21.9)**	**82 (30.0)**
≤4/≤3 units per day (m/f)	250 (28.1)	**153 (28.2)**	**97 (27.9)**	**124 (29.5)**	**54 (27.6)**	**72 (26.4)**
>4/>3 units per day (m/f)	440 (49.4)	**291 (53.6)**	**149 (42.8)**	**222 (52.7)**	**99 (50.5)**	**119 (43.6)**

Characteristic	Total	Sex		NS-SEC		
		Male (n=545)	Female (n=348)	Managerial and professional (n=422)	Intermediate (n=196)	Routine and manual (n=274)
General health[b]						
Very good/good	751 (84.1)	458 (84.0)	293 (84.2)	365 (86.5)	164 (83.7)	222 (81.0)
Less than good health	142 (15.9)	87 (16.0)	55 (15.8)	57 (13.5)	32 (16.3)	52 (19.0)
Longstanding illness[b]						
None	590 (66.1)	360 (66.1)	230 (66.1)	277 (65.6)	124 (63.3)	189 (69.0)
At least one	303 (33.9)	185 (33.9)	118 (33.9)	145 (34.3)	72 (36.7)	85 (31.0)
Blood pressure medication[b]						
No	227 (75.2)	**108 (69.7)**	**119 (81.0)**	101 (79.5)	57 (72.2)	69 (72.6)
Yes	75 (24.8)	**47 (30.3)**	**28 (19.0)**	26 (20.5)	22 (27.8)	26 (27.4)
Cholesterol medication[b]						
No	253 (83.8)	**112 (72.3)**	**141 (95.6)**	108 (85.0)	64 (81.0)	80 (84.2)
Yes	49 (16.2)	**43 (27.7)**	**6 (4.1)**	19 (15.0)	15 (19.0)	15 (15.8)
NS-SEC[b]						
Managerial & professional	422 (47.3)	**246 (45.1)**	**176 (50.7)**	-	-	-
Intermediate	196 (22.0)	**113 (20.7)**	**83 (23.9)**	-	-	-
Routine and manual	274 (30.7)	**186 (34.1)**	**88 (25.4)**	-	-	-
**Health-related outcomes**						
BMI (kg/m^2)[c]	26.7 (24.0, 29.8)	**27.0 (24.6, 27.0)**	**26.1 (22.7, 29.9)**	26.2 (24.0, 29.6)	27.2 (23.8, 30.2)	27.0 (24.1, 30.0)
Waist circumference (cm)[c]	93.5 (83.3, 102.2)	**96.5 (90.0, 104.3)**	**84.2 (75.2, 94.3)**	92.8 (82.4, 101.4)	93.6 (82.4, 102.3)	94.8 (84.5, 103.6)
Total cholesterol (mmol/L)[a]	5.5 (1.1)	5.5 (1.0)	5.4 (1.1)	5.4 (1.0)	5.6 (1.1)	5.4 (1.0)
HDL cholesterol (mmol/L)[a]	1.5 (0.3)	**1.4 (0.3)**	**1.6 (0.3)**	1.5 (0.3)	1.5 (0.4)	1.4 (0.3)
HbA1c (%)[a]	5.5 (0.6)	5.6 (0.7)	5.5 (0.5)	5.5 (0.7)	5.6 (0.7)	5.5 (0.5)
Systolic bp (mmHG)[a]	126.3 (15.2)	**129.0 (13.4)**	**121.8 (17.0)**	125.1 (13.8)	127.6 (16.4)	127.6 (16.3)
Diastolic bp (mmHG)[a]	75.0 (10.7)	75.4 (10.5)	74.4 (10.9)	75.1 (10.3)	75.5 (11.9)	74.7 (10.5)

Characteristic	Total	Sex		NS-SEC		
		Male (n=545)	Female (n=348)	Managerial and professional (n=422)	Intermediate (n=196)	Routine and manual (n=274)
Musculoskeletal conditions[b]						
No	787 (88.1)	484 (88.1)	303 (87.1)	378 (89.6)	170 (86.7)	239 (87.2)
Yes	106 (11.9)	61 (11.2)	45 (12.9)	44 (10.4)	26 (13.3)	35 (12.8)
Mental and behavioural disorders[b]						
No	870 (97.4)	534 (98.0)	336 (96.6)	412 (97.6)	191 (97.5)	266 (97.1)
Yes	23 (2.6)	11 (2.0)	12 (3.4)	10 (2.4)	5 (2.6)	8 (2.9)
Diseases of the heart[b]						
No	829 (92.8)	**496 (91.0)**	**333 (95.7)**	395 (93.6)	179 (91.3)	255 (93.1)
Yes	64 (7.2)	**49 (9.0)**	**15 (4.31)**	27 (6.4)	17 (8.7)	19 (6.9)
GHQ-12[b]						
<4	777 (88.3)	**494 (92.3)**	**283 (82.0)**	373 (89.2)	172 (89.6)	232 (85.9)
≥4	103 (11.7)	**41 (7.7)**	**62 (18.0)**	45 (10.8)	20 (10.4)	38 (14.1)
EQ-5D[c]	1.0 (0.8, 1.0)	1.0 (0.8, 1.0)	1.0 (0.8, 1.0)	1.0 (0.9, 1.0)	1.0 (0.8, 1.0)	1.0 (0.8, 1.0)
**Accelerometer variables**						
Sedentary time[a] (mins per day/all week)	462.7 (99.0)	482.0 (105.5)	474.0 (88.1)	**515.19 (85.2)**	**471.1 (98.0)**	**428.2 (96.8)**
Sedentary time[a] (mins per day/all weekdays)	486.3 (111.7)	486.9 (118.5)	485.3 (100.3)	**531.8 (95.5)**	**475.7 (109.0)**	**423.1 (104.8)**
Sedentary time[a] (mins per day/work time)	221.8 (77.3)	**214.9 (80.6)**	**232.7 (70.4)**	**258.0 (65.1)**	**212.4 (78.4)**	**172.2 (63.3)**
Physical activity[c] (mins per day/all week)	30.0 (16.4, 46.3)	**34.7 (20.7, 51.4)**	**22.5 (12.9, 38.8)**	**30.5 (16.3, 45.0)**	**27.2 (15.4, 45.1)**	**32.1 (18.9, 52.0)**
Accelerometer wear time[a] (mins per day)	857.0 (74.5)	**866.6 (76.6)**	**842.0 (68.6)**	859.1(71.9)	850.9 (74.7)	858.3 (78.4)

[a]Continuous variable, mean (SD); [b]Categorical variable, n (%); [c]Continuous variable, median (IQR); [d]Equivalised household income quintiles: 1=<£10,671; 2=>=£10,671-<£17,789; 3=>=£17,789-<=£27,317; 4=>=27,317-<£44,200; 5=>=£44,200; NS-SEC=National Statistics Socio-economic Classification; BMI=body mass index; HDL=High-density lipoprotein; HbA1c=Haemoglobin A1c (glycated haemoglobin); GHQ=General Health Questionnaire; EQ-5D=EuroQol 5 dimensions; Significant differences (p<0.05) are shown in bold

5.2 Objective 4 results

4. *To identify associations between workplace sedentary behaviour and health-related outcomes using the derived cut-point from Study One.*

The variance inflation factors for the regression models for each health-related outcome, were examined for collinearity for the covariates in each of the models to check for independence between the sedentary behaviour and physical activity variables included in model 4 (Section 4.3.5.5). Generally, variance inflation factors greater than 10 suggest the presence of collinearity between the models' covariates (Mansfield & Helms, 1982). For all the models in this study (for each health-related outcome), variance inflation factors were all less than two, indicating that collinearity was not an issue that warranted further investigation in these analyses.

5.2.1 Waist circumference

The effect of sedentary time on both waist circumference and BMI were modelled using quantile regression, due to the non-normal distributions of these two variables. As opposed to linear regression that models the mean of the dependent variable (for normally distributed dependent variables), quantile regression looks at the relationship between the independent variables and the conditional quantiles of the dependent variable. Quantile regression models can give a more comprehensive picture of the effect of the independent variables on the dependent variable, as it can show if the effect of the independent variables vary along the distribution of the dependent variable. For example, the regression models for waist circumference address the question as to whether occupational sedentary time influences waist circumference differently for different quantiles of waist circumference.

The models for the 50th percentile[60] were built for each of the objectively derived mean daily sedentary time variables (week, weekdays, work times); in addition, models for the four sedentary behaviour cut-points (derived, 50, 100, 150) were compared to determine if the derived cut-points and previous proposed cut-points lead to different effect values and model interpretation. For the waist circumference and BMI models, each of the models from the hierarchy of regression models are presented (Section 4.3.5.5).[61]

The beta coefficients for the regression models for waist circumference are presented in Table 5.3. There are four main findings that can be deduced from these results:

1. The effect sizes for the different cut-points (derived, 50, 100, 150) were not significantly different; this finding was consistent for each of the sedentary time variables, and for each of the hierarchy of regression models.

2. Secondly, for each 10-minute increase per day in sedentary time, the models consistently suggested significant associations with an increase in waist circumference, for the week and weekday models. For example, for each 10-minute increase per day in daily sitting time there was an increase in waist circumference of 0.15cm (this is from model 1, for the derived cut-point [weekdays]).

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[60] The 0.5 quantile can be referred to as the 50th percentile, and regression models based on the 50th percentile are often referred to as median regression.

[61] Model 1: age, sex, accelerometer wear time; Model 2: age, sex, accelerometer wear time, ethnicity, fruit and vegetables, alcohol, smoking, income; Model 3: age, sex, accelerometer wear time, ethnicity, fruit and vegetables, alcohol, smoking, income, general health, [longstanding conditions], [BMI]; Model 4: age, sex, accelerometer wear time, ethnicity, fruit and vegetables, alcohol, smoking, income, general health, [longstanding conditions], [BMI], physical activity; [Model 5: age, sex, accelerometer wear time, ethnicity, fruit and vegetables, alcohol, smoking, income, general health, [longstanding conditions], [BMI], physical activity, non-occupational sedentary time]; Models for blood pressure and cholesterol levels were also adjusted for either blood pressure medication or cholesterol medication respectively (added to Model 4).

3. Looking at the models from the derived cut-points only, the significant associations between sedentary time and waist circumference were no longer significant after adjusting for physical activity in model 4.

4. Lastly, the significant associations between total daily sedentary time and waist circumference, for the week and weekday models, were not as consistent in the work time models. The addition of leisure-time sedentary time to the work time models (model 5) did not improve the fit of the models and was not a significant predictor of waist circumference.

Table 5.3   β coefficients for regression models for waist circumference

	Model	β	Low 95% CI	High 95% CI	p-value	β	Low 95% CI	High 95% CI	p-value	β	Low 95% CI	High 95% CI	p-value	β	Low 95% CI	High 95% CI	p-value
		Derived cut-point				**50 counts per minute cut-point**				**100 counts per minute cut-point**				**150 counts per minute cut-point**			
All 7 days																	
	1	**0.17**	**0.10**	**0.24**	**<0.001**	**0.17**	**0.07**	**0.26**	**0.001**	**0.17**	**0.08**	**0.27**	**<0.001**	**0.18**	**0.07**	**0.28**	**<0.001**
	2	**0.17**	**0.14**	**0.33**	**0.032**	**0.18**	**0.03**	**0.32**	**0.017**	**0.18**	**0.08**	**0.28**	**<0.001**	**0.21**	**0.09**	**0.32**	**<0.001**
	3	**0.09**	**0.02**	**0.15**	**0.006**	**0.08**	**0.11**	**0.16**	**0.023**	**0.09**	**0.01**	**0.17**	**0.027**	**0.09**	**0.01**	**0.17**	**0.031**
	4	0.08	-0.01	0.16	0.054	**0.08**	**0.02**	**0.14**	**0.015**	**0.09**	**0.01**	**0.16**	**0.020**	**0.09**	**0.01**	**0.17**	**0.023**
Weekdays																	
	1	**0.15**	**0.05**	**0.24**	**0.002**	**0.15**	**0.07**	**0.23**	**<0.001**	**0.16**	**0.60**	**0.26**	**0.002**	**0.17**	**0.06**	**0.27**	**0.003**
	2	**0.14**	**0.04**	**0.24**	**0.006**	**0.14**	**0.03**	**0.24**	**0.010**	**0.17**	**0.16**	**0.27**	**0.001**	**0.17**	**0.07**	**0.28**	**<0.001**
	3	**0.08**	**0.02**	**0.14**	**0.006**	**0.08**	**0.01**	**0.15**	**0.027**	**0.08**	**0.02**	**0.14**	**0.009**	**0.09**	**0.03**	**0.15**	**0.002**
	4	0.06	-0.01	0.13	0.090	**0.06**	**0.00**	**0.12**	**0.035**	**0.06**	**0.00**	**0.11**	**0.037**	0.06	-0.01	0.13	0.073
Work time																	
	1	**0.12**	**0.01**	**0.24**	**0.046**	0.12	-0.01	0.25	0.068	0.13	0.02	0.24	0.160	**0.15**	**0.02**	**0.27**	**0.023**
	2	0.11	-0.39	0.27	0.142	0.12	-0.03	0.27	0.134	0.11	-0.05	0.28	0.174	0.12	-0.02	0.26	0.104
	3	**0.10**	**0.02**	**0.17**	**0.013**	**0.10**	**0.13**	**0.18**	**0.024**	**0.10**	**0.01**	**0.19**	**0.028**	**0.10**	**0.00**	**0.20**	**0.045**
	4	0.07	-0.01	0.15	0.062	0.07	-0.04	0.18	0.188	0.07	-0.01	0.16	0.960	0.08	-0.01	0.16	0.076
	5	0.06	-0.02	0.14	0.132	0.06	-0.02	0.14	0.165	0.06	-0.01	0.13	0.071	0.06	-0.04	0.16	0.211

Model 1 adjusted for age, sex, accelerometer wear time; model 2 was further adjusted for ethnicity, fruit and vegetable consumption, alcohol consumption, smoking status, equivalised household income; model 3 was further adjusted for general health, longstanding illness, [BMI], model 4 was further adjusted for physical activity; model 5 was adjusted for non-work sedentary time in the work time models; significant effects ($p<0.05$) are shown in bold; β is the beta coefficient for the change in the health-related outcome; coefficients are given with 95% confidence intervals (CI); derived cut-points were 65 cpm for all 7 days; 60 cpm for weekdays; and 35 cpm for work time; BMI=Body mass index

Alongside the significant covariates of age and sex, physical activity had the most influential effect on waist circumference and attenuated any association with occupational sitting time. This can be seen graphically in Figure 5.5, which presents the beta coefficients (95% confidence intervals) for the occupational sedentary time covariate in models 3 and 4, and the beta coefficient for the physical activity variable in model 4. Figure 5.5 shows that occupational sedentary time was **not** a significant predictor of waist circumference after adjusting for moderate to vigorous physical activity.

Figure 5.5   **Coefficient plot for associations of occupational sedentary time and physical activity with waist circumference**

Figure 5.6 shows the effects of moderate to vigorous physical activity along the quantiles for waist circumference from model 5, using the derived cut-point. The green line represents the varying beta coefficients for each quantile of waist circumference (the grey areas are the 95% confidence intervals for the beta coefficients); the dashed black line is

the beta coefficient from the ordinary least squares regression model, which is constant across the quantiles of waist circumference. The graph shows that for each one-minute increase per day in moderate to vigorous physical activity, there were significant associations with reduced waist circumference (cm), and this effect varied with increasing quantiles of waist circumference: β coefficients for the 25th, 50th, 75th quantiles were -0.045, -0.065, -0.101, which were all significant. The effect of moderate to vigorous physical activity was greater for individuals with higher waist circumference.

Figure 5.6   **Effect of moderate to vigorous physical activity as a covariate in the quantile regression model for waist circumference**

5.2.2   *BMI*

The beta coefficients for the regression models for BMI are presented in Table 5.4. Similar to the models for waist circumference, there are four main findings that can be deduced from the results from the BMI models:

1. The effect sizes for the different cut-points (derived, 50, 100, 150) were not significantly different; this finding was consistent for each of the sedentary time variables, and for each of the hierarchy of regression models.

2. Secondly, for each 10-minute increase per day in sedentary time, the models consistently suggested significant associations with an increase in BMI, for the week and weekday models. For example, for each 10-minute increase per day in daily sitting time there was an increase in BMI of 0.04 (this is from model 1, for the derived cut-point [weekdays]).

3. Looking at the models from the derived cut-points only, the significant associations between sedentary time and BMI were no longer significant after adjusting for physical activity in model 4, in the models for the week and the weekdays. For the work time models, associations between sedentary time and BMI were only significant in model 3 and did not remain significant once physical activity had been adjusted for.

4. Lastly, the significant associations between total daily sedentary time and BMI, for the week and weekday models, were not apparent in the work time models. The addition of leisure-time sedentary time to the work time models (model 5) did not improve the fit of the models and was not a significant predictor of BMI.

Table 5.4   β coefficients for regression models for BMI

Model		Derived cut-point				50 counts per minute cut-point				100 counts per minute cut-point				150 counts per minute cut-point		
	β	Low 95% CI	High 95% CI	p-value	β	Low 95% CI	High 95% CI	p-value	β	Low 95% CI	High 95% CI	p-value	β	Low 95% CI	High 95% CI	p-value
All 7 days																
1	**0.05**	**0.01**	**0.09**	**0.027**	**0.05**	**0.01**	**0.09**	**0.025**	**0.05**	**0.01**	**0.09**	**0.013**	**0.05**	**0.02**	**0.09**	**0.006**
2	**0.05**	**0.01**	**0.09**	**0.016**	0.05	-0.01	0.10	0.063	**0.06**	**0.01**	**0.11**	**0.032**	**0.06**	**0.01**	**0.11**	**0.014**
3	**0.06**	**0.01**	**0.12**	**0.037**	**0.06**	**0.01**	**0.11**	**0.020**	**0.06**	**0.02**	**0.11**	**0.010**	**0.07**	**0.01**	**0.12**	**0.015**
4	0.04	-0.01	0.09	0.087	**0.04**	**0.01**	**0.08**	**0.028**	**0.05**	**0.01**	**0.09**	**0.038**	0.05	-0.01	0.10	0.058
Weekdays																
1	**0.04**	**0.01**	**0.07**	**0.013**	0.04	-0.01	0.08	0.103	**0.04**	**0.01**	**0.08**	**0.033**	**0.04**	**0.01**	**0.08**	**0.029**
2	**0.06**	**0.02**	**0.09**	**0.004**	**0.05**	**0.02**	**0.09**	**0.006**	**0.06**	**0.03**	**0.09**	**<0.001**	**0.07**	**0.02**	**0.11**	**0.007**
3	**0.06**	**0.02**	**0.09**	**0.003**	**0.06**	**0.01**	**0.10**	**0.008**	**0.06**	**0.02**	**0.10**	**0.002**	**0.07**	**0.02**	**0.11**	**0.003**
4	0.04	-0.01	0.09	0.112	-0.04	-0.01	0.07	0.083	0.04	-0.01	0.09	0.059	0.04	-0.01	0.09	0.067
Work time																
1	0.03	-0.02	0.07	0.299	0.02	-0.01	0.06	0.213	0.02	-0.01	0.07	0.164	0.03	-0.02	0.08	0.194
2	0.05	-0.01	0.11	0.116	**0.05**	**0.01**	**0.10**	**0.040**	0.06	-0.01	0.12	0.076	**0.06**	**0.02**	**0.10**	**0.003**
3	**0.05**	**0.01**	**0.10**	**0.026**	**0.06**	**0.01**	**0.11**	**0.032**	0.06	-0.01	0.12	0.063	**0.07**	**0.01**	**0.14**	**0.046**
4	0.06	-0.01	0.12	0.058	0.06	0.01	0.11	0.340	**0.06**	**0.01**	**0.12**	**0.048**	0.06	-0.02	0.13	0.129
5	0.05	-0.02	0.12	0.163	0.05	-0.01	0.12	0.094	0.05	-0.02	0.01	0.170	0.05	-0.01	0.01	0.094

Model 1 adjusted for age, sex, accelerometer wear time; model 2 was further adjusted for ethnicity, fruit and vegetable consumption, alcohol consumption, smoking status, equivalised household income; model 3 was further adjusted for general health, [longstanding illness], [BMI], model 4 was further adjusted for physical activity; model 5 was adjusted for non-work sedentary time in the work time models; significant effects (p<0.05) are shown in bold; β is the beta coefficient for the change in the health-related outcome; coefficients are given with 95% confidence intervals (CI); derived cut-points were 65 cpm for all 7 days; 60 cpm for weekdays; and 35 cpm for work time' BMI=Body mass index

Alongside the significant covariates of age, physical activity had the most influential effect on BMI, and attenuated any association with occupational sitting time. This is illustrated in the coefficient plot in Figure 5.7, which presents the beta coefficients (95% confidence intervals) for the occupational sedentary time covariate in models 3 and 4, and the beta coefficient for the physical activity variable in model 4. Figure 5.7 shows that occupational sedentary time was **not** a significant predictor of BMI after adjusting for moderate to vigorous physical activity.
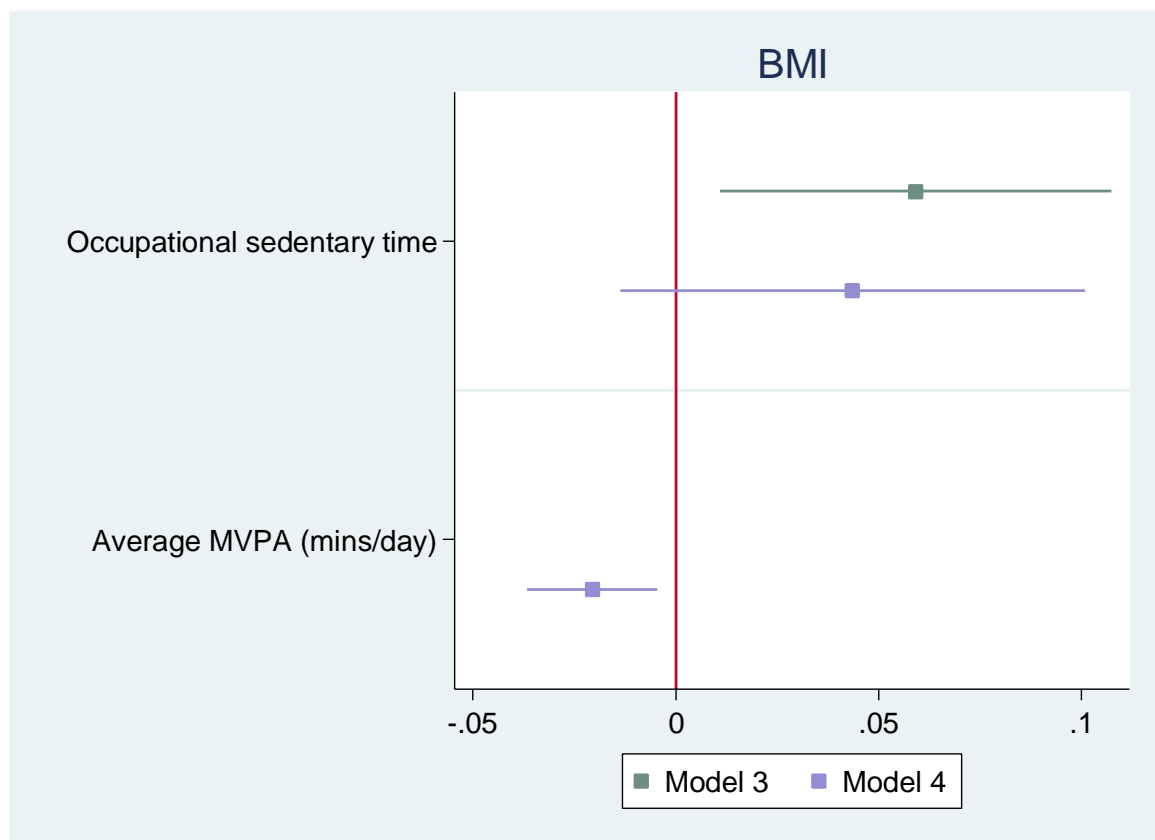
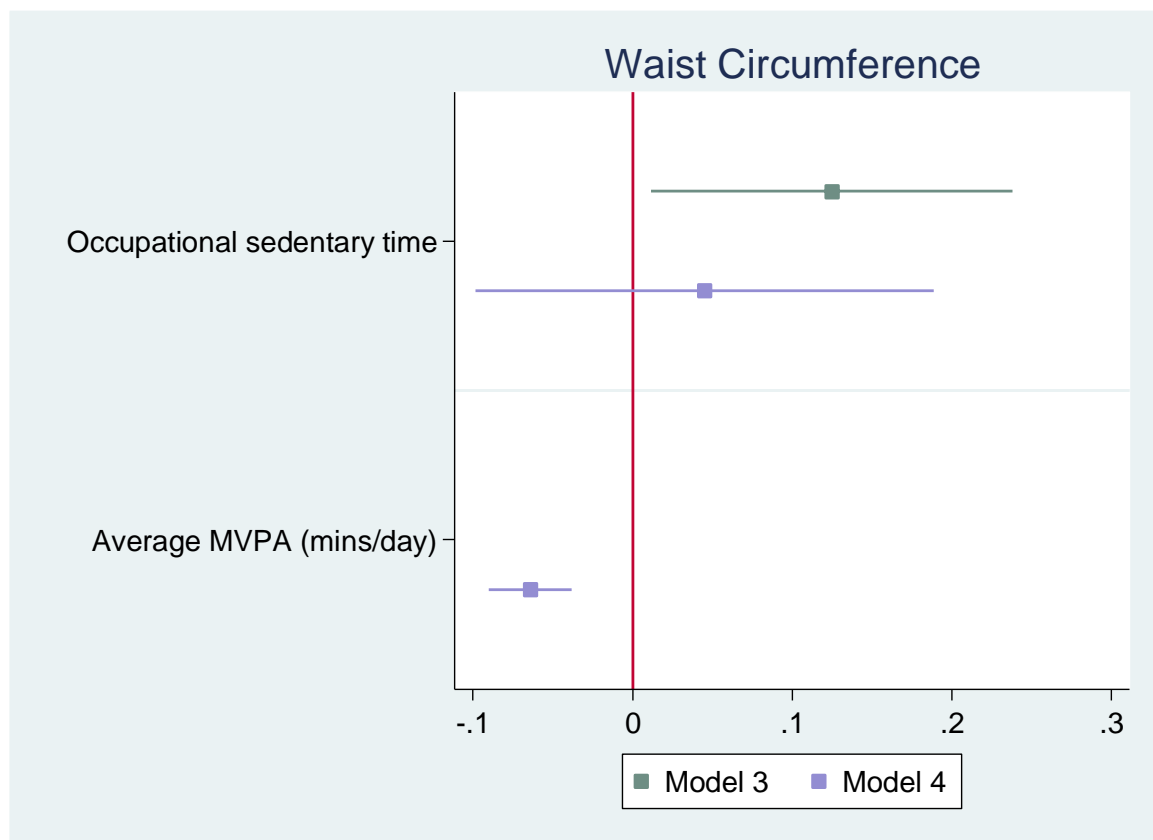**Figure 5.7**   **Coefficient plot for associations of occupational sedentary time and physical activity with BMI**

Figure 5.8 shows the effects of moderate to vigorous physical activity along the quantiles for BMI from model 5. For each one-minute increase per day in moderate to vigorous physical activity, there were significant associations with BMI, and this effect varied with increasing quantiles of BMI: β coefficients for the 25th, 50th, 75th quantiles were -0.011,

-0.021, -0.021 (the coefficients for the 50th and 75th quantiles were significant). The effect of moderate to vigorous physical activity was greater for individuals with higher values of BMI.

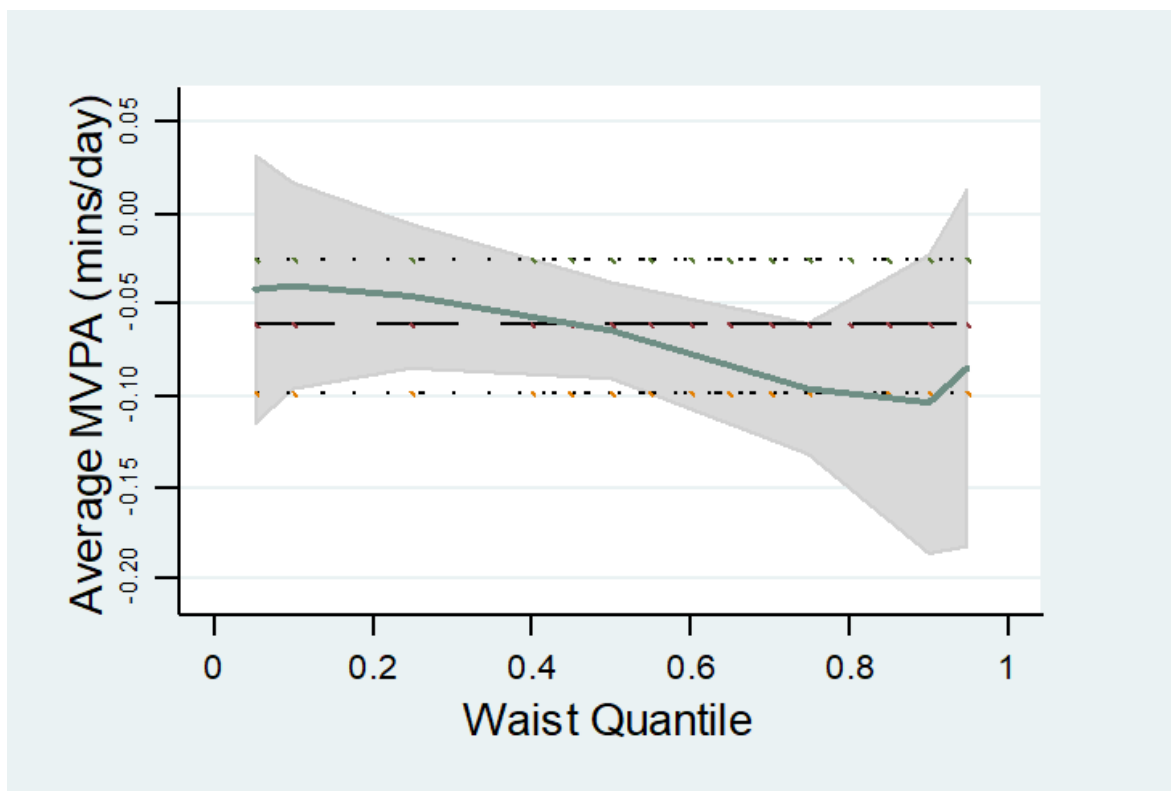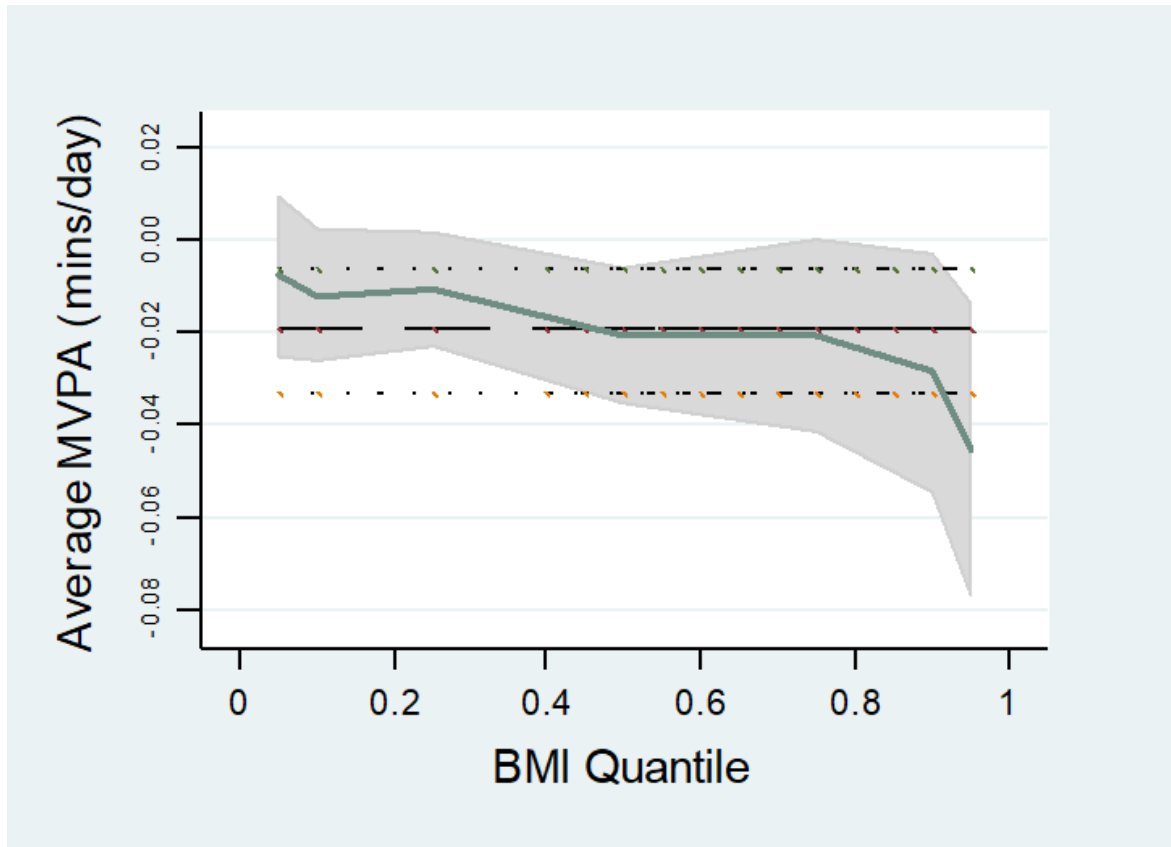**Figure 5.8**   **Effect of moderate to vigorous physical activity as a covariate in the quantile regression model for BMI**

The results from the models for waist circumference and BMI found that occupational sedentary time was not a significant predictor of adiposity after adjusting for moderate to vigorous physical activity. Moderate to vigorous physical activity **was** a significant predictor in change in adiposity markers, and this effect varied along the quantiles of both adiposity variables. Although the coefficients for moderate to vigorous physical activity in the median quantile regression analyses were not statistically significantly different to the ordinary least squares regression coefficient (Figure 5.6 and Figure 5.8), the magnitude of the coefficients decreased along quantiles for both adiposity variables.

5.2.3 *Systolic blood pressure, diastolic blood pressure, total cholesterol, HDL cholesterol, glycated haemoglobin, heart and circulatory conditions*

Table 5.5 presents the beta coefficients for the regression models for the other cardiometabolic markers (systolic blood pressure, diastolic blood pressure, total cholesterol, HDL cholesterol, glycated haemoglobin), and the prevalence rate ratios for heart and circulatory conditions. Since there were no differences in the effects from the models using the previously proposed cut-points, only the models for the derived cut-points are presented; similarly, no differences were observed between the reported effects for sedentary time between the hierarchy of regression models, and therefore results are shown from model 4 (for across the week and weekdays), or model 5 (for work times).

The beta coefficients in Table 5.5 show that none of the sedentary time variables were adversely associated with the other cardiometabolic health-related outcomes or heart and circulatory conditions. Increasing age and those in less than good health were consistently associated with these health-related outcomes; BMI was also significantly associated with three of the health outcomes (total cholesterol, HDL cholesterol, and HbA1c) (Figure 5.9).
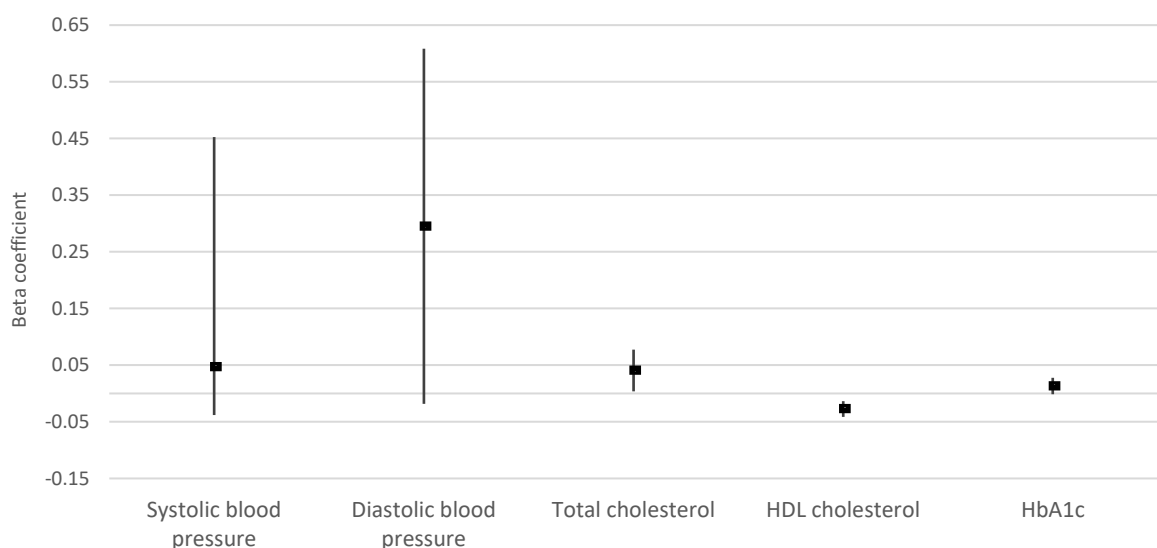
Figure 5.9   Beta coefficients for BMI in cardiometabolic health-related outcome models

Table 5.5 **β coefficients for regression models for cardiometabolic outcomes and heart conditions**

Health outcome	Sedentary time	β	Low 95% CI	High 95% CI	p-value
Systolic blood pressure					
(mmHg)	All 7 days	0.12	-0.12	0.34	0.326
	Weekdays	0.04	-0.16	0.25	0.672
	Work time	0.06	-0.22	0.34	0.667
Diastolic blood pressure					
(mmHg)	All 7 days	0.09	-0.09	0.27	0.305
	Weekdays	0.06	-0.10	0.22	0.445
	Work time	0.03	-0.18	0.25	0.763
Total cholesterol					
(mmol/L)	All 7 days	0.11	-0.01	0.33	0.260
	Weekdays	0.01	-0.01	0.02	0.179
	Work time	0.01	-0.02	0.03	0.686
HDL cholesterol					
(mmol/L)	All 7 days	-0.01	-0.01	0.01	0.357
	Weekdays	-0.01	-0.01	0.01	0.120
	Work time	-0.01	-0.01	0.01	0.225
HbA1c					
(%)	All 7 days	-0.10	-0.01	0.10	0.933
	Weekdays	-0.10	-0.01	0.10	0.655
	Work time	-0.10	-0.01	0.10	0.087
Heart conditions (PRR)					
	All 7 days	1.00	0.96	1.02	0.563
	Weekdays	1.00	0.96	1.02	0.549
	Work time	0.98	0.94	1.02	0.255

Adjusted model: age, sex, accelerometer wear time, ethnicity, fruit and vegetable consumption, alcohol consumption, smoking status, equivalised household income, general health, [longstanding illness], [BMI], physical activity, [non-work sedentary time]; significant effects ($p<0.05$) are shown in bold; β is the beta coefficient for the change in the health-related outcome; coefficients are given with 95% confidence intervals (CI); derived cut-points were 65 cpm for all 7 days; 60 cpm for weekdays; and 35 cpm for work time; BMI=Body mass index; HDL=High-density lipoprotein; HbA1c=Haemoglobin A1c (glycated haemoglobin); PRR=prevalence rate ratio

5.3   Objective 5 results

5. To examine if associations between workplace sedentary behaviour and health-related outcomes differ between occupational groups.

This section presents the results from the stratified analyses for the occupational classifications (managerial and professional occupations, intermediate occupations, routine and manual occupations). Results from, either model 4 (for the week and weekdays), or model 5 (for work times), using the derived cut-points from Chapter Three are presented in Table 5.6.

Significant positive associations were seen between sedentary time and BMI for the intermediate, and routine and manual occupation classifications; however, these associations were only significant in the models for the week and weekdays, and not for the occupational sedentary time model.

There was a significant association between time spent sedentary each day and total cholesterol: for each 10-minute increase in daily sedentary time, total cholesterol increased by 0.05mmol/L. This association was only seen in managerial and professional occupations in the model for weekday sedentary time. No significant associations were seen for the other health-related outcome models (waist circumference, systolic and diastolic blood pressure, HDL cholesterol, HbA1c, and heart conditions).

Similar to the models presented in Section 5.2, time spent in moderate to vigorous physical activity was a significant predictor in the waist circumference and BMI models. Likewise, BMI was a significant predictor for the same three cardiometabolic risk factor models (total and HDL cholesterol, and HbA1c).

Table 5.6   β coefficients for regression models for stratified analyses

Health outcome	Sedentary time	Managerial and professional (n=422)				Intermediate (n=196)				Routine and manual (n=274)			
		β	Low 95% CI	High 95% CI	p-value	β	Low 95% CI	High 95% CI	p-value	β	Low 95% CI	High 95% CI	p-value
Waist													
(cm)	All 7 days	0.03	-0.11	0.17	0.669	-0.01	-0.17	0.17	0.975	0.06	-0.10	0.23	0.450
	Weekdays	0.03	-0.08	0.13	0.597	-0.03	-0.19	0.13	0.730	0.02	-0.11	0.15	0.754
	Work time	0.01	-0.13	0.15	0.918	-0.09	-0.29	0.10	0.348	0.02	-0.17	0.21	0.835
BMI													
(kg/m²)	All 7 days	-0.01	-0.09	0.08	0.877	**0.12**	**0.02**	**0.21**	**0.014**	**0.12**	**0.01**	**0.22**	**0.026**
	Weekdays	0.01	-0.06	0.07	0.933	**0.13**	**0.04**	**0.22**	**0.006**	**0.12**	**0.04**	**0.19**	**0.001**
	Work time	-0.03	-0.12	0.04	0.422	0.11	-0.01	0.22	0.061	0.16	-0.07	0.38	0.174
Systolic blood pressure													
(mmHg)	All 7 days	-0.08	-0.50	0.35	0.704	0.01	-0.54	0.60	0.971	0.36	-0.15	0.86	0.165
	Weekdays	-0.20	-0.61	0.21	0.323	-0.14	-0.48	0.46	0.951	0.22	-0.25	0.68	0.357
	Work time	-0.24	-0.74	0.26	0.336	0.04	-0.61	0.69	0.901	0.63	-0.27	1.54	0.165
Diastolic blood pressure													
(mmHg)	All 7 days	-0.03	-0.42	0.35	0.865	0.14	-0.31	0.59	0.531	0.11	-0.17	0.40	0.428
	Weekdays	-0.06	0.43	0.31	0.762	0.05	-0.33	0.44	0.774	0.11	-0.15	0.37	0.389
	Work time	-0.18	-0.63	0.27	0.429	0.03	-0.50	0.57	0.902	0.30	-0.21	0.81	0.239
Total cholesterol													
(mmol/L)	All 7 days	0.04	-0.01	0.08	0.082	0.01	-0.03	0.06	0.529	0.01	-0.31	0.05	0.659
	Weekdays	**0.05**	**0.01**	**0.02**	**0.021**	0.01	-0.02	0.05	0.439	0.01	-0.03	0.04	0.750
	Work time	0.04	-0.01	0.08	0.144	0.02	-0.03	0.07	0.457	-0.04	-0.10	0.02	0.202
HDL cholesterol													
(mmol/L)	All 7 days	-0.01	-0.02	0.01	0.172	-0.01	-0.02	0.02	0.781	0.01	-0.01	0.02	0.140
	Weekdays	-0.01	-0.02	0.01	0.209	-0.01	-0.02	0.01	0.590	0.01	-0.01	0.01	0.514
	Work time	-0.01	-0.02	0.01	0.420	-0.01	-0.02	0.02	0.874	-0.01	-0.02	0.01	0.284
HbA1c													
(%)	All 7 days	0.01	-0.01	0.02	0.297	0.01	-0.01	0.02	0.820	-0.01	-0.02	0.01	0.131
	Weekdays	0.01	-0.01	0.01	0.575	0.01	-0.01	0.01	0.984	-0.01	-0.01	0.01	0.129
	Work time	0.01	-0.01	0.02	0.560	-0.02	-0.03	0.01	0.051	-0.01	-0.02	0.01	0.175
Heart conditions (PRR)													
	All 7 days	0.96	0.91	1.02	0.221	1.06	0.97	1.15	0.210	0.97	0.93	1.02	0.202
	Weekdays	0.96	0.91	1.01	0.112	1.04	0.98	1.11	0.208	0.98	0.93	1.02	0.298
	Work time	0.95	0.89	1.02	0.168	1.03	0.92	1.15	0.588	0.94	0.86	1.02	0.134

Adjusted model :age, sex, accelerometer wear time, ethnicity, fruit and vegetable consumption, alcohol consumption, smoking status, equivalised household income, general health, [longstanding illness], [BMI], physical activity, [non-work sedentary time]; significant effects (p<0.05) are shown in bold; β is the beta coefficient for the change in the health-related outcome; coefficients are given with 95% confidence intervals (CI); derived cut-points were 65 cpm for all 7 days; 60 cpm for weekdays; and 35 cpm for work time; BMI=Body mass index; HDL=High-density lipoprotein; HbA1c=Haemoglobin A1c (glycated haemoglobin); PRR=prevalence rate ratio

Table 5.7 presents the beta coefficients for the mutually exclusive categories of high/low sedentary times and high/low physical activity: these four variables were created by dichotomising the sedentary time variables using the median minutes of time spent sedentary per day, and physical activity was dichotomised into those meeting or not meeting 150 mins of moderate to vigorous physical activity each week.

Results are presented compared to the high sedentary/low physical activity group, for either model 4 (for the week and weekdays), or model 5 (for work times), using the derived cut-points from Chapter Three. Significant associations between sedentary time and health-related outcomes were only seen in the BMI model; however, the results were not consistent for the sedentary time variables. For example, in comparison to the high sedentary/low physical activity category (n=191), those in the low sedentary/high physical activity had a significantly lower BMI (β=-1.6 (95% CI -2.9, -0.3); p=0.014) in the work time model only. A significant association was also seen in the work time model for BMI, for the low sedentary/low physical activity category. In comparison to the high sedentary/low physical activity category (n=191), those in the high sedentary/high physical activity group had a significantly lower BMI, but this was only observed in the weekday model. The two significant results in the work time models suggest that the reciprocity between occupational sedentary time and weekly physical activity plays an important role with respect to the association with BMI.

Table 5.7 **β coefficients for regression models for low/high categories to sedentary time and time spent in moderate to vigorous physical activity**

Health outcome	Sedentary time	Low sedentary/high activity (n=320)				High sedentary/high activity (n=256)				Low sedentary/low activity (n=126)			
		β	Low 95% CI	High 95% CI	p-value	β	Low 95% CI	High 95% CI	p-value	β	Low 95% CI	High 95% CI	p-value
Waist													
(cm)	All 7 days	-0.74	-2.34	0.96	0.366	0.52	-	2.09	0.519	-0.78	-3.23	1.66	0.529
	Weekdays	-0.68	-2.74	1.38	0.515	0.53	-	2.33	0.564	-0.37	-2.47	1.73	0.727
	Work time	-1.15	-3.34	1.05	0.306	0.56	-	2.50	0.569	-1.92	-4.97	1.13	0.218
BMI													
(kg/m^2)	All 7 days	-1.49	-3.20	0.23	0.090	-1.24	-	0.20	0.091	**-1.90**	**-3.40**	**-0.40**	**0.014**
	Weekdays	-1.50	-3.00	0.02	0.054	**-1.21**	**-**	**-0.03**	**0.044**	-1.42	-3.00	0.17	0.080
	Work time	**-1.60**	**-2.90**	**-0.30**	**0.014**	-0.80	-	0.70	0.302	**-1.23**	**-2.40**	**-0.04**	**0.042**
Systolic blood pressure													
(mmHg)	All 7 days	-1.10	.7.7	5.40	0.734	-1.27	-	4.50	0.665	0.35	-6.00	6.72	0.914
	Weekdays	2.24	-4.35	8.82	0.504	1.50	-	7.26	0.607	1.76	-4.57	8.09	0.584
	Work time	1.71	-4.38	7.80	0.580	2.94	-	8.84	0.324	3.53	-2.45	9.51	0.246
Diastolic blood pressure													
(mmHg)	All 7 days	0.21	-4.78	5.19	0.935	-1.02	-	3.35	0.645	-0.18	-5.02	4.65	0.941
	Weekdays	2.01	-3.07	7.09	0.436	1.38	-	5.82	0.541	0.73	-4.16	5.62	0.768
	Work time	0.10	-4.58	4.78	0.967	3.31	-	7.83	0.150	1.29	-3.29	5.89	0.577
Total cholesterol													
(mmol/L)	All 7 days	-0.27	-0.81	0.03	0.328	-0.22	-	0.25	0.351	-0.05	-0.60	0.50	0.868
	Weekdays	-0.30	-0.87	0.28	0.315	-0.17	-	0.32	0.500	-1.00	-0.63	0.43	0.708
	Work time	-0.21	-0.74	0.32	0.442	-0.14	-	0.35	0.578	-0.02	-0.53	0.49	0.930
HDL cholesterol													
(mmol/L)	All 7 days	0.01	-0.11	0.25	0.482	-0.08	-	0.07	0.293	0.11	-0.07	0.29	0.240
	Weekdays	0.07	-0.11	0.26	0.433	-0.04	-	0.12	0.596	0.14	-0.03	0.31	0.111
	Work time	0.01	-0.16	0.19	0.905	-0.06	-	0.10	0.473	0.09	-0.07	0.26	0.286
HbA1c													
(%)	All 7 days	-0.12	-0.31	0.01	0.187	-0.14	-	0.02	0.087	-0.76	-0.25	0.10	0.400
	Weekdays	-0.11	-0.29	0.07	0.240	-0.15	-	0.01	0.071	-0.02	-0.20	0.15	0.795
	Work time	-0.04	-0.22	0.13	0.616	-0.10	-	0.06	0.231	0.12	-0.05	0.29	0.162
Heart conditions (PRR)													
	All 7 days	1.07	0.43	2.68	0.888	0.75	0.35	1.61	0.464	1.19	0.52	2.70	0.681
	Weekdays	0.81	0.32	2.05	0.655	0.76	0.38	1.50	0.424	1.07	0.40	2.85	0.893
	Work time	0.91	0.38	2.22	0.841	0.68	0.32	1.44	0.320	1.12	0.47	2.71	0.798

Adjusted model :age, sex, accelerometer wear time, ethnicity, fruit and vegetable consumption, alcohol consumption, smoking status, equivalised household income, general health, [longstanding illness], [BMI], physical activity, [non-work sedentary time]; significant effects (p<0.05) are shown in bold; β is the beta coefficient for the change in the health-related outcome; coefficients are given with 95% confidence intervals (CI); derived cut-points were 65 cpm for all 7 days; 60 cpm for weekdays; and 35 cpm for work time; BMI=Body mass index; HDL=High-density lipoprotein; HbA1c=Haemoglobin A1c (glycated haemoglobin); PRR=prevalence rate ratio

5.4 Objective 6 results

6. *To determine if there are associations between workplace sedentary behaviour and mental ill-health and musculoskeletal disorders.*

This section presents the results for the regression models for mental-ill health and musculoskeletal disorders. These two conditions are responsible for the majority of work-related ill health and days absent from work (Health and Safety Executive, 2018); however, there has been limited research that has examined the association between occupational sitting time and these two conditions. Results for these two conditions are presented for either model 4 (for the week and weekdays), or model 5 (for work times), using the derived cut-points from Chapter Three; prevalence rate ratios are shown in the models for musculoskeletal conditions, mental disorders, and GHQ-12, and beta coefficients are presented for the EQ-5D models.

Table 5.8 presents the prevalence rate ratios and beta coefficients for the regression models for mental ill-health and musculoskeletal disorders. Significant associations were seen for mental disorders, for the models for all sedentary time variables; the prevalence rate ratios ranged from 1.06 in the weekdays model to 1.09 in the work time model. The prevalence rate ratio for the work time model (1.09) implies that for each 10-minute increase of occupational sedentary time, participants were 9% more likely to report having a mental disorder.

Neither BMI nor physical activity were significant predictors for mental ill-health and musculoskeletal disorders; alongside age and sex, general health was an important predictor for these two conditions.

Table 5.8   **Prevalence rate ratios and β coefficients for regression models for mental ill-health and musculoskeletal disorders**

Health outcome	Sedentary time	β	Low 95% CI	High 95% CI	p-value
Musculoskeletal conditions (PRR)					
	All 7 days	1.01	0.99	1.03	0.528
	Weekdays	1.01	0.99	1.03	0.290
	Work time	1.02	0.99	1.05	0.249
Mental disorders (PRR)					
	All 7 days	**1.08**	**1.01**	**1.14**	**0.019**
	Weekdays	**1.06**	**1.01**	**1.11**	**0.023**
	Work time	**1.09**	**1.03**	**1.15**	**0.002**
GHQ-12 (PRR)					
	All 7 days	0.99	0.97	1.02	0.873
	Weekdays	1.00	0.98	1.02	0.897
	Work time	1.00	0.97	1.03	0.965
EQ-5D					
	All 7 days	0.01	-0.01	0.01	0.365
	Weekdays	0.01	-0.01	0.01	0.220
	Work time	0.01	-0.01	0.01	0.419

Adjusted model: age, sex, accelerometer wear time, ethnicity, fruit and vegetable consumption, alcohol consumption, smoking status, equivalised household income, general health, [longstanding illness], [BMI], physical activity, [non-work sedentary time]; significant effects ($p < 0.05$) are shown in bold; β is the beta coefficient for the change in the health-related outcome; coefficients are given with 95% confidence intervals (CI); derived cut-points were 65 cpm for all 7 days; 60 cpm for weekdays; and 35 cpm for work time; BMI=Body mass index; GHQ=General health questionnaire; EQ-5D=EuroQol 5 dimensions; PRR=prevalence rate ratio

The results from the stratified analyses for mental ill-health and musculoskeletal disorders are presented in Table 5.9. Significant prevalence rate ratios were seen for mental disorders only, in the intermediate, and routine and manual occupations. For each 10-minute increase in occupational sedentary time, mental disorders were 29% more likely to be reported in intermediate occupations, and 18% more likely in routine and manual occupations. Those in intermediate occupations also reported a positive association between daily sedentary time and mental disorders in the model for the week.

Table 5.9   Prevalence rate ratios and β coefficients for regression models for stratified analyses for mental ill-health and musculoskeletal disorders

Health outcome		Managerial and professional (n=422)				Routine and manual (n=274)				Intermediate (n=196)			
	Sedentary time	β	Low 95% CI	High 95% CI	p-value	β	Low 95% CI	High 95% CI	p-value	β	Low 95% CI	High 95% CI	p-value
Musculoskeletal conditions (PRR)													
	All 7 days	1.01	0.97	1.05	0.590	1.01	0.95	1.07	0.822	1.03	0.99	1.07	0.101
	Weekdays	1.03	0.99	1.06	0.177	1.01	0.96	1.05	0.878	1.03	0.99	1.06	0.078
	Work time	1.02	0.98	1.07	0.322	1.03	0.97	1.10	0.308	1.03	0.98	1.07	0.281
Mental disorders (PRR)													
	All 7 days	1.08	0.97	1.19	0.158	**1.86**	**1.23**	**2.81**	**0.003**	1.05	0.97	1.15	0.238
	Weekdays	1.09	0.99	1.19	0.870	1.18	0.98	1.42	0.075	1.06	0.96	1.18	0.213
	Work time	1.04	0.88	1.24	0.616	**1.29**	**1.07**	**1.29**	**0.007**	**1.18**	**1.02**	**1.37**	**0.025**
GHQ-12 (PRR)													
	All 7 days	1.03	0.99	1.08	0.124	0.98	0.94	1.03	0.486	0.99	0.95	1.02	0.371
	Weekdays	1.02	0.98	1.06	0.340	0.99	0.95	1.03	0.685	0.99	0.96	1.02	0.571
	Work time	1.03	0.98	1.10	0.271	0.99	0.93	1.06	0.829	0.98	0.93	1.03	0.363
EQ-5D													
	All 7 days	-0.01	-0.01	0.01	0.963	-0.01	-0.01	0.01	0.217	-0.01	-0.01	0.01	0.777
	Weekdays	-0.01	-0.01	0.01	0.772	-0.01	-0.01	0.01	0.138	-0.01	-0.01	0.01	0.764
	Work time	-0.01	-0.01	0.01	0.875	-0.01	-0.01	0.01	0.246	-0.01	-0.01	0.01	0.770

Adjusted model :age, sex, accelerometer wear time, ethnicity, fruit and vegetable consumption, alcohol consumption, smoking status, equivalised household income, general health, [longstanding illness], [BMI], physical activity, [non-work sedentary time]; significant effects (p<0.05) are shown in bold; β is the beta coefficient for the change in the health-related outcome; coefficients are given with 95% confidence intervals (CI); derived cut-points were 65 cpm for all 7 days; 60 cpm for weekdays; and 35 cpm for work time; BMI=Body mass index; GHQ=General health questionnaire; EQ-5D=EuroQol 5 dimensions; PRR=prevalence rate ratio

Table 5.10 presents the beta coefficients for the mutually exclusive categories of high/low sedentary times and high/low physical activity: the only significant association was seen in the work time model, in the low sedentary/high physical activity group. Compared to the high sedentary/low physical activity category (n=191), those in the low sedentary/high physical activity category were 88% less likely to report having a mental disorder (PRR 0.12 (95% CI 0.02, 0.68)).

Table 5.10 Prevalence rate ratios and β coefficients for regression models for low/high categories to sedentary time and time spent in moderate to vigorous physical activity for mental ill-health and musculoskeletal disorders

Health outcome	Sedentary time	Low sedentary/high activity (n=320)				High sedentary/high activity (n=256)				Low sedentary/low activity (n=126)			
		β	Low 95% CI	High 95% CI	p-value	β	Low 95% CI	High 95% CI	p-value	β	Low 95%	High 95%	p-value
Musculoskeletal conditions (PRR)													
	All 7 days	0.70	0.35	1.41	0.322	0.88	0.47	1.67	0.701	0.95	0.50	1.78	0.862
	Weekdays	0.64	0.90	1.04	0.070	0.90	0.56	1.44	0.659	0.73	0.41	1.32	0.300
	Work time	0.73	0.37	1.44	0.366	1.12	0.62	2.03	0.710	0.70	0.36	1.36	0.296
Mental disorders (PRR)													
	All 7 days	0.48	0.15	1.51	0.211	0.74	0.24	2.26	0.601	0.68	0.19	2.51	0.565
	Weekdays	0.34	0.08	1.48	0.152	0.85	0.23	3.21	0.816	0.66	0.16	2.72	0.565
	Work time	**0.12**	**0.02**	**0.68**	**0.017**	0.44	0.12	1.44	0.174	0.27	0.07	1.07	0.063
GHQ-12 (PRR)													
	All 7 days	1.08	0.60	1.94	0.811	0.88	0.47	1.66	0.704	0.66	0.33	1.33	0.246
	Weekdays	1.23	0.66	2.30	0.513	1.08	0.57	2.06	0.819	0.88	0.45	1.73	0.708
	Work time	1.23	0.61	2.45	0.563	1.48	0.76	2.87	0.249	1.25	0.66	2.40	0.483
EQ-5D													
	All 7 days	-0.01	-0.10	0.10	0.935	0.10	-0.10	0.10	0.842	-0.03	-0.11	0.06	0.567
	Weekdays	-0.01	0.10	0.10	0.868	0.10	-0.10	0.10	0.934	-0.03	-0.12	0.06	0.504
	Work time	-0.01	0.10	0.10	0.941	-0.01	0.10	0.07	0.776	-0.03	0.11	0.06	0.500

Adjusted model :age, sex, accelerometer wear time, ethnicity, fruit and vegetable consumption, alcohol consumption, smoking status, equivalised household income, general health, [longstanding illness], [BMI], physical activity, [non-work sedentary time]; significant effects (p<0.05) are shown in bold; β is the beta coefficient for the change in the health-related outcome; coefficients are given with 95% confidence intervals (CI); derived cut-points were 65 cpm for all 7 days; 60 cpm for weekdays; and 35 cpm for work time; BMI=Body mass index; GHQ=General health questionnaire; EQ-5D=EuroQol 5 dimensions; PRR=prevalence rate ratio

5.5 Summary of key findings

- Accelerometer data were available for 893 full-time workers from the Health Survey for England 2008.

- Daily sedentary times were lower from the self-reported questions compared to the objective times from the accelerometer; conversely, self-reported physical activity times were higher than the objectively derived times for physical activity.

- The amount of sedentary time from the derived and previously proposed cut-points differed significantly; however, this did not affect the beta coefficients and the conclusions drawn from the regression models.

- In contrast to studies that have found associations with both total sedentary time and leisure-time sedentary behaviour and detrimental health outcomes, there was no evidence that occupational sedentary time is associated with health-related outcomes in the same way.

- Time spent in moderate to vigorous physical activity was a significant predictor in the waist circumference and BMI models for occupational sedentary time; furthermore, BMI was a significant predictor of cardiometabolic markers.

- It is not known if there are underlying mechanisms of sedentary behaviour in different domains that can explain these differences, and the effect that occupational sedentary time has on health.

- Results from the regression analyses suggest that the reciprocity between occupational sedentary time and weekly physical activity plays an important role with respect to the association with BMI.

Chapter 6 - Sequence analysis results

"A mathematician, like a painter or a poet, is a maker of patterns. If his patterns are more permanent than theirs, it is because they are made with ideas"

— G. H. Hardy

Table 6.1   Overview of Chapter 6

Chapter	Aims, objectives and research questions	Methods
Chapter 2	**Aim:** To provide an overview of the literature and to critique the current evidence of sedentary behaviour and work, focussing on the prevalence of sedentary behaviour at work, and its association with health-related outcomes	Structured literature review using six electronic databases
Chapter 3	**Aim:** To empirically derive a new accelerometer cut-point to define sedentary behaviour in adults **Objective 1:** To empirically derive an optimal threshold for classifying sedentary behaviour, using the counts per minute output from the ActiGraph GT3X+ accelerometer, when compared to the sedentary classification from the activPAL™ accelerometer in a free-living environment **Objective 2:** To ascertain whether thresholds for sedentary behaviour cut-points vary by day of the week and in working time versus non-working time **Objective 3:** To derive optimal cut-points for different classifications of sedentary behaviour using contextual data from a 24-hour activity log, and to examine if there are differences between them	Observational study in university workers and postgraduate students (n=30) Application of generalised estimating equations to 1-minute epoch data for the ActiGraph GT3X+ and the activPAL™ data
Chapter 4	**Aim:** To describe the methodology for the Health Survey for England 2008, and a critique of the strengths and limitations of using secondary analysis	Description of data collection and processing
Chapter 5	**Aim:** To apply the cut-point from *Study One* to data from the Health Survey for England (2008), in order to investigate the associations between sedentary behaviour, work, and health-related outcomes **Objective 4:** To identify associations between workplace sedentary behaviour and health-related outcomes using the derived cut-point from *Study One* **Objective 5:** To examine if associations between workplace sedentary behaviour and health-related outcomes differ between occupational groups **Objective 6:** To determine if there are associations between workplace sedentary behaviour and mental ill-health and musculoskeletal disorders	A secondary data analysis of the Health Survey for England 2008 Application of hierarchical regression models – type of regression model dependent on distribution of each dependent variable (health-related outcome)
Chapter 6	**Aim:** To apply the cut-point from *Study One* to data from the Health Survey for England (2008), in order to investigate the associations between sedentary behaviour, work, and health-related outcomes **Objective 7:** To explore the patterning and sequences of sedentary bouts across the day, and the relationship with measures of adiposity and other health-related outcomes	Sequence analysis to describe the characteristics of time-related sequences of sedentary behaviour
Chapter 7	**Aim:** To discuss and critically appraise the studies within this thesis and to outline implications for policy and future research	Discussion and conclusions

Chapter Six presents the results from the sequence analysis to address objective seven, to explore the patterning and sequences of sedentary bouts across the day, and the relationship with measures of adiposity and other health-related outcomes. The first section of this chapter describes how the sequences of physical behaviour were constructed from the Health Survey for England 2008 accelerometer data and defines the cardiometabolic risk factor variables to be used in the sequence analysis. The second section presents the descriptive statistics of the sequence patterning for the cardiometabolic risk factors; the results and analysis of the cluster profiles from the hierarchical cluster analyses are presented in the final section.

6.1 Constructing the sequences

Sequence analysis was carried out in Stata, using the *SQ* sequence analysis package (Brzinsky-Fay et al., 2006), which requires that the sequence data appear in a specific structure for each participant (Figure 6.1). The data should initially be in a wide format, with one row for each participant: Figure 6.1 shows an arbitrary example of a set of sequence data for a participant (with identification number 43), who has a sequence containing 10 positions (variables *st1-st10)*, and the elements in each position are coded as either, *3, 2,* or *5*, to represent a particular behaviour or life event. Data in a wide format allows for other variables of interest (i.e. demographic information and health-related outcomes) to be appended to the dataset at this stage.

	st1	st2	st3	st4	st5	st6	st7	st8	st9	st10
43.	3	3	3	2	2	2	2	2	5	5

Figure 6.1   Sequence data format in Stata (Brzinsky-Fay, Kohler, & Luniak, 2006, p. 437)

The sequences chosen for the sequence analysis were for one working day (Lesnard, 2010; Pieter Van Tienoven & Minnen, 2011; Xiao, Gerth, & Hanrahan, 2006), between the hours of 9:00am to 5:00pm on a weekday, and the chosen time interval for each element was five-minutes (Hall, 2017; Maxhuni et al., 2016; Ryan et al., 2011) (Section 4.3.6.3). The accelerometer data files for each participant from the Health Survey for England 2008 contained a maximum of 10,080 rows of data (minutes in a week), in the full-time workers sample. Consequently, the rows of data that represented the first working day of data collection for participants between the hours of 9:00am to 5:00pm were retained (to ensure representation of working days); this resulted in 588 participants (out of the 893 full-time workers with at least one day of valid data) who had complete accelerometer data for eight 'working hours' on a weekday. The 480 rows of data across the eight hours were then collapsed into 96 rows to represent each five-minute interval, and the main activity (sedentary behaviour, light physical activity, or moderate to vigorous physical activity) that occurred in that interval ('element') was calculated. The 96 rows were *reshaped* in Stata from long to wide format, so that each participant only had one row of data in a sequence of elements of behaviours across the 96 positions across the working day; these sequences were then merged into the cleaned dataset of covariates. For example, Figure 6.2 shows the first two elements and the last six elements for a participant; the data shows that the first two elements have been classified as *1* to indicate sedentary time (*state1* and *state2)*, and the final 25 minutes (*state92* to *state96)* of the working day were classified as *2*, showing that the participant was engaged in light physical activity during this time; the final two columns in sequence present two of the matched covariates, showing that these data are for a male participant with a systolic blood pressure measure of 136.5 mmHg.

state1	state2		state91	state92	state93	state94	state95	state96	sex	sbp
1	1	..	1	2	2	2	2	2	men	136.5	..

Figure 6.2   Row of sequence data from the Health Survey for England 2008

To describe the sequences with respect to health-related outcomes, the cardiometabolic risk factors that were available from the Health Survey for England 2008 were dichotomised according to the American Heart Association/National Heart, Lung, and Blood Institute criteria (2004), into 'raised' and 'not raised' categories (HDL cholesterol was classified as 'low' or 'high') (Kassi et al., 2011):

- Waist circumference 102 cm or greater in men, 88 cm or greater in women

- HDL cholesterol < 40 mg/dl in men and < 50 mg/ dl in women

- Blood pressure 130/85 mmHg or greater

- Fasting[62] glucose 100 mg/dl or greater[63]

Total cholesterol (dichotomised at <5/≥5 mmol/L using NHS recommendations[64]) and BMI (dichotomised for obesity at <30/≥30 kg/m^2) were also included in the sequence analysis.

6.2   Objective 7 results: descriptive statistics

7. *To explore the patterning and sequences of sedentary bouts across the day, and the relationship with measures of adiposity and other health-related outcomes.*

The majority of working hours were on average spent sedentary (282 minutes, 58.8%), with 38.8% spent in light physical activity (186.2 minutes), and 2.4% of the time was spent in moderate to vigorous physical activity (11.6 minutes). The mean length of episodes

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[62] The blood samples in the Health Survey for England 2008 were non-fasting
[63] Glucose measurement in mg/dL (US standard) was converted to UK standard measurements https://www.diabetes.co.uk/blood-sugar-converter.html
[64] https://www.nhs.uk/conditions/high-cholesterol/cholesterol-levels/

(referred to as bouts going forward for these analyses) for each type of activity across the working day, and the mean number of bouts of each activity type were calculated, for both normal and raised values of each health-related outcome. To examine differences between the normal and raised values of mean length of bout and mean number of bouts for each health-related outcomes, t-tests were carried out (Table 6.3); t-tests and ANOVA were used to examine differences between the mean length of bout and mean number of bouts for gender and occupational groups respectively (Table 6.2).

Men were significantly more likely to accumulate their occupational sedentary time in fewer (12.8 vs. 13.4; p<0.001), and shorter average bout lengths compared to women (24.84 vs. 26.11 minutes; p<0.001); they also accrued longer bouts of light physical activity (15.05 vs. 12.71 minutes; p<0.001), and moderate to vigorous physical activity in longer average bout lengths compared to women (8.51 vs. 8.07 minutes; p<0.001) (Table 6.2). There was a significant difference in the average sedentary bout length by occupational classification, with managerial and professional workers having longer average sedentary bout lengths (30.81 minutes) compared to intermediate (24.89), and routine and manual workers (16.45) (p<0.001); the opposite trend was seen for light physical activity bouts, with mean bout length highest in manual and routine workers (Table 6.2). Routine and manual workers accrued a higher amount of moderate to vigorous physical activity at work (17.69 minutes [2.3 x 7.69 minutes]), compared to intermediate workers (9.17 minutes [1.2 x 7.64 minutes]) and managerial and professional workers (9.18 minutes); however, the mean length of bouts of this activity was significantly higher in managerial and professional workers (p<0.001) (Table 6.2).

Table 6.2   **Mean length of bouts and mean number of bouts for each activity across the day**

	Sedentary time		Time in LPA		Time in MVPA	
Risk factor	Mean length of bouts (mins)	Mean number of bouts	Mean length of bouts (mins)	Mean number of bouts	Mean length of bouts (mins)	Mean number of bouts
Men	**24.84**	12.8	**15.05**	13.8	**8.51**	1.7
Women	**26.11**	13.4	**12.71**	13.7	**8.07**	0.9
Occupational classification						
Managerial and professional	**30.81**	12.8	**10.86**	13.0	**9.18**	1.0
Intermediate	**24.89**	13.0	**15.69**	13.6	**7.64**	1.2
Routine and manual	**16.45**	13.5	**18.83**	15.2	**7.69**	2.3

Mean length of bouts in minutes; Significant differences ($p < 0.05$) are shown in bold: t-tests were used to examine differences between men and women; ANOVA was used to examine differences between occupational classification

State distribution graphs can help to identify any fluctuations and changes in the proportion of specific elements across the sequence positions: they display the overall pattern of the data across all the positions of the sequence (Cornwell, 2015). In a state distribution graph, the proportion of participants in each behaviour/social event is shown for each position. The state distributions graphs for these analyses show the data across the 96 positions; the *x*-axis represents the sequence position from 1 to 96 across the working hours, and the *y*-axis shows the proportion of participants in each activity (sedentary behaviour, light physical activity, moderate to vigorous physical activity) at each position.

The proportion of women engaged in sedentary behaviour at each time point is greater compared to men, and the proportion of men engaged in moderate to vigorous physical activity is greater than women across the working day (Figure 6.3).

Figure 6.3   State distribution graph for gender

The state distribution graph for occupational classification clearly shows the differences in how the three classifications accrue their activities across the day; at all time points, a greater proportion of managerial and professional workers are engaged in sedentary behaviour compared to the other intermediate and routine occupations (Figure 6.4). This is due to professional workers spending proportionally more of their working time in sedentary behaviours. The graph for professional workers is consistent throughout the day; however, there are more fluctuations in how the physical behaviours are accrued in intermediate workers, and a higher proportion of routine workers are engaged in light physical activity in the morning compared to later on in the afternoon.
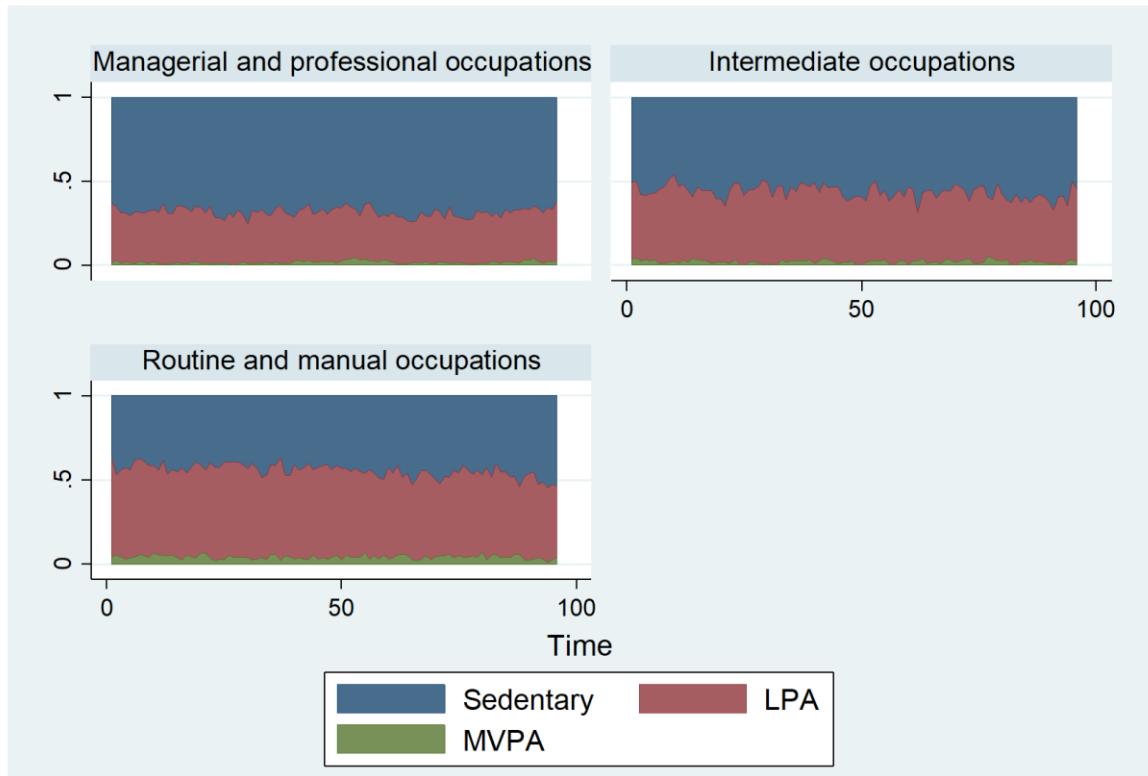
Figure 6.4 **State distribution graph for occupational classifications**

Table 6.3 shows the mean length of bouts for each type of activity, and the mean number of bouts, for both normal and raised values of each health-related outcome. Participants with less favourable health-related outcomes tended to have shorter average bout lengths of sedentary time compared to those with 'normal' values; this was significant for all health-related outcomes with the exception of the adiposity markers. Conversely, those with 'normal' values of each health-related outcome were significantly more likely to accrue their moderate to vigorous physical activity in longer duration bouts and in a greater number of bouts, compared to those with raised values. Therefore, for working hours, those with raised values of cardiometabolic risk factors had on average lower sedentary times (accrued in shorter bout lengths), and also lower total times spent in moderate to vigorous physical activity (accrued in shorter bout lengths). There was no consistent pattern in the mean length of light physical activity bouts between those with 'normal' and raised values of the cardiometabolic risk factors. Consequently, the way in which we

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accumulate these different behaviours across the day may have differing impacts on our health outcomes.

Table 6.3   **Mean length of bouts and mean number of bouts for cardiometabolic risk factors**

Risk factor		Sedentary time		Time in LPA		Time in MVPA	
		Mean length of bouts (mins)	Mean number of bouts	Mean length of bouts (mins)	Mean number of bouts	Mean length of bouts (mins)	Mean number of bouts
Waist circumference	Not raised	25.07	**12.8**	14.54	**13.7**	**8.80**	**1.6**
	Raised	25.21	**13.4**	14.38	**14.1**	**7.03**	**1.2**
HDL cholesterol	Low	**22.96**	**13.2**	**13.88**	13.7	**7.81**	**0.9**
	High	**24.54**	**13.0**	**14.64**	13.8	**8.74**	**1.5**
Blood pressure	Not raised	**26.05**	**12.9**	**14.08**	**13.7**	8.53	1.5
	Raised	**21.72**	**13.2**	**16.21**	**14.1**	8.43	1.4
HbA1c	Not raised	**25.43**	**13.1**	**13.65**	**13.9**	**8.80**	**1.5**
	Raised	**23.19**	**12.9**	**15.73**	**13.7**	**8.37**	**1.4**
Total cholesterol	Not raised	**27.03**	**12.5**	**14.16**	**13.1**	9.24	1.4
	Raised	**23.09**	**13.3**	**14.75**	**14.2**	8.33	1.4
BMI	Not raised	24.80	12.9	14.30	13.8	8.73	1.5
	Raised	27.22	13.3	13.15	13.9	7.47	1.1

Mean length of bouts in minutes; Significant differences ($p<0.05$) are shown in bold: t-tests were used to examine differences between raised/not raised levels of each cardiometabolic risk factor (HDL cholesterol was classified as 'low' or 'high'): waist circumference 102 cm or greater in men, 88 cm or greater in women; HDL cholesterol < 40 mg/dl in men and < 50 mg/ dl in women; blood pressure 130/85 mmHg or greater; fasting glucose 100 mg/dl or greater (glucose measurement in mg/dL (US standard) was converted to UK standard measurements for HbA1c %); total cholesterol <5/≥5 mmol/L; BMI dichotomised for obesity at <30/≥30 kg/m^2 (Section 6.1); BMI=body mass index; HDL=High-density lipoprotein; HbA1c=Haemoglobin A1c (glycated haemoglobin)

The state distribution graph for HDL cholesterol is shown in Figure 6.5: for participants with high HDL cholesterol (i.e. 'good' cholesterol) the proportion of people in the three activities at each time point was more consistent across the day compared to those with low HDL cholesterol. Although people with low HDL cholesterol had on average shorter bouts of sedentary time compared to those with high HDL cholesterol, the number of participants engaged in sedentary behaviour at each time point fluctuated greatly for those with low HDL cholesterol. HDL cholesterol has been used here to illustrate the differences in

fluctuations and changes in the proportion of people engaged in the activities across the day; the state distribution graphs for the other risk factors can be seen in Appendix 13.
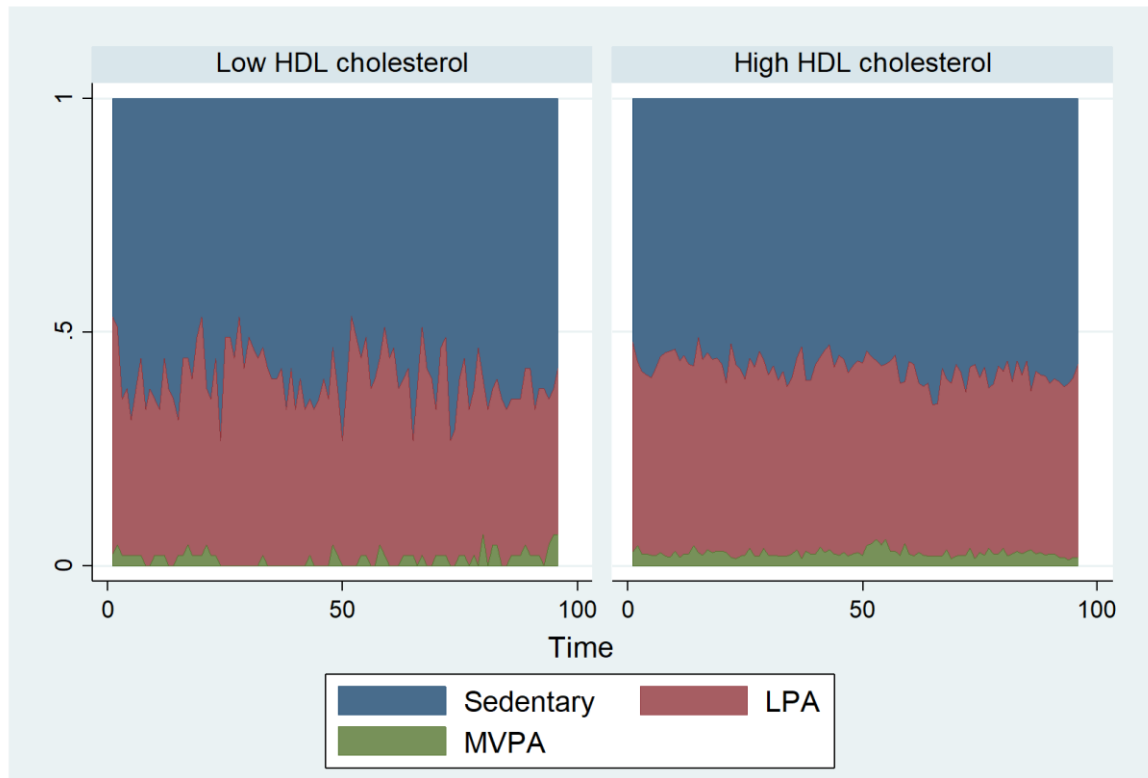

Figure 6.5 **State distribution graph for HDL cholesterol**

6.3 Objective 7 results: Optimal matching and hierarchical cluster analysis

Optimal matching and a hierarchical cluster analysis were employed to create a typology of the activities of the full-time workers across the day. The optimal matching procedure was used to compute the minimum 'distance' for each pair of sequences, i.e. the minimum number of operations needed to transform one sequence into another, using the *SQ* package in Stata. These distances were then stored in the dissimilarity matrix: the dimensions of the dissimilarity matrix for this analysis was a 588 x 588 matrix (to indicate the distance calculated for each pair of sequences). Hierarchical cluster analysis was then applied to the dissimilarity matrix to generate clusters of the full-time workers with similar physical behaviours sequences structures.

The hierarchical cluster analysis can be illustrated using a dendrogram (Figure 6.6) (Eriksson, 2018; Köppe, 2017). The *x*-axis for the full dendrogram included the original 588 sequences as separate clusters; the *y*-axis shows the threshold at which the clusters can be combined based on their distances from the dissimilarity matrix. Only the top 20 branches of the hierarchical cluster analysis are shown in Figure 6.6, as the lower levels of a large dendrogram can become crowded (Brzinsky-Fay et al., 2006).
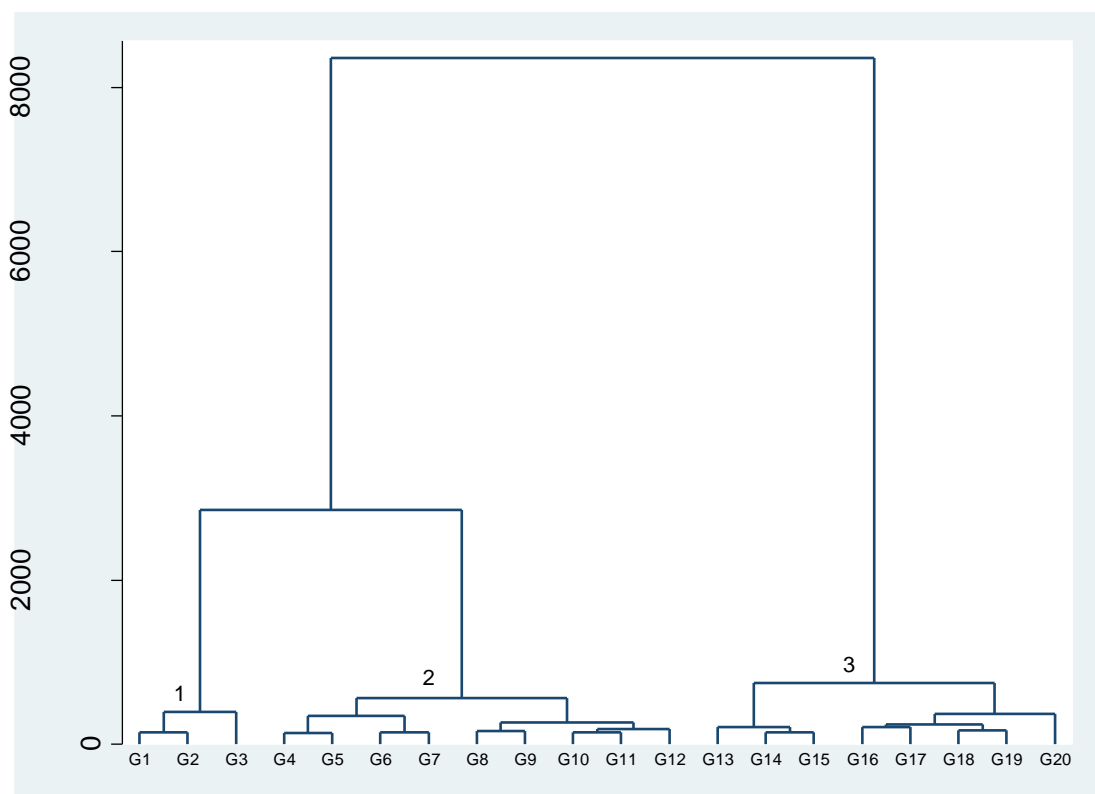
Figure 6.6   **Dendrogram for the hierarchical cluster analysis**

To determine the final cluster solution, an heuristic approach was used by visually inspecting the dendrogram to establish a meaningful number of clusters, which best represent the data (Cornwell, 2015; Eriksson, 2018; Köppe, 2017). Three clusters were chosen that had similar thresholds with respect to the dissimilarity measure; these can be seen in Figure 6.6, as numbers, 1, 2, and 3.

The participants were evenly matched across the clusters with 33% in cluster 1, 37% in cluster 2 and 30% in cluster 3 (Table 6.4). With respect to the three physical behaviours on which the original sequences were defined, there was a significant decrease in the mean length of sedentary behaviour bouts from cluster 1 (37.53 minutes), to cluster 2 (18.78), and to cluster 3 (11.91). Furthermore, a significant increase in the length of light physical activity bouts was also seen from cluster 1 to cluster 3 (7.88, 11.32, 20.54 minutes). No significant differences were seen in the mean length of moderate to vigorous physical activity bouts between the clusters (p=0.075) (Table 6.4).

Table 6.4   **Mean bout lengths for each physical behaviour, within each cluster**

	Cluster 1 (n=193, 33%)	Cluster 2 (n=218, 37%)	Cluster 3 (n=177, 30%)	p-value
Sedentary behaviour bouts (mins)	37.53	18.78	11.91	**<0.001**
Light physical activity bouts (mins)	7.88	11.32	20.54	**<0.001**
Moderate to vigorous physical activity bouts (mins)	8.28	8.66	7.97	0.075

Mean length of bouts in minutes; Significant differences ($p<0.05$) are shown in bold: ANOVA was used to examine differences between clusters

The differences between the clusters with respect to the percentage of people engaged in each physical behaviour at each time interval can be clearly seen in the state distribution graph for each cluster Figure 6.7.
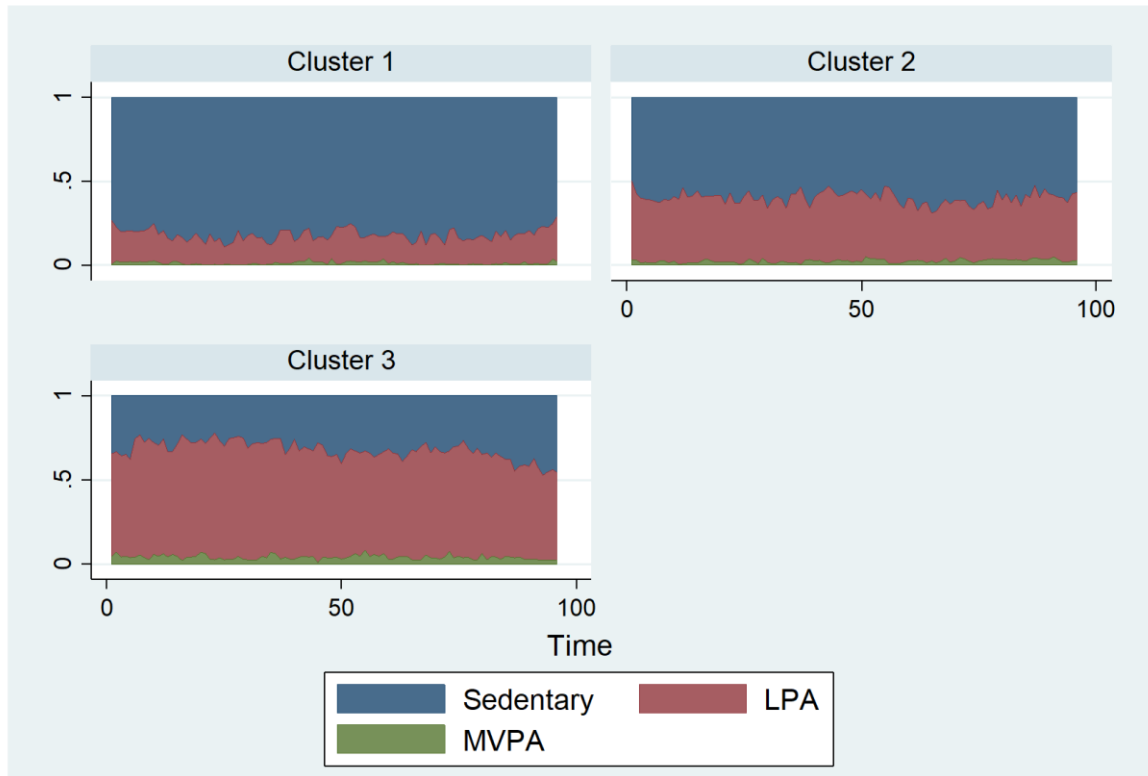
Figure 6.7 **State distribution graph for the three identified clusters**

Table 6.5 shows the characteristics of the three clusters with respect to age, gender, occupational classification, and cardiometabolic risk factors. The profiles of the three clusters have been compared using ANOVA to examine differences between normally distributed continuous variables; Kruskal-Wallis tests for non-normally distributed continuous variables; and, chi-square tests were used to assess for associations between categorical variables (Table 6.5).

Table 6.5   Characteristics and cardiometabolic profiles for the three clusters

	Cluster 1 (n=193, 33%)		Cluster 2 (n=218, 37%)		Cluster 3 (n=177, 30%)		p-value
	Mean	**SD**	**Mean**	**SD**	**Mean**	**SD**	
Age	**42.03**	**12.1**	**45.50**	**12.2**	**45.70**	**12.8**	**0.004**
Males (n, %)	**110**	**57%**	**131**	**60%**	**128**	**72%**	**0.006**
Occupational classification (n, %)							
Managerial and professional	**142**	**74%**	**109**	**50%**	**38**	**22%**	**<0.001**
Intermediate	**33**	**17%**	**48**	**22%**	**45**	**25%**	
Routine and manual	**18**	**9%**	**61**	**28%**	**94**	**53%**	
Systolic blood pressure (mmHG)	**124.13**	**13.6**	**128.85**	**16.3**	**128.00**	**16.0**	**0.020**
Diastolic blood pressure (mmHG)	74.15	10.4	76.60	11.2	74.40	10.2	0.074
Total cholesterol (mmol/L)	**5.28**	**1.1**	**5.60**	**1.0**	**5.50**	**1.1**	**0.049**
HDL cholesterol (mmol/L)	1.43	0.3	1.50	0.4	1.46	0.4	0.364
HbA1c (%)	5.51	0.7	5.52	0.6	5.60	0.6	0.479
Waist circumference (cm) (median, IQR)	93.38	(82.55-102)	93.30	(82.3-100.55)	95.40	(86.95-103.53)	0.109
BMI (kg/m^2) (median, IQR)	26.18	(23.91-29.65)	26.76	(23.96-30.07)	26.81	(24.29-29.49)	0.731

Values are the mean (SD) unless stated; Significant differences (p<0.05) are shown in bold: ANOVA was used to examine differences between clusters, for age, systolic blood pressure, diastolic blood pressure, total cholesterol, HDL cholesterol, and HbA1c; Kruskal-Wallis tests were used to examine differences between clusters, for waist circumference and BMI; and, chi-square tests were used to assess for associations between clusters, for gender and occupational classification; BMI=body mass index; HDL=High-density lipoprotein; HbA1c=Haemoglobin A1c (glycated haemoglobin); IQR=Interquartile range

Participants in cluster 1 were significantly younger (42.03), compared to cluster 2 (45.50) and cluster 3 (45.70) (p=0.004): participants in cluster 3 more likely to be male (72%) compared to cluster 1 and cluster 2, which had similar gender profiles (57% and 60% males respectively) (p=0.006). The main differences between the three clusters were the distribution in occupational classifications. Cluster 1 contained 74% participants in managerial and professional occupations, compared to 50% and 22% in clusters 2 and 3;

cluster 3 was more likely to contain participants in routine and manual occupations (53%) compared to clusters 1 and 2 (9% and 28% respectively) (p<0.001).

With respect to the cardiometabolic profiles of each cluster, significant differences were only seen for systolic blood pressure and total cholesterol. Cluster 1 was seen to have significantly lower values of systolic blood pressure (124.13 mmHG; p=0.020) and total cholesterol (5.28 mmol/L: p=0.049) when compared to both cluster 2 (128.85 mmHG and 5.60 mmol/L) and cluster 3 (128.00 mmHG and 5.5 mmol/L) respectively, suggesting that demographic data and occupational classification may play an important role in the associations with sedentary behaviour and health-related outcomes.

6.4 Summary of key findings

- The use of sequence analysis is a novel approach to examine the patterning of physical behaviours during working hours.
- Those with raised values of cardiometabolic risk factors accumulated their sedentary time, on average in shorter bout lengths, compared to those with 'normal' values. The way in which we accumulate these different behaviours across the day may have differing impacts on our health outcomes.
- Sequence analysis methods can be used to identify common sequence typologies with respect to physical behaviours and cardiometabolic profiles
- The three identified clusters differed significantly with respect to the average length of sedentary behaviour and light physical activity bouts.
- The underlying mechanisms of sedentary time in the occupational domain appear to be complex with respect to cardiometabolic risk factors.
- Occupational classification may play an important role in the associations with sedentary behaviour and health-related outcomes.

Chapter 7 - Discussion and conclusions

"I have always loved to begin with the facts, to observe them, to walk in the light of experiment and demonstrate as much as possible, and to discuss the results."

— Giovanni Arduino

Table 7.1   Overview of Chapter 7

Chapter	Aims, objectives and research questions	Methods
Chapter 2	**Aim:** To provide an overview of the literature and to critique the current evidence of sedentary behaviour and work, focussing on the prevalence of sedentary behaviour at work, and its association with health-related outcomes	Structured literature review using six electronic databases
Chapter 3	**Aim:** To empirically derive a new accelerometer cut-point to define sedentary behaviour in adults **Objective 1:** To empirically derive an optimal threshold for classifying sedentary behaviour, using the counts per minute output from the ActiGraph GT3X+ accelerometer, when compared to the sedentary classification from the activPAL™ accelerometer in a free-living environment **Objective 2:** To ascertain whether thresholds for sedentary behaviour cut-points vary by day of the week and in working time versus non-working time **Objective 3:** To derive optimal cut-points for different classifications of sedentary behaviour using contextual data from a 24-hour activity log, and to examine if there are differences between them	Observational study in university workers and postgraduate students (n=30) Application of generalised estimating equations to 1-minute epoch data for the ActiGraph GT3X+ and the activPAL™ data
Chapter 4	**Aim:** To describe the methodology for the Health Survey for England 2008, and a critique of the strengths and limitations of using secondary analysis	Description of data collection and processing
Chapter 5	**Aim:** To apply the cut-point from *Study One* to data from the Health Survey for England (2008), in order to investigate the associations between sedentary behaviour, work, and health-related outcomes **Objective 4:** To identify associations between workplace sedentary behaviour and health-related outcomes using the derived cut-point from *Study One* **Objective 5:** To examine if associations between workplace sedentary behaviour and health-related outcomes differ between occupational groups **Objective 6:** To determine if there are associations between workplace sedentary behaviour and mental ill-health and musculoskeletal disorders	A secondary data analysis of the Health Survey for England 2008 Application of hierarchical regression models – type of regression model dependent on distribution of each dependent variable (health-related outcome)
Chapter 6	**Aim:** To apply the cut-point from *Study One* to data from the Health Survey for England (2008), in order to investigate the associations between sedentary behaviour, work, and health-related outcomes **Objective 7:** To explore the patterning and sequences of sedentary bouts across the day, and the relationship with measures of adiposity and other health-related outcomes	Sequence analysis to describe the characteristics of time-related sequences of sedentary behaviour
Chapter 7	**Aim:** To discuss and critically appraise the studies within this thesis and to outline implications for policy and future research	Discussion and conclusions

7.1 Principal findings

7.1.1 *Empirically derived accelerometer cut-points to define sedentary behaviour in adults*

7.1.1.1 *Main findings for objectives 1 and 2*

1. *To empirically derive an optimal threshold for classifying sedentary behaviour, using the counts per minute output from the ActiGraph GT3X+ accelerometer, when compared to the sedentary classification from the activPAL™ accelerometer in a free-living environment.*

2. *To ascertain whether thresholds for sedentary behaviour cut-points vary by day of the week and in working time versus non-working time.*

Most existing studies that have used an ActiGraph accelerometer to describe time spent in sedentary behaviours have used an arbitrary threshold of 100 counts per minute to define sedentary behaviour; however, this cut-point was not empirically derived in adults. This study found an empirically derived cut-point across all days of the week of 65 counts per minute; the cut-points for individual days of the week were significantly different, ranging from 41-60 counts per minute, with the exception of Saturday, which was substantially higher at 97 counts per minute. In addition, the derived sedentary behaviour threshold for week days was lower than that derived cut-point for weekend days (60 counts per minute vs. 74 counts per minute). Notably, cut-points for working hours were significantly lower compared to non-working times (35 counts per minute vs. 73 counts per minute respectively) (Figure 7.1).

Validation studies of the 100 counts per minute cut-point for ActiGraph accelerometers have found conflicting findings in working age adults. Kozey-Keadle et al. (2011) found that

the ActiGraph GT3X underestimated sedentary time by 4.9% using the 100 counts per minute threshold, compared to direct observation, in a small cohort of overweight university workers (n=20; mean BMI 33.7±5.7 kg/m^2). The same study suggested that 150 counts per minute may be the most appropriate cut-point to define sedentary behaviour from the ActiGraph GT3X. Conversely, Crouter et al. (2013) found that the 100 counts per minute threshold from the ActiGraph GT1M, overestimated sedentary time in working-age adults by 9.9%, compared to indirect calorimetry in a free-living environment, over six hours (n=29; mean BMI 25.0 ±4.6 kg/m^2). This is similar to the study carried out to address the first aim of this thesis, which found the 100 counts per minute cut-point overestimated sedentary time by 12.9% compared to the sedentary classification of the activPAL3™ accelerometer. The lower empirically derived cut-point of 65 counts per minute (for the week) also overestimated sedentary time, but with a lower mean bias of 5.35%.
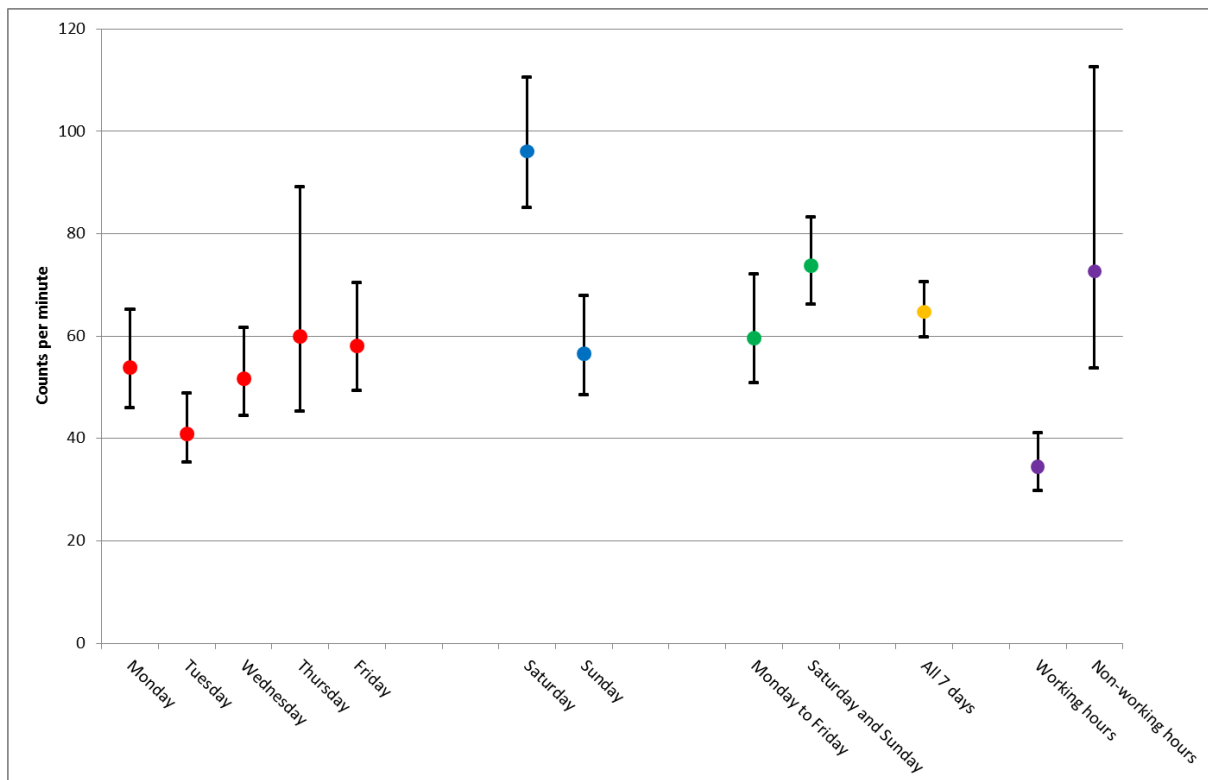

Figure 7.1   **ActiGraph GT3X+ accelerometer-derived cut-points (95% CI) for sedentary behaviour from GEE regression models**

The overestimation in sedentary time by the ActiGraph may be explained by misclassification of some non-ambulatory standing activities that can produce low counts per minute (Crouter et al., 2006; Matthews et al., 2008). A study by Hart et al. (2011) examined the convergent validity of the activPAL™, the ActiGraph GT1M and an activity record (the Bouchard Activity Record), in healthy adults (n=32; mean BMI 23.0kg/m^2). They found moderate agreement between sedentary time for the ActiGraph GT1M compared to the activPAL™ (κ=0.47); sedentary time was also found to be 25% higher using a 100 counts per minute threshold from the ActiGraph GT1M compared to the sedentary classification of the activPAL3™.

Differences in the methodologies between these validation studies included:

1. Different criterion measures (direct observation (Kozey-Keadle et al., 2011); indirect calorimetry (Crouter et al., 2013); sedentary classification of activPAL, this study and Hart et al. (2011)).

2. Time of studies (direct observation and indirect calorimetry was six hours (Kozey-Keadle et al., 2011; Crouter et al., 2013); waking hours over one day (Hart et al., 2011); seven days, this study).

3. Choice of ActiGraph model, and use (or no use) of the low-frequency extension during data processing, which impacts on comparability between studies (Cain et al., 2013). Cain et al. (2013) found that data from different generations of ActiGraph devices are comparable for moderate to vigorous physical activity, but not at the lower end of the movement continuum; this is thought to be due to the more recent models (GT3X and later) requiring larger accelerations to record non-zero counts. Applying the low-frequency extension enables greater comparability with studies that have used older

model ActiGraph devices when comparing sedentary time. Studies by Kozey-Keadle et al. (2011) and Aguilar-Farías et al. (2013) used the low-frequency extension during data processing; studies by Crouter et al. (2013) and Hart et al. (2011) used the ActiGraph GT1M device and were carried out before the low-frequency recommendation by Cain et al. (2013).

4. Finally, the three studies that were carried out in healthy adults of normal weight all found an overestimate of sedentary time compared to the 100 counts per minute threshold: the exception was the study by Kozey-Keadle et al. (2011), which was in 20 overweight university workers where the 100 counts per minute underestimated sedentary time. It is not clear why overweight individuals might have different cut-points. There has been some conflicting reports of the effect of waist adiposity on the tilt angle of the monitor, and consequently on the output of some activity devices (Swartz et al., 2009). However, the accuracy of the output from ActiGraph devices has been shown not to be affected by the differences in tilt angle that occur in individuals with different BMI (Feito et al., 2011). Lower thresholds of <22 and <25 counts per minute have been suggested as more appropriate to define sedentary behaviour in older adults (Aguilar-Farías et al., 2013; Koster et al., 2016).

There seems to be no consensus for accelerometer cut-points for sedentary behaviour, and those proposed vary widely. Combined, these findings suggest that maybe there should be different cut points for different populations.

7.1.1.2   Main findings for objective 3

3. *To derive optimal cut-points for different classifications of sedentary behaviour using contextual data from a 24-hour activity log, and to examine if there are differences between them.*

Cut-points based on energy expenditure from calibration studies can vary in estimates of time spent in different activity categories (Crouter et al., 2006; Crouter et al., 2013). The definition of sedentary behaviour from the Sedentary Behavior Research Network (2012 and 2017) classifies both posture and energy expenditure; however, there is currently no instrument that can measure free-living sedentary behaviour accurately using this definition (Granat, 2012). While the 100 counts per minute threshold from the ActiGraph provides a useful measure of sedentary behaviour, it generally overestimates time spent in these behaviours (Crouter et al., 2013; Hart et al., 2011).

In this study, the prevalence of sedentary time recorded by both the activPAL3™ and the ActiGraph GT3X+ (using the 100 counts per minute cut-point) were similar (65.1% vs. 64.4%); however, based on the physical behaviour classification from the activPAL3™ (sitting/lying, standing, stepping), the ActiGraph GT3X+ 100 counts per minute cut-point misclassified 16.9% of minutes as either standing or stepping, and the cut-point for light physical activity contained nearly 40% of sitting or lying. The use of a new sedentary behaviour cut-point in a specific setting, for example the 35 counts per minute cut-point derived in this study for office workers, would reduce misclassification of non-sedentary activities such as filing, which have previously been found to have an average counts per minute of 60 (Crouter et al., 2006).

The use of the contextual information from the Bouchard activity record within the participants' diary enabled further cut-points to be derived for different classifications of sedentary behaviour. Similar to the cut-points derived for days of the week, the majority of cut-points for the different sitting contexts were less than 100 counts per minutes. The exception was the cut-point derived for whilst driving a car, which was 187 counts per minute, which may due to the ActiGraph GT3X+ accelerometer registering accelerations due to the movement of the car (Lyden et al., 2019). Furthermore, the agreement in total sedentary time from the two accelerometers may be explained by the misclassification in the different physical behaviour classifications. For example, standing is misclassified by the ActiGraph, therefore increasing sedentary time, and car-travel (with a cut-point of 187 counts per minute) would be misclassified as light physical activity, therefore reducing sedentary time.

7.1.1.3   Strengths and limitations

This is the first time that a threshold for counts per minute for sedentary behaviour has been empirically derived from an observational study in a free-living environment, using the activPAL3™ sedentary behaviour classification as the criterion measure. The activPAL™ has been shown to provide a valid and precise measure of sedentary time (Grant et al., 2006; Kozey-Keadle et al., 2011). However, there are some limitations to this study. Although the accelerometer manufacturers employ proprietary algorithms to reduce the raw acceleration data to counts per minute or to classify posture, there are still a large amount of data cleaning and data reduction decisions to be made, which can have an impact on estimates of physical behaviour variables; choice of non-wear algorithm can also influence the eligible sample size and estimates of wear time (Keadle, Shiroma, Freedson,

& Lee, 2014). It is important that studies detail these processes with respect to future harmonisation of accelerometery data (Wijndaele et al., 2015).

The definition of sedentary behaviour used in this study, defined as any waking behaviour in a sitting or reclining position, with energy expenditure ≤1.5 METs (Sedentary Behaviour Research Network, 2012), does not include *active* sitting (sitting characterised by an energy expenditure >1.5 METs) (Tremblay et al., 2017). Furthermore, the sedentary behaviour classification from the activPAL3™ used as the criterion measure to empirically derive the sedentary threshold from the ActiGraph GT3X+ does not exclude *active* sitting: due to its placement on the thigh, the activPAL3™ may not capture energy expenditure related with movement of the upper body, such as weight-lifting, rowing, and the use of strength training equipment (Colley et al., 2011). Although participants in this study recorded any periods of non-step-based activities, such as cycling and swimming, which were removed as part of the data reduction process, it is not known how many minutes of *active* sitting were included. However, activities such as weight-lifting and rowing, which can be defined as *active* sitting, are reported by fewer than 0.5% of those who participate in sport at least once a week; therefore, the number of minutes of *active* sitting within this cohort is expected to be negligible (Sport England, 2017).

A further limitation of matching data from two different accelerometers, is the possibility of clock drift in the matched output, and whether potential adjustments need to be considered (Barreira, Zderic, Schuna, Hamilton, & Tudor-Locke, 2015; Edwardson, Winkler, et al., 2016). There is limited literature that has compared clock drift between accelerometer-based devices and other types of sensors (i.e. global positioning systems); however, clock drift has been reported to be minimal over a 7-day data collection period

and unlikely to lead to significant changes when matching data over longer epochs (i.e. >15-seconds) (Howie, McVeigh, & Straker, 2016; Steel, Bejarano, & Carlson, 2019). Nevertheless, modern accelerometers do not require the complex calibration techniques compared to previous generations, and are more precise with respect to clock drift over time (Lowe & ÓLaighin, 2014; Mathie, Coster, Lovell, & Celler, 2004).

Since the aim of this study was to derive accelerometer cut-points, it was the quality of the data that was deemed to be important and not the quantity of minutes included. Therefore, aggressive data reduction rules were applied that used a combination of times from an activity diary and a non-wear algorithm. A strength of this study is the large amount of data (11 hours 27 minutes: 82% of waking time), despite the data reduction.

The accelerometer cut-points derived in this study were in university workers, who spent most of their day sitting in front of a computer. The cut-point for sedentary behaviour across the whole week (65 counts per minute) may be limited to working adults, and the lower cut-point of 35 counts per minute may only be generalisable to other office-based workers. Barnett and Cerin (2006) found considerable individual variability in calibration regression lines for accelerometer counts versus walking speed, and wide between-subject differences in mean bias are often reported for sedentary behaviour cut-points as evidenced in this study and also in Crouter et al. (2013).

7.1.2 *Study to investigate the associations between sedentary behaviour, work, and health-related outcomes*

7.1.2.1 *Main findings for objective 4*

4. *To identify associations between workplace sedentary behaviour and health-related outcomes using the derived cut-point from Study One*

There is a wealth of literature that has found associations between sedentary behaviour and health-related outcomes, independent from levels of physical activity (de Rezende et al., 2014). Many of these studies have measured total sitting time across the day, or leisure-time sedentary behaviour (most commonly television viewing): few studies have assessed if there are the same associations with health for occupational sedentary time, despite that occupational sedentary time makes up the majority of total daily sedentary time for those who are economically active (Clemes et al., 2015). It has been suggested that sedentary time in the leisure and work domains may represent differing associations with health-related outcomes: for example, both Pinto Pereira et al. (2012) and Saidj et al. (2013) found associations between leisure-time sedentary behaviour and cardiometabolic markers, but not for occupational sitting time and cardiometabolic markers.

This study used a secondary data analysis of a large national survey, in which a sub-sample wore an accelerometer for a week to objectively measure sedentary behaviour: this is one of the first studies to objectively examine the associations between occupational sedentary behaviour for a range of health-related outcomes. The derived cut-points from Chapter Three were used alongside the previously proposed cut-points of 50, 100, and 150 counts per minute to calculate different sedentary time variables. There were 893 full-time workers with accelerometer data who were included in the final sample.

The main findings with respect to objective four were:

– Higher objectively measured sitting times were seen on weekdays compared to weekend days, and this was significant in the full-time workers sample; this finding is supported by other studies that have examined the prevalence of occupational sitting time in office workers (Clemes et al., 2015; Hadgraft et al., 2015; Kirk et al., 2016; Parry & Straker, 2013).

– There were differences in reported sedentary times depending on which cut-point was applied to the accelerometer data; reported sedentary times were approximately 90 minutes a day higher in the variables that used the 150 counts per minute cut-point compared to the 50 counts per minute cut-point. However, the use of different cut-points did not affect the beta coefficients, or the conclusions drawn from the regression models.

– Occupational sitting time was only associated with waist circumference and BMI; however, occupational sitting time was no longer significant when the model was adjusted for physical activity. Moderate to vigorous physical activity was a significant predictor of both waist circumference and BMI, and from the quantile regression analysis, this effect varied along the quantiles of both adiposity variables.

– Occupational sitting time was not associated with cardiometabolic markers; these results from an objective measure of occupational sitting time are similar to those from studies by Pinto Pereira et al. (2012) and Saidj et al. (2013), which used subjective measures of occupational sitting time. A study that used both subjective and objective measures of sedentary time found significant associations with cardiometabolic markers using the subjective measure, and found associations for only total cholesterol

when sedentary time was measured objectively; however, this study did not look at occupational sitting behaviour separately, but limited their sample to working age adults (Stamatakis, Hamer, et al., 2012).

– Furthermore, BMI was a significant predictor for total cholesterol, HDL cholesterol, and HbA1c.

– Other studies that have examined occupational sitting time (using self-reported measures) have also found that BMI confounds any associations between sedentary time and health (Pinto Pereira et al., 2012; Stamatakis & Hamer, 2012), with the study by Stamatakis and Hamer (2012) suggesting that the role of adiposity may be that of a mediator variable between sedentary behaviour and cardiometabolic markers using the self-reported sedentary behaviour data from the Health Survey for England 2008.

7.1.2.2   Main findings for objective 5

5. *To examine if associations between workplace sedentary behaviour and health-related outcomes differ between occupational groups*

Significant positive associations were seen between sedentary time and BMI for the intermediate, and routine and manual occupation classifications; however, these associations were only significant in the models for the week and weekdays, and not for the occupational sedentary time model. For the managerial and professional occupations, there was a significant association between sedentary time on weekdays and total cholesterol. There were no significant associations between occupational sedentary behaviour and health-related outcomes in this sub-sample; even though the sample of full-time workers was large (n=893), data on job titles were not available, and therefore the

data could not be interrogated further to identify different roles, such as desk-based workers.

Bakrania et al. (2016) used the same dataset to compare mutually exclusive groups, and found more favourable cardiometabolic health profiles for those in the low sedentary/high physical activity group compared to the high sedentary/low physical activity; however, this analysis was carried out in all adults with accelerometer data in the sub-sample, who were more likely to be older, retired and have a longstanding illness, compared to participants from the whole sample (Roth et al., 2013). In addition, the dichotomous variable for sedentary time was based on a sedentary behaviour to light-intensity physical activity ratio, not on the median minutes of sedentary time per day as in this study. Furthermore, the restriction of the dataset to full-time workers may have resulted in a sample that were subject to the 'Healthy Worker Effect', whereby those in employment have better health profiles compared to the general population (Bowling, 2009).

Although the interaction between occupational sitting time and physical activity was not considered in this analysis, the levels of physical activity per day were high (>30 minutes), especially in those with managerial and professional occupations: recent studies have found that physical activity may have some protection against long periods of sitting with respect to health-related outcomes (Ekelund et al., 2016; Stamatakis et al., 2019), and therefore the reciprocity between occupational sitting time and physical activity may play an important role in associations with health, specifically with respect to the associations in the BMI models.

7.1.2.3 Main findings for objective 6

6. *To determine if there are associations between workplace sedentary behaviour and mental ill-health and musculoskeletal disorders*

No associations were seen between sedentary times for musculoskeletal conditions, a measure of quality of life, the EQ-5D, or a measure of psychological distress, the GHQ-12; with significant associations only seen between sedentary time and having a mental disorder. A previous study using the same accelerometer data (but for all adults) found a significant association between GHQ-12 and the highest tertile of sedentary behaviour (Hamer et al., 2014). The results for mental ill-health and musculoskeletal disorders, may also be explained by the 'Healthy Worker Effect'; people with chronic mental ill-health and musculoskeletal conditions may be less likely to have been in work the week before the Health Survey for England interview. There was no further specific information in the secondary dataset to determine what type of conditions these might have been; for example, low back pain and neck pain may have different associations between occupational classifications (Gupta et al., 2015; Hallman et al., 2015).

7.1.2.4 Strengths and limitations

The secondary dataset used for these analyses were from a well-designed national survey, and therefore, this allowed the regression models to be controlled for by a large number of covariates; however, there could also have been some residual confounding. The blood samples were non-fasting, which can affect associations with cardiometabolic markers (Bansal et al., 2007). Some of the variables, such as occupational classification and longstanding conditions, were too *general* to be able to explain any of the associations/lack of associations found. However, the Health Survey for England provided a large sample of

working adults with objectively measured physical behaviour data, which were able to address the objectives for the second aim of this thesis.

The accelerometer data were not available with the main dataset from the UK Data Service, and therefore these data had to be retrieved directly from NatCen in London. This involved time in getting processes in place for NatCen to agree to release the data; also, Stata programmes had to be written and implemented within the NatCen offices, which meant that the format of the processed accelerometer data was no longer compatible with the ActiLife software; consequently, this provided the opportunity to have the Stata programmes used to clean and derive the accelerometer variables to be validated by another research group.

In order to derive variables for occupational sedentary time, work hours were assumed to be between 9:00am and 5:00pm on weekdays; although this is not ideal, and does not take into account those who work shifts and weekends, other studies have used generic working patterns in health research (Hall, 2017; Maxhuni et al., 2016; Ryan et al., 2011).The Office for National Statistics does not collect data on start and finish times as part of its Labour Force Survey; this emphasises the importance of have a diary or log for participants to record this contextual information alongside an objective measure of physical behaviour (Healy et al., 2011).

The main limitation of using the Health Survey for England 2008 dataset is its cross-sectional design. Cross-sectional studies are not able to measure causality to determine the temporality between the dependent and independent variables (Rothman, 2002; Silman & Macfarlane, 2002). The use of the Health Survey for England as a secondary cross-sectional dataset, with a large range of variables that used standard measures, was time

and cost-effective in comparison to collecting primary data that may not have best addressed the research objectives (Hox & Boeije, 2005; Kiecolt & Nathan, 1985).

7.1.3 *Study to explore the patterning and sequences of sedentary bouts across the day*

7.1.3.1 *Main findings for objective 7*

7. *To explore the patterning and sequences of sedentary bouts across the day, and the relationship with measures of adiposity and other health-related outcomes*

The associations between occupational sitting behaviour and health-related outcomes appear to be complex, and therefore it is important for studies to be able to accurately measure occupational sitting time, to determine the independent effects of physical activity, and carry out studies that have robust designs (Chinapaw et al., 2015). Other studies have found beneficial effects to health by breaking up prolonged periods of sitting throughout the day, specifically for cardiometabolic markers (Dunstan, Kingwell, et al., 2012; Healy et al., 2008; Henson et al., 2016). Therefore, the pattern in which we accumulate sedentary behaviour and physical activity should also be considered when designing a study.

A sequence analysis was carried out on the Health Survey for England 2008 accelerometer data to describe the bouts and episodes for different cardiometabolic markers. A sequence analysis with optimal matching, and a hierarchical cluster analysis was also carried out to generate clusters of participants who have similar behaviour sequence structures.

The main findings were that those with raised values of cardiometabolic markers accumulated their sedentary time, on average in shorter bout lengths, compared to those

with 'normal' values. The sequence analysis identified three clusters, which differed significantly with respect to the average length of sedentary behaviour and light physical activity bouts; differences were also seen between the clusters for occupational classifications, systolic blood pressure and total cholesterol.

7.1.3.2   *Strengths and limitations*

The use of sequence analysis is a novel approach to examine the patterning and accumulation of sedentary behaviour during working hours, making use of more of the accelerometer data compared to traditional regression methods.

Although five minute intervals have been employed in time use studies that have carried out sequence analysis (Fisher et al., 2000), and can capture prolonged sitting bouts (Kim, Welk, et al., 2015), they may overestimate total sedentary time. Kim, Welk, et al. (2015) reported that 70% of sedentary bouts are less than five minutes, and therefore using this length of time interval in sequence analyses may lose some information on transitions to other behaviours within this period. There needs to be a balance between the length of the intervals so that the sequences don't become too heterogeneous (Cornwell, 2015).

7.2   Future research

Future research to examine the associations between occupational sitting behaviour and health-related outcomes should consider how to accurately measure occupational sitting time, how to 'manage' physical activity in the analyses, and how to do this using a robust research design.

The associations that are seen between total sedentary time and leisure-time sedentary behaviour, and health-related outcomes are not as consistent for occupational sitting time,

especially after adjusting for BMI. In fact, the second study in this thesis found that it was moderate to vigorous physical activity that was the main predictor for adiposity measures and not occupational sitting time; and BMI was a predictor variable for cardiometabolic markers. The combination of physical activity and sedentary time may also have an influence on our health, with recent studies showing that high levels of physical activity eliminate the risks of mortality using self-reported measures of physical behaviour (Ekelund et al., 2016; Stamatakis et al., 2019). In addition, a group of researchers have found that for blue-collar workers, occupational physical activity leads to an increased risk in long term sickness absence, while leisure-time physical activity is associated with a reduced risk of long terms sickness absence, including adjusting for BMI: they have coined this phenomenon of people meeting the physical activity guidelines at work, but at risk of health problems, the 'physical activity paradox' (Holtermann, Hansen, Burr, Søgaard, & Sjøgaard, 2012; Holtermann, Krause, van der Beek, & Straker, 2018). With the results from the studies in this thesis, and the work by Pinto Pereira et al. (2012) and Saidj et al. (2013), which found associations between leisure-time sedentary behaviour and cardiometabolic markers, but not for occupational sitting time and cardiometabolic markers, could there by a 'sedentary behaviour paradox'? With differential effects between leisure time and occupational sedentary behaviour, the sedentary time we accrue in the workplace may not be as relevant to our health markers compared to the physical behaviours in our leisure time. To be able to model this, it is important to study the reciprocity between sedentary behaviour and physical activity.

There is also the need to consider the multifaceted nature of obesity and its association with physical behaviours, sleep, diet, and health-related outcomes, and to identify

appropriate statistical techniques that can take into account these possible interactions; this is especially relevant for informing public health policy and guidance on sedentary behaviour. The obesity pandemic is seen as a 'wicked issue' in the public health field – the term 'wicked issue' implies that it has multiple causes and that there is no simple solution (Hunter, 2009): factors contributing to its cause include, an increase in the consumption of processed sugar and saturated fats, a change in sleeping patterns and declining energy expenditure from physical inactivity (Cappuccio et al., 2008; Drewnowski, 2007; Patel & Hu, 2008; Spiegel, Leproult, & Van Cauter, 1999; Timmermans et al., 2017).

Figure 7.2 shows a proposed pathway model between physical behaviours, BMI, and health-related outcomes, based on the studies in this thesis:

- Occupational sitting time was found to be associated with BMI.

- After adjusting for physical activity, occupational sitting time was no longer associated with BMI, and physical activity became a predictor for BMI.

- BMI was found to be an important predictor for a number of health-related outcomes in the study (mainly cardiometabolic markers); sedentary behaviour and physical activity were not significant predictors in these models.

- It is also known that there is an interaction between physical activity and sedentary behaviour and that the combination of these behaviours influence health-related outcomes.

- Other studies have also suggested that BMI is a mediator variable between sedentary behaviour and health-related outcomes.

- Therefore, if the interaction between sedentary behaviour and physical activity is important to health, and we know that BMI is a mediating variable between our

physical behaviours and health-related outcomes, the proposed pathway in Figure

7.2 may help to design studies that can model this.

– It is also important to note the influence that sleep, and diet has on both physical

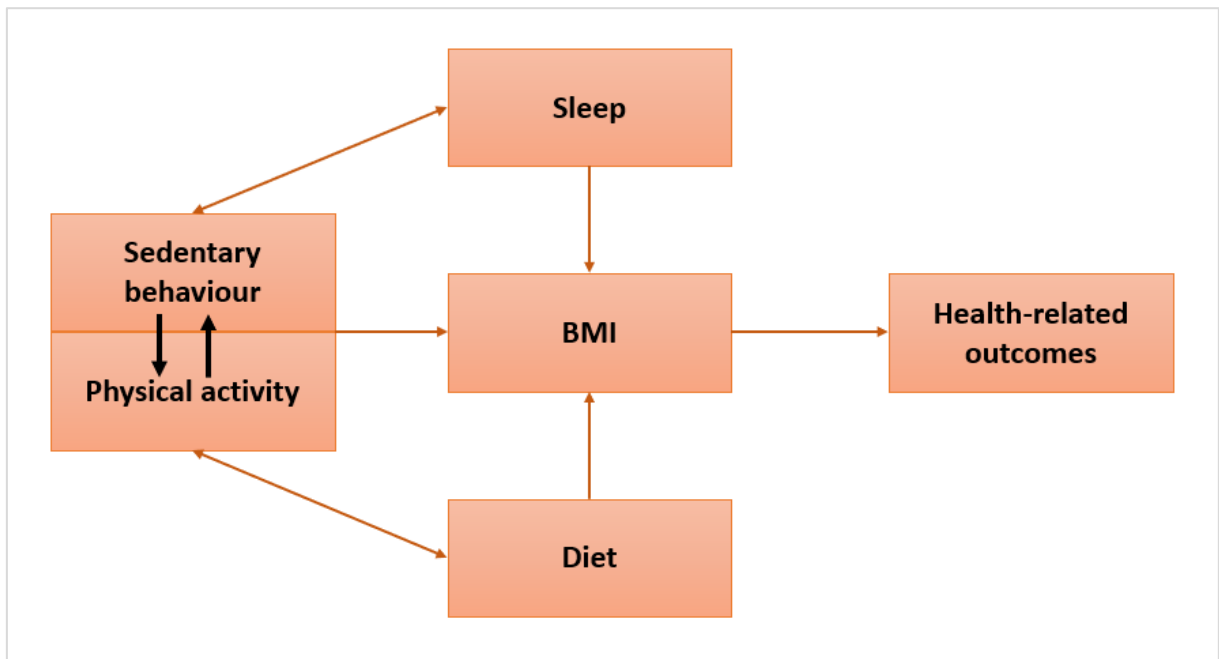behaviours and BMI; at present, few studies are able to measure and model all of

these factors.

Figure 7.2   Pathway between physical behaviours, BMI, and health-related outcomes

Alongside the complex pathway between physical behaviour, BMI, and health-related

outcomes, the pattern in which we accumulate our behaviours may also have an important

impact on health outcomes. How can we disentangle these behaviours with respect to

health-related outcomes? The use of sequence analyses is a step in the right direction, as

this type of analysis can take into account the pattern of accumulation of sedentary time

across the day. Other recent developments in analysis methods for physical behaviour

include, compositional data analysis, isotemporal substitution, and latent class analysis

(Chastin et al., 2015; Evenson, Herring, & Wen, 2017; Stamatakis et al., 2015). Although

each method is novel in its own right within physical behaviour research, each of these

techniques considers the combination of the different behaviours, but not the pattern of accumulation across the day. Sequence analysis techniques for the social sciences are constantly improving, with the recent addition of the sequence network framework: this method treats the sequence elements as nodes in a social network and examines the linkages between them (Cornwell, 2015). This may be one way to start to explore the pathway model in Figure 7.4 to help to examine the associations between people and everyday behaviours.

7.3   Conclusions

The overarching aim of this thesis was to derive an accelerometer cut-point for the ActiGraph GT3X+ accelerometer for sedentary behaviour: this was achieved through a convenience sample of university staff who wore an ActiGraph GT3X+ and an activPAL3™ accelerometer for seven days. Generalised estimating equations were used to statistically derive cut-points for the week, weekdays, weekend days, each day of the week, and work times and non-worktimes. A further analysis within this study also derived cut-points for different 'types' of sedentary behaviour, e.g. whilst in a car, and watching television. The derived cut-points in general, were significantly less than the 100 counts per minute cut-points that is commonly used in the literature.

These cut-points were then used in a secondary analysis of a large national survey to identify associations between workplace sedentary behaviour and health-related outcomes. Although different cut-points resulted in different amounts of estimated daily sedentary time, there were no significant differences in the effect sizes of the regression models to examine associations between occupational sitting time and health-related outcomes. Associations between occupational sitting behaviour were eliminated after

taking into account physical activity and BMI; no obvious differences were seen in models within different occupational categories.

A novel analysis method of sequence analysis was used to explore the patterning and sequences of sedentary bouts across the day, and the relationship with measures of adiposity and other health-related outcomes. The sequence analysis identified three clusters: the profiles of these clusters differed significantly for occupational classifications, systolic blood pressure and total cholesterol.

Future research should aim to develop these methods to take into account the complex interactions between physical behaviour, BMI, sleep, diet, and health-related outcomes.

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Appendix 1   **Literature review search strategy**

CINAHL (Cumulative Index to Nursing and Allied Health Literature)

29	S26 AND S27 AND S28
28	S20 OR S21 OR S22 OR S23 OR S24 OR S25
27	S9 OR S10 OR S11 OR S12 OR S13 OR S14 OR S15 OR S16 OR S17 OR S18 OR S19
26	S1 OR S2 OR S3 OR S4 OR S5 OR S6 OR S7 OR S8
25	MH obesity
24	MH mental health
23	MH heart
22	MH rheumatic diseases
21	MH musculoskeletal diseases
20	MH neoplasms or cancer
19	TI employment OR AB employment
18	(MH "Employment") OR (MH "Employment Status")
17	(MH "Occupations and Professions")
16	TI (work N2 (place* or site* location*)) OR AB (work N2 (place* or site* location*))
15	TI work-site OR AU work-site
14	TI worksite OR AB worksite
13	TI work-place OR AB work-place
12	TI workplace OR AB workplace
11	(MH "Work Environment")
10	TI work*
9	(MH "Work")
8	(MH "Life Style, Sedentary")
7	TI seated
6	TI sit
5	TI sat
4	TI sitting
3	TI physical* N2 inactive* OR AB physical* N2 inactiv*
2	TI sedentary N2 lifestyle* OR AB sedentary N2 lifestyle*
1	TI sedentary N2 behavi*r* OR AB sedentary N2 behavi*r*

The Cochrane Library

#1   (sedentary near/2 behvai*r*):ti

#2   (sedentary near/2 behavi*r*):ab

#3   (sedentary near/2 lifestyle*):ti

#4   (sedentary near/2 lifestyle*):ab

#5   (physical* near/2 inactiv*):ti

#6   (physical* near/2 inactiv*):ab

#7   sitting:ti

#8   sat:ti

#9   sit:ti

#10   seated:ti

#11   MeSH descriptor: [Sedentary Lifestyle] explode all trees

#12   MeSH descriptor: [Work] this term only

#13   work:ti

#14   MeSH descriptor: [Workplace] this term only

#15   workplace:ti

#16   workplace:ab

#17   work-place:ti

#18   work-place:ab

#19   worksite:ti

#20   worksite:ab

#21   work-site:ti

#22   work-site:ab

#23   (work near/2 (place* or site* or location)):ti

#24   (work near/2 (place* or site* or location)):ab

#25   MeSH descriptor: [Occupations] this term only

#26   occupation*:ti

#27   occupation*:ab

#28   MeSH descriptor: [Employment] this term only

#29   employment:ti

#30   employment:ab

#31   MeSH descriptor: [Neoplasms] this term only

#32   MeSH descriptor: [Musculoskeletal Diseases] this term only

#33   MeSH descriptor: [Cardiovascular Diseases] this term only

#34   MeSH descriptor: [Metabolic Syndrome X] this term only

#35   MeSH descriptor: [Occupational Diseases] this term only

#36   MeSH descriptor: [Diabetes Mellitus] this term only

#37   MeSH descriptor: [Mental Disorders] this term only

#38   MeSH descriptor: [Obesity] this term only

#39   #1 or #2 or #3 or #4 or #5 or #6 or #7 or #8 or #10 or #11

#40   #12 or #13 or #14 or #15 or #16 or #17 or #18 or #19 or #20 or #21 or #22 or #23 or #24 or #25 or #26 or #27 or #28 or #29 or #30

#41   #31 or #32 or #33 or #34 or #35 or #36 or #37 or #38

#42   #39 and #40 and #41

HMIC (Health Management Information Consortium)

1. (sedentary adj2 behavio*r*).ti,ab.
2. (sedentary adj2 lifestyle*).ti,ab.
3. (physical* adj2 inactiv*).ti,ab.
4. sitting.ti.
5. sat.ti.
6. sit.ti.
7. seated.ti.
8. exp *Sedentary Life/
9. *Work/
10. work*.ti.
11. *Workplace/
12. workplace.ti,ab.
13. work-place.ti,ab.
14. worksite.ti,ab.
15. work-site.ti,ab.
16. (work adj2 (place* or site* or location*)).ti,ab.
17. *Occupations/
18. occupation*.ti,ab.
19. *Employment/
20. employment.ti,ab.
21. exp *neoplasms by site/
22. exp *joint diseases/ or exp *muscular diseases/ or exp *rheumatic diseases/
23. exp *heart diseases/ or exp *vascular diseases/
24. exp *Metabolic Diseases/
25. exp *Occupational Diseases/
26. exp *diabetes mellitus/
27. exp *Mental Disorders/
28. exp *Obesity/
29. 1 or 2 or 3 or 4 or 5 or 6 or 7 or 8
30. 9 or 10 or 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20
31. 21 or 22 or 23 or 24 or 25 or 26 or 27 or 28
32. 29 and 30 and 31

MEDLINE (Medical Literature Analysis and Retrieval System Online)

1. (sedentary adj2 behavio*r*).ti,ab.
2. (sedentary adj2 lifestyle*).ti,ab.
3. (physical* adj2 inactiv*).ti,ab.
4. sitting.ti.
5. sat.ti.
6. sit.ti.
7. seated.ti.
8. exp *Sedentary Lifestyle/
9. *Work/
10. work*.ti.
11. *Workplace/
12. workplace.ti,ab.
13. work-place.ti,ab.
14. worksite.ti,ab.
15. work-site.ti,ab.
16. (work adj2 (place* or site* or location*)).ti,ab.
17. *Occupations/
18. occupation*.ti,ab.
19. *Employment/
20. employment.ti,ab.
21. exp *neoplasms by site/
22. exp *joint diseases/ or exp *muscular diseases/ or exp *rheumatic diseases/
23. exp *heart diseases/ or exp *vascular diseases/
24. exp *Metabolic Diseases/
25. exp *Occupational Diseases/
26. exp *diabetes mellitus/
27. exp *Mental Disorders/
28. exp *Obesity/
29. 1 or 2 or 3 or 4 or 5 or 6 or 7 or 8
30. 9 or 10 or 11 or 12 or 13 or 14 or 15 or 16 or 17 or 18 or 19 or 20
31. 21 or 22 or 23 or 24 or 25 or 26 or 27 or 28
32. 29 and 30 and 31

PsychINFO

1. (sedentary adj2 behavio*r*).ti,ab.
2. (sedentary adj2 lifestyle*).ti,ab.
3. (physical* adj2 inactiv*).ti,ab.
4. sitting.ti.
5. sat.ti.
6. sit.ti.
7. seated.ti.
8. work*.ti.
9. workplace.ti,ab.
10. work-place.ti,ab.
11. worksite.ti,ab.
12. work-site.ti,ab.
13. (work adj2 (place* or site* or location*)).ti,ab.
14. *Occupations/
15. occupation*.ti,ab.
16. *Employment/
17. employment.ti,ab.
18. exp *neoplasms/
19. exp *joint disorders/ or exp *muscular disorders/
20. exp *blood pressure disorders/ or exp *cerebrovascular disorders/ or exp *heart disorders/ or exp *hypertension/ or exp *ischemia/
21. exp *metabolic syndrome/
22. exp *diabetes mellitus/ or exp *type 2 diabetes/
23. exp *obesity/
24. exp *mental disorders/
25. or/1-7
26. or/8-17
27. or/18-24
28. 25 and 26 and 27

Web of Science

21   #20 AND #19 AND #18

20   #17 OR #16 OR #15 OR #14 OR #13 OR #12 OR #11

19   #10 OR #9 OR #8 OR #7 OR #6

18   #5 OR #4 OR #3 OR #2 OR #1

17   TI=(obes*)

16   TI=(mental or depression or anxiety)

15   TI=(diabetes)

14   TI=(metabolic)

13   TI=(heart or cardiovascular)

12   TI=(("joint pain") or musculoskeletal or rheumat*)

11   TI=(cancer)

10   TOPIC: (employment)

9   TOPIC: (occupation*)

8   TS=((work NEAR/2 (place* OR site* OR location*)))

7   TS=(workplace or work-place or worksite or work-site)

6   TI=(work*)

5   TS=("sedentary lifestyle" or "sedentary behavi*r")

4   TI=(sitting or sat or sit or seated)

3   TS=(physical* NEAR/2 inactiv*)

2   TS=(sedentary NEAR/2 lifestyle*)

1   TS=(sedentary NEAR/2 behavio*r*)

Appendix 2   Permission to use work published in *Physiological Measurement* within this thesis
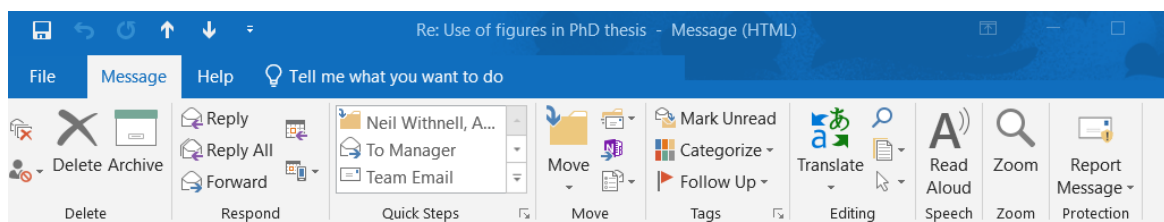
Wed 19/07/2017 11:01

Sarah Obertelli <Sarah.Obertelli@iop.org> on behalf of PMEA <pmea@iop.org>

Re: Use of figures in PhD thesis

To   Clarke-Cornwell Alexandra

You replied to this message on 19/07/2017 13:12.

Dear Miss Clarke-Cornwell,

Thank you for your message. Please can we inform you that when we take the assignment of copyright, we grant back to an author the right to include their work in any thesis or dissertation, so in this case there is no need for our permission.

Please do not hesitate to contact us if we can be of assistance to you.

Yours sincerely

Sarah Obertelli

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Appendix 3   Ethics approval from the University of Salford

Research, Innovation and Academic
Engagement Ethical Approval Panel

College of Health & Social Care
AD 101 Allerton Building
University of Salford
M6 6PU

T +44(0)161 295 2280
HSresearch@salford.ac.uk

www.salford.ac.uk/

17 April 2015

Dear Alexandra,

RE: ETHICS APPLICATION HSCR14-10 – Redefining sedentary behaviour study

Based on the information you provided, I am pleased to inform you that your request to amend application HSCR14-10 has been approved.

If there are any changes to the project and/ or its methodology, please inform the Panel as soon as possible by contacting HSresearch@salford.ac.uk

Yours sincerely,

Sue McAndrew
Chair of the Research Ethics Panel

Appendix 4   Activity diary

Activity diary

Office use: ActiGraph _____ activPAL™ _____ Date_____
Study to establish a new definition of sedentary behaviour from the ActiGraph GT3X+ accelerometer
Activity diary – Version 2 (08/04/14)

Activity diary instructions

Thank you for helping with our study. This activity diary will be used to record your sleeping hours, your working hours and any periods when either accelerometer is removed over the next 7 days.

For each day you will be asked to record:

- The time you wake up
- The time you start work/university
- The time you finish work/university
- The time you go to sleep
- Each time you remove one of the accelerometers and why e.g. showering, swimming, contact sport

For one day, whilst at work/university, you will also be asked to complete a more detailed activity log (see page 10). This is a self-reported activity log that consists of a table with each cell representing 15-minute intervals over a 24 hour period. For each 15-minute interval, you are asked to enter a number that corresponds to the *main* activity performed during those 15 minutes. Please familiarise yourself with the activity card (and corresponding values) on page 11 of this booklet to help with filling in this detailed activity log.

Problems or questions?

Please contact Alex Clarke-Cornwell on 0161-295-2805 or a.m.clarke-cornwell@salford.ac.uk

Appendix 5   Detailed activity log and corresponding coding values

Detailed activity log

To be completed for one working day only.

Date: _____

Please write in each cell of the table, the value that corresponds best to the **main** activity for each 15-minute interval. Please consult the activity card on page 11 to find the appropriate coding value.

Hour \ Mins.	0-15	16-30	34-45	46-60
Example	1	2a	2a	3
00:00				
01:00				
02:00				
03:00				
04:00				
05:00				
06:00				
07:00				
08:00				
09:00				
10:00				
11:00				
12:00				
13:00				
14:00				
15:00				
16:00				
17:00				
18:00				
19:00				
20:00				
21:00				
22:00				
23:00				

10

Activity card for detailed activity log, and corresponding coding values

Coding value	Examples of activities
1	Sleeping, resting in bed, lying down
	Sitting (where some part of body weight is supported by buttocks or thighs)
2a	Watching television; cinema etc.
2b	Sitting at work whilst using a computer
2c	Sitting at work, not using a computer (i.e. sitting at a desk, in a meeting)
2d	Sitting at home whilst using a computer, playing a video game etc.
2e	Relaxing but in a sitting position e.g. listening to music, reading
2f	Driving a car
2g	Sitting on public transport or in a car (not as the driver)
2h	Eating, social sitting (e.g. eating at home/work/restaurant, having coffee, chatting)
2i	Cycling
2j	Sitting other
3	Light activity: standing, washing, shaving, combing/brushing hair, cooking etc.
4	Slow walk (<2.5 mph; <4 km/h), to dress, to shower etc.
5	Light manual work: floor sweeping, window washing, painting, waiting on tables, nursing chores, several house chores, electrician, barman, walking at 2.5 to 4 mph; 4 to 6 km/h
6	Leisure activities and sports in a recreational environment: baseball, golf, volleyball, canoeing or rowing, archery, bowling, table tennis, etc.
7	Manual work at moderate pace: mining, carpentry, house building, lumbering and wood cutting, snow shovelling, loading and unloading goods, etc.
8	Leisure and sport activities of higher intensity (not competitive): canoeing (3 to 5 mph; 5 to 8 km/h), dancing, skiing, badminton, gymnastics, swimming, tennis, horse riding, walking (>4 mph; >6 km/h), etc.
9	Intense manual work, high intensity sport activities or sport competition: tree cutting, carrying heavy loads, jogging and running (> 5.5 mph; >9 km/h), racquetball, badminton, swimming, tennis, cross country skiing (>5 mph; >8 km/h), hiking and mountain climbing, etc.

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Appendix 6   Participant Information Sheet

Participant Information Sheet

Study Title: Redefining sedentary behaviour study
Study co-ordinator: Alexandra Clarke-Cornwell
Institute: University of Salford

You are being asked to take part in a research study. Before you decide whether you are willing to take part, it is important for you to understand why the research is being done and what it will involve. Please take the time to read the following information carefully, and take your time to decide whether or not to take part.

What is the purpose of the study?
The purpose of the study is to find the best way to measure sedentary behaviour in adults. Sedentary behaviour is sitting or lying down. The best way to do this might be to use a device called an accelerometer. However, we do not currently know exactly how the output from the device (which, for example, may measure the position of your leg 100 times a second) actually relates to your sitting behaviour. When I have worked out how the data from the devices relate to actual sitting behaviour, I will be able to analyse a large dataset that has already been collected on thousands of people, which also used accelerometers. I will then be able to look in detail at the association between sedentary behaviour and health-related issues such as diabetes and heart disease.

What is an accelerometer?
An accelerometer is a small device that records information about activity and posture. They record body movements during normal daily activities, such as sitting, lying, walking and jogging. Many people use similar devices to measure their activity when they are doing physical exercise or training. The accelerometers record no other information that is harmful in any way.

Why have I been chosen to participate?
You have been invited to participate in this study because you work (or are a postgraduate student) at the University of Salford and will spend part of your day sitting (at a desk). In order to derive a new understanding of how to measure sedentary behaviour using accelerometer data, it is important to study people who sit down for a proportion of their day.

Do I have to take part?
Participation in this study is entirely voluntary; you are not obliged to participate and if you do participate you can withdraw at any time.

What will happen to me if I take part?
Participants will be asked to wear two types of accelerometer simultaneously for seven days whilst carrying out your daily activities as normal.

You will also be asked to fill out a simple daily log that will be used to record sleeping hours, the time you started and finished work, and details if the accelerometers were removed (e.g. showering, swimming, contact sports). For one day, participants will be asked to fill out a detailed activity log that will provide information on the main activity carried out for each

15-minute interval (an activity card with examples of activities and corresponding coding values will be provided).

Participants will be also be directly observed (via video) whilst at work for one day (the same day that you fill out the detailed activity log). A stationary video camera will be positioned in the workplace to observe when you sit, and compare and validate the results with the activPAL™ accelerometer. The video will not record any sound, and you will be shown how to turn the video on and off, in case there are parts of the day you do not want to be recorded, i.e. if you are working at your desk with another member of staff.

What will I have to do?
You will be asked to wear the ActiGraph GT3X+ accelerometer during all waking hours for seven days. You would be requested to put the accelerometer on when you get up in the morning and take it off before you go to bed. The ActiGraph GT3X+ accelerometer is to be worn on the waist using an elastic belt, which will be provided. The belt is to be worn snugly on the waist so that the device rests on the right side of your body above your right hip. It can be worn below or above clothing. The study co-ordinator will also demonstrate how the device is to be worn.

You will be asked to wear the activPAL™ accelerometer for 24 hours a day unless bathing or swimming. The accelerometer is attached using a special hypo-allergenic adhesive pad to the front of the right thigh. You would be asked to remember to take it off when you shower, have a bath or go swimming, and you would be issued with a supply of fresh adhesive pads so that you can re-attach the activPAL™. The study co-ordinator will demonstrate how the device is to be worn.

You will be asked to complete an activity diary for seven days that will record your sleeping hours, your work hours and details of when either accelerometer is removed and why. For one day, you will be asked to complete a more detailed activity diary. The study co-ordinator will go through the activity diary and show you an example of how it should be filled out.

What are the possible risks and disadvantages from being in this study?
There are no risks involved with taking part in this study. No personally identifiable information will be held by the research team. If you consent to pictures or videos from the direct observation being using for presentation purposes, your identification will be anonymised (e.g. head shots will be pixelated).

The activPAL™ accelerometer is fixed directly to the skin using a hypoallergenic adhesive pad. This should not cause any discomfort or irritation, but if it does you can either place the device on the opposite leg or remove the device and return it to the study co-ordinator. The chances of any skin irritation are negligible; however, if irritation does occur, participants are advised to seek medical advice from a pharmacist or GP, and also inform the study co-ordinator.

What are the possible benefits from being in this study?
You may not benefit from taking part in this study. We cannot promise the study will help you but the information we get from this study will help to increase the understanding of sedentary behaviour, and the risk of associated health-related outcomes.

What if there is a problem?
If you have a concern about any aspect of this study you should contact the study co-ordinator or Professor Lindsey Dugdill (PhD supervisor), whose details are provided at the end of this document

Will my taking part in the study be kept confidential?
Yes. All the information provided by you in this study will remain confidential. The information that you provide from the accelerometers and the activity diary will be stored anonymously on a computer. None of the information held by the researcher will identify you by name. The procedures for handling, processing, storage and destruction of your data are compliant with the Data Protection Act 1998.

What will happen if I decide to withdraw from the study?
Participants may withdraw at any time without any effects to employment status or health. If you decide to withdraw from this study all the information and data collected from you, to date, will be destroyed and your name removed from all the study files.

What will happen to the results of the research study?
The results from the study may be published in a peer reviewed journal or elsewhere without giving your name or disclosing your identity. The results from this study, and picture stills from the video observation (these will be pixelated so that no individual can be identified), may be used for teaching purposes or at conferences.

Who is organising or sponsoring the research?
This research study is being organised by the School of Health Sciences at the University of Salford and forms part of a PhD research programme.

If I have questions or concerns about this study, who can I contact?
You can contact the study co-ordinator or Professor Lindsey Dugdill (PhD supervisor) for questions specifically related to this study.

Alex Clarke-Cornwell
0161 295 2805
a.m.clarke-cornwell@salford.ac.uk
Room L731, Allerton Building
School of Health Sciences
The University of Salford
Salford
M6 6PU

Professor Lindsey Dugdill
0161 295 2365
l.dugdill@salford.ac.uk
Room L828, Allerton Building
School of Health Sciences
The University of Salford
Salford
M6 6PU

I

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Appendix 7   Consent form

Research Participant Consent Form

Title of Project: Redefining sedentary behaviour study

Ethics Ref No:

Name of Researcher: Alexandra Clarke-Cornwell

(Delete as appropriate)

- I confirm that I have read and understood the information sheet for the above study (Version -29/01/14) and what my contribution will be

| Yes | No |

- I have been given the opportunity to ask questions (face to face, via telephone and e-mail)

| Yes | No |

- I agree to wear an ActiGraph GT3X+ accelerometer for seven days

| Yes | No |

- I agree to wear an activPAL™ accelerometer for seven days

| Yes | No |

- I agree to completing an activity diary

| Yes | No |

- I agree to being video recorded for one day

| Yes | No |

- I agree to being contacted each morning by text/phone/e-mail (delete as appropriate) to be reminded to wear the accelerometers

| Yes | No |

- I agree to anonymised stills or video content to be used for presentation purposes

| Yes | No |

- I understand that my participation is voluntary and that I can withdraw from the research at any time **without giving any reason**

| Yes | No |

- I understand how the researcher will use my responses, who will see them and how the data will be stored

| Yes | No |

- **I agree to take part in the above study**

| Yes | No |

Name of participant   ....

Signature   ....

Date   ....

Name of researcher taking   ....
consent

Researcher's e-mail address   ....

How will you change the picture this year?

All this information gives a vital snapshot of the health of the nation, and helps plan more effective health services in the future. We rely on the goodwill and voluntary co-operation of people like you to make the study a success. Please help us help make a difference to the health of England. Thank you.

We need your help with the Health Survey for England.

An interviewer from NatCen will call at your address and will be able to explain more about the study. In the meantime, you can find out more at

healthsurveyforengland.org

Who is carrying out the study?

The Health and Social Care Information Centre has asked NatCen Social Research and the Department of Epidemiology and Public Health at University College London (UCL) to carry out the survey. The Health and Social Care Information Centre is a special health authority and is part of the NHS. It is responsible for collecting information about all aspects of health and health services, on behalf of the Department of Health.

Contact Emma Fenn, NatCen, 0800 526 397 NatCen, 35 Northampton Square, London EC1V 0AX Email: info@natcen.ac.uk

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13.07i_v0.1 Nov 2012, 12/sc/0317

NatCen Social Research that works for society

NHS The Information Centre

UCL

The Health Survey for England

A bite-sized introduction

NatCen Social Research

We interview around 10,000 people each year

as part of the **Health Survey for England**. It's an annual study that looks into the changing health and lifestyle habits of people living all over England.

We also asked how people felt about a range of lifestyle topics. Everything is done with voluntary co-operation and in confidence.

Key measurements include height, weight and blood pressure.

In recent years we found out that...

The average man is 5 foot 9 inches and weighs 13 stone 3 pounds.

The average woman is 5 foot 3 inches and weighs 11 stone.

3in5 men and women were **overweight**. This includes a quarter who were obese.

Boys and girls ate 3 portions of fruit and veg a day on average.

Adults aged 16-24 were least likely to eat the recommended daily intake of fruit and veg.

Around 3 in 10 adults had high blood pressure. This proportion increased with age, rising to more than 3 in 5 among people aged 65 and over.

Around **3/4** of men and women said their health was 'good' or 'very good'.

1 in 7 men and women had some form of cardiovascular disease.

In an average week **a third of young people** drink more than twice the recommended daily intake of alcohol on at least one day.

1/3

Just over **1 in 5** adults currently smokes.

The Health Survey for England 2013

Information for participants

This survey is being carried out for the Health and Social Care Information Centre, by NatCen Social Research, an independent research institute, and the Department of Epidemiology and Public Health at UCL (University College London).

This leaflet tells you more about the survey and why it is being carried out.

What is it about?

The Health and Social Care Information Centre would like information about the health of adults and children in England. This is so that new and better ways can be developed to help people maintain healthy lifestyles and provide the necessary services for people who need treatment at times of ill health.

The Health Survey for England is an annual survey designed to provide information about the health of people in England. Each year a fresh set of people is interviewed.

The 2013 survey has questions about your general health, and about factors that can affect your health, including behaviours such as smoking and drinking. The survey also collects, if you agree, some physical measurements such as height, weight, and waist and hip measurements. (We will give you more information about this later on. You can agree to take part in some sections of the survey and not others). Some personal details such as age, sex and employment are needed to interpret this information.

Why have we come to your household?

To visit every household in England would take too long and cost too much money. Instead we select a sample of addresses and ask the people at each address to take part in the 2013 Health Survey.

Is the survey confidential?

Yes. We take great care to protect the confidentiality of the information we are given, and take careful steps to ensure that the information is secure at all times. The survey results will not be presented in a form which can reveal your identity. This will only be known to certain members of the NatCen/ UCL research team. The information collected is used for research and statistical purposes only and is dealt with according to the 1998 Data Protection Act. We would only have to tell someone else what you say if, during the interview, you tell us about possible harm to yourself or others.

If you agree, however, your name, address and date of birth, but no other information, will be passed to the National Health Service Central Register, Cancer Registry and Hospital Episode Statistics register. This would help us if we wanted to follow up your health status in the future.

Is the survey compulsory?

No. In all our surveys we rely on voluntary co-operation. The success of the survey depends on the goodwill and co-operation of those asked to take part. The more people who do take part, the more useful the results will be. You are free to withdraw from the survey at any time. However, we will not be able to remove individual information after the survey results have been published.

How long will the survey take?

This varies from person to person and depends on how many people there are in a household. The interviewer will discuss this with you and will arrange a time to suit you.

What will happen after the interview?

After the interview, if you agree, the interviewer will arrange for a qualified nurse to visit at a time convenient for you, so that some measurements can be taken. There are different measurements for different age groups.

The nurse will measure blood pressure (for all those aged 5 and over) and waist and hip circumferences (for all those aged 11 and over). For

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everyone aged 4 and over, the nurse will ask for consent to collect a sample of saliva (spit). For adults (aged 16 and over) the nurse will ask for consent to collect a blood sample.

The nurse will have to get your written permission before a sample of saliva or blood can be taken. You are of course free to choose not to give a sample, even if you are willing to help the nurse with everything else.

The analysis of all the measurements and samples will tell us a lot about the health of the population. During the visit, the nurse will be able to explain the importance of these measurements and answer any questions.

Do I get anything from the survey?

If you wish, you may have a record of your measurements and blood sample results. Also, if you give consent, your blood pressure and blood sample results can be sent to your GP, who will be able to interpret them for you and give you advice if necessary. Your GP may also want to include the results in any future report about you.

Other benefits from the survey will be indirect and in due course will come from any improvements in health and in health services which result from the survey.

Will I be able to see the survey results?

Each year a report is published about Health Survey results. You can find the reports on the Health and Social Care Information Centre's website:

www.ic.nhs.uk/pubs/hse11report

You can also find more information about the survey at our website:

www.healthsurveyforengland.org

What if I don't speak English?

The survey is carried out in English, so we are not able to include people who do not speak English well enough to take part.

Who has reviewed the study?

The survey has been looked at by an independent group of people called a Research Ethics Committee, to protect your safety, rights, wellbeing and dignity. This study has been given a favourable opinion by the Oxford A Research Ethics Committee (Reference no. **12/SC/0317**).

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If I have any other questions?

We hope this leaflet answers the questions you may have, and that it shows the importance of the survey. If you have any other questions or concerns about the survey, please ask the interviewer, or ring one of the contacts listed below, or look at our website.

If I have a complaint?

If you have a complaint about something related to the survey, please contact Emma Fenn using the details below, or contact Carol Babicz, Freelance Resources Supervisor on 01277 690118 in office hours, or email info@natcen.ac.uk.

For further information, please contact:

Emma Fenn
Kings House
101-135 Kings Road
Brentwood, Essex
CM14 4LX
Tel: 0800 526 397

Dr. Jennifer Mindell
Department of Epidemiology and Public Health
UCL (University College London)
1-19 Torrington Place
London
WC1E 6BT
Tel: 020 7679 5646

www.healthsurveyforengland.org

Thank you very much for your help with this survey

* * * * *

We would like to hear your views!

To give feedback about the survey go to www.healthsurveyforengland.org
Any feedback you give us will be completely anonymous and will not be linked to your survey answers.

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P3327

The Health Survey for England 2013
Information for participants

This survey is being carried out for the Health and Social Care Information Centre, by NatCen Social Research and the Department of Epidemiology and Public Health at UCL (University College London). You have already taken part in the first stage of the survey which consisted of an interview and some measurements (height and weight).

This leaflet tells you more about the second stage of the survey.

The Second Stage

A registered nurse/midwife will ask you some further questions and will ask permission to take some measurements. The measurements are described overleaf. Like the first stage of the survey, the nurse visit is entirely voluntary and you are free to withdraw from the survey at any time. You need not have any measurements taken if you do not wish but, of course, we very much hope you will agree to them as they are a valuable part of this survey. If the survey results are to be useful to the Health and Social Care Information Centre we need information from all types of people in all states of health. As with information obtained in the first part of the survey, we take care to protect the confidentiality of all information and test results.

Who has reviewed the study?

The survey has been looked at by an independent group of people called a Research Ethics Committee, to protect your safety, rights, wellbeing and dignity. This study has been given a favourable opinion by the Oxford A Research Ethics Committee (Reference number **12/SC/0317**).

Is the survey confidential?

Yes. We take great care to protect the confidentiality of the information we are given, and take careful steps to ensure that the information is secure at all times. The survey results will not be presented in a form which can reveal your identity. This will only be known to certain members of the NatCen/ UCL research team. The information collected is used for research and statistical purposes only and is dealt with according to the 1998 Data Protection Act.

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The Measurements

- *Blood pressure (Age 5 years and over)*

Blood pressure is measured using an inflatable cuff that goes around the upper arm. High blood pressure can be a health problem. However, blood pressure is difficult to measure accurately. A person's blood pressure is influenced by age and can vary from day to day with emotion, meals, tobacco, alcohol, medication, temperature and pain. The nurse will tell you your blood pressure along with an indication of its meaning, but a diagnosis cannot be made on measurements taken on a single occasion.

- *Waist and hip measurements (Age 11 years and over)*

Lately there has been much discussion about the relationship between weight and health. We have already recorded your weight and height but another factor is the distribution of weight over the body. Your waist and hip measurements are most useful for assessing this.

- *Saliva sample (Age 4 years and over)*

We would like to take a sample of saliva (spit). This simply involves sucking on an absorbent swab (for adults) or dribbling saliva down a straw into a tube (for children). The sample will be analysed for cotinine. Cotinine is related to the intake of cigarette smoke and is of particular interest to see whether non-smokers may have raised levels as a result of 'passive' smoking. The saliva will only be tested for cotinine. It will not be tested for other substances, like drugs or alcohol.

- *Blood sample (Age 16 years and over)*

We would also like to take a sample of blood. The analysis of the blood samples will tell us a lot about the health of the population. You are, of course, free to choose not to give a blood sample and the nurse will ask for your written permission before a blood sample is taken.

This part of the survey involves a small amount of blood (no more than 20ml or four teaspoons) being taken from your arm by a registered, qualified nurse. The blood sample will be sent to a medical laboratory for testing.

What will happen to the blood sample I give?

The blood sample will be tested for a number of biological markers, including the following:

Cholesterol, which is a type of fat present in the blood, related to diet. Too much cholesterol in the blood increases the risk of heart disease, except for the 'good' HDL cholesterol.

Glycated haemoglobin, which is an indicator of long-term blood sugar levels.

Some blood samples may also be tested for the presence of flu antibodies.

The blood samples will *not* be tested for the HIV virus.

Will I get any feedback from my blood sample?

If you agree, we will send you your results for the tests we carry out on your blood sample that are useful for individuals. We can also send these same results to your GP if you would like this. We will need your consent to do this. Note that if you don't want your results sent to your GP, we will not be able to let them know if we find anything serious (although we would be able to let you know, unless you have asked us not to tell you).

What will happen to the blood sample after the tests?

We would like to store a small amount of blood. The sample may be used for future studies investigating the causes, diagnosis, treatment and outcome of disease. This means that we will be able to learn more about the health of the population by doing further tests of the blood samples in the future. The samples will be stored with no identification except a coded study number. Only the authorised members of the research team for this study would be able to find out who the codes referred to.

Before being used in future research, some details of the information we have collected in this survey (but not any details which would identify you) may be attached to the sample, but the study number code will then be removed from the blood sample and the other information. The stored blood will not be available for commercial purposes. When the sample is tested for research, it will no longer be possible to link it to you, so you will not be told the results of the testing. It will not be possible to remove your results from reports, as the results cannot be linked to you. You can withdraw your consent to store your blood at any time, without giving any reason, by asking the investigators in writing for your blood to be removed from storage and destroyed (see contact details later in this leaflet).

We will ask separately for your written permission to store blood.

Will any genetic tests be made?

The blood samples will *not* be tested for the HIV virus. The initial tests we do now will not involve DNA or genetic analysis, but if you agree that we can store some of your blood, it is possible that at some time in the future, the anonymous samples might be tested for DNA or genetics. Any analysis like this could not be linked to you. Stored blood will only be analysed in future studies if permission for that particular study is obtained from the Health and Social Care Information Centre and from a Research Ethics Committee.

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Might there be implications for insurance cover?

If you agree to your results being sent to your GP, then he/she may use them in medical reports about you. This may occur if you apply for a new life assurance policy, or for a new job. Insurance companies may ask those who apply for new policies if they have had any medical tests. If so, the insurance company may ask if they can obtain a medical report from the GP. Because of the Access to Medical Reports Act 1988 an insurance company cannot ask your GP for a medical report on you without your permission. Having given your permission, you then have the right to see the report before your GP sends it to the insurance company and you can ask for the report to be amended if you consider it to be incorrect or misleading.

The purpose of a medical report is for the company to judge whether to charge normal premiums, whether to charge higher premiums or whether, in exceptional circumstances, to turn down life insurance on account of the person's health. If you think you may apply for health insurance in the future, you can choose not to know the results of any tests and not to let your GP know these results.

If I have any other questions or wish to make a complaint?

We hope this leaflet answers the questions you may have, and that it shows the importance of the survey. If you have any other questions or concerns about the nurse measurements, results or samples please do not hesitate to ring one of the contacts listed below. Your co-operation is very much appreciated.

If you have a complaint about any aspect of the nurse visit, please contact one of the people below, or contact Carol Babicz, Field Services Manager, on 01277 690 118 in office hours, or email info@natcen.ac.uk.

Emma Fenn NatCen Social Research Kings House 101-131 Kings Road Brentwood, Essex CM14 4LX Tel: 0800 526 397	Dr Jennifer Mindell Dept Epidemiology and Public Health UCL Medical School, 1-19 Torrington Place, London WC1E 6BT Tel: 020 7679 5646

Thank you very much for your help with this survey

* * * * *

We would like to hear your views!

To give feedback about the survey go to www.healthsurveyforengland.org

Any feedback you give us will be completely anonymous and will not be linked to your survey answers.

Appendix 9   ActiGraph Information Leaflet

Health Survey for England 2008

Actigraph Information leaflet

The Health Survey for England is an annual survey which looks at the health and lifestyles of different people living in England. This year, the survey will focus on different aspects of physical activity.

As part of this survey, we would like participants to wear an activity monitor called an **'Actigraph'**. The activity monitor is like a pedometer and records different types of movement. This leaflet provides more information about the Actigraph.

Light orange **CA**

P2827 Actigraph Information Adults

What is the 'Actigraph' monitor?

The Actigraph is a small machine that records information about physical activity patterns. The monitor records body movements during normal daily activities such as walking and jogging. The monitor records no other information and is not harmful in any way.

What am I supposed to do with the monitor?

You are asked to wear the monitor during the time you are awake, for 7 days. Please put the monitor on when you get up in the morning and take it off before you go to bed.

- Please remove the monitor before you shower, have a bath or go swimming, as if it gets wet it may be damaged (if you forget to take the monitor off before swimming or having a bath, you will not be harmed).
- Please keep the monitor away from children under 4 years and pets to avoid accidents.

How am I supposed to wear the monitor?

The monitor is worn on the waist using the elastic belt provided. Attach the belt snugly around your waist so that the monitor rests on the right side of your body, above your right hip. Ideally you should wear the monitor under your clothes. It is best to keep the monitor fastened on the belt to reduce the risk of losing it. Please put the monitor on during your waking hours and take it off before you go to bed each day.

What do I do after I have worn the monitor for 7 days?

The interviewer will arrange an appointment for the nurse to collect the monitor. Until then, please take off the monitor and keep it in a safe place.

Is participation compulsory?

No. In all our surveys we rely on voluntary co-operation. The success of the survey depends on the goodwill and co-operation of those asked to take part. The more people who do take part, the more useful the results will be. You are free to withdraw from the study at any time.

Is the study confidential?

Yes. We take very great care to protect the confidentiality of the information we are given. The study results will not be in a form that can reveal your identity. This will only be known to the National Centre / UCL research team

Do I get anything for wearing the actigraph?

You will be sent a high street voucher as a token of appreciation for your time and to thank you for taking part.

If I have any other questions?

We hope this leaflet answers the questions you may have, and that it shows the importance of the survey. If you have any other questions about the survey, please do not hesitate to ring either Lesley Mullender or Sue Roche on freephone 0800 526 397.

Frequently Asked Questions

Q. Will the Actigraph harm me in any way?
A: No, the Actigraph cannot harm you. The rechargeable battery is securely housed in the device shell. The monitor does not emit radiation, electrical current, vibration, or heat and it can be worn under your clothing without causing discomfort.

(Frequently Asked Questions)

Q. The light on the monitor is flashing, does this mean that something is wrong?
A: No, this just indicates how much battery life is left.

Q. I play a team sport, is it OK to keep the monitor on? What if we are not allowed to wear jewellery?
A: Please keep the monitor on unless you are playing vigorous contact sports like rugby, martial arts and so on. We can provide you with a spare copy of this information sheet to show to your coach or anyone else who asks about the monitor, e.g. whether it counts as jewellery (No – it is a piece of scientific equipment).

Q. What do I need to do if I go through a metal detector (e.g. at an airport)?
A: Please take the belt off and put it in the tray to be screened. Please keep the information sheet to show to the security personnel.

Q. I swim/cycle/row, what do I need to do?
A: Please record these activities (as well as sleeping times) in your activity log booklet because the monitor does not collect this information. Please take the monitor off before swimming, as it may be damaged if it gets wet.

Q. What if I lose or damage the monitor?
A: The monitor is an expensive piece of equipment. We would appreciate your help in keeping it safe at all times.

Q. What if I am sick or I cannot do much physical activity for any reason during the week I am wearing the monitor?
A: Please wear the monitor as normal. We are interested in your physical activity patterns no matter how active or inactive you are.

Q. What if I work shifts?
A: Please wear the monitor all the time you are awake, whether this is during the day or night. Please record the time you put the monitor on and took it off in your log booklet.

END USER LICENCE

PUBLIC VERSION
14 FEBRUARY 2013
Version: 04.00

T +44 (0)1206 872572
E susan@essex.ac.uk
www.data-archive.ac.uk

UK DATA ARCHIVE
UNIVERSITY OF ESSEX
WIVENHOE PARK
COLCHESTER
ESSEX, CO4 3SQ

WE ARE SUPPORTED BY THE **UNIVERSITY OF ESSEX**, THE **ECONOMIC AND SOCIAL RESEARCH COUNCIL**, AND THE **JOINT INFORMATION SYSTEMS COMMITTEE**

Contents

1.   End User Licence (EUL) text

This Agreement is made between you and the University of Essex (also referred to as the "registrar") and the service funders in order to provide you (the "End User") with the right to use the collections provided via the UK Data Service, according to the terms below.

In this agreement:

"Data Team" means in relation to a particular data collection, the registrar, the relevant data service providers, and (to the extent that the Special Conditions and/or metadata specific to a particular data collection expressly provide) the service funders, data collection funders and/or original data creators or depositors.

"data service provider" means the persons or organisations that directly provide you with the data collections (on behalf of the service funder). The data service provider for a particular data collection is identified in the Special Conditions and/or metadata applicable to that data collection;

"service funder" means the persons or organisations that fund the data service provider as defined above. The service funder for a particular data collection is identified in the Special Conditions and/or metadata applicable to that data collection;

"data collection funder" means the persons or organisations that funded the collection and/or creation of the data collections. The data collection funder for a particular data collection is identified in the Special Conditions and/or metadata applicable to that data collection;

"original data creator or depositor" means the persons or organisations that originally collected, created or deposited the materials making up the data collections and/or who own the intellectual property rights in the data collections. The original data creator or depositor for a particular data collection is identified in the Special Conditions and/or metadata applicable to that data collection;

"registrar" means the person or organisation responsible for the system that registers End Users and issues them with End User Licences (being the University of Essex);

"Special Conditions" means any further conditions applicable to the use of one or more data collections by an End User, as notified to the End User in accordance with paragraph 5 of the End User Licence;

"metadata" means any additional or bibliographic information about one or more of the data collections, as notified to the End User from time to time. Metadata may be supplied by electronic means.

I (the "End User") agree to the following conditions of use in consideration of the data collections being made available to me through the various contributions of each member of the Data Team:

1. To use the data collections only in accordance with this End User Licence and to notify promptly the registrar and the data service provider of any breach of its terms in writing or of any infringements of the data collections of which I become aware.

2. To use and to make personal copies of any part of the data collections only for the purposes of not-for-profit research or teaching or personal educational development. To obtain permission prior to using part or all of the data collections for commercial purposes by contacting the registrar and/or relevant data service provider, where relevant, in order to obtain an appropriate licence from the rights holder(s) in question or their permitted licensee if one is available.

This document is based on UKDA137-EndUserLicence

3. That this Licence does not operate to transfer any interest in intellectual property from the data collection funders, service funder(s), the data service providers, the original data creators, producers, depositors, copyright or other right holders (including without limitation the ONS or the Crown) to me. That any rights subsisting in materials derived now or in the future from the data collections which are the intellectual property of the Crown are hereby assigned (by way of assignment of present and future intellectual property) to the Crown by this Licence to the extent not already vested in the Crown. To take all steps necessary to give effect to this Clause (including by executing further written documentation).

4. That the Licence and the data collections are provided by the Data Team on an "as is" basis and without warranty or liability of any kind. Any representations or warranties given by any member of the Data Team relating to this licence, expressed or implied, are excluded to the maximum extent permitted by law.

5. To abide by any further conditions notified to me from time to time by the registrar or the relevant data service provider that may apply to the access to, or use of, specific materials within the data collections or particular data collections. Notice of further conditions under this paragraph may be given to me by electronic means, for example, by way of a pop-up window upon my ordering one or more data collections. My acceptance of the further conditions shall be required before I gain access to the data collections in question. In this Agreement such further conditions are referred to as Special Conditions.

6. To give access to the data collections, in whole or in part, or any material derived from the data collections, only to registered End Users who have entered into an End User Licence and accepted the relevant Special Conditions necessary to access and use the data collections (with the exception of data collections or material derived from data collections supplied for the stated purpose of teaching or included in publications made for the purposes set out in paragraph 2).

7. To ensure that the means of access to the data (such as passwords) are kept secure and not disclosed to a third party except by special written permission or licence obtained from the original data service provider.

8. To preserve at all times the confidentiality of information pertaining to individuals and/or households in the data collections where the information is not in the public domain. Not to use the data to attempt to obtain or derive information relating specifically to an identifiable individual or household, nor to claim to have obtained or derived such information. In addition, to preserve the confidentiality of information about, or supplied by, organisations recorded in the data collections. This includes the use or attempt to use the data collections to compromise or otherwise infringe the confidentiality of individuals, households or organisations.

9. To acknowledge, in any publication, whether printed, electronic or broadcast, based wholly or in part on the data collections, the original data creators, depositors or copyright holders, the service funders and the data service provider(s) in the form specified on the data distribution notes or in accompanying metadata received with the dataset or notified to me and without prejudice to paragraph 5 above to comply with any restrictions on my use of the data collections referred to or referenced therein or otherwise notified to me from time to time. To cite, in any publication, whether printed, electronic or broadcast, based wholly or in part on the data collections, the data collections used in the form specified on the data distribution notes or in accompanying metadata received with the dataset or notified to me.

10. To supply the relevant data service provider with the bibliographic details of any published work based wholly or in part on the data collections.

11. That the members of the Data Team may hold and process any personal data submitted by me for validation and statistical purposes, and for the purposes of the management of the service or for any other lawful purpose notified to me and to which I have consented under this Agreement in relation to a particular data collection, and they may also pass the information on to other parties such as: (i) depositors and distributors of material contained in or accessed via the data service provider; (ii) copyright and other intellectual property rights owners whose material is held by the data service

provider; as well as (iii) each member of the Data Team's organisation and (iv) my own institution or organisation, in compliance with the Data Protection Act 1998.

12. To notify the data service provider of any errors discovered in the data collections.

13. That any personal data submitted by me is accurate to the best of my knowledge, and that any changes in that personal data, including my educational or employment status, will be made known to the registrar at the earliest possible opportunity.

14. To meet any charges that may from time to time be levied by any member of the Data Team for the supply of the data collections including, where relevant, annual service fees and royalty fees.

15. At the conclusion of my research (or if earlier at any time at the request of a member of the Data Team), to offer for deposit in the data collection(s) on a suitable medium and at my own expense any new data collections which have been derived from the materials supplied or which have been created by the combination of the data supplied with other data. The deposit of the derived data collection(s) will include sufficient explanatory documentation to enable the new data collection(s) to be accessible to others.

16. I understand that breach of any of the provisions of this Agreement will lead to immediate termination of my access to all services provided by the Data Team either permanently or temporarily, at the discretion of a member of the Data Team, and may result in legal action being taken against me. I understand that where there is no breach of this Licence, it may be terminated, or its terms altered, by a member of the Data Team either after 30 days notice; or, if a service charge has been paid in advance, at the end of the period for which payment has been made, whichever is the longer. The failure to exercise or delay in exercising a right or remedy provided by this Agreement or by law does not constitute a waiver of the right or remedy or a waiver of other rights or remedies.

DISCLAIMERS

To the extent that applicable law permits:

a. The members of the Data Team bear no legal responsibility for the accuracy or comprehensiveness of the data supplied.

b. The members of the Data Team accept no liability for, and I will not be entitled to claim against them in respect of, any direct, indirect, consequential or incidental damages or losses arising from use of the data collections, or from the unavailability of, or break in access to, the service, for whatever reason.

c. Whilst steps have been taken to ensure all licences, authorisation and permissions required for the granting of this Licence have been obtained, this may not have been possible in all cases, and no warranties or assurance are given in this regard. To the extent that additional licences, authorisations and permissions are required to use the data collections in accordance with this Licence, it is the End User's responsibility to obtain them.

d. I agree to indemnify and shall keep indemnified each member of the Data Team against any costs, actions, claims, demands, liabilities, expenses, damages or losses (including without limitation consequential losses and loss of profit, and all interest, penalties and legal and other professional costs and expenses) arising from or in connection with any third party claim made against any member of the Data Team relating to my use of the data collections or any other activities in relation to the data where such use is in breach of this licence.

If the whole or any part of a provision of this Agreement is void, unenforceable or illegal for any reason, that provision will be severed and the remainder of the provisions of this Agreement will continue in full force and effect as if this Agreement had been executed with the invalid provision eliminated.

This Agreement may be enforced separately in relation to each data collection provided to the End User by any member of the Data Team and the End User. No other persons may enforce this Agreement under the Contract (Rights of Third Parties) Act 1999.

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This Agreement (which is the entire agreement between the parties and supersedes any previous agreement between them) may be varied in writing by agreement of the relevant service funders, the registrar, and the End User (who may give its consent to such variations by electronic means). No consent from any other party is required to vary or rescind this Agreement.

This Agreement and any documents to be entered into pursuant to it shall be governed by and construed in accordance with the laws of England and Wales and each Party irrevocably submits to the exclusive jurisdiction of the courts of England and Wales over any claim or matter arising under or in connection with this Agreement and the documents entered into pursuant to it.

2.   End User Licence (EUL) summary text

Seventeen points to help you understand the End User Licence (EUL). These pointers are for general guidance and you must read and understand the full EUL before agreeing to it. By accepting the EUL, you agree:

1. to use the data in accordance with the EUL and to notify the UK Data Service of any breach you are aware of

2. not to use the data for commercial purposes without obtaining permission and, where relevant, an appropriate licence if commercial use of the data is required

3. that the EUL does not transfer any interest in intellectual property to you

4. that the EUL and data collections are provided without warranty or liability of any kind

5. to abide by any further conditions notified to you

6. to give access to the data collections only to registered users (who have accepted the terms and conditions, including any relevant further conditions). There are some exceptions relating to teaching.

7. to ensure that the means of access to the data (such as passwords) are kept secure and not disclosed to anyone else

8. to preserve the confidentiality of, and not attempt to identify, individuals, households or organisations in the data

9. to use the correct methods of citation and acknowledgement in publications

10. to send the UK Data Service bibliographic details of any published work based on our data collections

11. that personal data about you may be held for validation and statistical purposes and to manage the service, and that these data may be passed on to other parties

12. to notify the UK Data Service of any errors discovered in the data collections

13. that personal data submitted by you are accurate to the best of your knowledge and kept up to date by you

14. to meet any charges that may apply

15. to offer for deposit any new data collections which have been derived from the materials supplied

16. that any breach of the EUL will lead to immediate termination of your access to the services and could result in legal action against you

Appendix 11 Non-wear algorithm

```
1    ***********************************************************************
2    // 1.  set up global macros for the directories
3    ***********************************************************************
4    // maintained by Alex Clarke-Cornwell
5    // within the main folder, you will need a folder for the raw .csv files,
6    // a folder for the .dta files, and a folder for the cleaned stata files
7    global projdir C:\NatCen folder\Analysis
8    global data $projdir/datasets/hse_data
9    global adai $projdir/datasets/hse_data/adults_dayafterinterview
10   global aid $projdir/datasets/hse_data/adults_interviewdate
11   global ald $projdir/datasets/hse_data/adults_logdate
12   global cdai $projdir/datasets/hse_data/children_dayafterinterview
13   global cid $projdir/datasets/hse_data/children_interviewdate
14   global cld $projdir/datasets/hse_data/children_logdate
15   global log_files $projdir/log_files
16   global external $projdir/external_data
17
18   clear
19   set more off
20
21   set maxvar 32767, perm
22
23   // log .do file if needed
24   // log using "$log_files/cleaning_log.log", text replace
25
26   ***********************************************************************
27   // 2.  create local macro of id numbers from id_list excel sheet
28   ***********************************************************************
29
30   // change excel sheet to set of data analysing
31   // if analysing all data in one go, id's will already in be in Sheet 1
32   // if analysisng each set of data separate, change line below to relevant sheet
33   //// import excel "$external/id_list.xlsx", sheet("adai")
34   //// import excel "$external/id_list.xlsx", sheet("aid")
35   //// import excel "$external/id_list.xlsx", sheet("ald")
36   //// import excel "$external/id_list.xlsx", sheet("cdai")
37   //// import excel "$external/id_list.xlsx", sheet("cid")
38   import excel "$external/id_list.xlsx", sheet("cld")
39
40   rename A pserial
41   // save as string (str9) variablelog
42   tostring pserial, replace
43   format pserial %9s
44   sort pserial
45   // check for duplicates
46   duplicates report pserial
47   // no duplicates
48   levelsof pserial, local(id)
49   clear
50
51   /*
52
53   ***********************************************************************
54   // 3.  import .dta files with day of data collection and 'clean',
55   //      so in same format as other studies
56   //      (spurious data is also chnaged to missing here)
57   ***********************************************************************
58
```

```
59   foreach i of local id {
60   display "participant `i'"
61
62   //// use "$adai/`i'.dta"
63   //// use "$aid/`i'.dta"
64   //// use "$ald/`i'.dta"
65   //// use "$cdai/`i'.dta"
66   //// use "$cid/`i'.dta"
67   //// use "$cld/`i'.dta"
68
69   rename pserial participant
70   tostring participant, replace
71   label variable participant "participant id"
72   rename cpm axis1
73   label variable axis1 "vertical axis"
74   rename time_mins time
75   label variable time "time in minutes"
76   order participant time axis1 dayofdata dayofweek month quarter
77
78   ***********************************************************************
79   // remove spurious data, and change to missing
80   ***********************************************************************
81
82   codebook axis1
83   // check for any missing data and range of data
84   replace axis1=. if axis1>20000
85   compress
86
87   //// save "$adai/dta/participant_`i'.dta", replace
88   //// save "$aid/dta/participant_`i'.dta", replace
89   //// save "$ald/dta/participant_`i'.dta", replace
90   //// save "$cdai/dta/participant_`i'.dta", replace
91   //// save "$cid/dta/participant_`i'.dta", replace
92   //// save "$cld/dta/participant_`i'.dta", replace
93
94   clear
95   }
96
97   */
98   ***********************************************************************
99   // 4.  open .dta files from step 3 and run troiano non-wear algorithm
100  //      each step is described within the notes
101  //      all looped
102  ***********************************************************************
103
104
105  foreach j of local id {
106  display "participant `j'"
107
108  //// use "$adai/dta/participant_`j'.dta", clear
109  //// use "$aid/dta/participant_`j'.dta", clear
110  //// use "$ald/dta/participant_`j'.dta", clear
111  //// use "$cdai/dta/participant_`j'.dta", clear
112  //// use "$cid/dta/participant_`j'.dta", clear
113  use "$cld/dta/participant_`j'.dta", clear
114
115  ***********************************************************************
116  // 5.  generate participant variable from file name; already there for hse data
```

```
117  ***********************************************************************
118
119  // gen participant="`j'"
120  // label variable participant "participant id"
121  // order participant time axis1
122
123
124  ***********************************************************************
125  // 6.  time series data into spells and sequences
126  ***********************************************************************
127
128  summ dayofdata
129  return list
130  foreach num of numlist 2/`r(max)' {
131  replace time=time+(86400000*(`num'-1)) if dayofdata==`num'
132  }
133  // tsset and generate panels for each participant
134  tsset time, delta(1 min)
135  // creates panels
136  tsspell, f(L.time == .)
137  label variable _spell "panel for each wear time"
138  label variable _seq "sequence order within panel"
139  drop _end
140  // create order variable
141  gen order=_n
142  label variable order "order"
143  sort order
144  // should have one spell, and sequence and order variables should be the same
145  // even though have changed spurious data, only changed to missing and kept
146  // continuous time (in minutes)
147  // could do a check here that _seq==order, and if not, this will stop program
148  gen test=_seq-order
149  summ test
150  display r(mean)
151  if r(mean)~=0 {
152  exit
153  }
154
155  drop test _seq _spell
156
157
158  ***********************************************************************
159  // 7.  create day of week and day of data collection variables; already there
160  ***********************************************************************
161
162  /*gen time2=dofc(time)
163  format time2 %td
164  gen dayofweek=dow(time2)
165  label variable dayofweek "day of week"
166  recode dayofweek 0=7
167  label define days  1 "monday" 2 "tuesday" 3 "wednesday" 4 "thursday" //
168                     5 "friday" 6 "saturday" 7 "sunday"
169  label values dayofweek days
170  // day of data collection
171  egen dayofdata=group(time2)
172  label variable dayofdata "day of data collection"
173  drop time2*/
174
```

```
175  ***********************************************************************
176  ***********************************************************************
177  // 8.  set rule to troiano algorithm
178  ***********************************************************************
179
180  ***********************************************************************
181  // a non-wear time period ends - see SAS code from NHANES:
182  // i) if >100 count
183  // ii) missing minute (spurious data)
184  // iii) 3 minutes with counts between 1 and 100
185  // iv)  last minute of the day (the algorithm was applied across a floating
186  //      window, rather than daily)
187  // (the code for daily application is below, if needed)
188  ***********************************************************************
189
190  generate non_wear=.
191  // i)
192  recode non_wear .=1 if axis1>100 & axis1~=.
193  // ii)
194  recode non_wear .=2 if axis1==.
195  // iii)
196  sort order
197  gen seq=_n
198  replace seq=seq[_n-1] if axis1>=1 & axis1[_n-1]>=1  & axis1<=100 & axis1[_n-1]<=100
199  egen seq_id=group(seq)
200  bysort seq_id: gen count=_N
201  sort order
202  recode non_wear .=1 if count>=3
203  drop seq seq_id count
204  /*
205  // iv)
206  gen hrs=hh(time)
207  gen mins=mm(time)
208  replace non_wear=1 if hrs==23 & mins==59
209  */
210
211  ***********************************************************************
212  // 9.  create possible non-wear/wear variable
213  ***********************************************************************
214
215  recode non_wear .=2
216  label define nw 1 "wear" 2 "possible non-wear"
217  label values non_wear nw
218
219
220  ***********************************************************************
221  // 10.  steps 10-12 are initial run of creating sequences of possible non-wear
222  //       subsequent runs are looped from 13.
223  //       create sequences, with total length of possible non-wear
224  ***********************************************************************
225
226  sort order
227  gen seq=_n
228  replace seq=seq[_n-1] if non_wear==2 & non_wear[_n-1]==2
229  egen seq_id=group(seq)
230  bysort seq_id: gen count=_N
231  replace count=. if non_wear==1
232  // don't include possible non-wear if less than 60 minutes
```

349

```
233  replace count=. if count<60
234  drop seq seq_id
235  recode non_wear 2=1 if count==. & axis1~=.
236
237
238  //***************************************************
239  //  11. need to start non-wear period on a 0 cpm, therefore if any possible
240  //      non-wear sequences start with >0,
241  //      will need to go onto n+1 or n+2 (won't be n+3, as will be recorded
242  //      as wear above)
243  //***************************************************
244
245  sort order
246  gen seq=_n
247  replace seq=seq[_n-1] if non_wear==non_wear[_n-1]
248  egen seq_id=group(seq)
249  bysort seq_id: gen count1=_n
250  replace count1=. if count==.
251  drop seq seq_id
252  replace non_wear=1 if count1==1 & axis>0 & axis~=.
253  replace non_wear=1 if count1==2 & non_wear[_n-1]==1 & axis1>0 & axis~=.
254  // recreate sequences of possible non-wear, so start on a 0 cpm
255  // see code above
256  drop count count1
257  sort order
258  gen seq=_n
259  replace seq=seq[_n-1] if non_wear==2 & non_wear[_n-1]==2
260  egen seq_id=group(seq)
261  bysort seq_id: gen count=_N
262  replace count=. if non_wear==1
263  replace count=. if count<60
264  drop seq seq_id
265
266
267  //***************************************************
268  //  12. need to look at whether have up to 2 minutes of counts between 1 and 100
269  //      create counter variables
270  //***************************************************
271
272  // gen counter variable that ==1 in possible non-wear periods, where cpm>=1
273  // (and <=100; implicit)
274  gen counter=1 if count~=. & axis1~=0 & axis~=.
275  // create sequences for possible non-wear periods, with corresponding
276  // incremental count
277  sort order
278  gen seq=_n
279  replace seq=seq[_n-1] if non_wear==non_wear[_n-1]
280  egen seq_id=group(seq)
281  bysort seq_id: gen count1=_n
282  replace count1=. if count==.
283  drop seq
284  replace seq_id=. if count==.
285  // generate cumulative counter of 1-100cpm within each sequence of possible
286  // non-wear time
287  sort seq_id count1
288  bysort seq_id: gen cumcounter=sum(counter)
289  sort order
290  replace cumcounter=. if count==.
291  // generate total counter of 1-100 cpm within each sequence of possible
292  // non-wear time
293  sort seq_id count1
294  bysort seq_id: egen totalcounter=total(counter)
295  sort order
296  replace totalcounter=. if count==.
297  summ totalcounter
298  return list
299  display `r(max)'
300
301
302  //***************************************************
303  //  13.  now need to loop
304  //***************************************************
305  while `r(max)'>2 {
306
307  replace non_wear=1 if cumcounter==3 & counter==1 & count1>60
308  gen test=1 if cumcounter==3 & counter==1 & count1<=60
309  forvalues m=1/60 {
310  replace test=1 if test[_n+`m']==1 & seq_id==seq_id[_n+`m']
311  }
312  replace non_wear=1 if cumcounter==1 & counter==1 & test==1
313  drop count counter seq_id count1 cumcounter totalcounter test
314
315
316  //***************************************************
317  //  14. (same as 10.) create sequences of possible non-wear, with total
318  //      length of possible non-wear
319  //***************************************************
320
321  sort order
322  gen seq=_n
323  replace seq=seq[_n-1] if non_wear==2 & non_wear[_n-1]==2
324  egen seq_id=group(seq)
325  bysort seq_id: gen count=_N
326  replace count=. if non_wear==1
327  // don't include possible non-wear if less than 60 minutes
328  replace count=. if count<60
329  drop seq seq_id
330  recode non_wear 2=1 if count==. & axis1~=.
331
332
333  //***************************************************
334  //  15. (same as 11.) need to start non-wear period on a 0 cpm, therefore
335  //      if any possible non-wear sequences start with >0, will need to go
336  //      onto n+1 or n+2 (won't be n+3, as will be recorded as wear above)
337  //***************************************************
338
339  sort order
340  gen seq=_n
341  replace seq=seq[_n-1] if non_wear==non_wear[_n-1]
342  egen seq_id=group(seq)
343  bysort seq_id: gen count1=_n
344  replace count1=. if count==.
345  drop seq seq_id
346  replace non_wear=1 if count1==1 & axis>0 & axis~=.
347  replace non_wear=1 if count1==2 & non_wear[_n-1]==1 & axis1>0 & axis~=.
348  // recreate sequences of possible non-wear, so start on a 0 cpm
349  // see code above
350  drop count count1
351  sort order
352  gen seq=_n
353  replace seq=seq[_n-1] if non_wear==2 & non_wear[_n-1]==2
354  egen seq_id=group(seq)
355  bysort seq_id: gen count=_N
356  replace count=. if non_wear==1
357  replace count=. if count<60
358  drop seq seq_id
359
360
361  //***************************************************
362  //  16. (same as 12.) need to look at whether have up to 2 minutes of counts
363  //      between 1 and 100 create counter variables
364  //***************************************************
365
366  // gen counter variable that ==1 in possible non-wear periods, where cpm>1
367  // (and <=100; implicit)
368  gen counter=1 if count~=. & axis1~=0 & axis~=.
369  // create sequences for possible non-wear periods, with corresponding
370  // incremental count
371  sort order
372  gen seq=_n
373  replace seq=seq[_n-1] if non_wear==non_wear[_n-1]
374  egen seq_id=group(seq)
375  bysort seq_id: gen count1=_n
376  replace count1=. if count==.
377  drop seq
378  replace seq_id=. if count==.
379  // generate cumulative counter of 1-100cpm within each sequence of possible
380  // non-wear time
381  sort seq_id count1
382  bysort seq_id: gen cumcounter=sum(counter)
383  sort order
384  replace cumcounter=. if count==.
385  // generate total counter of 1-100cpm within each sequence of possible
386  // non-wear time
387  sort seq_id count1
388  bysort seq_id: egen totalcounter=total(counter)
389  sort order
390  replace totalcounter=. if count==.
391  summ totalcounter
392  return list
393  display `r(max)'
394  if (`r(N)'<1) continue, break
395  }
396
397
398  //***************************************************
399  //  17. change non-wear times so can't end on a 1-100 count
400  //      delete non-wear time if non-wear time period becomes less than
401  //      60 minutes
402  //***************************************************
403
404  // check for one 1-100 at the end
405  tsspell, p(count)
406  replace non_wear=1 if _end==1 & counter==1
407  replace count=. if non_wear==1
408  drop _seq _spell _end
409  // check for second 1-100 at the end
410  tsspell, p(count)
411  replace non_wear=1 if _end==1 & counter==1
412  replace count=. if non_wear==1
413  drop _seq _spell _end
414  drop counter seq_id count1 cumcounter totalcounter
415  // delete if non-wear time has become less than 60 minutes
416  sort order
417  gen seq=_n
418  replace seq=seq[_n-1] if non_wear==2 & non_wear[_n-1]==2
419  egen seq_id=group(seq)
420  bysort seq_id: gen count1=_N
421  replace count1=. if non_wear==1
422  replace non_wear=1 if count1<60 & count~=.
423  drop seq seq_id count count1
424
425
426  //***************************************************
427  //  18. drop possible non-wear variable and create wear/non-wear
428  //***************************************************
429
430  gen wear=non_wear
431  replace wear=1 if non_wear==1
432  replace wear=2 if non_wear==2
433  label define wear 1 "wear time" 2 "non-wear time"
434  label values wear wear
435  label variable wear "Wear or non-weartime"
436  drop non_wear
437
438
439  //***************************************************
440  //  19. create variables to count wear/non-wear each day
441  //***************************************************
442
443  generate wt_day=1 if wear==1
444  sort dayofdata order
445  by dayofdata: egen test1=total(wt_day)
446  drop wt_day
447  rename test1 wt_day
448  label variable wt_day "weartime per day"
449  generate nwt_day=1 if wear==2
450  sort dayofdata order
451  by dayofdata: egen test2=total(nwt_day)
452  drop nwt_day
453  rename test2 nwt_day
454  label variable nwt_day "non-weartime per day"
455
456
457  //***************************************************
458  //  20. drop days where less than 10 hours wear
459  //***************************************************
460  // change this line to /* if not doing steps 20-22
461  //***************************************************
462
463  // may not need this for natcen, as people will want to set own rules
464  // run separately for work with hidde, and also for natcen as separate files
```

```
465    // will need to change where save below though
466    ***********************************************************************
467    ***********************************************************************
468
469    drop if wt_day<600
470    // will now need to look at number of valid days, as may be <1
471    set obs `=_N+1'
472    replace participant="." in `=_N'
473    egen test=group(dayofdata)
474    drop dayofdata
475    rename test dayofdata
476    label variable dayofdata "day of data collection"
477    // create total number of days of data collection
478    egen totaldays=max(dayofdata)
479    label variable totaldays "total days of data"
480
481
482    ***********************************************************************
483    //  21. create total weartime/non-wear time variables for valid days
484    //      will also run on empty files where no days of valid data are recorded
485    ***********************************************************************
486
487    gen wt_total=1 if wear==1
488    egen test1=total(wt_total)
489    drop wt_total
490    rename test1 wt_total
491    label variable wt_total "total weartime (mins)"
492    gen test1=wt_total*60
493    egen wt_total_dhm=elap(test1)
494    drop test1
495    label variable wt_total_dhm "total weartime (days,hours,mins)"
496
497    gen nwt_total=1 if wear==2
498    egen test2=total(nwt_total)
499    drop nwt_total
500    rename test2 nwt_total
501    label variable nwt_total "total non-weartime (mins)"
502    gen test2=nwt_total*60
503    egen nwt_total_dhm=elap(test2)
504    drop test2
505    label variable nwt_total_dhm "total non-weartime (days,hours,mins)"
506
507
508    ***********************************************************************
509    //  22. if no data, put participant id back in
510    //      if data, drop last observation where participant=="."
511    ***********************************************************************
512
513    drop in L if _N>1
514    replace participant="`j'" if participant=="."
515    egen test=ends(participant), punct(_) last
516    drop participant
517    rename test participant
518    label variable participant "participant id"
519    */
520
521    ***********************************************************************
522    //  23. save here as clean data, before analysis and collapsing
```

```
523    ***********************************************************************
524
525    compress
526    //// save "$adai/cleaned/clean_participant_`j'.dta", replace
527    //// save "$aid/cleaned/clean_participant_`j'.dta", replace
528    //// save "$ald/cleaned/clean_participant_`j'.dta", replace
529    //// save "$cdai/cleaned/clean_participant_`j'.dta", replace
530    //// "$cid/cleaned/clean_participant_`j'.dta", replace
531    //// save "$cld/cleaned/clean_participant_`j'.dta", replace
532
533    // only use cleaned_valid if included steps 20-22
534    //// save "$adai/cleaned_valid/cleanv_participant_`j'.dta", replace
535    //// save "$aid/cleaned_valid/cleanv_participant_`j'.dta", replace
536    //// save "$ald/cleaned_valid/cleanv_participant_`j'.dta", replace
537    //// save "$cdai/cleaned_valid/cleanv_participant_`j'.dta", replace
538    //// save "$cid/cleaned_valid/cleanv_participant_`j'.dta", replace
539    save "$cld/cleaned_valid/cleanv_participant_`j'.dta", replace
540
541
542    ***********************************************************************
543    //  24. calculate min/day of wear time (then collapse and append)
544    ***********************************************************************
545
546    gen min_day_wt=wt_total/totaldays
547    collapse (mean) totaldays wt_total min_day_wt, by(participant)
548
549    gen test=round(wt_total*60)
550    egen str wt_total_dhm=elap(test)
551    drop test
552
553    gen test=round(min_day_wt*60)
554    egen str min_day_wt_dhm=elap(test)
555    drop test
556
557    format min_day_wt %9.2f
558    order participant totaldays wt_total wt_total_dhm min_day_wt min_day_wt_dhm
559    label variable totaldays "total days of data"
560    label variable wt_total "total weartime (mins)"
561    label variable wt_total_dhm "total weartime (days,hours,mins)"
562    label variable min_day_wt "average minutes per day of weartime"
563    label variable min_day_wt_dhm "average minutes per day of weartime (hours,mins)"
564
565    //// save "$adai/collapsed_valid/collapsedv_participant_`j'.dta", replace
566    //// save "$aid/collapsed_valid/collapsedv_participant_`j'.dta", replace
567    //// save "$ald/collapsed_valid/collapsedv_participant_`j'.dta", replace
568    //// save "$cdai/collapsed_valid/collapsedv_participant_`j'.dta", replace
569    //// save "$cid/collapsed_valid/collapsedv_participant_`j'.dta", replace
570    save "$cld/collapsed_valid/collapsedv_participant_`j'.dta", replace
571
572    clear
573    }
574
575    // start appended file on correct participant
576    //// use "$adai/collapsed_valid/collapsedv_participant_adai_100226102.dta", clear
577    //// use "$aid/collapsed_valid/collapsedv_participant_aid_100217102.dta", clear
578    //// use "$ald/collapsed_valid/collapsedv_participant_ald_100217102.dta", clear
579    //// use "$cdai/collapsed_valid/collapsedv_participant_cdai_100213104.dta", clear
580    //// use "$cid/collapsed_valid/collapsedv_participant_cid_100213104.dta", clear
```

```
581    use "$cld/collapsed_valid/collapsedv_participant_cld_100213104.dta", clear
582    foreach j of local id {
583    //// append using "$adai/collapsed_valid/collapsedv_participant_`j'.dta"
584    //// append using "$aid/collapsed_valid/collapsedv_participant_`j'.dta"
585    //// append using "$ald/collapsed_valid/collapsedv_participant_`j'.dta"
586    //// append using "$cdai/collapsed_valid/collapsedv_participant_`j'.dta"
587    //// append using "$cid/collapsed_valid/collapsedv_participant_`j'.dta"
588    append using "$cld/collapsed_valid/collapsedv_participant_`j'.dta"
589    }
590    drop if _n==1
591    replace totaldays=0 if totaldays==.
592    replace min_day_wt=0 if min_day_wt==.
593
594    // change appended file to correct data set
595    //// save "$adai/appended/adai_appended_basic.dta", replace
596    //// save "$aid/appended/aid_appended_basic.dta", replace
597    //// save "$ald/appended/ald_appended_basic.dta", replace
598    //// save "$cdai/appended/cdai_appended_basic.dta", replace
599    //// save "$cid/appended/cid_appended_basic.dta", replace
600    save "$cld/appended/cld_appended_basic.dta", replace
601
602    // log close
603
```

Appendix 12   Coding schedule

Variable	Name	Coding	Label	Notes
age	age at interview			Derived, (rounded to nearest integer) to use as a continuous variable in models
alcohol	alcohol limits	0= none 1= <=4 units/day (men), <=3 (women) 2= >4 (men), >3 (women)	alclimit07b	Based on units drunk on heaviest day in last seven days
bmi	bmi value			Treated as a continuous variable
bp_med	taking drugs prescribed for blood pressure	0=no 1=yes	noyes	
chol_hdl	hdl cholesterol			Treated as a continuous variable
chol_total	total cholesterol			Treated as a continuous variable
conditions	number of longstanding conditions	0=none 1=1 or more		Could chose up to 6
dbp	diastolic blood pressure			Measured three times and mean of 2nd and 3rd readings was used
eq5d	eq-5d utility score			Censored at 1 and -0.594
ethnicity	ethnicity groups (2)	1=white 2=non=white	ethnicity2	
fruit	fruit and veg portions			Treated as a continuous variable
genhealth	general health(2)	1=very good/good 2=less than good health	genhelf2	
ghq4	ghq12 – 4 cut-off	1=0-3 2=4+	ghq4	
hba1c	glycated haemoglobin			Treated as a continuous variable
heart	vii heart and circulatory system	0=no 1=yes	noyes	Longstanding illness, linked to ICD10 categories; could chose up to 6 conditions
income	household equivalised income	1= <£10,671 2= >=£10,671-<£17,789 3= >=£17,789-<=£27,317 4= >=27,317-<£44,200 5= >=£44,200	income	Derived variable in quintiles; takes into account household composition
lipid	taking drugs prescribed for cholesterol	0=no 1=yes	noyes	

Variable	Name	Coding	Label	Notes
mental	v mental disorders	0=no 1=yes	noyes	Longstanding illness, linked to ICD10 categories; could chose up to 6 conditions
msk	xiii musculoskeletal system	0=no 1=yes	noyes	Longstanding illness, linked to ICD10 categories; could chose up to 6 conditions
nssec	nssec groups(3)	1=managerial and professional occupations 2=intermediate occupations 3=routine and manual occupations	nssec3	Derived
pa_week	physical activity - 7 days			Objective measure – mins/day
pa_weekdays	physical activity - weekdays			Objective measure – mins/day
pa10_week	physical activity (mins/day) – 10+ week(sr)			Self-reported – taken from total for week variable (in bouts of >=10 mins) and divided by 7
participant	serial number of individual			Unique id
sbp	systolic blood pressure			Measured three times and mean of 2nd and 3rd readings was used
sex	sex	1=men 2=women	sex	
smoking	smoking status	1=current 2=ever 3=never	smoking	Never category includes those who said never smoked at all and those who said used to smoke cigarettes occasionally
st_nonworktime100	sedentary time - non-worktime(100)			Objective measure – mins/day
st_nonworktime150	sedentary time - non-worktime(150)			Objective measure – mins/day
st_nonworktime50	sedentary time - non-worktime(50)			Objective measure – mins/day
st_nonworktime73	sedentary time - non-worktime(73)			Objective measure – mins/day (derived)
st_week	sedentary time (mins/day) - week(sr)			Self-reported – calculated from above two
st_week100	sedentary time - 7 days(100)			Objective measure – mins/day
st_week150	sedentary time - 7 days(150)			Objective measure – mins/day
st_week50	sedentary time - 7 days(65)			Objective measure – mins/day

Variable	Name	Coding	Label	Notes
st_week65	sedentary time - 7 days(50)			Objective measure – mins/day (derived)
st_weekday	sedentary time (mins/day) - weekday(sr)			Self-reported – based on average weekday
st_weekday100	sedentary time - weekdays(100)			Objective measure – mins/day
st_weekday150	sedentary time - weekdays(150)			Objective measure – mins/day
st_weekday50	sedentary time - weekdays(50)			Objective measure – mins/day
st_weekday60	sedentary time - weekdays(60)			Objective measure – mins/day (derived)
st_weekend	sedentary time (mins/day) - weekend(sr)			Self-reported – based on average weekday
st_work	sedentary time (mins/day) – at work(sr)			Self-reported – based on average workday
st_worktime100	sedentary time - worktime(100)			Objective measure – mins/day
st_worktime150	sedentary time - worktime(150)			Objective measure – mins/day
st_worktime35	sedentary time - worktime(35)			Objective measure – mins/day (derived)
st_worktime50	sedentary time - worktime(50)			Objective measure – mins/day
waist	waist circumference value			Valid mean waist (cm) from two measurements; a raised waist circumference has been taken to be greater than 102cm in men and greater than 88cm in women

Appendix 13 **State distribution graphs for cardiometabolic markers and other health-related outcomes**