Novel Sedentary Behaviour Measurement Methods: Application for Self-Monitoring in Adults

By

James Patrick Sanders

Doctoral Thesis

Submitted in partial fulfilment of the requirements for the award of Doctor of Philosophy of Loughborough University

Date September 2016

Abstract

With the introduction of the technological age, increasing mechanisation has led to labour saving devices which have all-but engineered physical activity out of our lives and sedentary behaviour has now become the default behaviour during waking hours. Interventions that previously focused on improving levels of physical activity are now attempting to concurrently increase levels of physical activity and decrease time spent in sedentary behaviour. One method that has shown promise in interventions to increase physical activity and healthy eating in adults is the behaviour change technique of self-monitoring. There is now a robust set of literature indicating self-monitoring as the most promising behaviour change technique in this area. Self-monitoring is tied inherently into the recent rise in wearable technology. These new devices have the ability to track a variety of behavioural and physiological parameters and immediately make the information returnable to the user via connected mobile applications. The potential pervasive nature of these technologies and their use of robust behaviour change techniques could make them a useful tool in interventions to reduce sedentary behaviour. Therefore the overall purpose of this three study dissertation was to identify and validate technology that can self-monitor sedentary behaviour and to determine its feasibility in reducing sedentary behaviour.

Study 1

Purpose: The aim of this study was to review the characteristics and measurement properties of currently available self-monitoring devices for sedentary behaviour and/or physical activity. **Methods:** To identify technologies, four scientific databases were systematically searched using key terms related to behaviour, measurement, and population. Articles published through October 2015 were identified. To identify technologies from the consumer electronic sector, systematic searches of three Internet search engines were also performed through to October 1st, 2015. **Results:** The initial database searches identified 46 devices and the Internet search engines identified 100 devices yielding a total of 146 technologies. Of these, 64 were further removed because they were currently unavailable for purchase or there was no evidence that they were designed for, had been used in, or could readily be modified for self-monitoring purposes. The remaining 82 technologies were included in this review (73 devices self-monitored physical activity, 9 devices self-monitored sedentary time). Of the 82 devices included, this review identified no published articles in which these devices were used for the purpose of self-monitoring physical activity and/or sedentary behaviour; however, a number of technologies were found via Internet searches that matched the criteria for self-monitoring and provided immediate feedback on physical activity (ActiGraph Link, Microsoft Band, and Garmin Vivofit) and sedentary behaviour (activPAL VT, the LumoBack, and Darma). **Conclusions:** There are a large number of devices that self-monitor physical activity; however, there is a greater need for the development of tools to self-monitor sedentary time. The novelty of these devices means they have yet to be used in behaviour change interventions, although the growing field of wearable technology may facilitate this to change.

Study 2

Purpose: The aim of this study was to examine the criterion and convergent validity of the LumoBack as a measure of sedentary behaviour compared to direct observation, the ActiGraph wGT3X+ and the activPAL under laboratory and free-living conditions in a sample of healthy adults. **Methods:** In the laboratory experiment, 34 participants wore a LumoBack, ActiGraph and activPAL monitor and were put through seven different sitting conditions. In the free-living experiment, a sub-sample of 12 participants wore the LumoBack, ActiGraph and activPAL monitor for seven days. Validity were assessed using Bland-Altman plots, mean absolute percentage error (MAPE), and intraclass correlation coefficient (ICC). T-test and Repeated Measures Analysis of Variance were also used to determine any significant difference in measured behaviours. **Results:** In the laboratory setting, the LumoBack had a mean bias of 76.2, 72.1 and -92.3 seconds when compared to direct observation, ActiGraph and activPAL, respectively, whilst MAPE was less than 4%. Furthermore, the ICC was 0.82 compared to the ActiGraph and 0.73 compared to the activPAL. In the free-living experiment, mean bias was -4.64, 8.90 and 2.34 seconds when compared to the activPAL for sedentary behaviour, standing time and stepping time respectively. Mean bias was -38.44 minutes when compared to the ActiGraph for sedentary time. MAPE for all behaviours were <9%, and the ICC were all >0.75. **Conclusion:** The LumoBack has acceptable validity and reliability as a measure of sedentary behaviour.

Study 3

Purpose: The aim of this study was to explore the use of the LumoBack as a behaviour change tool to reduce sedentary behaviour in adults. **Methods:** Forty-two participants (≥25 years) who had an iPhone 4S or later model wore the LumoBack without any feedback for one week for baseline measures of behaviour. Participants then wore the LumoBack for a further five weeks whilst receiving feedback on sedentary behaviour via a sedentary vibration from the device and feedback on the mobile application. Sedentary behaviour, standing time, and stepping time were objectively assessed using the LumoBack. Differences in behaviour were determined between baseline, week 1 and week 5. Participant engagement with the LumoBack was determined using Mobile app analytics software. **Results:** There were no statistically significant differences in behaviour between baseline and the LumoBack intervention period ($p>0.05$). Participants engaged most with the Steps card on the LumoBack app with peaks in engagement seen at week 5. **Conclusion:** This study indicates that using the LumoBack on its own was not effective in reducing sedentary behaviour in adults. Self-monitoring and feedback may need to be combined with other behaviour change strategies such as environmental restructuring to be effective.

General Conclusion

This thesis found that there are currently an abundance of technologies which self-monitors physical activity but a lack of devices which measuring sedentary behaviour. One such device, the LumoBack, has shown to have acceptable validity as a measure of sedentary behaviour. Whilst the use of the LumoBack as a behaviour change tool did not elicit any significant changes, its ability to be a pervasive behavioural intervention and the use of user-defined nudging can make the LumoBack, and other similar low cost, valid objective sedentary behaviour self-monitors key components in multi-faceted interventions.

Dedication

This dissertation is dedicated to Eileen and Jess, the two people without which I wouldn't have been able to achieve this. To Eileen, you raised me into the man I am today (not sure you will want to take credit for that :P), you have always been there to help me along, in any way that I needed, and there is no way that I can ever repay you for that. Jess, where to even begin? Without you I wouldn't have been able to get through the PhD, let alone those last trying months. Your love and support, your ability to always calm me down, your capacity to always think of others before yourself and your unrelenting encouragement to help me continue on when I didn't think I could, are what has gotten me through this thesis. Every day with you is an absolute pleasure. Like the Claddagh ring I once gave you, you will always have my Love, Loyalty and Friendship.

I love you both very much.

Acknowledgements

Firstly, to Dr Dale Esliger, for initialling seeing something in me that was worth taking a chance on. And secondly, for your tireless advice and ideas throughout the PhD. At times, I’m sure you felt like your office was a train station, or that your office door was more like a revolving one, but I will forever be grateful for your support. For also allowing me to follow interests outside of academia, like attending UEFA Champion League football matches (and being paid to do so). Your triumvirate approach to supervision to offer opportunities in research, teaching and enterprise has led me to discover interests I wasn't aware I had and to develop long standing career ambitions. I hope that we can work together in the future on our mutual interests in enterprise. Thank you.

To Professor Stuart Biddle, many thanks for helping to start this whole thing off. You honesty, knowledge and inspiration during the Master’s to lead to a PhD are things I will always be grateful for.

To Dr Lauren Sherar, you may have only become my supervisor during my final year, but your willingness to always offer up a helpful suggestion (particularly in our Friday group meetings in the pub) for the entirety of my PhD experience, is something that I will be indebted to you for. Additionally, once you became my formal supervisor, for making sure that mine and Dale’s imaginations didn't run away from us and keeping us tethered to the here and now.

To all the Loughborough gang (Vero, Carl, Yoyo, KJ, Louisa, Sam, Maedeh, Emily, Jose, Moss, Tom Rebecca, and of course Mavis), thank you for the stress relieving pub trips, the intellectual debate (“What would you do in a Zombie apocalypse?”) and those well-co-ordinated Christmas Meals. A special mention has to go to Adam, we started the Master’s together, and we started the PhD together, thanks for always offering a listening ear to the issues of the PhD, despite your constant blinkers surrounding Tom Cleverly and Danny Welbeck’s concentric circle running – and if we do hire a barge the mooring better be tenable – I don't want any Geese sketching me out.

To the rest of you (Sarah, Alex B, Steve, Dave, Fran, Ross, Chris, Ferg, Alex O, Alex W and Billy), your constant banter and friendship has given me something to always look forward too during the PhD.

To Clare and Andre, your example of hard work and determination was and always will be contagious.

And finally to my family, warm thanks must go to you guys for your continued and unending support during these last 4 years.

J.P.S

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List of Abbreviations

@	At
?	Unknown
ANOVA	Analysis of Variance
API	Application Programming Interface
BLE	Bluetooth Low Energy
BMI	Body Mass Index
CE	Consumer Electronic
cm	Centimetres
CPM	Counts per minute
g	Grams
GPS	Global Positioning System
HDL	High Density Lipoprotein
HR	Heart Rate
Hz	Hertz
ICC	Intra-Class Correlations
IDEEA	Intelligent Device for Energy Expenditure Assessment
IPAQ	International Physical Activity Questionnaire
kg	Kilograms
kg/m^2	Kilogram per metre squared
LCD	Liquid Crystal Display
LDL	Low Density Lipoprotein
LED	Light Emitting Diode
m	Metres
MAPE	Mean Absolute Percentage Error
METS	Metabolic Equivalents
min	Minutes
Mmol/l	Millimoles per litre
mmHg	Millimetres of Mercury
MVPA	Moderate to vigorous physical activity
n	Sample Size
NHANES	National Health and Nutrition Examination Survey
NHS	National Health Service
P	P-Value
POC	Point-of-Care
RCT	Randomised Controlled Trial

RR	Relative Risk
SD	Standard Deviation
SDK	Software Development Kit
SE	Standard Error
SpO2	Arterial Blood Oxygen Saturation
SPSS	Statistical Packages for Social Sciences
TV	Television
USB	Universal Serial Bus
$\mathbf{Y_{PA}}$	Yes – Physical Activity
$\mathbf{Y_{PI}}$	Yes – Physical Inactivity
$\mathbf{Y_{SB}}$	Yes – Sedentary Behaviour

Chapter 1 - Introduction

Physical activity has a long standing and established beneficial relationship with health. Indeed, increasing levels of physical activity has been shown to have a beneficial relationship with a number of non-communicable health related outcomes (1–3) including all-cause mortality (4), coronary heart disease (5), high blood pressure, stroke (6), type 2 diabetes (7), metabolic syndrome (8), certain site-specific cancers (9–11), and depression (12,13) with even small increases in physical activity having beneficial effects on health (14). In spite of the large evidence base supporting the health benefits of physical activity, population levels of physical activity are low (15). Moreover, the prevalence of sufficient physical activity is slow to improve and is worsening in some countries (16). According to the World Health Organisation, approximately 3.2 million deaths each year are attributable to insufficient physical activity and recent estimates suggest that the cost of physical inactivity to health-care systems was (international) $53.8 billion worldwide in 2013, of which $31.2 billion was paid by the public sector (17). Furthermore, objective data using accelerometers suggests there is low compliance with guideline fulfilling physical activity (e.g. 150 minutes of moderate to vigorous physical activity [MVPA] per week (18)), at around five percent in British (19) and American adults (20), and approximately 15% in Canadian adults (21,22).

The current levels of physical inactivity are partly related to insufficient participation in physical activity due to reduced amounts of leisure time physical activity and partly related to increases in sedentary behaviours during occupational and domestic activities (23). Increasing automation at work and travel combined with more attractive sedentary options for leisure time is engineering physical activity out of daily life and reducing physical activity levels (24). Therefore, the nature in which we execute aspects of our daily lives have changed in no small part due to these advancements in technology (25), which, in turn, has led to substantial reductions in the demands for physical activity (26). Consequently, this transition has led to increases in a distinct but related health related behaviour – sedentary behaviour.

Sedentary behaviour is a prominent, insidious behaviour, which has been linked to deleterious effects on cardio-metabolic biomarkers associated with an array of non-communicable diseases, independent of MVPA, including type 2 diabetes (27), cardiovascular disease (28,29) and some site-specific cancers (30). Combine this with large segments of the day now being spent in sedentary behaviours (31) accurate and objective exposure measurement is essential to identify causal associations with health outcomes, to quantify precisely the magnitude of these associations and to describe dose-response relationships. Moreover, accurate measurement is required to document patterns of, and changes in, sedentary behaviour between and within individuals over time (32,33). This is currently conducted effectively in the physical activity portion of the movement continuum (a model used to conceptualise the part sedentary behaviour plays as a distinct behaviour in our daily physical activity. Theorising sedentary behaviour as distinct from a lack of physical activity is important due to the unique nature of sedentary behaviour), however, it is less well conducted at the sedentary behaviour segment of the continuum.

With sedentary behaviour now being seen as a distinct risk factor for health (28), it has necessitated a paradigm shift in the way interventions are conducted. Previously, interventions targeted increasing physical activity or reducing sedentary behaviour; however, interventions are now targeted at concurrently decreasing the amount of time spent in sedentary pursuits as well as increasing levels of physical activity (34,35). Whilst interventions to reduce sedentary behaviour have used a variety of methodologies, from educational programmes (36) to environmental restructuring (traditionally via sit-stand desks in office-based workers (37–40)), one method of decreasing sedentary behaviour, which is particularly promising is utilising the behaviour change technique of self-monitoring (41). Self-monitoring has a growing base of consistent evidence demonstrating its beneficial effect, when in conjunction with other self-regulatory behaviour change techniques, on levels of physical activity and healthy eating (42). Furthermore, a recent systematic review has found self-monitoring to be a particularly promising intervention modality for reducing sedentary behaviour in adults (41). Consequently, its use as a modality for inducing beneficial changes on sedentary behaviour warrants further investigation.

Current research grade measurement technologies do not have the ability to readily self-monitor and provide feedback on sedentary behaviour, however, there are a plethora of new commercially available technologies, which can measure (with varying levels of accuracy) a number of both behavioural parameters, most prominent of which is step tracking, distance travelled and estimated caloric expenditure, and physiological parameters, such as heart rate and breathing rate. Furthermore, these consumer trackers have a mobile application (mobile app) associated with them, which are used for self-monitoring, providing feedback, goal-setting and monitoring of progression towards goals. Moreover, mobile phones and smart tablets are now a pervasive accessory to a majority of individuals and consumer trackers are a fast and rapidly growing area of consumer electronics. Traditionally, these consumer activity tracker measure areas related to physical activity; however, as already alluded to, sedentary behaviour is the dominant daily behaviour; it is, therefore, worthy to investigate whether these devices can be an appropriate intervention tool to decrease levels of sedentary behaviour.

1.2 General Aim

Therefore the aim of this thesis is to identify and validate technology that can self-monitor sedentary behaviour and to determine its ability to reduce sedentary behaviour.

Chapter 2 – Literature Review

2.1 Sedentary Behaviour

Sedentary behaviour (from the Latin ‘sedere’ which means ‘to sit’) is defined as any waking behaviour characterized by an energy expenditure ≤1.5 METs (Metabolic Equivalent and is equal to 3.5ml/kg/minute of oxygen consumption) while in a sitting or reclining posture (43,44). Therefore, sedentary behaviour would not include active sitting behaviours such as riding a bike, since it involves an energy expenditure of over 1.5 METs. Sedentary behaviour has been previously conceptualised as reflecting the low end of the physical activity continuum (i.e. being physically inactive). However, physical inactivity is now defined as an individual who does not meet physical activity guidelines (e.g. in adults not meeting 150 minutes of MVPA per week in bouts of 10 minutes or more (18) would be defined as inactive). Evidence is now suggesting that sedentary behaviour has quantitatively different effects on human metabolism and health outcomes (44–48), with these effects largely occurring independent of MVPA (28).

The movement continuum, (49) illustrated in Figure 2.1, helps to conceptualise the part sedentary behaviour plays in our daily physical activity, theorising sedentary behaviour as distinct from a lack of physical activity is important due to the unique nature of sedentary behaviour. Approaches needed to reduce sedentary behaviour may be different to those designed to increase physical activity. For example, Prince et al (35) in a meta-analysis of the effectiveness of controlled interventions with a focus on physical activity and/or sedentary behaviour for reducing time spent sedentary in adults, found consistent evidence that large meaningful reductions in time spent sedentary can be expected from interventions with a focus on reducing sedentary behaviour. Those interventions with a physical activity or a combined physical activity and sedentary behaviour component produced less consistent findings and generally resulted in modest reductions in sedentary time than sedentary behaviour intervention in isolation (35). Given that the majority of interventions included in the systematic review focused on increasing physical activity (e.g. increasing MVPA) and reductions in sedentary behaviour were a secondary outcome, there is a scientific rationale for why this might be occurring. A systematic review conducted by Mansoubi and colleagues (50) showed that, in studies conducted using objectively measured sedentary time and physical activity, there were small to medium inverse associations between sedentary time and MVPA and medium to large inverse associations between sedentary time and light intensity physical activity (50). Given that light physical activity typically involves standing and light ambulation; these incidental behaviours tend to be more prevalent when an individual is not sedentary, as opposed to moderate to vigorously active, which is likely to occur through more structured activity in adults. (50).

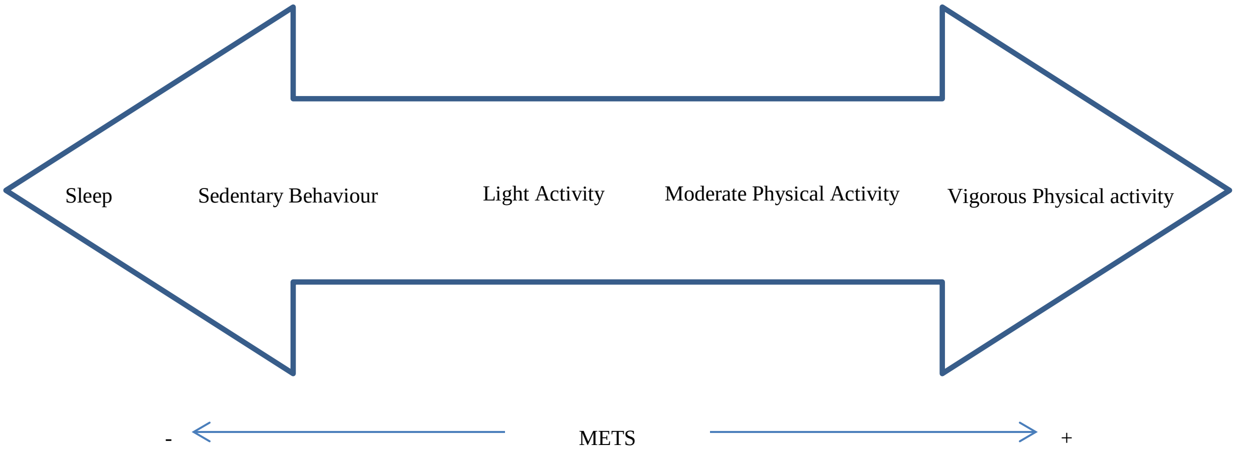


Figure 2.1 - The Movement Continuum, illustrating the different aspects of physical behaviours throughout the day. Adapted from Tremblay et al (2010)

2.2 Prevalence of Sedentary Behaviour

Sedentary behaviours are a ubiquitous component of modern society. This has been exemplified in a study analysing five decades of energy expenditure data from the U.S. Bureau of Labor Statistics which found a steady shift towards more sedentary occupations since 1960 in the USA (51). The use of sophisticated physical activity monitors (that provides, valid and reliable, duration, amount, frequency and time of data on sedentary and activity time) in population-based studies has provided insights into how adults spend their day, and more specifically, the large contribution that sedentary behaviour makes to overall waking hours (52). For example, analysis of accelerometer data from over 600 participants (aged >20 years) in the 2003-2006 US National Health Nutrition Examination Survey (NHANES) found that mean accelerometer-derived sedentary time across 10 year age categories ranged between 7.3 and 9.3 h/day, with older adults generally the most sedentary (31). In proportional terms, it can be estimated that 60-70% of adults total waking hours are spent sedentary (31,48). In contrast, MVPA accounted for only 5% of the total time across the sample, with the remainder being spent in light intensity physical activity (20). Further epidemiological data, using objective methods of measurement indicated that adults spend approximately 55-70% of their waking hours engaged in sedentary time (21,31,48,53), with one study reporting greater than 9 hours per day, on average, spent sedentary (54). However, these population studies have traditionally utilised accelerometers as their measurement modality, which measure inactivity rather than posture. More recently, The Maastricht Study (55), measured the physical activity and sedentary behaviour levels of 2,449 participants between the ages 40-75 years using the activPAL (PAL technologies ltd, Glasgow, UK). This study revealed that participants spent between 58.7-63.0% of their day sitting and lying, providing similar prevalence levels to studies utilising accelerometers.

Looking to the future, a study by Ng and Popkin (56) assessed time-use in physical activity and sedentary behaviour using detailed historical self-report data from 1965-2005 and used this to interpolate to 2020 and 2030. The results from their forecast suggest that time spent in leisure sedentary pursuits will increase to over 51 hour/week by 2030 (56). Given the high prevalence of this behaviour it is important to understand its relationship with health.

2.3 Sedentary Behaviour and Health Outcomes

While this is a relatively new area of health-behaviour research, compared to research investigating the effects of physical activity on health, the effects of prolonged sitting have been observed since the 1950's. Jerry Morris' London bus drivers and conductors study demonstrated that there was a two-fold increase in the risk of myocardial infarction in the sedentary bus drivers compared to their active conductor colleagues (57). Since its emergences as a distinct risk factor for chronic disease, there has been an increasing body of research describing the effect of sedentary behaviour on health outcomes in adults (58).

Thorp and colleagues (59) systematically reviewed longitudinal studies (since 1996) reporting the relationship between self-reported sedentary behaviour and device-based measures of sedentary time with health-related outcomes in adults 18 years and older. The review identified 48 longitudinal studies; of these, 46 incorporated self-reported measures of total sitting time; TV viewing time only; TV viewing time and other screen-time behaviours; and TV viewing time plus other sedentary behaviours. The findings from this review indicated a consistent relationship of self-reported sedentary behaviour with mortality and with weight gain from childhood to the adult years. However, mixed findings were observed for associations with disease incidence, weight gain during adulthood, and cardio-metabolic risk. Of the three studies that used device based/objective measures of sedentary time, one study showed that markers of obesity predicted sedentary time whereas inconclusive findings have been observed for markers of insulin resistance (59), with similar findings being reported by Proper and colleagues (60) when systematically reviewing the literature on the relationship between sedentary behaviours and health outcomes.

Moreover, a systematic review and meta-analysis examining the association between sedentary behaviour and diabetes, cardiovascular disease and cardiovascular and all-cause mortality found eighteen studies (16 prospective, two cross-sectional; all self-reported sedentary behaviour). When comparing the greatest time spent sedentary to the lowest, there was a 112% increase in the relative risk (RR) of diabetes (RR: 2.12; 95%CI: 1.61, 2.78), a 147% increase in the RR of cardiovascular events (RR: 2.47; 95% CI: 1.44, 4.24), a 90% increase in the risk of cardiovascular mortality (RR: 1.90; 95% CI: 1.36, 2.66) and a 49% increase in the risk of all-cause mortality (RR: 1.49; 95% CI: 1.14, 2.03). The effects reported were largely independent of MVPA, suggesting that the deleterious effects of higher levels of sedentary behaviour are not mediated through lower amounts of MVPA (28). Furthermore, an update of this systematic review published by Bauman and colleagues (29) corroborated these results and found that there is moderately consistent evidence for an association between total sitting time and all-cause mortality, even when adjusted for or stratified by self-reported leisure time physical activity (29). More recently, Biswas and colleagues (61) conducted a systematic review and meta-analysis to quantify the association between sedentary time and hospitalisations, all-cause mortality, cardiovascular disease, diabetes and cancer in adults independent of physical activity. The review found 47 articles (44 prospective designs, 46 self-reported). Significant associations were found with all-cause mortality (HR, 1.240 [95% CI,1.090 to 1.410]), cardiovascular disease mortality (HR, 1.179 [CI, 1.106 to 1.257]), cardiovascular disease incidence (HR, 1.143 [CI, 1.002 to 1.729]), cancer mortality (HR, 1.173 [CI, 1.108 to 1.242]), cancer incidence (HR, 1.130 [CI, 1.053 to 1.213]), and type 2 diabetes incidence (HR, 1.910 [CI, 1.642 to 2.222]). Despite the marked heterogeneity in the research designs and the assessment of physical activity and sedentary time, the authors concluded that prolonged sedentary time was independently associated with deleterious health outcomes regardless of physical activity (61).

Further research has been published on the relationship between high levels of sedentary behaviour and all-cause mortality. A meta-analysis looking only at the association between all-cause mortality and daily total sitting, it was reported that each hour of daily sitting is associated with an overall 2% increased risk of all-cause mortality. However, this relationship was nonlinear, with a 5% increased risk for each one-hour increment for adults sitting >7 hours/day and dose response modelling suggesting a 34% higher mortality risk in adults sitting 10 hours/day, after taking levels of physical activity into account. The authors also calculated an overall weighted population attributable fraction (the proportional reduction in population disease or mortality that would occur if exposure to a risk factor were reduced to an alternative ideal exposure scenario) for all-cause mortality for total daily sitting time of 4.9%, after adjustment for physical activity (62). The results from these studies show increasing evidence of the detrimental effect of sedentary behaviour on all-cause mortality.

Theoretically, prolonged sedentary behaviour should be related to a reduction in total energy expenditure, and hence might contribute to weight gain due to the energy imbalance. A number of cross-sectional (63–66) and large cohort (67–69) studies have shown significant increases in weight among those at the highest levels of sedentary behaviours. However, a more recent longitudinal study has shown a mixed pattern, suggesting that obesity was associated with subsequent sedentary behaviour, but that sitting did not show a prospective association with weight gain (70). Furthermore, a review into whether dietary intake is associated with sedentary behaviour in adults, indicated that there is a clear small-to-moderate association with elements of a less healthy diet including lower fruit and vegetable consumption; higher consumption of energy-dense snacks, drinks and fast-foods; and higher total energy intake and sedentary behaviour (largely self-report measurement of TV viewing) (71), which may further contribute to the energy imbalance and subsequent weight gain.

Sedentary behaviour has also been shown to have a relationship with various site specific cancers. A review of 18 articles evaluating the research on sedentary behaviour and cancer found a statistically significant, positive association with colorectal, endometrial, ovarian and prostate cancer risk (30). The review of the literature further comments on the potential biological pathways by which sedentary behaviour may influence site-specific cancer risk. It hypothesizes the role of adiposity and metabolic dysfunction as mechanisms operant in the association between sedentary behaviour and cancer.

Research is further increasing concerning the possible links between sedentary behaviour and indices of psychological well-being. Typically, in addition to depression and cognitive function, these associations include generic measures of well-being, such as health-related quality of life. Teychenne and colleagues (13) conducted a systematic review on depression and sedentary behaviour in adults. Seven observational (five cross-sectional and two longitudinal) and four intervention studies were included. Of the observational studies, six out of the seven studies showed a positive association between sedentary behaviour and depression, showing that higher sedentary behaviour was associated with greater depression. The one of the seven observational studies also showed similar findings for time spent surfing the internet, but reported negative associations for depression with hours spent emailing and using chat rooms. This suggests that the type of sedentary behaviour may be an important moderator of any association between sedentary behaviour and depression (13).

A recent harmonised meta-analysis of data from more than 1 million men and women as part of the Lancet Physical Activity series however, found that high levels of physical activity (35.5 MET-h per week or approx. 60-75 of moderate intensity physical activity per day) seem to eliminate the increased risk of death associated with high sitting time (72). While this amount of physical activity is beyond the level of most physical activity recommendation, 60-75 minutes of moderate intensity physical activity is congruent with the level of physical activity showing maximum mortality benefit in a large meta-analysis (73). That said, large scale nationwide surveillance studies have indicated that small amounts of the population are meeting national physical activity guidelines (e.g. 4% women and 6% men meeting physical activity guidelines in England (19)) so using 60-75 minutes of moderate intensity physical activity per day as a public health message should be treated with caution.

The majority of the evidence to date has focused on the link between total sedentary time and/or individual sedentary behaviours, in particular TV viewing, and health. However, emerging evidence is suggesting that the nature in which sedentary behaviour is accumulated may also be important. For example, it might be informative to know if periods of sitting are prolonged or whether they take place in a more sporadic form. Healy et al. (74) found that objectively assessed breaks in sedentary time were beneficially associated with waist circumference, BMI, triglycerides and 2-h plasma glucose, and these associations were independent of total sedentary time and MVPA (74). Similarly, Henson et al. (75), in a study of adults at risk of diabetes found that breaks in sedentary time were inversely associated with measures of adiposity but no other cardio-metabolic outcomes. Increasing the number of breaks from sedentary time may be important for health, independent of total sedentary time (75). Furthermore, a recent systematic review and meta-analysis aimed at investigating the relationship between breaks in sedentary time and cardio-metabolic health (13 studies included – seven observations [all objectively measured – six ActiGraph, one Actical], six experimental) found that breaks in sedentary time of at least light intensity physical activity may have a positive effect on glycaemia but not on lipidemia in adults. The results from this review suggests that breaking prolonged sitting with light intensity physical activity breaks may be adequate for counteracting some acute detrimental effects of sedentary behaviour on cardio-metabolic health. In contrast, the evidence from observational studies involved in this review tends to suggest that there is no detrimental association of prolonged sitting on these same cardio-metabolic health markers. Furthermore, the observational studies found consistent associations were not found between breaks in sedentary behaviour and any of the cardio-metabolic markers other than with BMI (76). From this overview, there appears to be a growing wealth of evidence correlating prolonged sedentary behaviour with detrimental cardio-metabolic health markers, it is important therefore to have an understanding of what physiologically might be occurring to cause these detrimental cardio-metabolic effects.

2.4 Physiology of Sedentary Behaviour

There is increasing evidence surrounding the physiological mechanism underpinning the reasoning for sedentary behaviour being detrimental to one's health. The current theory on sedentary behaviour physiology posits that the unloading of large skeletal muscles in the back, trunk and legs associated with sitting is thought to lead to a cascade of events, which consequently leads to metabolic deregulation (46). The biological plausibility for sitting and poor health outcomes has come from two key areas of research: bed rest studies in healthy human participants (77–86) and hind limb suspension in rats (45–47).

Bed rest studies have consistently found that prolonged muscle inactivity (1-3 weeks) incurs a series of pathophysiological responses, including glucose intolerance and impaired lipid metabolism (77). Although, the physiological mechanisms remain unclear, analysis of skeletal muscle that have been biopsied pre and post exposure to prolonged sedentariness suggest a down regulation of key enzymes involved in glucose and lipid metabolism (29), in particular a reduced activity of GLUT4 [a glucose transporter (87,88)] and lipoprotein lipase [LPL – an enzyme that facilitates the uptake of free-fatty acids into skeletal muscle and adipose tissue (45,46)]. For example, studies in rats that have been immobilised (and not allowed to stand or ambulate) have shown a 22% decrease in plasma HDL cholesterol (so called 'good cholesterol' they act as cholesterol scavengers, picking up excess cholesterol in the blood stream and taking it to the liver where it is broken down. i.e. increased HDL = decreased "bad" cholesterol) on the first day of immobilisation. Furthermore, the rats' quadriceps (used in postural support) lost more than 75% of their ability to siphon off the fat circulating in the lipoproteins from the bloodstream when incidental activity was reduced (47). One important factor to consider is that these studies involving bed rest and rodent models involved a large amount of unbroken time spent sedentary, far more than might be spent by healthy free-living adults, and therefore, these findings might not be wholly generalisable to human physiology (29,77); however, it has been suggested that it may be a helpful short-term model to investigate the effects of sedentary living (78).

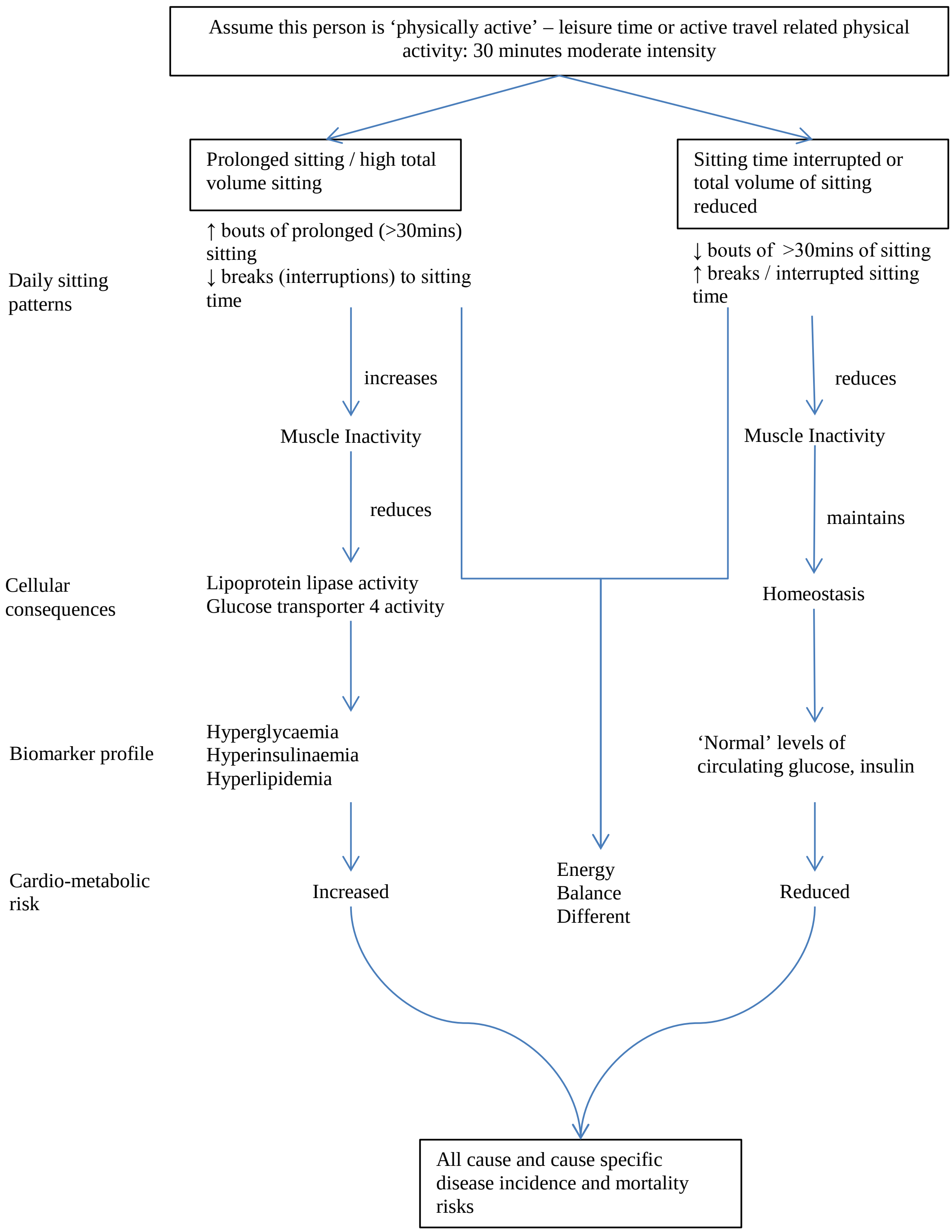


Figure 2.2 - Theoretical model linking sedentary behaviour and health risks even in the presence of sufficient physical activity. Adapted from Bauman et al (2013)

Figure 2.2 provides a theoretical model of how these physiological effects of decreasing/breaking up sitting time may happen even in the presence of meeting physical activity guidelines. As Figure 2.2 shows, sedentary behaviour increases muscle inactivity, which in turn leads to a deregulation in lipoprotein lipase activity and GLUT 4 activity leading to the biomarker profile of hyperglycaemia, hyperinsulinaemia and hyperlipidemia.

As previously seen an increase in sedentary behaviour has been seen to increase the risk of weight gain or obesity. A study in adults conducted under the following conditions: 1) An active, no-sitting condition (energy intake matched to expenditure), 2) Low energy expenditure (sitting), with no reduction in energy intake (energy surplus) and; 3) Sitting with energy intake reduced to match low expenditure (energy balance), measured ghrelin (the so called appetite stimulating hormone) and leptin following a meal, and found ghrelin was lower in the sitting group compared to the standing group, with no change in appetite. When intake was reduced (i.e., the sitting but energy balanced group), the decrease in ghrelin when sitting was attenuated, hunger increased, and fullness decreased. Sitting but in energy balance led to an increase in ghrelin in the men but attenuated the leptin (the “satiety hormone,” used to help regulate energy balance by inhibiting hunger) response, reduced ghrelin, increased hunger, and decreased fullness in the participants. This led to the conclusion by the authors that prolonged sitting may promote excess energy intake through a hormonal response, leading to weight gain (89).

Although there is some overlap in energy expenditure between sitting and standing activities, it is invariably true that standing activities have slightly higher energy expenditure than sitting activities. Indeed, when undertaking the same task, such as typing, standing will always have higher energy expenditure than sitting because of greater muscle activation, driven by posture controlling muscles (29,45,46,77). Therefore, it is plausible that over recent decades, the reduction in standing and light movement throughout daily living and occupational activities has contributed in some part to the modern obesity epidemic. It has been shown that the reduction in occupational energy expenditure over the last five decades directly maps onto the obesity epidemic in the United States (51). Others have also noted that the sales of energy-saving devices, which have helped facilitate increasing sedentary behaviour, correlated with increasing levels of obesity, whereas changes in energy intake do not (90). Even in today’s environment, differing occupational roles can have a substantial effect upon daily energy expenditure. For example, it has been hypothesised that compared with a highly sedentary deskbound worker, a waiter or hospital nurse could expend up to 800 kcal/day more (91). Even a fairly modest increase in energy expenditure of 200 kcal/day would equate to over 4kg of weight loss over the course of a year; assuming an unchanged energy intake [based on a 90kg man (92)].

More recently, experimental studies have begun to look at the acute physiological effects of sedentary behaviour in adults. One such study investigated the effects of 1 day sitting (17houts/day objectively assessed) on whole body insulin sensitivity with a strict diet. Fourteen young non-obese fit men and women completed three 24-hour conditions:

1) An active, no-sitting condition (energy intake matched to expenditure).
2) Low energy expenditure (sitting), with no reduction in energy intake (energy surplus).
3) Sitting with energy intake reduced to match low expenditure (energy balance).

Their findings showed that an acute bout of prolonged sitting resulted in a 31% reduction in insulin sensitivity. These findings were attenuated when participants undertook their subsequent experimental condition in which sitting was reduced and displaced with walking and standing (93). However, reducing energy intake to match energy expenditure during a prolonged bout of sedentary behaviour reduced the deleterious impact on insulin sensitivity by roughly 50%.

As previously stated, the breaking up of sedentary behaviour has been shown to reduce the prolonged effects of sitting on cardio-metabolic health. Research into the physiological advantages of breaking up sitting time is now growing with studies showing that breaks in sedentary behaviour has beneficial cardio-metabolic effects. Dunstan et al. (58) examined the acute cardio-metabolic effects of breaking up sedentary behaviour; 19 middle-aged overweight and obese adults undertook 3 experimental conditions:

1) Uninterrupted sitting (approximately 7 hours)
2) Sitting interrupted with light-intensity walking every 20 minutes
3) Sitting interrupted with moderate intensity walking every 20 minutes.

Compared with uninterrupted sitting, plasma glucose was reduced by 23% in activity break conditions. Of note, there were no significant differences in plasma glucose between the light and moderate intensity conditions (58). These findings were corroborated in another small randomised controlled cross-over study (94). This study, conducted in healthy, normal weight adults, compared the effects of prolonged sitting (9 hours), continuous physical activity combined with prolonged sitting (1 × 30 minutes bout of walking) and regular light intensity walking breaks on postprandial metabolism (walking for 1 minute 40 seconds every 30 minutes). The results showed that regular activity breaks (with a 39% reduction in the glucose area under the postprandial curve) were more effective than continuous physical activity at decreasing postprandial glycaemia levels (94). This points to the added value of breaking up sedentary behaviour regularly throughout the day, rather than in a single bout, which has also been noted in other experimental (95) and epidemiological (74,75,96) studies. Further evidence suggests that increased standing, without walking, may have a significant effect on metabolic health. A randomised controlled trial examined the effect of 30 minute bouts of sitting and standing through the provision of sit-stand desks compared with prolonged sitting, on metabolic health in overweight/obese office workers during an 8-h working day. The glucose area under the postprandial curve was 11% lower in the sit-stand desk condition, although the difference in insulin failed to reach significance (97). This is consistent with a nonrandomised office-based study that found that glucose levels were reduced by 43% following an afternoon of standing compared with seated computer work (98). However, not all standing-based studies have yielded significant results, particularly in healthy, young adults (99,100).

Saunders and colleagues (86) attempted to systematically review interventions which have examined the impact of uninterrupted sedentary behaviour lasting <7 days (operationally defined as an "acute" bout) on insulin sensitivity, glucose tolerance and lipid, glucose and insulin levels in adults (86). The results indicated moderate quality evidence suggesting the acute bouts of uninterrupted sedentary behaviour lasting 2 hours to 7 days results in rapid and deleterious change in triglyceride levels, insulin sensitivity, and glucose tolerance. However, of the 29 articles found, 21 were bed rest studies and all except one of the 29 studies had a study duration of less than a day. Despite the fact that prolonged period of bed rest are not generalisable to everyday life, the metabolic impact of prolonged bed rest has received more attention than the metabolic impact of prolonged sitting. Furthermore it is unclear whether prolonged sitting and prolonged bed rest have a comparable impact on markers of cardio-metabolic risk (86).

Breaks in sedentary time have further been examined in relation to a number of other physiological outcomes including C-reactive protein (inflammatory marker associated with increased risk of several major diseases, including coronary heart disease and vascular mortality (101,102). Inflammation may be an adjunct pathway, along with reduced muscular contractions, through which prolonged sedentary time may impact on cardiovascular disease risk, depressive symptoms and skeletal muscle gene expression (101,102).

More recently, a review of the prospective experimental studies regarding the beneficial effects of breaking up prolonged sitting time on cardiometabolic risk factors, found that breaking up sitting time and replacing it with light-intensity physical activity and standing may be a stimulus sufficient enough to induce acute favourable changes in the postprandial metabolic parameters in physically inactive and type 2 diabetic participants. The exact frequency, intensity and type of activity will differ according to different subject characteristics, especially with respect to subjects' habitual physical activity with more intense breaks needed for healthy samples (103).

Given these findings, it is highly likely that, accurate measurement and innovative solutions are needed to promote reduced sedentary behaviour, for the betterment of cardio-metabolic health.

2.5 Measurement of Sedentary Behaviour

Valid and objective measurement of sedentary behaviour is of vital importance to assess the interaction between sedentary behaviour and health outcomes, namely because of the inherent disadvantages associated with subjective forms of measurement, notably their moderate reliability and slight to moderate validity (104), and susceptibility to social desirability bias (105). Furthermore, objective measurements can be used to quantify precisely the magnitude of the association between behaviour and health, to describe dose-response relationships and to document patterns of, and changes in sedentary behaviour between individuals over time (104) allowing for causal associations with health outcomes to be recognised (32,106). However, the majority of the research on sedentary behaviour to date has largely used proxy or self-reported measures although an increasing number of researchers are using objective methods as they become more readily available. There are numerous methods used to measure sedentary behaviour. In order to avoid confusion, throughout this thesis sedentary time will be defined as measurement of time spent sedentary using accelerometers whilst traditionally using a cut-point of ≤100 count per minute (CPM) whereas sedentary behaviour will be used when measured using posture sensors and/or subjective self-reported assessments.

2.5.1 Subjective Measurement

Questionnaires are historically the most commonly reported method of capturing sedentary behaviour, the majority of which are self-administered, although in-person, telephone interviews and diaries have also been used (107,108). To date, the majority of studies using self-report measures have centred on capturing daily TV viewing time as a proxy marker of overall sedentary behaviour (107,108). Many of the questionnaires used to capture TV viewing time have not reported reliability and validity data. Those that provided data in adults, showed that reliability coefficient were generally fair to high (test-retest r=0.32-0.93), but concurrent validity was highly variable (r=0.19-0.80) (107). In addition, the measurement of TV viewing time as an indicator of total sedentary behaviour is challenging, as this behaviour does not appear to be representative of overall time spent in sedentary behaviour (109,110). Consequently, the interpretation of overall sedentary behaviour from the assessment of TV viewing to make inferences should be interpreted with caution.

Other self-report questionnaires have focused more on global measures of sedentary behaviour, such as total daily sitting time, but similarly, the measurement properties of many such instruments have not been adequately demonstrated (111). The international physical activity questionnaire (IPAQ) was designed to provide an internationally standardised method of measuring physical activity and sedentary behaviour in surveillance studies (112). The sedentary item in the IPAQ has been shown to have moderate reliability (Spearman p>0.7 for test –retest data) but poor to moderate convergent validity ([the extent of the agreement with another non-criterion measure that should assess the same physical activity or sedentary parameter based on face and content validity (113)] Spearman rho<0.5) when compared with objectively measured sedentary behaviour (112).

Recent work has attempted to develop more refined measurement tools that assess multiple sedentary behaviours (e.g. TV viewing, reading, socializing) and/or domain-specific behaviours (e.g. sitting at work or at home and motorized transport) (111,114,115). These show promise, but further development and validation work is required. One study reported that when compared with accelerometer-assessed sedentary time, a single-item question significantly underestimated sitting time, whereas a domain-specific questionnaire, with multiple items, more accurately assessed average sedentary behaviour (116). However, the single item questionnaire had preferential limits of agreement, demonstrating smaller measurement error (both random and systematic), possibly because of fewer responses required. This may suggest that more detailed questionnaires will be needed for sedentary behaviour prevalence and surveillance studies, whereas single item questionnaires may be more appropriate for health-related epidemiology research, where ease of use and the ability to rank behaviours of interest are the dominant requirements.

The methodologies (e.g. recall period vs questionnaire response format) and mode of administration (e.g. interviewer vs self-administer) of existing self-report instruments are particularly diverse. Assessment of test-retest results in adults does not clearly demonstrate that one recall period is superior to another (104). There is evidence, however, that concurrent validity (assessment of convergent or criterion validity when measures taken at same time (113)) may be better in adults when participants recall a typical day compared with a 7-day recall period. However, these observations originate from studies in different populations and use different referent measures (107). In addition, adults appear better able to recall sedentary behaviour for weekdays than weekends, perhaps because of greater capriciousness in behavioural configurations at the weekend (111,116).

The strengths of self-report questionnaires include being cost effective, readily accessible to the majority of the population and have a relatively low participant burden (104). Self-report tools can also be used to identify the type of behaviour and the context in which it occurs, information that may be used to inform intervention design. However, as technology continues to advance, global positioning systems when combined with accelerometry can determine where activity takes place outdoors (117), yet, as the majority of time is spent indoors (118,119), further technological developments such as Real Time Location Systems and Radio Frequency Identification can be used to provide objectively measured detailed data on the context (such as temporally patterned location information, which can be matched to objective measures of behaviour) in which behaviours occur indoors (120).

An important limitation of self-report measures is that they consistently demonstrate poor validity (104,107). A major obstacle to establishing validity is the absence of an accepted ‘gold standard’(i.e. most valid) reference measure of sedentary behaviour (106). The use of one form of self-report to validate another is inappropriate because of the problem of propagation of uncertainty, the hypothesis that the unique variances of the associated indicators overlap. In other words, the specific nature of the shared variables remains unknown when one self-report measure is used to validate another (104). A further limitation of self-report is that they are susceptible to influence by cultural norms and perceived social desirability (104,105) for example, accomplishing linguistic and conceptual consistency in the translation of self-report tools is problematic, restricting the comparability of data collected in different populations who have different cultural and linguistic customs. Given the significant limitations of using subjective methods of quantifying sedentary behaviour, more accurate and objective methods have been sought (104).

2.5.2 Objective Measurement of Sedentary Behaviour

The use of objective measurement methods to determine levels of sedentary behaviour may be a relatively new area, however, the objective measurement of sitting time can be traced back to the late 1960's. Bloom et al (121) used the 90^{o} angle change at the knee that occurs with changes in position between sitting and standing to design a gravity-activated switch. The switch, after several modifications, was reduced in size making it possible to place it in a normal watch mechanism, which was then placed inside a watchcase. Since the switch works by gravity, and the position of the watch on the leg varies from person to person, an adjustable watch holder was made. This holder was pivot anchored to the strap band; therefore, once the clock is placed above the knee, the clock may be rotated in its holder to be certain that it stops on sitting down and starts on standing. The watch would be wound each time it was worn and set at 12:00. At the end of data collection, the watch was removed and its time would be recorded. A reading of 5:15 would indicate five hours and fifteen minutes of standing. Participants were fitted with the watch and readings were taken for various periods of time (2-35 days; 85% completed 6 days or longer). Results from the study found that obese participants spent 15% less time each day on their feet. The obese participants also spent significantly more time in bed and sitting than their lean counter-parts (121). Whilst this is a rudimentary method of measuring sedentary behaviour by not providing strong data on the temporality or intensity of behaviour, the clear advantage of using objective measures of behaviour should be apparent. With the advancements of technology over the last five decades since the Bloom and Eidex study, there are currently more novel objective measures of sedentary behaviour becoming available.

2.5.2.1 - Pedometers

Pedometers are a well-known and well-used method of physical activity measurement and behaviour change. Traditionally, pedometers have a lever arm that moves with each stride; making electrical contact compressing a piezoelectric crystal, with the electrical impulse generated recorded as a step. Pedometers have been used, sparingly, as a proxy measure of a sedentary lifestyle, defined by Tudor-Locke and colleagues (122) as a pedometer step count below 5000 steps/day. However, there are a number of limitations with this method. Firstly, they fail to produce any information on the length of time spent sedentary. Secondly, an individual could be in a non-sedentary job (e.g. bar staff) and could stand for prolonged period of time without accruing 5000 steps a day. This could lead to a misconception as to whether an individual has a sedentary lifestyle or not (122). Therefore, this sedentary lifestyle index is more a measure of physical inactivity than sedentary behaviour, which is the main reason why pedometers have been used sparingly as a measure of sedentary behaviour.

2.5.2.2 - Accelerometer

Accelerometers are small lightweight technologies that are usually worn on an elasticated belt positioned on the hip or lower back, which measure the frequency and amplitude of acceleration at the body segment to which they are attached and often integrate this information in the form of movement 'counts' (123). They can be used to estimate the total amount of sedentary time through the accumulation of low movement counts at specified cut points. They can also be used to detect short incidental breaks in sedentary time, defined by periods where movement counts exceed the specified cut point threshold set for sedentary time, which may not be feasibly be recorded by self-report measures (74). In addition, as the collected information is time stamped, specific segments of the day or week can be extracted, such as time at work.

Key issues in the use of accelerometry for the assessment of sedentary behaviour is that they do not measure posture, they only estimate sedentary time though lack of movement counts. Other issues include device initialization, post-processing, signal feature extraction and inference of specific outcome variables (124). There is a lack of consensus as to the most appropriate accelerometer data-processing protocol, restricting the comparability between studies and obstructing evidence synthesis. Nevertheless, accelerometers are now being used to assess sedentary time in research studies.

Previously, it was necessary to specify the sampling frequency (epoch) during device initialization, but in newer accelerometer modes that record raw accelerometer data, the epoch is overlaid during post-processing. A significant effect of epoch length on accelerometer determined sedentary time has been reported, but findings are inconsistent and the most appropriate sampling frequency for determining sedentary time has yet to be established (125,126). In general, however, it is beneficial for researchers to collect data in as short an epoch as possible, as this provides information on exposure at the highest possible resolution. Furthermore, data collected in shorter epochs can be summed into longer epochs, facilitating the process of directly comparing findings across studies. Importantly, data collected using longer epochs cannot be subdivided into short time frames. In the absence of a consensus regarding ideal epoch length, data collection using the smallest possible epoch, although potentially leading to the requirement of supplementary data processing procedures, allows for data to be re-integrated and compared between studies that would not otherwise be possible.

The monitoring period for accelerometer-based assessments of sedentary time has typically been seven days (31,127,128) with participants included in subsequent analysis if they provided data for at least 3-5 days usually including at least one weekend day. However, Matthews et al. (129) recommend that at least 7 days of monitoring may be required to obtain reliable estimates of habitual time spent inactive by adults.(129).

In studies with adults, a minimum of 10 hours of wear time has typically been required (31,127,130). Identification of non-wear time is typically conducted by selecting a period of consecutive zero counts about which it is deemed that the device must have been removed. These segments of zero counts are then removed from further analysis. In studies concerned with estimating sedentary time, non-wear criteria have varied from 10 to 60 minutes of consecutive counts (31). Using strings of zero counts to indicate non-wear time, however, this is problematic because a continuous zero reading may occur during periods of sedentary behaviour (131). Continuous zero counts may be recorded when a participant is sitting or lying still (while wearing the device), potentially resulting in the erroneous removal of sedentary time data because of misclassification as non-wear time. Improved methods of identifying non-wear time are therefore needed. One possible solution is to combine motion sensing with physiological assessments (such as heart rate (HR) (132), wherein the absence of physiological data may be used to signify non-wear time. Another potential solution is for devices to develop an electronic log of non-wear within the data stream.

ActiGraph (ActiGraph LLC, Pensacola, FL) and Actical accelerometers [(Respironics, Philips, N.V.) (uniaxial models)] defined sedentary time commonly using a count threshold of <100 counts per minute (CPM) in adults (31,48,127,133). However, despite the widespread use of this cut point, this value was not empirically derived, and studies reporting the validity of this cut point in adults are limited (31,134). Kozey-Keadle and colleagues (134) assessed the criterion validity (the extent of the agreement between a measure and another already held as being a standard) of a number of ActiGraph GT3X cut points (50, 100, 150, 200 and 250 CPM) for defining sedentary time against direct observation in a small sample of adults (n=20). Findings indicated that the ActiGraph 100 CPM cut point underestimated sedentary time by 4.9%. The cut point with the lowest bias was 150 CPM, which overestimated sedentary time by 1.8%. Another study investigated sedentary behaviour cut points for the Actical accelerometer (hip mounted), using the activPAL (thigh mounted; PAL technologies Ltd, Glasgow, UK) device as the criterion measure. It was concluded that a threshold of 0 counts/15s epoch provided the most accurate estimates of sedentary time. However, recognising the potential difficulties a zero-count cut point would raise in terms of distinguishing non-wear time, the authors recommend a threshold of 0-5 counts/15s epoch during the period when the device can be deemed to have been worn (135). However, the most common method of determining sedentary time using accelerometers is still the <100 CPM cut point.

A key limitation of traditional (count based) accelerometers as a measure of sedentary behaviour is that they assess intensity of movement and thus are less able to distinguish between postures, such as sitting and lying or standing still. Consequently, periods of standing still may be misclassified as sedentary behaviour and vice versa (116,136). Newer models of the ActiGraph include an inclinometer function, which classifies participant's posture into four categories (device removed, standing, lying, and sitting). Preliminary evidence, however, indicated that the validity of this function is limited and may be influenced by point of attachment (137). Furthermore, a recent study in adults reported excellent accuracy for the ActiGraph GT3X+ (attached to the thigh) when classifying sitting, standing and stepping (the majority of the activities were correctly classified more than 90% of the time for both monitors) during a laboratory-based protocol (138). In addition, the ActiGraph (attached to the thigh) provided similar estimates of sedentary time compared to the activPAL (64% versus 62%) under free-living conditions (138). Carr and Mahar (139) reported that the hip-based ActiGraph correctly classified 90% of time spent sedentary (defined as sitting and standing still) when using ≤150 CPM. However, the ActiGraph inclinometer function was less accurate in determining posture, classifying less than 70% of the time correctly as sitting, standing, or walking (139), providing further evidence of a point of attachment influence on the validity of the inclinometer function in the ActiGraph. However, it may not be pragmatic to have participants wear the ActiGraph at the thigh for prolonged periods of time.

2.5.2.3 – Heart Rate and Accelerometry

The assessment HR as a method for the studying of behaviour has a long history (140,141). Most epidemiological efforts, however, have concentrated on estimating total energy expenditure or time spent at moderate to vigorous intensity level, typically using the flex-heart rate (flex-hr) method (142). The individually established flex-hr point (a discriminatory threshold between rest and exercise) determines when data from free-living behaviour are translated as energy expenditure at rest or according to an established regression line from an exercise test. In free-living conditions, it has been shown that most time is spent below the flex-hr point (143). Subsequently, time below flex-hr has been used to estimate sedentary time and furthermore it has been found to be associated with insulin resistance (144). This measure of sedentary time generally has high specificity but low sensitivity (104).

Several studies have investigated the utility of combined HR and movement sensing to accurately assess physiological intensity across a wide range of behaviours (145–148). Defining sedentary behaviour in caloric terms (e.g. time spent at 1.5 METS or below) enables sedentary outcome variables to be derived from these methods. Combining accelerometry with heart-rate could be used to increase the accuracy of behavioural measurements above just accelerometry alone. This can be achieved by using the combination of the biomechanical and physiological information to determine whether the monitors have been worn.

2.5.2.4 – Posture Sensors

The activPAL is a small lightweight electronic device worn under clothing, attached directly to the skin on the midline of the anterior aspect of the thigh. The activPAL determines posture on the basis of thigh acceleration, including the gravitational component and uses proprietary algorithms to classify time as sitting/lying, standing or stepping. Information on cadence, number of steps taken, sit-to-stand and stand-to-sit transitions and estimates of energy expenditure are also provided (104).

The activPAL has been shown to be a reliable and valid measure of step counts in adults (149–154). However, relatively few studies have explored the criterion validity of the activPAL for measuring sedentary behaviour (134,136,155). In one validation study, a mean percentage difference of 0.19% (limits of agreement: -0.68% to 1.06%) between the activPAL monitor and direct observation for total time spent sitting was reported (155). More recently, Kozey-Keadle and colleagues (134) examined the validity of the activPAL in assessing sedentary behaviour and detecting reductions in sitting. The activPAL output was highly correlated with direct observation (r^2=0.94) and accurately identified investigator manipulated reduction in sitting time. These studies provide promising preliminary evidence that the activPAL may be a valid tool for the assessment of sedentary behaviour in adults (134). Similar to other accelerometer-based methods, the activPAL does not provide information on the type of behaviour being undertaken or the social or environmental context in which it occurs.

More recently, a new method of distinguishing posture is using a pressure sensor placed either in a foot-based monitor or in a seated cushion. The foot-based sensor typically utilises a combination of discrete resistive pressure sensors in combination with a triaxial accelerometer to provide raw sensor data to be analysed by proprietary algorithms and software. This software is used to identify specific postures and activities such as sitting, standing, walking, running, cycling and stair climbing, with an average of 98% accuracy. Energy expenditure was also determined with better than 95% accuracy (156–158). The technology can then be embedded in an insole of a shoe or even into the fabric of socks with a smartphone based biofeedback and coaching application also available.

The seat-based sensor comprises a cushion containing a medical grade pressure sensor which acts as a switch to detect transitions of greater than three seconds to and from the seat and typically a microcontroller which records a time stamp for each transition. Data tends to be downloaded either using proprietary software packages or to a smartphone app for data-analysis and feedback. For such a device like the one described here, the smallest mean difference, compared with direct observation, for sitting time and transitions was 0.30 ± 0.21 minutes and –0.46 ± 0.78 respectfully. During free-living, both the cushion sensor compared to the activPAL (set to record events greater than 3 seconds) showed excellent levels of agreement with direct observation for sitting time (0.999 and 0.990 respectively) and transitions (0.997 and 0.928 respectively). (159).

Whilst these two methods to measuring sedentary time might be novel, their feasibility to be used to measure sedentary behaviour for prolonged periods in a free-living setting has yet to be tested. Logically, their utility as measures of sedentary behaviour is most certainly going to be hampered by the fact that when sitting in numerous different locales over the course of the day individuals will require several of the seat-based sensors to capture all the different seated areas. As for the foot-based pressure sensor, unless participants were willing to use the same pair of shoes or purchase numerous pairs, it is unlikely that the shoe-based method is an appropriate tool for sedentary behaviour for use across prolonged periods of time (e.g. weeks)

2.5.2.5 – Multi-unit Sensors

The utility of multi-site/multi-sensor devices has been examined widely in the clinical setting [e.g. mobility assessment in older adults (160)], but their potential in other study types (e.g. interventions and epidemiological studies) is largely unknown. Typically, these devices use multiple accelerometers, inclinometers or physiological sensors attached at various points on the body. Sensor signals are then integrated to enable classification of different postures and types of movement. A number of such devices have been developed and examined for their accuracy in detecting posture and activity (both activity type and energy expenditure) in controlled laboratory settings (161–166). However, the validity and feasibility of using these devices under free-living conditions has not been comprehensively tested. Limitations in battery and memory capacity and the computational and analytical complexity associated with processing multi-unit sensor data also limits their applicability in a free-living setting. Furthermore, wearing multi-site sensors will increase the level of participant burden.

These devices may, however, be valuable as criterion measures in the validation of other sedentary behaviour measurement tools. For example, the Intelligent Device for energy Expenditure and Activity (IDEEA; MiniSun, Fresno, CA, USA) has demonstrated 98% accuracy in classifying 32 different types of activity and postures under laboratory conditions (161). Matthews et al (31) reported data from a small unpublished data set, which was conducted as part of their research in which the convergent validity of the ActiGraph 7164 100 CPM cut point for sedentary behaviour was compared against the IDEEA monitor in 19 free-living adults. The ActiGraph and IDEEA monitors displayed similar values for time spent sedentary (8.63 and 8.53 hours/day, respectively), there was a moderate association between the two devices (r=0.59) (31).

2.5.2.6 – New and Emerging Technologies

Moore's law (167) continues to predict with some accuracy that electronic devices will become smaller, more sophisticated and cheaper every 12-24 months. Technology for data capture, processing and storage often outpaces our ability to describe it in the scientific literature. It is also highly feasible that disposable omnidirectional accelerometers with inclinometric or gyroscopic capabilities will soon cost less than printing, sending, collecting and entering paper surveys (104). Because of this rapid innovation, new commercially available technologies to assess and track behaviour are proliferating. Corporations such as Fitbit (Fitbit, Inc, San Francisco, CA) , Jawbone (Jawbone, San Francisco, CA), and Misfit Shine (Misfit, Inc, San Francisco, CA) are at the forefront of this market, with wearable technology recognised as a leading technological trend in 2014/15 by many technological commentators and experts (168).

A major decision made by commercial users will concern the accuracy of the device verses the interface and usability of the device. Researchers are often concerned with evaluating the accuracy of the device whereas users are often more interested in the perceived usefulness and ease of use of the technology. Both these components could be highly related to wear compliance. To date, there is limited scientific research regarding the reliability and validity of these commercially available activity monitors as a measure of physical activity and sedentary behaviour. Furthermore, the research is limited to their use as measures of time spent physically active and not time spent sedentary (169).

To date, the Fitbit devices have received the majority of attention, with a number of studies scrutinising the validity of various outputs (170–179). Dannecker and colleagues (158) examined the ability of the original Fitbit (now superseded by a number of FitBit iterations) to measure active energy expenditure among 19 healthy young adults, and found that it underestimated 4-hour energy expenditure by 28% compared with indirect calorimetry (a criterion energy expenditure measure). More recently, Takacs and colleagues (170) examined the ability of the Fitbit "One" to count steps during treadmill walking among 30 healthy adults. Participants ambulated at five different speeds for five minutes at each speed, wearing three Fitbit devices (at each hip and in the front pocket of the dominant side). Using direct observation as the criterion, excellent validity (0.97-1.00) and inter-device reliability (99% agreement) were reported, regardless of walking speed or device wear site.

Given the large number of activity monitors now commercially available, methodologies which evaluate them simultaneously are required in order to determine the relative utility of these devices in comparison to both their commercial and research counterparts. A recent study compared the validity of the Fitbit Ultra (now superseded), Nike Fuelband and a traditional pedometer (Yamax SW-701) in people with stroke and traumatic brain injury (n = 50) during a two minute walk test. It was found that the Fitbit Ultra was the most accurate device (95% agreement with direct observation), followed by the Yamax (85%), and the Nike Fuelband (66% accuracy), highlighting that validity in wearable technologies can vary widely (180). Lee, Kim and Welk (181) also examined the validity of eight consumer-level devices for estimating energy expenditure in healthy young adults (n = 60). During a 69 minute protocol in a laboratory setting, the consumer-level devices were compared against an indirect calorimetry criterion. The devices were ranked based on percent accuracy, as follows: BodyMedia FIT (90.7% accuracy), Fitbit Zip (89.9%), Fitbit One (89.6%), Jawbone UP (87.8%), ActiGraph GT3X (87.4%), DirectLife (87.2%), Nike Fuelband (87%) and Basis BI Band (76.5%). To date, it appears that no studies have scrutinised a large number of devices simultaneously for other variables provided by the devices (e.g. sleep time and MVPA), and very few studies thus far have examined the devices in free-living conditions.

Many consumer-level devices have displays (usually LED/LCD) for immediate feedback and associated mobile and internet-based applications, providing users with feedback on a variety of metrics including (but not limited to) step count, calories burned, stairs climbed, distance travelled, active time and sleep. Some devices also offer the ability to interact with other users via online social networks and platforms which has been shown to have potential positive benefits for health behaviour change (182). Several manufacturers claim their devices accurately capture physical cactivity levels whilst worn on various body sites (e.g. Misfit Shine can be worn on a necklace, wrist band, bra or waist band). Furthermore, such devices typically cost 50-100 US dollars, making them considerably cheaper than research-grade activity monitors Considering these features and their agile nature, consumer-level activity monitors, coupled with smartphone technology, have vast potential to enhance user experience and utility (183).

These devices, however, have been created for the consumer market, battery life is a key component to allow for prolonged usage without the need to recharge. Because of this, compromises have needed to be made elsewhere, mainly in sampling frequency.

Traditionally, research grade accelerometers can measure acceleration at hertz level frequency, sometimes in excess of 100Hz. Whilst consumer activity trackers do also measure acceleration at hertz level frequencies, they do not make this readily available, as the data needs to be aggregated to minute level data to be transferred to the phone app via Bluetooth. This might have ramifications in terms of the level of acuity gained from higher resolution sampling frequency data. Furthermore, wearable technology traditionally connects to a mobile phone application for data feedback, which means that (depending on the device) the raw data are not available to the user.

The current method of objectively measuring sedentary behaviour is utilising research grade accelerometers and posture sensors. However, the priorities of the manufacturer of these research devices is not participant comfort or providing immediate feedback, instead they prioritise high resolution data collection, therefore reducing their ability to be used as an effective behaviour change tool. The current consumer electronic realm has manufacturers attempting to reach a compromise between high resolution data collection and the ability to provide immediate feedback to the wearer (something that is important to the consumer). Furthermore, due to the inherent ability of these devices to self-monitor and provide feedback, they provide a unique opportunity to be deployed as intervention modalities for behaviour change in reducing sedentary behaviour.

2.6 Health Behaviour Change

Understanding how behaviours are effected by different behaviour change techniques is important in developing interventions (184–186). Altering the incidence of any particular behaviour requires a change in their capability, motivation or opportunity to engage in the behaviour (185,187,188). Capability refers to the psychological and physical abilities to perform behaviour, and includes knowledge and skills. Motivation involves all the processes that energise and direct behaviour, including not just goals, plans and beliefs but also ‘automatic’ processes involving emotions, habits and impulses. And finally, opportunity involves all factors that are external to the individual that may influence engagement with an activity, ranging from the physical environments in which people spend time to the social cultural influences that dictates how we perceive and think about behaviour change interventions. It is important for designers of interventions to understand how these factors of capability, motivation and opportunity vary as a function of particular behaviours, target populations and contexts (185,189–191).

There is growing recognition that attempts to change behaviour should draw on theories of behaviour and behaviour change. In the United Kingdom, the Medical Research Council recommends beginning the development of any complex intervention by identifying relevant theories to advance an understanding of the likely process of change before conducting any exploratory piloting and formal testing (192–194). However, there is also a legitimate question as to how far explicit use of theory promotes the design of effective behaviour change interventions. In fact, interventions that have purportedly been informed by theory have not necessarily been found to be more effective than those that have not. Some reviews have found a positive association (191,195–198), but others have found no association, or, even a negative association (199). Some reviews have reported a mixture depending on the measure of effectiveness (200,201).

One factor that may contribute to this mixed picture is the way the theory has been used as a stepping off point for ideas versus being used in a systematic manner to develop intervention content. Unfortunately, it has been found that the reported use of theory in intervention design is generally inadequate. Another crucial factor is the choice of appropriate theory. For example, if behaviour is fundamentally under influence of habitual or emotional factors then a theory that focuses exclusively on beliefs and reflective thought processes may not be appropriate when informing intervention design.

2.6.1 Behaviour Change Techniques and Their Associated Theory

In order to improve the effectiveness of interventions to change behaviour, such as physical activity and/or sedentary behaviour, it is necessary to replicate and accumulate evidence across empirical studies. This is not straightforward, as interventions to change health-related behaviours are usually complex, comprising many, often interacting components (194). Systematic reviews of the effects of physical activity interventions on behaviour or health outcomes often conclude that both the interventions as well as the effect sizes are extremely heterogeneous (202–204). While some interventions are indeed highly effective in changing behaviour and relevant health outcomes, others fail to achieve such effects. Replication, accumulation and application of evidence depend on the ability to reliably specify the details of intervention content both for primary research and for secondary evidence syntheses.

Michie and colleagues (205) believed that the current reporting of interventions in published evaluations fell short of the detail required for reliably identifying intervention content (42,206,207) and hence they limit the possibility of identifying the effective components within interventions (42). Reporting of intervention content is often brief and imprecise with interventions being broadly characterised as, for example, ‘behavioural counselling’, ‘cognitive behavioural therapy’ or ‘motivational strategies’. In some cases, reporting does not mention content but, instead, describes mode of intervention delivery such as ‘face to face’ or ‘telephone delivered’ or in terms of number of intervention sessions. Where details of intervention content is provided, such as in published intervention protocols, terminology is variable across intervention descriptions; the same label may be applied to different behaviour change techniques or different levels applied to the same technique. An example of the former is ‘behavioural counselling’ described both as ‘educating patients about the benefits of lifestyle change, encouraging them, and suggesting what change could be made’ and ‘feedback on self-monitoring record, reinforcement, recommendations for change, answers to questions, and general support’. Therefore, standardised definitions of techniques were required. In an attempt to improve the reporting of use of theory in intervention design, a 19 item ‘Theory Coding Scheme’ has been developed (208). The scheme assesses whether theory was mentioned, how theory was used in intervention development, whether theory had an indirect influence on an intervention, how theory was used to explain intervention effects on outcomes and the implications for future theory development. This initiative created the ‘Taxonomy of Behaviour Change’ which describes 93 behaviour change techniques (209).

Michie and colleagues (42) then applied this taxonomy of behaviour change techniques to assess the effectiveness of behaviour change interventions designed to promote physical activity and healthy eating and investigate whether theoretically-specified behaviour change techniques improve outcomes. Active behaviour change interventions were only included, instead of both active and/or passive intervention techniques because active behaviour change techniques have been found to be more effective than passive interventions in other areas and, because of the sustained behaviour change necessary to translate dietary and physical activity in health benefits, self-regulatory processes are likely to be central to health-enhancing change (42). Moderator analysis, using both univariate and multivariate meta-regression, revealed that the number of theoretically-derived self-regulation techniques, in particular self-monitoring of behaviour was associated with improved effectiveness. Furthermore, interventions combining self-monitoring with one or more of four other self-regulation techniques, namely, prompting intention formation or goal setting, specifying goals in relation to particular contextualized actions, providing feedback on performance and reviewing previously-set goals in light of that feedback were significantly more effective than interventions not including self-monitoring and one other self-regulatory techniques from Control theory (pooled effect sizes for healthy eating: 0.54 versus 0.24; physical activity: 0.38 vs. 0.27; all interventions: 0.42 vs. 0.26) (42). Additionally, a further meta-regression investigating behavioural change interventions for obese adults with additional risk factors or co-morbidities, found self-monitoring to be a significant moderator of intervention effectiveness on weight (210).

The most well-known objective measurement of self-monitoring physical activity is the use of the pedometer. A systematic review to evaluate the association of pedometer use with physical activity and health outcomes among outpatients revealed pedometer users increased their physical activity by 26.9% over baseline. Furthermore, when all studies were combined, pedometer users significantly decreased their body mass index by 0.38 kg/m^2 (95% CI, 0.05-0.72; P = .03). Intervention participants also significantly decreased their systolic blood pressure by 3.8 mm Hg (95% CI, 1.7-5.9 mm Hg, $P < .001$) (211). The basic premise underlying the use of pedometers to increase physical activity is that the immediate visual feedback of cumulative step counts increases individual's awareness of how their personal behavioural choice affects their physical activity. Used as part of a guide and repetitive self-monitoring, feedback and goal-setting process, the pedometer is able to provide up-to-the-minute information which can be used to adjust these behavioural choices to achieve physical activity objectives.

The focus, however, of this thesis surrounds how sedentary behaviour can be influenced by self-monitoring. Gardner and colleagues (41) reviewed interventions to reduce sedentary behaviour and the behaviour change techniques that they used within the interventions. Interventions which used self-monitoring (n=15; of which n=13 used a self-reported measure of sedentary behaviour) were defined as "particularly promising" behaviour change techniques, with a promise ratio (metric devised as a measure of the behaviour change techniques contribution to the intervention promise) of 4.0, which was the highest promise ratio of all behaviour change techniques investigated (41). There is a logical basis for these findings. Interventions have been found to be more effective if they involve techniques that behaviour change theory predicts would act synergistically. Carver and Scheier's Control

Theory (212) specifies action control processes underpinning behaviour regulation. The theory proposes that setting goals, monitoring behaviour, receiving feedback and reviewing relevant goals in the light of feedback are central to self-management and behavioural control.

The accuracy with which self-monitoring is effective is dependent on the schedule of which the behaviour is monitored, the competitions from concurrent responses, and the valences of the target behaviour (213–215). Thus there are restrictions on the use of self-monitoring when precise numerical data about target behaviour are required. However, if certain conditions are met, self-monitoring data can still be used to provide estimates of behaviour or to monitor relative change in behaviour over time. Self-monitoring also serves as a number of functions that do not require absolute accuracy in recording. Self-monitoring can be used to obtain qualitative information that is relevant to diagnosis and treatment planning. For example, participants might self-monitor the antecedents and consequences of a target behaviour or to record their emotional states while engaging in the behaviour. Self-monitoring can also serve to increase participant's motivation for change. Baseline data, collected before treatment implementation, can provide an incentive for future change. Later in the intervention, the achievement of a criterion can be graphically displayed and can provide a visual guide for the administration of reinforcement (216). Self-monitoring is closely related to two linked psychological theories: Control Theory and Self-Regulation Theory. These are discussed below and examples are provided with how these theories can be used.

2.6.1.1 Control Theory

Control theory aims to provide a model of human functioning and behavioural regulation, explaining people's moment to moment actions, behaviour change and maintenance of physical health. The core component of the theory is a negative feedback loop, which functions to reduce or eliminate perceived discrepancies between current behaviour and a comparison value (such as a goal behaviour state).

A person perceives their current condition via an input function (e.g. pedometer determined step count) and compares that perception against a particular standard (e.g. 10,000 steps goal) through a mechanism termed a comparator. If the person perceives a difference between their current condition and the reference value they attempt to reduce the discrepancy by performing a behaviour (termed output function – e.g. increase their step count). Performance of the behaviour, in turn, has an impact on the environment, thus leading to changes in a person's perceptions of their current condition, and a new comparison with the reference value, and so on. Behaviour is governed by a closed loop of control which continuously functions to minimise discrepancies between a person's current situation and a particular standard of comparison.

There are two further influences on behaviour that are external to this closed loop. The first is disturbance, which refers to factors external to the system affecting a person's current condition. Disturbance does not affect the components of the model directly. However, it can modify perceptions entering the system via input function and lead to increased or decreased discrepancy from the standard. The second factor is the desired condition or comparison standard that is external to the closed loop, and is termed the reference value. The reference value arises from a hierarchy of systems of interconnected feedback loops. Each of these relates to superordinate (at the higher end of the hierarchy) or subordinate (at the lower end of the hierarchy) goals, where achievement of subordinate goals is necessary for the attainment of superordinate goal. The reference values for each level of control are set by the level above and at the highest level the reference value is derived from prior knowledge and experience. See Figure 2.3 for a diagrammatical representation of Control theory.

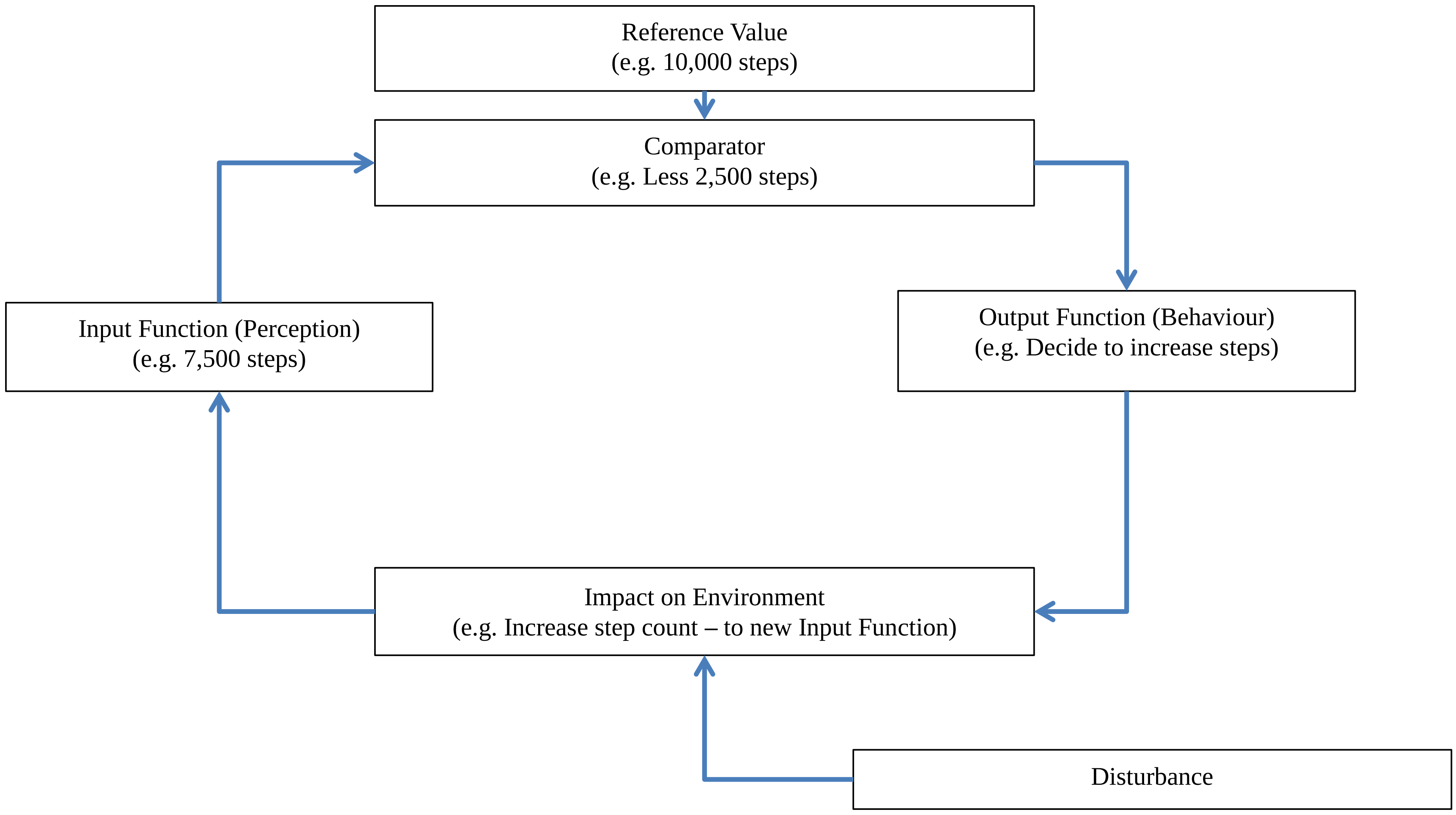


Figure 2.3 – Control theory's negative feedback loop. Adapted from Carver and Scheier (1982)

2.6.1.2 Self-regulation theory

Self-Regulation Theory proposes that behaviour is determined by three sources of control: a person's immediate environment, their biological systems and cues (arising from the person's cognitive and behavioural goals). These three factors interact to determine behaviour with the relative importance of each changing at different times and in different contexts [e.g. sitting behaviour might be primarily controlled by the biological system (need to sit for rest) at one point, but at another, environmental facts (such as the comfortable chair being in the vicinity) might become important]. According to the theory, adequate self-regulation can reduce the influence of fluctuations in biological and environmental factors upon behaviour, allowing for a more consistent pursuit of personally set goals over time and across contexts.

The theory is based upon the assumption that everyday behaviour consists of chains of behavioural responses, where each response is cued by the preceding response until an activity (e.g. driving to work) is completed. Such behavioural sequences relate to a mode of cognitive processing termed automatic processing. Self-regulation processes apply other cases – such as where learned behaviour chains are not available, are interrupted or become ineffective, or where choices between alternative responses need to be made. These self-regulation processes involve a qualitatively different mode of cognitive processing: controlled processing. Controlled processing requires continuous decision-making between response alternatives and attentional focus.

The self-regulation process first involves a self-monitoring stage, in which a person closely and deliberately monitors their own behaviour. Through past experience, people will develop expectations about acceptable behaviour within the relevant domain (e.g. a person self-monitoring their time spent sitting). These expectations form standards by which a person can judge their own behaviour. In the second stage, which is termed the self-evaluation stage, a person makes a comparison between the information about their own behaviour gathered during the self-monitoring stage and the standards for that behaviour. If self-monitoring has been insufficient or inaccurate, or if standards are unrealistic or poorly defined, effective self-regulation will be undermined at this stage. The third stage of self-reinforcement involves a person's reaction to the information gained during the self-evaluation stage, specifically their cognitive and emotional reactions of satisfaction or dissatisfaction thereby serving a motivational purpose. If a person notices no discrepancy between the standard and their own behaviour (or if their behaviour exceeds the standard), they will not be motivated to change their behaviour. However, if their behaviour falls short of the standard, the resultant dissatisfaction will result in attempt to change behaviour. During these attempts the self-regulation process is repeated until the standard is met or until efforts to change behaviour are abandoned. In cases where behaviour falls short of the standard and discrepancies are very large or are reacted to with self-punishment, the resultant emotions could lead to motivation to avoid rather than motivation to change behaviour (216). See Figure 2.4 for a diagrammatical representation of Self-regulation theory.

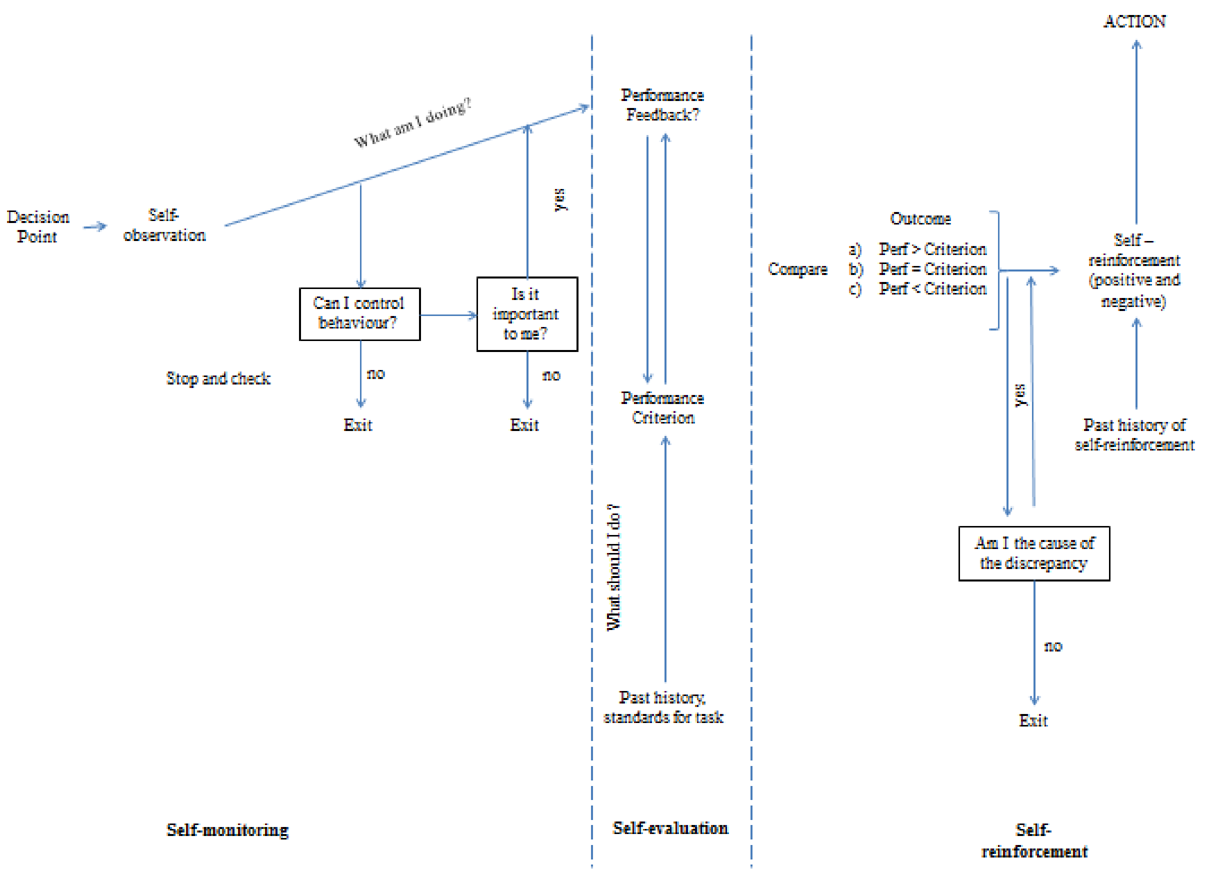


Figure 2.4 – Self-Regulation Model Kanfer (1991)

Note: Self-monitoring stage – person closely and deliberately monitors their own behaviours, self-evaluation stage where a person makes a comparison between the information about their own behaviour from the self-monitoring phases and the self –reinforcement involves a person's reaction to the information gathered in the self-evaluation stage; Perf = performance Kanfer (1991)

The resemblance between these ideas should be evident. The processes themselves are nearly identical; the existence of a reference value, the self-reflective comparison between that value and one's present state and the attempt to match the one with the other. Both these theories discuss the process of self-regulation as involving self-imposition of behavioural standards, observations of one's own actions (i.e. self-monitoring), and evaluation of the actions by comparing them with the standards. In addition, both discuss the importance of the person's expectancies of being able or unable to alter behaviour in the direction of the standard, viewing them as critical determinants of whether the person continues to strive or gives up the attempt. The importance of expectancies in the behaviour change process has also been verified empirically (217,218). Whilst self-monitoring of sedentary behaviour is possible, there are no real standards [apart from the recent Canadian guidelines (219)] that can be employed. However, the use of prompts or cues to alert people to prolonged bouts of sedentary behaviour will help individuals to keep track of their behaviour and make the appropriate evaluations of their actions.

2.7 Sedentary Behaviour Interventions in Adults

The majority of previous sedentary behaviour interventions have focused on reducing the behaviour in children and adolescents (220). However, there is a growing breadth of literature on interventions attempting to reduce sedentary behaviour in adults (34,41), but these are mostly small scale studies (221). Early interventions that have been suggested to change sedentary behaviour were most often physical activity interventions that assessed sedentary behaviour as a secondary outcome. For example, Chau et al. (222) conducted a systematic review on interventions to reduce sitting in the workplace. They included six studies in the review and found no evidence for intervention effectiveness as far as reducing sedentary behaviour was concerned. This finding is perhaps unsurprising given that all of the included studies were designed to increase physical activity and did not have a clear focus on sedentary behaviour reduction. In addition, the studies relied on self-reported measures of sedentary or sitting behaviour, of which only one specifically assessed occupational sitting (222).

More recently, studies have used a variety of approaches to target sedentary behaviour more directly and these provide better evidence on whether changing sedentary behaviour is possible and, if so, what are likely to be effective strategies, with the majority of these studies having been focused on office workplaces. A pilot quasi-experimental control study conducted on 18 adult office workers (aged 20-65 years) in Australia aimed to examine the efficacy of an intervention to reduce office workers' sitting time using commercially available sit-stand workstations. Intervention efficiacy was determined by change in time spent sitting, standing, and stepping at the workplace and during all waking time from baseline to 1 week and 3 months. Sedentary behaviour was objectively measured using the activPAL. Changes in fasting cholesterol, high density lipoprotein, triglycerides, and glucose levels were also assessed from baseline to 3 months. The intervention group reduced sitting time following one week by 143 minutes/day at the workplace and 97 minutes/day during waking time and these effects were maintained over the three month period. The intervention group saw significantly increased HDL cholesterol, however, no significant difference were observed in other biomarkers (223).

Another randomised controlled trial intervention, again in an office/workplace setting in the UK investigated the effects of point of choice prompting software on work computers, to reduce long uninterrupted sedentary periods and total sedentary time at work. The software reminded the participants to stand every 30 minutes during the 5-workday intervention period. An advice window reminding participants to take a break appeared on the monitor, for 1 minute every 30 minutes from the time the PC was switched on. Sedentary behaviour was measured using the activPAL. The results indicated that there was a reduction in the number and duration of sedentary bouts at work during the intervention phase compared to that at baseline. However, there were no significant differences in total sedentary behaviour between the control and the intervention group (224), suggesting a compensatory effect happening outside the workplace. A limitation of this study is the lack of information on the time participants spent at their PC. For example, the software would prompt the participant to stand every 30 minutes. However, this would not take into account whether the person might have been standing under their own volition at or away from their desk.

More recently Healy and colleagues (225) published data on reducing sitting time in office workers using a multicomponent intervention (225). The intervention emphasised three key messages: “Stand Up, Sit Less, Move More” and comprised organisational, environmental and individual elements. Relative to the controls, the intervention group significantly reduced workplace sitting time (mean change [95%CI]: −125 [−161, −89] min/8-h workday), with changes primarily driven by a reduction in prolonged sitting time (−73 [−108, −40] min/8-h workday). Workplace sitting was almost exclusively replaced by standing (+127 [+92, +162] min/8-h workday) (225).

Furthermore, a recent systematic review and meta-analysis into the evidence for activity permissive workstations on sedentary time, health-risk biomarkers, work performance and feasibility indicators in office workplaces found that the installation of workstations can lead to substantial reductions in sedentary time without impacting negatively on work-related outcomes; and that they are acceptable to workers. The study found no significant changes in health related outcomes; however, this was based on evidence from short-term studies with weak-to-moderate designs and/or insufficient statistical power, making it difficult to ascertain any conclusive findings (37).

Other systematic reviews have been conducted into the effect of workplace interventions to reduce sitting time, with some findings showing effective interventions effects (34,222,226), while the others are not (37,227). Inconsistency in the findings can be explained by differences in inclusion criteria between the different studies (e.g. studies included in the Martin et al. (34) review were only randomised controlled trials), as well as differences in the study strategies and implementation.

Very few interventions seeking to reduce sedentary behaviour in adults have been undertaken outside of the work place context. A novel randomised control trial (RCT) intervention examined the effects of a TV lock-out system to reduce TV viewing time on energy intake, energy expenditure, energy balance, body mass index and sleep in 36 overweight and obese adults (228). The lock-out system (BOB TV Time Manager; Hopscotch Technology, Boulder, Colorado) was attached by plugging the TV cord into the monitor and a four digit code was given to each household member to activate the system to turn on the TV. The system recorded total minutes per day of viewing per participant code. After the baseline measurement period, the intervention group had a weekly limit of 50% of their objectively measured TV viewing time form baseline placed on them. Activity behaviour was measured using the SenseWear Pro 3 Armband (BodyMedia Inc., Pittsburg, PA, USA). Although not statistically significant, both groups reduced their energy intake (-125kcal/day [95% CI. -303 to 52] vs -38kcal/day [95% CI. -265 to 190] p=0.52) for intervention and control groups respectively. The intervention groups significantly increased energy expenditure (119kcal/day [95% CI. 23 to 215]) compared to the controls (-95kcal/day [95% CI. -254 to 65] p=0.02). Energy balance was negative in the intervention group between phases (-244kcal/day [95% CI. -459 to -30]) but positive in controls (57 kcal/day [95% CI. -216 to 330]) p=0.07. The intervention group showed a greater reduction in BMI (-0.25 [95% CI. -

0.45 to -0.05] vs -0.06 [95% CI. -0.43 to 0.31] in controls) (p=0.33). There was no change in sleep (228).

One published feasibility study, 'Stand Up For Your Health', has shown favourable results in adults aged 60 years and older (n=59; (229)). This trial used a 45 minute face to face meeting to assist participants to reduce sitting time and to increase breaks in sedentary behaviour. The intervention was informed by Social Cognitive Theory and behavioural choice theory, and focused on building self-efficacy (via goal setting), self-control (via self-monitoring and goal-setting), outcome expectancies (via barriers and benefits), reinforcement (via rewarding behaviour change) and preference (via identifying enjoyable non-sedentary pursuits). During the intervention participants:

1) reviewed their accelerometer-assessed sedentary time from the previous day;
2) received normative feedback on their self-reported sedentary time, using graphs to compare to an average Australian of a similar age and gender;
3) completed a goal-setting exercise to reduce sedentary time and increase the number of breaks in prolonged sedentary time, and
4) formulated a behaviourally specific action plan.

Generic strategies to reduce and break up sedentary time were suggested, and participants identified strategies specific to their circumstances. The participants were also encouraged to self-monitor their sitting behaviour using a tracker. Sedentary time was derived from the ActiGraph accelerometer and defined as <100 CPM. At the end of the first week of data collection participants received the intervention and were then monitored for another week. During the post-intervention week there was a small but significant reduction in sedentary time of 3.2% and an increase in the number of breaks from sedentary time. Participants reduced their sedentary time mainly during the day, and increased their breaks in sedentary time in the evening. This intervention is promising but full randomised trials with representative sample are required before a definitive conclusion about its effectiveness can be made (229).

More recently, Martin et al. (34) systematically reviewed and meta-analysed the effect of interventions which included sedentary behaviour as an outcome measure in adults. The review found clear evidence that it is possible to intervene to reduce sedentary behaviour in adults by 22 mins/day in favour of the intervention group. Moderate to high quality evidence on the efficacy of lifestyle interventions for reducing sedentary behaviour suggests that this may be a promising approach. Interventions focusing on sedentary behaviour only result in the greatest reduction in sedentary time (42 min/day), however this was based on only two studies of low to medium quality. Findings also suggests that intervention duration up to 3 months and interventions targeting men and mixed genders can produce significant reductions in sedentary behaviour (34).

The results from this systematic review are consistent with those of Prince et al. (35) in relation to the effect of physical activity and sedentary behaviour intervention and interventions focusing on sedentary behaviour only, despite there being no overlap of included studies in the latter. However, in contrast, the systematic review by Martin and colleagues (34) found no evidence of a beneficial effect on sedentary behaviour from interventions focused on increasing physical activity. This difference in findings could be attributed to the differences in the definitions of lifestyle interventions and physical activity interventions between the two systematic reviews (34,35).

With the mixed picture of interventions effectiveness in reducing sedentary behaviour, the increasing amount of commercially available technology which inherently contains different behaviour change techniques, allows them to be potentially useful in interventions to reduce sedentary behaviour and increases physical activity.

2.7.1. New and Emerging Technology and Behaviour Change

The wearables market is a newly established digital health market segment. Whilst they are not as well adopted as mHealth apps (mobile health - a term used for the practice of medicine and public health supported by mobile devices; mHealth apps are often free), and their wearable counter-part come at a premium, which has helped sales in this new market grow at a fast rate. According to early estimates, health and fitness wearables account for just 30% of the total wearables market, at £1.5 billion in 2014, growing to £3.1 billion by 2018 (230). Over 3 million wrist-worn wearable devices such as fitness bands and smartwatches are estimated to have been sold in the UK in 2015, up 11% from unit sales in 2014. In 2015, 63% of wrist-worn wearable devices sold were fitness bands, compared to 37% which were smartwatches. Currently one in seven of the UK population own any kind of wearable device (231,232). Consumers age 16-34 years show the strongest interest in wearables, being about three times more likely than those aged 35+ years to own a fitness band. Indeed, 13% of

British people aged 16-34 years currently own a fitness band compared to 4% of those over age 35 years (232).

Whilst wearable technology is increasing rapidly in popularity at the moment, wearable computers for personal advantage have been around for decades. The first documented occurrence of wearable technology is of Ed Thorpe's and Claude Shannon's cigarette pack-sized pocket computer that was designed to predict roulette wheels in the early 1960's. The computer itself consisted of 12 transistors that allowed its wearer to time the revolutions of the ball on the roulette wheel and determine where it would end up. Wires led down from the computer to switches in the toes of each shoe, which let the wearer covertly start time to the ball as it passed a reference mark. Another set of wires led up to an earpiece that provided audible feedback in the form of musical cues – eight different tones represented an octant in the roulette wheel. When everything was in sync, the last tone heard indicated where the person at the table should place their bet. The system provided the wearer with a 44% edge in roulette.

Modern day consumer wearables can deliver personalised, immediate and goal orientated feedback on specific tracking data obtained via sensors and provide long lasting wear without requiring continual charging (e.g. > 7days battery life). Their small form factor makes them easier to wear continuously, and whilst smartphones are still required to process the incoming data for most consumer wearables, it is conceivable that in the near future all processing functionality will be self-contained.

At present, wearables are more likely to be purchased by individuals who already lead a healthy lifestyle and want to quantify their progress (233). The majority of wearable manufacturers (e.g. FitBit, Jawbone, and Garmin) stress the potential of their devices to become an "all-in-one" platform for improving physical performance and positive habit formation. Wearable manufactures utilise a range of digital persuasive techniques and social influence strategies to increase user engagement, including the gamification of activity with competition and challenges, publication of visual feedback on performance utilising social influence principles, or reinforcements in the form of virtual rewards for achievement.

The most successful vendors will likely be those that give consumers a clear path for action-taking and behaviour change with their products and services (234). Consumers can be directed through a road map designed to increase their engagement as the technology continues to benefit them. This road map could include the steps of getting the consumer to try quantified tracking with the solution, see the value provided by the solution, continued engagement, change behaviour, and maintain the behaviour change. Since even the simple act of tracking has been shown to have an impact, individuals can start with this light touch behaviour. Some of the benefits of self-tracking alone in affecting behaviour change have been seen in weight loss diary keeping (234,235) and home power consumptions. Electricity consumption was reduced when individuals could self-monitor and obtain feedback about their resource use: 7-10% reductions with smart meters and other feedback (236,237), and a 32% reduction with feedback plus incentives (238). If wearable tracking can be made extremely easy (ideally automated), fun (with gamification and social engagement), and even remunerative (with rebates and cost-savings), then there could be significant growth in the types of things individuals are willing to track and wearable data streams as a result.

But do wearables make people healthier through increasing physical activity? Currently empirical data in this area are lacking. Lewis et al. (239) systematically reviewed the literature on the efficacy and feasibility of interventions using electronic activity monitor systems within published physical activity literature. Of the 11 studies, four used commercially available devices for individuals to use (Gruve, PAM, Fitbit), the rest were only available through distributors and traditionally to researchers. Feedback from the electronic activity monitoring systems was administered for differing monitoring periods. Those interventions involving commercially available monitors showed significant pre-post intervention increases in physical activity, whilst also displaying significant pre-post decreases in sedentary behaviour although sedentary behaviour was not the main outcome. Encouragingly, the interventions involving the Gruve and Fitbit had an 80% or better retention rate potentially due to their better aesthetics and comfort of wear.

Research projects using wearable technology that have integrated behaviour change–based text messages in their interventions have resulted in considerable increments in physical activity in adults (240). This is the case of interventions where participants who were provided with physical activity tracking and received feedback through automated and tailored text messages increased their daily step-count by 2,334 steps/day (25%) compared with those randomised to physical activity alone. Total physical activity time and aerobic time also increased in the text receiving group by 21 and 13 min/day, respectively when compared to the blinded and unblinded – no text groups (240). In another study by Compernolle et al. (241), participants in the intervention arm were given information on how to increase steps, a digital pedometer with 7 day memory, and were granted access to tailored web-based step advice (241). A recommended 10,000 daily step goal was used. The intervention resulted in an increase of 1,056 daily steps in the intervention group compared with a reduction of 256 daily steps in the control group using only a blinded pedometer (241).

The majority of interventions using wearable technology or consumer electronic devices have been aimed at increasing physical activity, in no small part, due to the fact that most consumer electronic devices track steps as their main tracking outcome. There is therefore a dearth of research examining the use of consumer electronic devices examining their ability to decrease sedentary behaviour which needs to be addressed in the future.

2.8 General Summary

Sedentary behaviour has a clear and established inverse relationship with markers of cardio-metabolic and psychological health. Accurate measurement of sedentary behaviour is therefore of vital importance. The majority of measures of sedentary behaviour have been conducted using self-reported questionnaires however, these are open to a variety of biases. More objective measures have therefore been sought. In search of objective measures of sedentary behaviour; researchers are now using accelerometers to quantify sedentary time. However, accelerometers also have their own pitfalls. They assess intensity of movement and thus are less able to distinguish between postures (a key variable in the definition of sedentary behaviour) such as sitting and lying. In lieu of this limitation, posture sensors are being used to quantify sedentary behaviour. However, there is currently a paucity of sensors used in published research, which accurately measures sedentary behaviour to its current definition.

Interventions aimed at reducing sedentary behaviour currently show a mixed picture. They are either interventions that aim to increase physical activity and measure sedentary behaviour as a secondary outcome, or these interventions tend to target office workers to reduce desk-based sedentary behaviour. However, it has been shown in the literature that utilising the self-regulatory behaviour change technique of self-monitoring could be a promising avenue to decreasing sedentary behaviour. The boom in commercially available behavioural trackers provides a unique opportunity to utilise these devices to both accurately and objectively measure sedentary behaviour and also to utilise them as an intervention modality for reducing sedentary behaviour as they inherently allow their users to self-monitor and receive feedback on behaviour.

2.9 Aims

Therefore the aim of this thesis is to identify and validate technology that can self-monitor sedentary behaviour and to determine its ability to reduce sedentary behaviour.

2.9.1 Aim of Study 1

The purpose of this study was to, by way of a systematic review, scope the current technologies that could be used to self-monitor and provide feedback on time spent in physical activity and/or sedentary behaviours. Secondly, the study aimed to quantify the level of self-monitoring and feedback attributes of these technologies.

2.9.2 Aim of Study 2

From the systematic review, a technology was chosen based on its ability to self-monitor and provide feedback on sedentary behaviour. The purpose of this study, therefore, was to determine the validity and reliability of the LumoBack Posture Sensor (LumoBody Tech, Inc, Palo Alto, CA) as a measure of sedentary behaviour under both laboratory and free living conditions.

2.9.3 Aim of Study 3

Having determined the validity of the LumoBack in Study Two, the LumoBack was repurposed to be a device that provides feedback (in the form of prompts/cues) on time spent sedentary. The aims of this study therefore were:

1. To determine whether a repurposed LumoBack Posture Sensor can reduce sedentary behaviour in a sample of healthy adults over the course of five weeks.
2. To quantify the engagement of the participants with the technology determined by time engaging with the mobile application associated with the LumoBack.

In an attempt to understand potentially why individuals engaged with the intervention, investigation of health outcome data was also determined to quantify to whether those with the “most to gain” (health-wise) were more engaged.

Chapter 3 - Devices for self-monitoring sedentary behaviour and/or physical activity: A systematic scoping review

This study has been published as an original article in a peer-reviewed journal (Sanders, J. P., Loveday, A., Pearson, N., Edwardson, C., Yates, T., Biddle, S. J., & Esliger, D. W. (2016). Devices for Self-Monitoring Sedentary Time or Physical Activity: A Scoping Review. Journal of Medical Internet Research, 18(5), e90). With the exception of some minor wording and/or format changes, it is presented in its published form. The introduction section below may repeat aspects of the literature review directly pertinent to the purpose of the study.

JPS was involved in concept and design, acquisition of data, analysis and interpretation of data. Additionally JPS drafted the manuscript. AL was involved in the acquisition of data by checking for bias and inter-rater reliability as well as revising it critically for important intellectual content. NP was involved in the concept and design of the review as well as the initial acquisition of data, and revising it critically for important intellectual content. CE, TY, and SJHB were involved in the concept and design of the review as well as being involved in revising it critically for important intellectual content. DWE was involved in the concept and design, analysis and interpretation of the data, as well as revising it critically for important intellectual content.

3.1 Introduction

Modern environments and technological advancements have radically altered the way we live our lives (25). The need to undertake purposeful physical activity has all but disappeared and sedentary behaviour, defined as ‘any waking behaviour in a sitting or reclining posture with an energy expenditure ≤1.5 metabolic equivalent’ (43) is the dominant behaviour. Low levels of moderate to vigorous physical activity (MVPA) have been consistently associated with the risk of developing chronic diseases, such as type 2 diabetes, cardiovascular disease, and some cancers (242). In addition, increasing the total level of daily movement, such as the number of steps taken, has also been strongly inversely associated with the risk of developing chronic diseases (203,243). There is also mounting evidence that the amount of time spent sedentary is an important determinant of health status independent of physical activity levels. For example, Wilmot and colleagues (28) found that when comparing those with the highest levels of sedentary behaviour with the lowest, independent of physical activity levels, there was a 112%, 147%, 90% and 49% increase in the relative risk of type 2 diabetes, cardiovascular disease, cardiovascular mortality and all-cause mortality, respectively (28). Moreover, how sedentary behaviour and physical activity are accumulated throughout the day may also be important, with frequent breaks to sedentary behaviour associated with a healthier metabolic profile (74). This has necessitated a paradigm shift, which focuses on both the accumulation of MVPA (the traditional focus of lifestyle interventions), and the importance of postural allocation throughout the waking hours.

Over the last decade, there has been a plethora of tools that have been developed to support sedentary behaviour and physical activity behaviour change, of which the greatest growth has been seen in self-monitoring tools. Self-monitoring, defined as ‘a person closely and deliberately monitors their own behaviour’ (209,216) and ‘allowing the modification of their behaviours to achieve predetermined goals or outcomes’ (244), for behaviour change has a strong theoretical foundation. Self-regulation theory posits that self-monitoring precedes self-evaluation of progress made towards one’s goal and self-reinforcement for progress to be made (216).. Furthermore, Control Theory proposes that self-monitoring of behaviour, setting goals, receiving feedback, and reviewing relevant goals in the light of feedback work synergistically and are central to self-management and behavioural control (42,212). Self-monitoring, therefore, can increase an individual’s personal responsibility, promote independence and, by taking an active rather than physical activity passive role, individuals can create their own pathways towards goal achievement (245). When included in behaviour change interventions, self-monitoring has proven to be an effective behaviour change strategy across a variety of behaviours including smoking, diet and physical activity and as such is considered a foundation of lifestyle behaviour change interventions (42,246).

Traditionally, self-monitoring of physical activity and sedentary behaviour occurred via paper based journal methods (246); however, more recently the pedometer became a popular method of self-monitoring for interventions designed to increase physical activity with individuals who used pedometers increasing their physical activity by 26.9% from baseline (211). Subsequently, advances in technology have led to an explosion of bodily worn electronic devices becoming available that go beyond simply measuring and providing feedback on the number of steps per day (e.g., Fitbit, Jawbone). Along with physical activity, electronic devices are also starting to measure sitting time, providing real-time feedback, as well as encouraging interruptions in prolonged sitting. It has been suggested that the use of these electronic approaches to self-monitor might lessen the burden of traditional methods and may improve adherence to self-monitoring and thus result in greater achievement towards behavioural goals (247).

This increased availability of electronic self-monitoring devices provides an opportunity for researchers to utilise these novel technologies as an aid for behaviour change in physical activity and sedentary behaviour on a large scale. Furthermore, wearable technologies are increasingly being integrated into healthcare systems. Recent reports from the National Information Board in a review of the National Health Service in the United Kingdom (UK) indicate the need for "citizens" to start playing a more active role in their healthcare, by accessing, entering and uploading data into their own online medical record. Under these new plans citizens will be able to access and download their detailed GP records as well as contributing to it with information held by their personal wearable technology or biosensors (248,249). In addition, as more health care providers in the United States move to a value-based care system (i.e., "reward points" for positive lifestyle alterations which can be redeemed for discounts on a range of products and/or activities) mobile technologies that promote health and well-being by engaging in important health behaviours (e.g., increased MVPA) will continue to grow and have the potential to be an integral piece of future health care systems. In light of this, a review of the current tools used to self-monitor physical activity and/or sedentary time has the potential to be a valuable resource to researchers, clinicians, healthcare providers and the general public.

Therefore, it seems timely to review the characteristics and measurement properties (e.g., wear location, integrated sensors, outcomes measured), of currently available self-monitoring devices, both consumer marketed and those used in research settings, that have been (or could be) utilised in, or developed for, real time self-monitoring of sedentary behaviour and/or physical activity.

3.2 Methods

3.2.1 Searches

The search strategy was built around three groups of key words: behaviour (i.e. physical activity and sedentary behaviour), measurement, and population. A detailed description of the keywords used and method of combination can be found in Appendix 1.1 (page 211). For the purposes of this study, tools were deemed to measure sedentary behaviour if they could measure the users sitting and/or reclining posture. Scopus, MedLINE, Web of Science and Institute of Electrical and Electronic Engineers (IEEE) databases were searched using these key terms from the inception of the databases to October 1, 2015. In addition, manual searches of personal files were conducted as were screening of reference lists of primary studies.

3.2.2 Internet Search Engines

Due to the rapid release of technology in the consumer electronic (CE) area, a grey literature search of relevant websites was conducted for technologies that allow the self-monitoring of physical activity and sedentary behaviour but may not have made it into the published research to date. Keywords based on the same groups as the database searches were used to search the internet engines Google, Bing and Yahoo. Searches were extracted for later review using a specialised browser plug-in [SEOquake (www.seoquake.co.uk) a browser plugin software providing the search engine optimisation metrics]. The first 200 search results from each search engine were extracted for further review; this was a pragmatic approach as it was deemed that results after the first 200 were either not relevant (i.e. did not meet inclusion/exclusion criteria) or were repetitive. This ensured that the results were unaffected by the changing algorithms of web search engines. Searches were completed on October 1, 2015.

3.2.3 Study Inclusion and Exclusion criteria

Two sets of inclusion criteria were developed for research articles and websites. For inclusion in the review, studies were required to i) include adults aged ≥ 18 years; ii) be published in English; iii) describe a device that objectively self-monitors physical activity, physical inactivity and/or sedentary behaviour/sitting and can, or has the potential to, provide feedback to the user. Traditionally, there would also be a criteria based around study type; however, in order to obtain the widest variety of device, this wasn't included.

For inclusion in the review, i) websites from manufacturers were included only, therefore blogs or consumer review pertaining to technologies of interest were excluded and ii) devices that had the ability to self-monitor and were available to purchase at the time of the review were included.

3.2.4 Data Extraction

Potentially relevant articles were selected by i) screening titles, ii) screening abstracts, and iii) if abstracts were not available or did not provide sufficient data, the entire article was sought and screened to determine whether it met the inclusion criteria. Relevant websites were selected by i) screening web page titles and ii) screening devices on relevant web pages to determine whether it met the inclusion criteria. Data were extracted on standardised forms developed for this review.

Information on the devices was extracted from papers and cross-referenced with device manufacturer information. Validity data on each device was not extracted, instead papers with relevant validity data, where available (151,153,158,168,170,171,176,177,181,250–260), have been referenced in the data table as the authors chose to focus this review on the characteristics of the devices to allow the reader to make a judgement about their efficacy as self-monitoring tools.

A 10% sub-sample of potentially relevant articles retrieved for full paper screening were extracted by a second author (AL) to determine inter-rater agreement. Inter-rater agreement was high (Cohen's Kappa = 0.81). If any discrepancies arose, these were resolved by discussion between authors.

3.2.5 Self-monitor Scoring

Each device was designated a self-monitoring code;

- Y_{PA} : Yes – Self-monitors Physical Activity;
- Y_{PI}: Yes – Self-monitors Physical Activity/Physical Inactivity (i.e self-monitoring and feedback on lack of movement);
- Y_{SB}: Yes – Self-monitors Sedentary behaviour.

The different attributes of the self-monitoring devices were based on Control Theory (212), specifically the ability to receive feedback (defined as the provision of informative and actionable insights on the performance of the behaviour) and the ability to set goals (defined as agreeing on a goal/target defined in terms of the behaviour to be achieved, (209). Aspects included the different types of feedback; vibratory, auditory, omnipresent - in the form of colours or lights - or potentially via push notifications. Also included, was the timing of the feedback (i.e., immediate or delayed). Other features included the way in which the data are portrayed (e.g., numeric data/graphical representation of the data). Additionally the platform pervasiveness was also included (i.e., how many different devices can the data be viewed on and on what operating systems). Each of these aspects were broken in to what feedback attributes were available on either the device or the backend platform (defined as the smart device/software that the technology connects to). Other attributes included were goal setting capability of the device and whether the device or associated software could be customised by the end user via some method, usually an application programming interface or software development kits. Table 3.1 provides a detailed description of each self-monitoring attribute. Each attribute is split into whether the attribute is present on the device itself (denoted as a D_) or whether it is present on the backend platform (i.e. smartphone/tablet etc; denoted with BP_).

Each device was given a score between 1 and 6 for each attribute of behaviour change. This score was used to describe two factors i) whether or not that device contains that behaviour change attribute and ii) to what extent it does or does not contain the attribute. Below is the self-monitoring scoring system that has been used for each attribute;

1) Yes
2) Yes – Difficulties (e.g. proximity to computer)
3) Yes – Lack of evidence to suggest this
4) No – But present in future iterations
5) No – But possible (with Application Programming Interface or Software Development Kit)
6) Not described/Not featured

This scoring system is meant to be a descriptive tally of the behaviour change attributes and not a judgement on the effectiveness of the various features.

Table 3.1 - Description of the self-monitoring attributes coded

Self-monitoring Attribute	Description
Auditory	Feedback on behaviour provided verbally from device (e.g. via Sensoria – voice over feedback regarding ground contact from smartphone/smart mp3).
Vibratory	Haptic feedback on pre-determined behavioural thresholds provided using vibrations (e.g. LumoBack)
Omnipresent	Feedback that is visible all the time, usually in the form of a changing progression bar which changes with advancement towards pre-determined goals (e.g. FitBit Flower)
Push Notification	The delivery of information regarding behavioural goals from a software application to a computing device without a specific request from the user.
Immediate	Whether the data/feedback are immediate in its return to the user (e.g. LumoBack).
Delayed	Whether the data/feedback are delayed in its return to the user (e.g. ActiGraph).
Numeric	Data are returned in the form of numbers/figures or statistics.
Graph	Data are returned in the form of graphical representation.
Written/Text Feedback	Data are returned in the form of textual feedback.
'Ometer	Data are returned in the form of a growing or shrinking picture/image based upon completion towards a pre-determined goal (e.g. UbiFit Garden).
Application	What Operating System the mobile application can it be accessed on for viewing the data/feedback.
Software	If a piece of computing software is present for use at viewing the data – what operating system can it be accessed on.
Website	Can the data/feedback be view on a website?
Goal Setting Capability	Can pre-determined goals be set by the user?

3.3 Results

3.3.1 Review Statistics

Database searches identified 49,956 articles (Figure 3.1), of which 462 were deemed to be potentially relevant and thus retrieved for full text analysis. Papers (n=337) were excluded for a number of reasons:

1) Pedometer Studies: Pedometer studies were excluded if no evidence could be found that the pedometer in question provided temporally stamped data;

2) Prototypes: that were not commercially available or where no data currently existed for the prototype and only proof of concept information was available;
3) Health Outcome: papers were excluded if they examined the relationship between behaviour (e.g. sedentary behaviour and/or physical activity) and a particular health outcome (e.g. blood pressure, lipid profile) and the measurement tool of choice was not the main focus of the paper;
4) Miscellaneous: articles were excluded if the purpose of the study was to examine a new algorithm or data processing procedure for device analysis.

The remaining 125 studies (on 46 devices) and 90 websites yielded 146 devices (see supplementary table 1 http://www.jmir.org/2016/5/e90/) that were then selected for detailed scrutiny. Of these 64 were further removed because there was no evidence that they were designed for, have been used in, or could readily be modified for real-time self-monitoring purposes or that they are not currently available for purchase (see supplementary Table 2 http://www.jmir.org/2016/5/e90/).

The remaining 82 (261–341) technologies were included in this review. Seventy three (261–332) technologies measured/self-monitored physical activity, of which 16 (265,267,277,278,280,284–288,303,308,312,313,316,325,329–331) provided some measure of physical inactivity (see Table 3.2 and 3.4). Nine (333–341) technologies measured self-monitored sedentary behaviour. (see Table 3.3 and 3.5), 8 (333,334,336–341) of which measured both physical activity and sedentary behaviour. Figure 3.2 (page 78) displays the number of self-monitoring attributes apparent in each of the devices found to measure/self-monitor physical activity. Figure 3.3 (page 79) documents the popularity of the self-monitoring attribute. Figure 3.4 (page 80) displays the number of self-monitoring attributes apparent in each of the devices found to measure/self-monitor sedentary behaviour. Figure 3.5 (page 80) documents the popularity of the self-monitoring attributes with sedentary time self-monitoring devices.

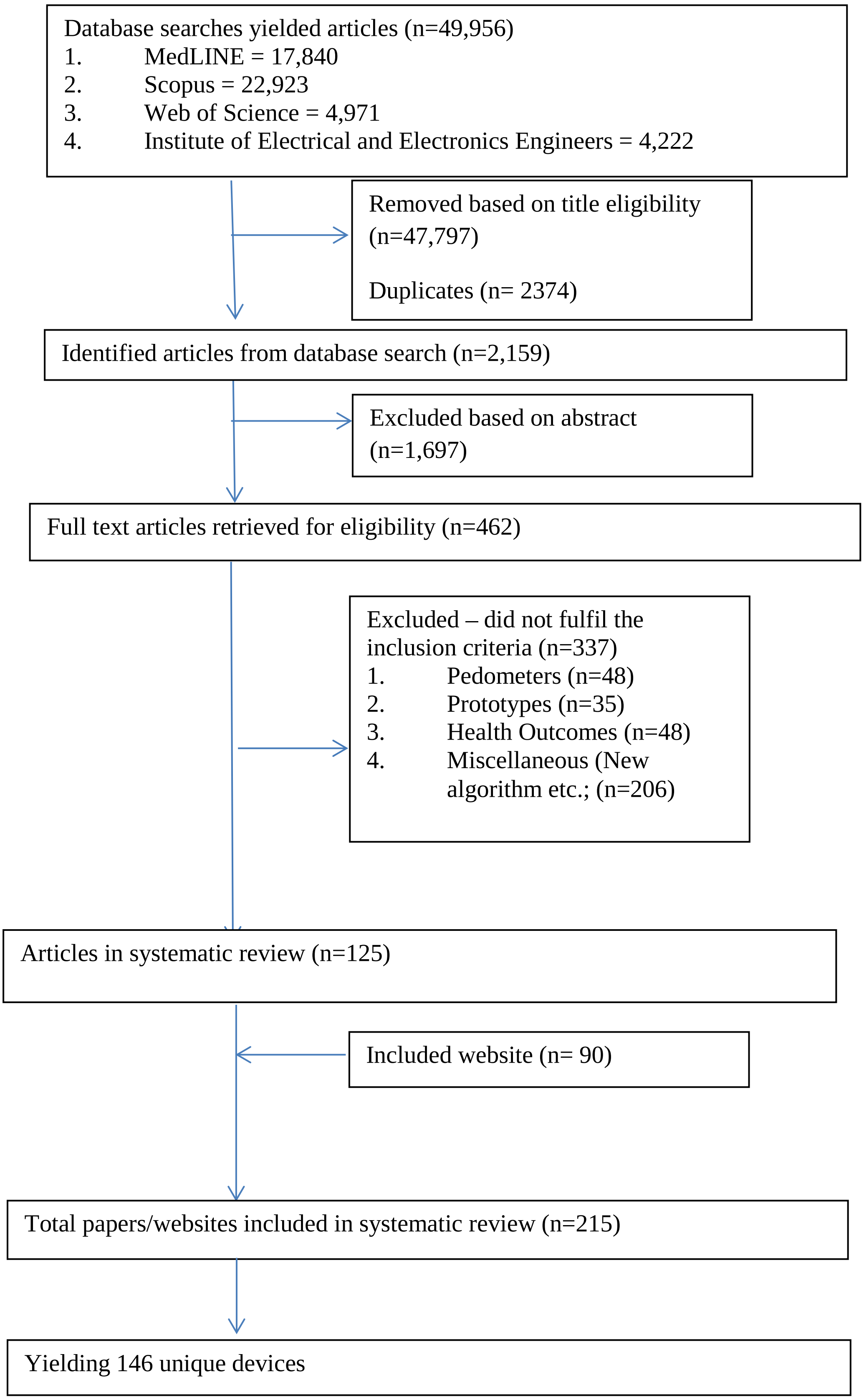


Figure 3.1 – Study/website selection

Table 3.2 - Devices that self-monitor physical activity

Name	Manufacturer	Size	Weight	Battery Life	Placement	Sampling rate / Epoch Length	Data Storage	Sensor	Interface	Wireless	Software for Data Processing	SDK	Outcome (Calculated)	Self-Monitoring	Cost*	Reference
ActiGraph Link	ActiGraph LLC, Pensacola, FL	3.5 x 3.5 x 1cm	14g	14 days (wireless disabled, 30Hz sample rate, gyro disabled, sleep mode)	wrist, waist	30-100Hz	240 days/ 4GB	Triaxial Accelerometer, Gyroscope, Magnetometer	USB	Yes, BLE	Actilife Software/ ActiLife Mobile Application	No	Energy Expenditure, activity intensity level, body position and amount of sleep	YPA	$275	(261)
ActiGraph wGT3X+ BT	ActiGraph LLC, Pensacola, FL	4.6 x 3.3 x 1.5cm	19g	25 days (wireless disabled, 30 Hz sample rate)	Ankle, Waist, thigh or wrist	30-100Hz	120 days at 30Hz	Triaxial Accelerometer, Ambient Light Photodiode and inclinometer	USB	Yes, BLE	Actilife Software/ ActiLife Mobile Application	No	Energy Expenditure, activity intensity level, body position and amount of sleep	YPA	$225.	(262)
Adidas Fit Smart	Adidas International Trading	3.4 x 1.2 x (1.8 or 2.0)cm	47 - 50g	5 days	Wrist	?	up to 10 hours workout data	Accelerometer, Mio Continuous optical heart rate	USB	Yes, BLE	Adidas MiCoach train and run app	No	Heart rate, calories, pace/speed, distance and stride rate	YPA	£145	(263)
Amiigo	Amiigo, Inc.	One size – Micro Adjustable	?	3 days	Wrist and shoe clip	?	6 days	Triaxial Accelerometer, pulse oximeter, temperature sensor	BLE	Yes, BLE	Amiigo App	No	Activity Recognition, resting heart rate, calories burned, step counting, exercise tracking, sleep tracking.	YPA	$179	(264)

Apple Watch	Apple Inc., Cupertino, CA, USA	two case sizes heights 3.8 or 4.2 cm	?	?	Wrist	?	?	Triaxial Accelerometer, GPS, Heart Rate Sensor	Lightening USB	Yes, BLE	Apple iOS	No	Total Body Activity, step counting, calories burned, numbers of times stand up	YPI	£215	(265)
Archos Activity Monitor	ARCHOS	5.9 x 2.9 x 1.0	8g	7 days	Wrist	1 Min	7 days	Triaxial Accelerometer	USB	Yes, BLE	ARCHOS Connected Self App	No	Steps, calories burned, walking distance	YPA	£50	(266)
Basis Peak	BASIS Science, Inc., San Francisco, CA	?	?	4 days	Wrist	?	?	Triaxial Accelerometer, Optical Heart Rate Sensor, Galvanic Skin Response, and Skin Temperature	Wireless sync	Yes, BLE	Basis - Fitness, Sleep and Stress tracker	No	Steps, Calories Burned, Heart Rate, Perspiration, Skin Temperature	YPI	$200	(267)
Bowflex Boost	Nautilus, Inc. Vancouver WA	?	?	11 days	Wrist	?	11 days	Triaxial Accelerometer	No	Yes, BLE	Bowflex Boost App	No	Activity Level, Calories, distance, steps and sleep	YPA	£83	(268)
Epson Pulsense 100 Wristband	Epson America, Inc.	?	?	?	Wrist	?	20 days	Triaxial Accelerometer, Heart rate Monitor	USB	Yes, BLE	Pulsense Mobile App and Website	Yes	Heart rate zone, steps, calories burned, sleep patterns	YPA	$129	(269)
Epson Pulsense 500 watch	Epson America, Inc.	?	?	?	Wrist	?	?	Accelerometer, Heart rate Monitor	?	Yes, BLE	Pulsense Mobile App and Website	Yes	Heart rate zone, steps, calories burned, sleep patterns	YPA	$199	(269)
Fitbit Charge	Fitbit UK	14 - 23.1 cm in circumference	?	7 days	Wrist	60 seconds	7 days	Triaxial Accelerometer	?	Yes, BLE	Fitbit App	No	Steps taken, distance travelled, calories burned, floors climbed and active minutes.	YPA	£100	(270)
Fitbit Flex	Fitbit, Inc. San Francisco, CA	14 - 20.9 cm circumference - 1.3cm width	?	5 days	Wrist	60 seconds	30 days	Triaxial Accelerometer	Wireless Sync Dongle	Yes, BLE	Fitbit Flex App and Fitbit Website	No	Calories Burned, distance travels, steps, and sleep quality.	YPA	£80	(146,159,164,165, 169,252)

Fitbit One	Fitbit, Inc. San Francisco, CA	4.8 x 1.9 x 9.6cm	8g	10-14 days	Waist, wrist	60 seconds	7 Days @1min epoch 23 days overall data	Triaxial Accelerometer and Altimeter	USB	Yes, BLE	Fitbit App	No	Steps, Distance, Calories Burned, and Floors Climbed.	YPA	£80	(156,158, 163,253)
Fitbit Surge	Fitbit UK	15 - 23.1 cm in circumference	?	7 days	Wrist	60 seconds	7 days	Triaxial accelerometer, Triaxial gyroscope, Optical Heart rate monitor, digital compass, altimeter, ambient light sensor, vibration motor	?	Yes, BLE	Fitbit App	No	Steps taken, distance travelled, calories burned, floors climbed and active minutes, heart rate, GPS tracking, multi-sport tracking, sleep tracking	YPA	£200	(273)
Fitbug Orb	Fitbug Ltd	5 x 5 x 5 cm	?	4 months	Anywher e	?	?	Accelerometer	Wireless Sync	Yes, BLE	Fitbug Activity App and Fitbug website	No	Calories burned, total activity, total steps, aerobic steps	YPA	$50	(274)
FlyFit	FlyFit, Inc.	2.9 x 1.7 x 1.0cm	<100g	5-7 days with off-sync mode or 8 hours with real-time sync	Ankle	?	?	Triaxial Accelerometer	?	Yes, BLE	FlyFit Mobile App	No	Steps, step speed, step distance, stairs climbed, calories burned, bike distance, bike speed,	YPA	$199 - pre order price	(275)
Free Wavz	Free Wavz	?	16g	6-8 hours	Ear-phone/pl ug	?	?	Triaxial Accelerometer, Infra-red and red pulse oximeter	?	Yes, BLE	Free Wavz Mobile App	No	Step, Heart Rate, O2 saturation, average speed, distance, and calories burned.	YPA	$219	(276)
Garmin VivoFit	Garmin Ltd	12-21cm	25.5g	1 year or greater	Wrist	?	1Month	?	USB	Yes, BLE	Garmin Connect App	No	Daily Step Count, goal countdown, distance, calories, heart rate and heart rate zone.	YPI	£100	(277)

Garmin Vivo Smart	Garmin Ltd	12.7 to 22.1 circumference	18.7 - 19.0g	7 days	Wrist	?	3 weeks of 24/7 activity data or 2 weeks if heart rate monitor is used 1 hour per day	Accelerometer and Heart Rate Monitor (optional)	Wireless Sync	Yes, BLE	Garmin Connect App and Garmin on Computer	No	Step Counts, calories and distance	YPI	$170-200	(278)
GoBe Activity Monitor	HealBe GoBE	?	?	3 days	Wrist	?	?	Triaxial Accelerometer, heart rate sensor, and impedance sensor	Wireless Sync	Yes, BLE	GoBe Body Manager Mobile App	No	Calorie Intake, Calories Burned, Hydration Levels, Heart Rate, Blood Pressure, Stress Levels, Distance Travelled.	YPA	$300	(279)
GOQii Band	GOQii	?	?	4-5 days	Wrist	?	?	Accelerometer	Wireless Sync	Yes, BLE	GOQii Mobile App	No	Steps, distance travelled, calories burned, time spent active, sleep quality	YPI	£70	(280)
Hexoskin	Hexoskin, Montreal, Quebec.	Shirt Size	41g	14 hours	Shirt	64Hz	157 hours	3 x heart rate sensor, 2 x breathing rate sensors, Triaxial accelerometer	USB	Yes, BLE	Hexoskin App	No	Heart rate, Heart Rate Variability, Breathing Rate, Breathing Volume, Steps, cadence and calories burned, sleep.	YPA	$400	(281)
iBitz	GeoPalz, LLC, CO	4.8 x 3.0 x 2.0cm	?	?	Waist or shoe	60sec	30 days	Triaxial Accelerometer	BLE	Yes, BLE	iBitz Unity App	No	Steps, calorie burned, distance, average speed	YPA	£20	(282)
iHealth Wireless Activity and Sleep Tracker	iHealth Lab Inc.	?	?	5-7 days	Wrist, Waist	60 seconds	14 days	Accelerometer	Wireless Sync	Yes, BLE	iHealth MyVitals App	No	Steps, calories burned and distance travelled	YPA	$60	(283)

Jawbone UP	JAWBONE, San Francisco, CA	14 – 20cm in circumference	19-23g	10 days	Wrist	?	10 Days	Triaxial Accelerometer	3.5mm headphone port	No	UP by Jawbone App	No	Distance, calories burned, active time, and active intensity	YPI	£65	(156,163, 265)
Jawbone UP2	JAWBONE, San Francisco, CA	22 x 1.15 x 0.3-0.85 cm	25g	10 days	Wrist	?	9 Months	Triaxial Accelerometer	USB	Yes, BLE	UP by Jawbone App	No	Steps, exercise and calories burned, sleep tracking, food logging	YPI	£90	(285)
Jawbone UP24	JAWBONE, San Francisco, CA	small - 5.2 x 3.5cm, Medium - 6.3 x 4.0, Large - 6.9 x 4.3	19g, 22g, or 23g	14 days	Wrist	?	?	Triaxial Accelerometer	USB	Yes, BLE	UP by Jawbone App	No	Steps, Activity Classification, Calories Burned.	YPA	£130	(164,165, 267)
Jawbone UP3	JAWBONE, San Francisco, CA	22 x 1.15 x 0.3-0.85 cm	29g	7 days	Wrist	?	9 Months	Triaxial Accelerometer, heart rate sensor, respiration and galvanic skin response sensors	Magnetic USB	Yes, BLE	UP by Jawbone App	No	Steps, exercise and calories burned, sleep tracking, food logging, heart rate.	YPI	£130	(287)
Jawbone UP4	JAWBONE, San Francisco, CA	22 x 1.15 x 0.3-0.85 cm	29g	7 days	Wrist	?	9 Months	Triaxial Accelerometer, heart rate sensor, respiration and galvanic skin response sensors	Magnetic USB	Yes, BLE	UP by Jawbone App	No	Steps, exercise and calories burned, sleep tracking, food logging, heart rate.	YPI	$200	(288)
Ki Fit	Ki Performance	6.2 x 5.5 x 1.3cm unit + 4 cm diameter Ki Fit Display	45.5g	5-7 days	Upper Arm Armband + Wrist	?	14 days	Triaxial Accelerometer, Heat Flux sensor, Skin Temperature sensor, Galvanic skin response sensor	USB	Yes, BLE	BodyMedia App and Online Activity Manager	No	Tracks calories burned, moderate and vigorous activity, steps, sleep, and goals	YPA	£269 + £60 for display	(289)
LEO	Gesture Logic	3.7cm in diameter	?	?	Thigh	?	2GB of flash memory	Triaxial Accelerometer, Bioimpedence, Heart Rate Sensor, Muscle Tracking sensor	Wireless Sync	Yes, BLE	LeoHelps Mobile App	No	Steps, Calories Burned, Heart Rate, Activity Recognition, Cadence, Muscle Monitoring, Hydration Levels, Lactic	YPA	$299	(290)

													Acid Levels.			
LG Activity Tracker	LG Electronics,	18 x 1.7 x 1.0cm	45g	2-3 days	Wrist	?	?	Triaxial Accelerometer, Altimeter	?	Yes, BLE	LG Fitness App	No	Steps, Distance, Speed, Calories, pace and elevation.	YPA	$150	(291)
LifeBeam Hat	LifeBEAM	?	?	?	Head	?	?	Triaxial Accelerometer, optical Heart rate sensor	Wireless Sync	Yes, BLE & ANT+	Compatible with a number of Health and Fitness Apps	No	Calories Burned, Cadence and steps, Heart Rate measurement	YPA	$99	(292)
LifeTrak Core C200	Salutron Inc.,	Watch head size - 5.3 x 2.8, Strap length - 21.7cm	?	1 year	Wrist	?	7 days of hourly data	Accelerometer and Heart Rate Monitor (optional)	?	?	?	No	Steps, heart rate, calories burned, distance.	YPA	$59.99	(293)
LifeTrak Core C210	Salutron Inc.,	Watch head size - 5.3 x 2.8, Strap length - 21.7cm	?	1 year	Wrist	?	7 days of hourly data	Accelerometer and Heart Rate Monitor (optional)	?	?	?	No	Steps, heart rate, calories burned, distance, sleep tracking	YPA	$70	(294)
LifeTrak Move C300	Salutron Inc.,	?	?	1 year	Wrist	?	7 days	Triaxial Accelerometer and Optical Heart Rate Sensor	USB	Yes, BLE	LifeTrak App and Compatible with many different Health and Fitness Apps	No	Steps, calories distance and heart rate	YPA	$80	(295)
LifeTrak Zone C410	Salutron Inc.,	Watch head size - 5.3 x 3.0, Strap length - 21.7cm	?	1 year	Wrist	?	7 days of hourly data	Accelerometer and Heart Rate Monitor (optional)	?	Yes, BLE	LifeTrak App	No	Steps, heart rate, calories burned, distance, sleep tracking	YPA	$100	(296)
LUMOlift	LUMO Body Tech, Inc., Palo Alto, Ca	4.45 x 2.5 x 1.2cm	11.5g	5 days	Chest	?	4 weeks	Triaxial Accelerometer	Wireless Sync	Yes, BLE	LUMOlift App	No	Calories Burned, Steps, Sitting and Standing Postures	YPI	$100	(297)

Magellan EchoFit	MiTac Int Corp	4.6 x 4.9 x 1.3cm	44g	6 - 11 months	Wrist	?	?	Accelerometer and Heart Rate Monitor (Optional)	?	Yes, BLE	Echo Utility App, Compatible with a number of Health and Fitness Apps	No	Steps, distance , calories burned, sleep, elevation	YPA	$100	(298)
Microsoft Band	Microsoft	1.1 x 3.3cm	?	48 hours	Wrist	?	?	Optical Heart rate sensor, triaxial accelerometer, triaxial gyroscope, GPS, Ambient light sensor, Skin Temperature sensor, UV sensor, Capacitive sensor, Galvanic skin response.	Magnetic USB	Yes, BLE	Microsoft Health	No	Heart Rate Monitor, steps, pace, calorie tracking, sleep tracking.	YPA	$200	(299)
Misfit Flash	Misfit Wearables San Francisco, CA	2.85 x 0.8 x 2.85 cm	6.0g	6 months	Necklace , Wrist, Waist, Shoe	?	30 days	Triaxial Accelerometer	BLE	Yes, BLE	Shine App	No	Step count, distance moved, calories expended, sleep quality and duration	YPA	$50	(300)
Misfit Shine	Misfit Wearables San Francisco, CA	2.75 x 0.33 x 2.75 cm	9.4g	6 months	Necklace , Wrist, Waist, Shoe	?	30 days	Triaxial Accelerometer	BLE	Yes, BT	Shine App	No	Step count, distance moved, calories expended, sleep quality and duration	YPA	$100	(156,164, 165,282)
Moto 360	Motorola Mobility	4.6 diameter x 1.1 height cm	?	1 day	Wrist	?	4GB internal storage + 512MB RAM	Triaxial Accelerometer and Optical Heart Rate Sensor	?	Yes, BLE	?	No	Heart rate and steps	YPA	$250	(302)
My Wellness Key	Technogym Gambettola Italy	8.5 x 2.0 x 0.7cm	18.7g	?	Waist	16Hz	30 days	Uniaxial Accelerometer	USB as part of the device	No	Online Activity Manager	No	Energy Expenditure and Activity intensity level	YPI	Price available on Request	(252–254,303)

New Balance Body TRNr	New Balance,	?	?	?	Wrist	?	30 days	Triaxial Accelerometer	Wireless Sync	Yes, BLE	New Balance SmartTRNr	No	Steps, distance, calories burned	YPA	$60	(304)
New Balance Life TRNr	New Balance	?	?	?	Wrist	?	7 days	Triaxial accelerometer and Heart Rate Monitor	Wireless Sync	Yes, BLE	New Balance SmartTRNr	No	Steps, distance, calories burned, heart rate	YPA	$80	(305)
Nike+ Fuelband SE	Nike	14.7 - 19.7cm	27 - 32g	4 days	Wrist	?	?	Triaxial Accelerometer and ambient light sensor.	USB	Yes, BLE	Nike+ Fuelband App	No	Nike fuel, steps, calories, distances, and time	YPA	£89	(156,163–165,241, 287)
Omate X	Omate	4.5 x 4.1 x 1.12cm	?	7 days	Wrist	?	128MB Internal Storage + 32MB RAM	Triaxial Accelerometer and Triaxial Gyroscopes	USB	Yes, BLE	Compatible with a number of Health and Fitness Apps	No	Steps	YPA	$149	(307)
PAM AM200	Doorwerth, Netherlands	5.8 x 4.2 x 1.3cm	28g	>1 year	Waist	1 second to 1 minute	3 Months	Uniaxial Accelerometer	Micro - USB	No	PAM Coach Computer Application	No	PAM Points	YPI	€79	(308)
PAM AM300	Doorwerth, Netherlands	6.8 x 3.3 x 1.0cm	20g	>1 year	Waist	?	?	Triaxial Accelerometer	Micro - USB	No	PAM Coach computer and Mobile Application	No	physical activity score per day, number of minutes in three different intensity zones	YPA	€99	(309)
Pavlok	Behavioral Technology Group	?	few Oz	4 days	Wrist	?	?	?	Micro - USB	Yes, BLE	Pavlok Mobile App	No	Activity and Sleep Tracking	YPA	$175	(310)
Pebble	Pebble Technology	5.03 x 3.2 x 0.8 cm	38g	7 days	Wrist/ Bike handlebar	?	7 Days	Triaxial accelerometer and light sensor	USB	Yes, BLE	Pebble App	-	Speed, Distance and Pace data, walking, running, biking and sleep.	YPA	$99	(311)
Polar Loop	Polar Electro,	?	?	?	Wrist	?	?	Accelerometer	USB	Yes, BLE	Polar Flow app and Polar Flow Web Service	No	daily activity, calories burned, steps taken,	YPI	£85	(176,312)

Polar V800	Polar Electro,	?	?	?	Wrist	?	?	Accelerometer and Heart Rate Monitor (optional), altimeter, barometer, GPS	Custom USB	Yes, BLE	Polar Flow app a and Polar Flow Web Service	No	daily activity, calories burned, steps taken, distance and heart rate	YPI	£400	(313)
Razer Nabu	Razer. Inc.	?	?	7 days	Wrist	?	?	Accelerometer and Altimeter	USB	Yes, BLE	Fitness for Nabu app	Yes	Calories Burnt, Step Taken, Floors climb, distance travelled, hours slept	YPA	?	(314)
Razr Nabu X	Razer. Inc.	?	?	7 days	Wrist	?	?	Accelerometer and Altimeter	USB	Yes, BLE	Fitness for Nabu app	Yes	Calories Burnt, Step Taken, Floors climb, distance travelled, hours slept	YPA	?	(315)
RT6	Stayhealthy	5.1 x 5.1 x 1.3cm	51g	48hours @ 10Hz	Waist	5-20Hz	25-103 hours	Triaxial Accelerometer and Triaxial Gyroscopes	USB	No	Stay Healthy Assist Software	No	Energy Expenditure	YPI	Price available on Request	(316)
Samsung Gear Fit	SAMSUNG	2.3 x 5.7 x 1.2cm	27g	3-5days	Wrist	?	?	Accelerometer, Heart rate sensor, gyroscope	?	Yes, BLE	On-board Samsung OS	No	Pedometer; Exercise; Sleep; Heart Rate;	YPA	$150	(317)
Spree	Hothead Technologies, Inc.	?	?	8 Hours @ non-stop use	Head	?	?	Triaxial Accelerometer, Optical Heart Rate sensor and temperature sensor	?	Yes, BLE	Spree Apps	No	Body Temperature, Heart Rate, Movement	YPA	$199	(318)
Stay healthy Activity Monitor	StayHealthy	5.1 cm x 5.1 cm x 1.3 cm	51g	14-20 Days	Waist	10Hz 6mins	3.6 years	Triaxial Accelerometer	USB	No	Stay Healthy Assist Software	No	Energy Expenditure	YPA	Price available on Request	(319)
Striiv Band	Striiv, Inc.	?	?	7 days	Wrist	?	?	Accelerometer	?	Yes, BLE	Striiv App	No	Steps, Miles, Calories, Minutes of Activity	YPA	$70	(320)
Striiv Fusion	Striiv, Inc.	?	?	5 days	Wrist	?	?	Triaxial Accelerometer	Micro USB	BLE	Striiv App	No	Steps, Calories Burned, sleep	YPA	$60	(321)

													monitor			
Striiv Fusion Bio	Striiv, Inc.	?	?	5 days	Wrist	?	?	Triaxial Accelerometer and optical heart rate monitor	Micro USB	BLE	Striiv App	No	Steps, Calories Burned, sleep monitor	YPA	$80	(322)
Striiv Fusion Lite	Striiv, Inc.	?	?	5 days	Wrist	?	?	Triaxial Accelerometer	Micro USB	BLE	Striiv App	No	Steps, Calories Burned, sleep monitor	YPA	$100	(323)
Striiv Touch	Striiv, Inc.	?	?	5 days	Wrist	?	?	Accelerometer	?	Yes, BLE	Striiv App	No	Steps, Miles, Calories, Minutes of Activity	YPA	$100	(168,324)
Suunto Ambit3	Amer Sports Company	5.0 x 5.0 x 1.7cm	92g	2-3 days with GPS - 30 days in time mode	Wrist	Heart rate 10 seconds, GPS 10 seconds	?	Accelerometer, GPS	USB	Yes, BLE	Suunto Moves count App	No	Steps, Heart rate, speed, pace and distance/	YPI	£450	(325)
Sync Burn	SYNC	?	?	1 year	Wrist	?	7 days	Accelerometer	Wireless Sync	Yes, BLE	Map My Fitness Mobile App	No	Calories Burned, Heart Rate, % of Max HR, distance tracking, steps,	YPA	$38	(326)
Sync Elite	SYNC	?	?	1 year	Wrist	?	30 days	Accelerometer	Wireless sync	Head Phone Jack	Map My Walk	No	Step tracking, distance, calories burned, activity time and fat burning, pace tracking, speed, auto stride length	YPA	$18	(327)
Sync Fit	SYNC	?	?	1 year	Wrist	?	7 days	Accelerometer	?	?	?	No	Calories Burned, Heart Rate, % of Max HR, distance tracking, steps,	YPA	£70	(328)
TracmorD / Philips DirectLife	Philips New Wellness Solutions	3.2 x 3.2 x 0.5cm	12.5g	3 weeks	Lower Back or in pocket	?	22 Weeks	Triaxial	USB	No	The DirectLife Program	No	Energy Expenditure, minutes spent walking, minutes spent running.	YPI	$199	(146,231, 232,310)

Vivago	Vivago Wellness	?	?	?	Wrist	40Hz / 1min	?	Triaxial accelerometer	USB	?	?	No	Energy Expenditure	YPI	€439	(258,330)
Wello graph	Wellograph Co., Ltd	4.2 x 3.2 x 1.25cm	55g	7 days	Wrist	?	4 months @ non-stop use	Tri-LED heart rate sensor, 9-axis motion sensor	Micro USB	Yes, BLE	The Wellograph App	No	Activity, BPM, Exercise, Fitness, Steps	YPI	$349	(331)
Withings Pulse	Withings, Fr	4.3 x 2.2 x 0.8cm	8g	2 weeks	Waist, Wrist	?	?	Triaxial Accelerometer and Optical Heart Rate Sensor and SpO2 sensor	Micro-USB	Yes, BT	Withings Health Mate App	No	Steps taken, Floors Climbed, Distance travelled, Calories Burned, HR, Blood Oxygen level, Sleep quality and duration	YPA	£100	(156,165, 313)

? = Unknown, Hz = Hertz, ANT+ - A proprietary wireless technology, Oz = Ounces, GPS = Global Positioning System, @ = at, SpO2 = Arterial Oxygen Saturation, BLE = Bluetooth low energy, USB = Universal Serial Bus YPA : Yes = Self-monitors Physical Activity. YPI: Yes = Self-monitors Physical Activity/Physical Inactivity (i.e self-monitoring and feedback on lack of movement). YSB: Yes = Self-monitors Sedentary behaviour. *Price has been rounded to the nearest Great British Pound, US Dollar or Euro.

3.3.2 Physical Activity Self-monitoring Technologies

The device with the highest number of feedback attributes was the MicroSoft Band (299) with 18 of the 28 feedback possibilities that were coded. The most common feedback attribute used in the devices found was joint numeric and graphical data feedback on the associated backend platform, with 94% of the devices that self-monitor physical activity displaying these attributes. The least common form of feedback attribute was auditory feedback from the device (D_Auditory). This particular type of feedback was only present in 2% of cases (Figure 2.4).

3.3.3 Sedentary Time Self-monitoring Technologies

The device with the highest number of feedback attributes was the LumoBack posture sensor and feedback coach (338) with 13 of the 28 feedback possibilities that were coded. The most common feedback attribute used in the devices found was joint numeric and graphical data feedback on the associated backend platform, with 81% of the devices that self-monitor sedentary time displaying these attributes. The least common form of feedback attribute was push notification of feedback from the device of sedentary time on the device. This particular type of feedback was present in none of the devices found.

Table 3.3 - Devices that self-monitor sedentary behaviour

Name	Manufacturer	Size	Weight	Battery Life	Placement	Sampling rate / Epoch Length	Data Storage	Sensor	Interface	Wireless	Software for Data Processing	SDK	Outcome (Calculated)	Self-Monitoring	*Cost	Reference
Activ8	VitaMove, Veldhoven, Netherlands	3.4 x 3.0 x 1.0cm	20g	50days	Trouser Pocket or thigh using elastic strap	12.5Hz	1-5days	Triaxial accelerometer	USB	No	PC Application	No	Posture and movement recognition (lying, sitting, standing, walking, cycling, running) and energy expenditure	YSB	€ 99	(333)
ActivPAL VT	PAL Technologies Ltd, Glasgow, UK	5 x 3.5 x 0.7cm	15g	10days	Midline of the anterior aspect of the thigh	20Hz (1 second to 1 min)	16MB (10days)	Triaxial accelerometer	Micro USB	No	activPAL Software	No	Time spent in sitting/lying, upright and stepping activities, step counts, stepping cadence, activity score	YSB	£380	(139,141, 236–238,315)
Darma	Darma Inc.	40 x 40 x 3cm	?	One Month	Seat	?	128MB	Patented fibre optic sensors	?	Yes, BLE	Darma Mobile App	No	Posture, Time spent sitting Heart Beat, Respiration, Stress Level	YSB	$149	(342)
Foot Logger	3L Labs	?	?	24 hours	Insole	?	50,000 footprints	Triaxial Accelerometer, pressure sensor, optional sensors available	USB	Yes, BLE	LASIS - Life Log Acquisition and Analysis Service using Insole Sensor	No	Activity tracking, balancing assessment, failing accident, time spent, walking running sitting standing.	YSB	Price Available on Request	(336)

Gruve	Gruve Technologies, Inc., Anoka, MN.	?	?	?	Waist	?	?	NEAT Activities	Micro-USB	No	Interactive Gruve Website	No	Sedentary Time (calculated from lack of movement), light intensity and moderate intensity physical activity and Energy Conservation Point	YSB	$180	(337)
LumoBack	LUMO Body Tech, Inc., Palo Alto, Ca	4.15 x 10 x 0.8cm	25g	5-7days	Lower Back	?	One month	Posture Sensors and Triaxial accelerometer	USB	Yes, BLE	LumoBack App	Yes	Slouch vs. straight tracking, sit time vs. active tracking, stand up tracking, sleep position tracking	YSB	$70	(163,165, 324)
Moticon OpenGo	Moticon	Shoe Insole	?	?	Insole	100Hz	?	13 Pressure sensors, Triaxial Accelerometer, Temperature Sensor	USB	Yes, ANT	Beaker Software	Yes	Current Applications - Gait Analysis, motion analysis	YSB	Price Available on Request	(344)
OM Everyday	OM Signal	Under Shirt	?	2-3 days	Shirt	?	?	?	?	Yes, BLE	OM Mobile App	No	Heart Rate, Breathing Rate, activity intensity, steps walked, calories burned and posture	YSB	$199	(340)
Sensoria Fitness	Heapsylon, Redmond, WA	Sock of shoe size and anklet	?	?	Sock and Ankle	?	18 days	Pressure Sensors (Sock) and Triaxial Accelerometer (Anklet)	USB and BLE	Yes, BT	Sensoria App	Yes	Steps, speed, calories, altitude, distance, cadences, foot landing technique, and weight distribution of the foot	YSB	$199	(345)

? = Unknown, Hz = Hertz, ANT+ - A proprietary wireless technology, Oz = Ounces, GPS = Global Positioning System, @ = at, SpO2 = Arterial Oxygen Saturation, BLE = Bluetooth low energy, USB = Universal Serial Bus YPA : Yes = Self-monitors Physical Activity. YPI: Yes = Self-monitors Physical Activity/Physical Inactivity (i.e self-monitoring and feedback on lack of movement). YSB: Yes = Self-monitors Sedentary behaviour. *Price has been rounded to the nearest Great British Pound, US Dollar or Euro.

Table 3.4 – Self-monitoring attributes of devices that measure physical activity

Name	Type: Device – Auditory	Type: Device – Vibratory	Type: Device – Omnipresent	Type: Device – Push Notification	Type: Backend platform – Auditory	Type: Backend platform – Vibratory	Type: Backend platform – Omnipresent	Type: Backend platform – Push Notification	Timing: Device – Immediate	Timing: Device – Delayed	Timing: Backend Platform – Immediate	Timing: Backend Platform – Delayed	Feedback in: Device – Numeric	Feedback in: Device – Graph	Feedback in: Device – Written/Text Feedback	Feedback in: Device – ‘Ometer	Feedback in: Backend Platform – Numeric	Feedback in: Backend Platform – Graph	Feedback in: Backend Platform – Written/Text Feedback	Feedback in: Backend Platform – ‘Ometer	Backend Platform: Application – iOS	Backend Platform: Application – Android	Backend Platform: Application – Windows	Backend Platform: Software – Mac	Backend Platform: Software – PC	Backend Platform: Website	Goal Setting Capabilities
ActiGraph Link	6	6	1	6	6	6	2	6	1	6	1	1	1	6	6	6	1	1	6	6	6	6	6	1	1	6	6
ActiGraph wGT3X+BT	6	6	6	6	6	6	2	6	6	6	1	1	6	6	6	6	1	1	6	6	6	6	6	1	1	6	6
Adidas Fit Smart	6	6	1	6	6	6	1	6	1	1	1	1	1	6	6	6	1	1	6	6	1	1	6	6	6	1	1
Amiigo	6	6	6	5	6	6	1	6	6	1	1	1	6	6	6	6	1	1	5	5	1	1	1	6	6	6	1
Apple Watch	6	1	1	1	6	6	1	1	1	6	1	1	1	1	6	1	1	1	1	6	1	6	6	1	6	6	1
Archos Activity Monitor	6	6	1	6	6	6	1	6	1	1	1	1	1	6	6	6	1	1	6	6	1	1	6	6	6	6	1
Basis Peak	6	6	1	4	6	6	1	4	1	6	1	1	1	1	1	6	1	1	1	6	1	1	6	6	6	6	1
Bowflex Boost	6	6	1	6	6	6	1	6	1	6	1	1	6	6	6	1	1	1	6	6	1	1	6	6	6	1	1
Epson Pulsense 100 Wristband	6	6	1	1	6	6	1	6	1	6	1	1	6	6	6	1	1	1	6	6	1	4	6	6	6	1	1

Epson Pulsense 500 watch	6	6	1	6	6	6	1	6	1	6	1	1	6	6	6	1	1	1	6	6	1	4	6	6	6	1	1
Fitbit Charge	6	6	1	6	6	6	1	6	1	6	1	1	6	6	6	1	1	1	6	6	1	1	6	6	6	1	1
Fitbit Flex	6	6	1	6	6	6	1	6	1	6	1	1	6	6	6	1	1	1	6	6	1	1	6	6	6	1	1
Fitbit One	6	6	1	6	6	6	1	6	1	1	1	1	1	6	6	1	1	1	6	6	1	1	6	6	6	1	1
Fitbit Surge	6	6	1	6	6	6	1	6	1	6	1	1	1	1	6	6	1	1	6	6	1	1	1	6	6	1	1
Fitbug Orb	6	6	6	6	6	6	1	6	6	6	1	1	6	6	6	6	1	1	6	1	1	1	6	6	6	1	1
FlyFit	6	6	6	6	6	6	1	6	6	6	1	1	6	6	6	6	1	1	6	1	1	1	6	6	6	1	1
Free Wavz	1	6	6	6	6	6	1	6	1	6	1	1	6	6	6	6	1	1	6	6	4	4	6	6	6	6	1
Garmin VivoFit	6	6	1	6	6	6	1	6	1	1	1	1	1	6	6	1	1	1	6	6	1	1	6	6	6	1	1
Garmin VivoSmart	6	6	1	6	6	6	1	6	1	1	1	1	1	6	6	1	1	1	6	6	1	1	6	6	6	1	1
GoBe Activity Monitor	6	6	6	6	6	6	6	6	6	6	1	1	6	6	6	6	1	1	6	6	1	1	6	1	1	6	1
GOQii Band	6	1	1	1	6	6	1	6	1	1	1	1	1	6	1	6	1	1	1	6	1	1	6	6	6	6	1
Hexoskin	6	6	6	6	6	6	1	5	6	6	1	1	6	6	6	6	1	1	6	6	1	1	1	6	6	6	1
iBitz	6	6	6	6	6	6	6	5	6	6	1	1	6	6	6	6	1	1	6	1	1	6	6	6	6	6	1
iHealth Wireless Activity and Sleep	6	6	1	6	6	6	1	6	1	1	1	1	1	6	6	6	1	1	6	6	1	1	6	6	6	6	1

Tracker																											
Jawbone UP	6	1	6	6	6	6	1	5	6	6	1	1	6	6	6	6	1	1	5	5	1	1	1	6	6	6	1
Jawbone UP2	6	1	1	6	6	6	1	1	1	1	1	1	6	6	6	1	1	1	6	6	1	1	1	6	6	6	1
Jawbone UP24	6	1	6	6	6	6	1	5	6	6	1	1	6	6	6	6	1	1	5	5	1	1	1	6	6	6	1
Jawbone UP3	6	1	1	6	6	6	1	1	1	1	1	1	6	6	6	1	1	1	6	6	1	1	1	6	6	6	1
Jawbone UP4	6	1	1	6	6	6	1	1	1	1	1	1	6	6	6	1	1	1	6	6	1	1	1	6	6	6	1
Ki Fit	6	6	6	6	6	6	1	6	6	6	1	1	6	6	6	6	1	1	6	6	1	1	6	1	1	1	1
LEO	6	6	6	6	6	6	1	6	6	6	1	1	6	6	6	6	1	1	6	6	1	1	6	1	1	6	1
LG Activity Tracker	6	1	1	6	6	6	1	6	1	1	1	1	1	6	6	6	1	1	6	6	1	1	6	6	6	6	1
LifeBeam Hat	6	6	6	6	6	6	1	6	6	6	1	1	6	6	6	6	1	1	6	6	1	1	6	6	6	6	1
LifeTrak Core C200	6	6	1	6	6	6	6	1	1	1	1	1	1	6	6	6	1	1	6	6	1	1	6	6	6	6	1
LifeTrak Core C210	6	6	1	6	6	6	6	1	1	1	1	1	1	6	6	6	1	1	6	6	1	1	6	6	6	6	1
LifeTrak Move C300	6	6	1	6	6	6	1	5	1	1	1	1	1	1	6	6	1	1	6	6	1	1	6	6	6	6	1
LifeTrak Zone C410	6	6	1	6	6	6	1	5	1	1	1	1	1	1	6	6	1	1	5	5	1	1	6	6	6	6	1
LUMOlift	6	5	6	7	6	6	1	1	1	1	1	1	6	6	6	6	1	1	6	6	1	1	6	4	4	6	1
Magellan EchoFit	6	6	1	6	6	6	1	6	1	1	1	1	1	6	6	6	1	1	6	6	1	1	6	6	6	6	1

Microsoft Band	1	1	1	1	6	6	1	1	1	1	1	1	1	6	1	6	1	1	6	6	1	1	1	6	6	6	1
Misfit Flash	6	6	1	6	6	6	1	5	1	1	1	1	6	6	6	1	1	1	6	1	1	4	6	1	6	6	1
Misfit Shine	6	6	1	6	6	6	1	5	1	1	1	1	6	6	6	1	1	1	6	1	1	4	6	1	6	6	1
Moto 360	6	6	1	6	6	6	6	6	1	1	6	6	1	1	6	6	6	6	6	6	6	1	6	6	6	6	1
MyWellness Key	6	6	1	6	6	6	1	6	1	1	1	1	6	6	6	1	1	1	6	6	6	6	6	1	1	6	1
New Balance Body TRNr	6	6	1	6	6	6	1	6	1	1	1	1	1	6	6	6	1	1	6	6	1	1	6	6	6	6	1
New Balance Life TRNr	6	6	1	6	6	6	1	6	1	1	1	1	1	6	6	6	1	1	6	6	1	1	6	6	6	6	1
Nike+ Fuelband SE	6	6	1	6	6	6	1	6	1	1	1	1	1	6	6	6	1	1	6	6	1	1	6	6	6	6	1
Omate X	6	6	1	1	6	6	1	1	1	1	1	1	1	1	6	6	1	1	6	6	6	6	6	6	6	6	6
PAM AM200	6	6	1	6	6	6	1	6	1	1	1	1	1	6	6	6	1	1	6	6	6	6	6	6	1	6	1
PAM AM300	6	6	1	6	6	6	1	6	1	1	1	1	1	6	6	6	1	1	6	6	6	6	6	6	1	6	1
Pavlok	6	1	6	6	6	6	1	1	1	1	1	1	6	6	6	6	1	1	6	6	1	1	6	6	6	1	1
Pebble	4	4	1	6	6	6	6	6	1	1	6	6	1	1	6	6	6	6	6	6	1	1	5	5	5	6	1
Polar Loop	6	6	1	6	6	6	1	6	1	1	1	1	1	1	6	6	1	1	1	6	1	1	6	6	6	1	1
Polar V800	6	6	1	6	6	6	1	6	1	1	1	1	1	1	6	6	1	1	1	6	1	1	6	6	6	1	1
Razer Nabu	6	1	1	1	6	6	1	1	1	1	1	1	1	6	1	6	1	1	6	6	1	1	6	6	6	6	1

Razr Nabu X	6	1	1	6	6	6	1	1	1	6	1	6	1	6	6	6	1	1	6	6	4	1	6	6	6	6	1
RT6	6	6	1	6	6	6	6	6	1	1	2	1	1	6	6	6	1	1	6	6	6	6	6	6	1	6	6
Samsung Gear Fit	6	6	1	1	6	6	1	6	1	6	1	1	1	6	6	6	1	1	6	6	6	1	6	6	6	6	1
Spree	6	6	6	6	6	6	1	6	6	6	1	1	6	6	6	6	1	1	6	6	1	1	6	6	6	6	1
Stayhealthy Activity Monitor	6	6	1	6	6	6	6	6	1	1	2	1	1	6	6	6	1	1	6	6	6	6	6	6	1	6	6
Striiv Band	6	6	1	6	6	6	1	6	1	6	1	1	6	6	6	1	1	1	6	6	1	1	6	6	6	6	1
Striiv Fusion	6	6	1	1	6	6	1	6	1	1	1	1	1	6	6	6	1	1	6	6	1	1	4	6	6	6	1
Striiv Fusion Bio	6	6	1	1	6	6	1	6	1	1	1	1	1	6	6	6	1	1	6	6	1	1	4	6	6	6	1
Striiv Fusion Lite	6	6	1	6	6	6	1	6	1	1	1	1	1	6	6	6	1	1	6	6	1	1	4	6	6	6	1
Striiv Touch	6	6	1	6	6	6	1	6	1	6	1	1	6	6	6	1	1	1	6	6	1	1	6	6	6	6	1
Suunto Ambit3	6	6	1	6	6	6	1	6	1	6	1	1	1	6	6	6	1	1	6	6	1	1	6	6	6	6	1
Sync Burn	6	6	1	6	6	6	1	6	1	6	1	1	1	1	6	6	1	1	6	6	1	1	6	6	6	6	1
Sync Elite	6	6	1	6	6	6	1	6	1	6	1	1	1	6	6	6	1	1	6	6	1	1	6	6	6	6	1
Sync Fit	6	6	1	6	6	6	6	6	1	6	6	6	1	1	6	6	6	6	6	6	1	1	6	6	6	6	1
TracmorD (Philips DirectLife)	6	6	1	6	6	6	6	6	1	1	6	1	6	6	6	6	1	1	6	6	6	6	6	1	1	6	1

Vivago	6	6	1	6	6	6	6	6	1	6	6	6	1	1	6	6	6	6	6	6	6	6	6	1	6	6	6
Wellograph	6	6	1	1	6	6	1	1	1	1	1	1	1	1	6	6	1	1	6	6	1	1	6	6	6	6	1
Withings Pulse	6	6	1	6	6	6	1	6	1	1	1	1	1	6	6	6	1	1	6	6	1	1	6	6	6	6	1

1=Yes, 2 = Yes – Difficulties (e.g. proximity to computer) 3 = Yes – Lack of evidence to suggest this 4=No – But present in future iterations 5 = No – But possible (with Application Programming Interface or Software Development Kit) 6= Not described/Not featured

Table 3.5 – Self-monitoring attributes of devices that measure sedentary behaviour

Name	Type of Feedback								Timing Of Feedback				Feedback in								Backend Platform						Goal Setting Capabilities
	Device				Backend Platform				Device		Backend Platform		Device				Backend Platform				Application			Software		Website	
	Auditory	Vibratory	Omnipresent	Push Notification	Auditory	Vibratory	Omnipresent	Push Notification	Immediate	Delayed	Immediate	Delayed	Numeric	Graph	Written/Text Feedback	‘Ometer	Numeric	Graph	Written/Text Feedback	‘Ometer	iOS	Android	Windows	Mac	PC		
Activ8	6	1	1	6	6	1	1	5	1	1	6	1	6	6	6	1	1	1	6	5	6	5	6	6	6	1	1
ActivPAL VT	6	1	6	6	6	6	6	6	1	6	6	1	6	6	6	6	1	1	6	5	6	5	6	6	1	6	6
Darma	6	6	6	6	1	6	1	1	6	6	1	6	6	6	6	6	1	1	1	0	1	0	6	6	6	6	1
FootLogger	6	6	6	6	5	5	5	5	6	6	5	5	6	6	6	6	5	5	5	4	1	0	6	6	6	6	5
Gruve	6	1	1	6	6	6	6	6	1	6	6	1	6	6	6	1	1	1	6	5	6	5	6	6	1	1	1
LumoBack	6	3	6	6	6	6	1	1	1	6	1	1	6	6	6	6	1	1	1	1	1	1	3	6	6	6	1
Moticon OpenGo	6	6	6	6	5	5	5	5	6	6	5	5	6	6	6	6	5	5	5	4	5	4	5	4	5	5	5
OM Everyday	6	6	6	6	6	6	1	1	6	6	1	6	6	6	6	6	1	1	6	5	1	0	6	5	6	6	1
Sensoria Fitness	1	6	6	6	6	6	6	1	1	1	1	1	6	6	6	6	1	1	5	4	1	0	6	5	6	6	1

1=Yes, 2 = Yes – Difficulties (e.g. proximity to computer) 3 = Yes – Lack of evidence to suggest this 4=No – But present in future iterations 5 = No – But possible (with Application Programming Interface or Software Development Kit) 6= Not described/Not featured

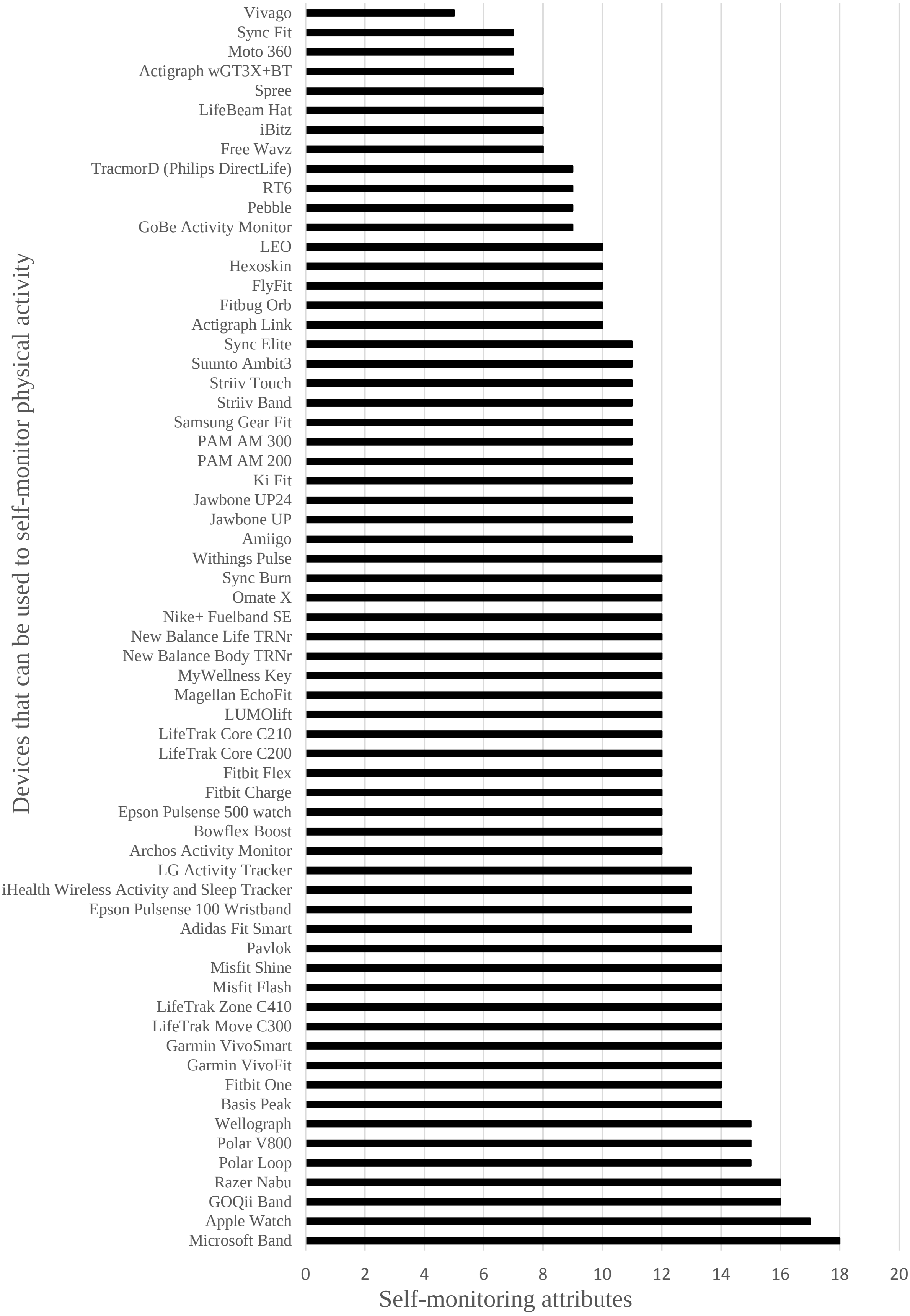


Figure 3.2 - Technologies found that can be used to self-monitor and provide feedback on physical activity ordered by number of self-monitoring attributes that were found to be present in the technologies

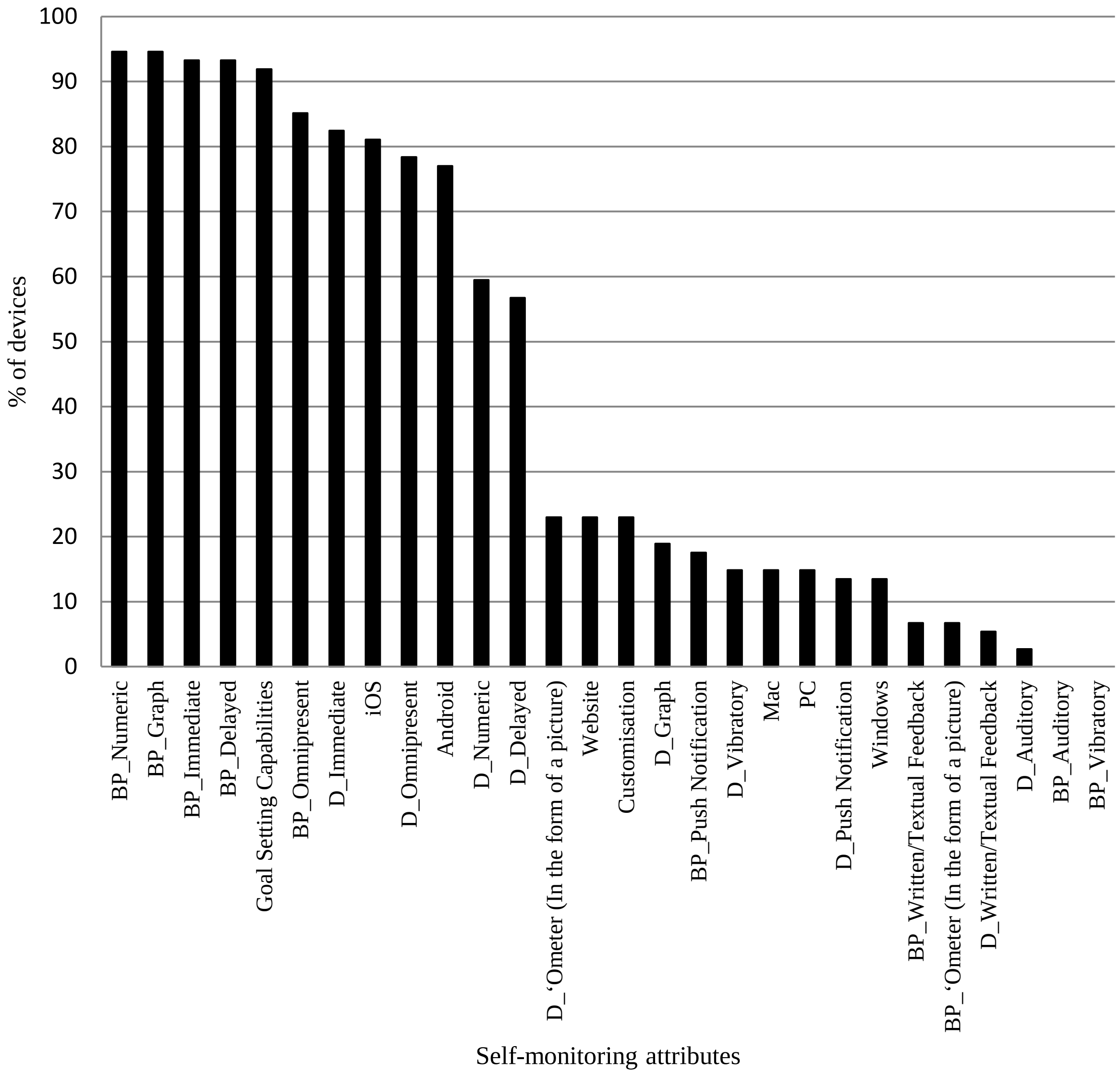


Figure 3.3 - Proportion of devices that can be used to self-monitor and provide feedback on physical activity which have the specific self-monitoring attributes

Each attribute is split into whether the attribute is present on the device itself (denoted is a D) or whether it is present on the backend platform (i.e. smartphone/tablet etc; denoted with BP)

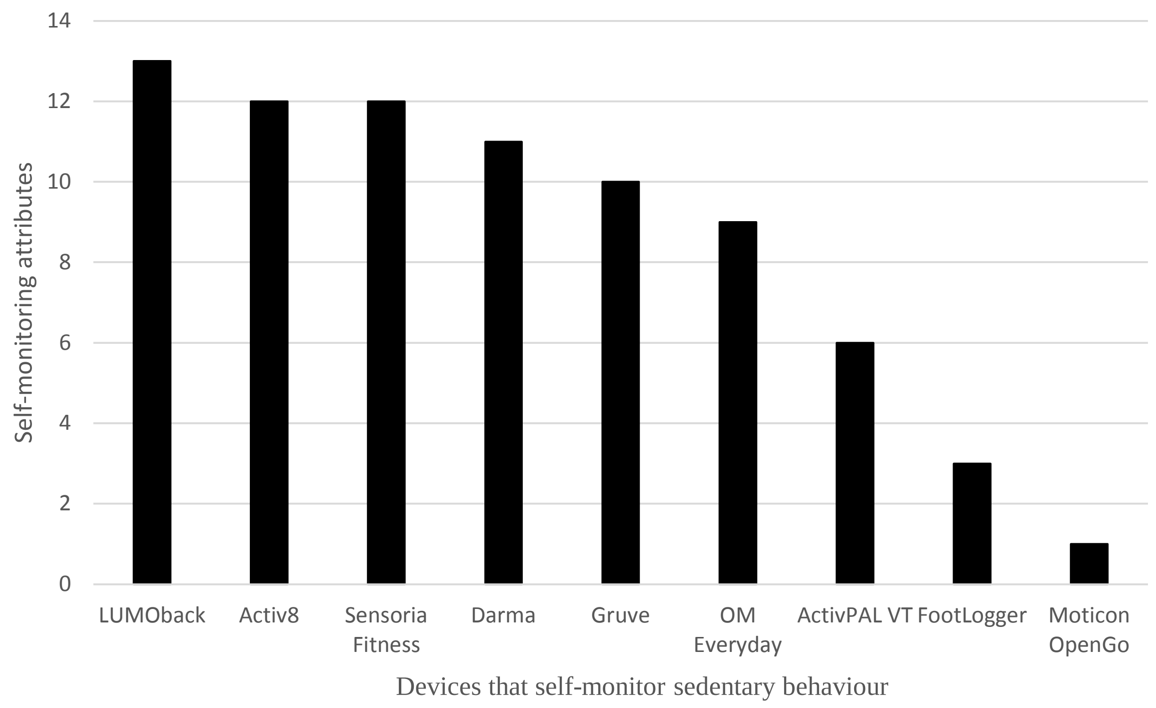


Figure 3.4 - Technologies found that can be used to self-monitor and provide feedback on sedentary time ordered by number of feedback elements that were found to be present in the technologies

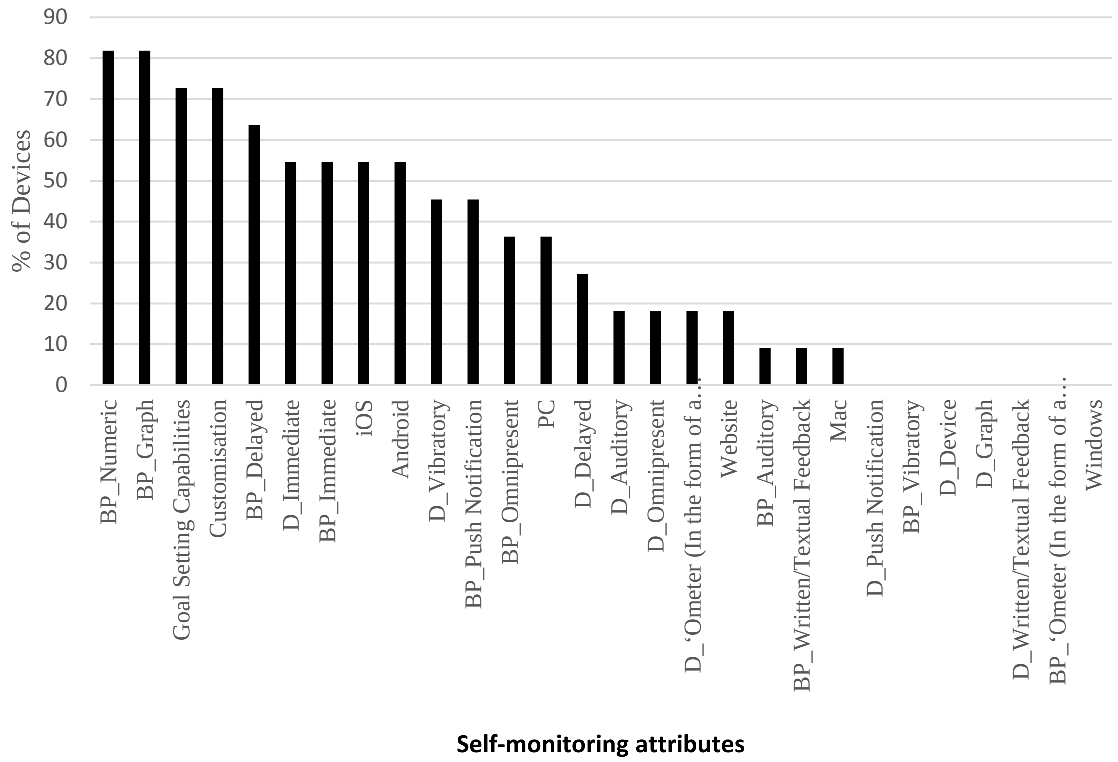


Figure 3.5 - Proportion of sedentary behaviour devices that can be used to self-monitor and provide feedback on sedentary time which have the specific self-monitoring attributes

Each attribute is split into whether the attribute is present on the device itself (denoted is a D) or whether it is present on the backend platform (i.e. smartphone/tablet etc; denoted with BP)

3.4 Discussion

The present systematic review sought to identify current measurement technologies available that could be used for real time self-monitoring of sedentary behaviour and/or physical activity. The review identified 125 papers on 46 devices and 90 websites, giving a combined total of 146 technologies that monitor sedentary behaviour and/or physical activity. Of these, 82 devices were considered capable of self-monitoring sedentary behaviour and/or physical activity. These devices can be used by researchers, clinicians and the general public.

Technologies that self-monitor physical activity mainly come from the consumer health and fitness market. In general, these devices consist of an accelerometer for activity measurement (steps, calories burned, distance travelled) with varying secondary sensors including, gyroscope, inclinometer, lux sensors, skin sweat sensors and many more that will provide additional pieces of information. However, these devices will provide feedback only on physical activity, and increases in physical activity do not automatically lead to decreases in sedentary time (35). Additionally, more and more of these devices are providing feedback on not only the amount of physical activity, but the length of time spent inactive.

There are devices from both the commercial and research sectors that self-monitor sedentary behaviour. These devices tend to measure sedentary behaviour in two differing ways. Firstly, posture sensors measure sedentary behaviour either through accelerometry in conjunction with gravitational components and proprietary algorithms (e.g. activPAL) or through the alignment of the area of the body surrounding the pelvic area (i.e., pelvic alignment is different depending on standing sitting and lying). The other way in which technologies tend to measure sedentary behaviour is via pressure sensors. These pressure sensors are either located in a sock, shoe or chair. When placed in a sock or shoe the pressure can determine standing when there is pressure on the sensor and when there is less pressure the wearer is sitting or lying. Located on the chair, there is a simple binary outcome that suggest when the pressure sensor is active the user is sitting and when inactive there is no sitting behaviour at that site.

Both physical activity and sedentary behaviour devices usually provide either via vibratory feedback (e.g. Jawbone UP) or via an omnipresent display on the device (e.g. Garmin Vivofit). These devices tend to, but not exclusively, connect to a mobile application for feedback on the nature of the physical activity and sedentary behaviour. For physical activity, this usually takes the form of energy expenditure or proprietary company points (e.g. Nike Fuel). For sedentary behaviour, this usually takes the form of time spent sitting (e.g. LumoBack). These mobile applications allow the wearer to receive real time continuous feedback along with goal-setting capabilities and customisation of type and timing of feedback, an aspect not traditionally offered by research devices.

With the plethora of devices now available, with differing attributes and cost, it is unsurprising that these devices are growing in popularity. However, and perhaps paradoxically, there are a small number of devices specifically designed to measure sitting time. Furthermore, the small number of devices that do provide feedback on sitting were either not originally designed for its measurement (e.g. LumoBack) or are still mainly research tools to be used in scientific studies (e.g. activPAL VT).

Self-monitoring technologies need to provide real-time feedback on aspects of physical activity and sitting that are personalised and relevant to the individual (i.e., the attributes of real-time feedback must resonate with the individual and not simply information that has been presupposed for them). Additionally, the immediate feedback should be of a low cognitive load so that it can resonate immediately with the end user (346,347). For example, the Fitbit One has a growing flower as a feedback indication of progression towards a user defined goal. Using a pictorial representation of this nature will resonate easier with the user (348,349). However, more detailed information on, for example, the temporal patterning of the behaviour should be accessible from a mobile application, website or software.

The likelihood of the feedback being acted upon could be increased if it is provided in a manner that is context aware. In other words, the feedback must be given at a time when it can be acted upon by the user. For example, to reduce sitting provide feedback whilst watching television rather than sitting in an exam or during a prolonged dental procedure. If these attributes could be integrated into a single device it would help facilitate its use by differing populations regardless of technological ability. These devices need to have a substantial battery life and memory capacity, as well as keeping the costs reasonable. For this to occur there is a need for co-operative work across different research disciplines and commercial fields, to develop these context-aware, personalised feedback devices. Not every user will have the same needs, and the presentation of actionable information will need to be tailored to fit individual needs. In addition, simply providing more medical data to patients not only fails to guarantee improved outcomes but also could potentially lead to negative consequences (350). Activity trackers have had a poor evidence of prolonged use, with a conservatively estimated one-third discontinuing use by 6 months after initiation (351). A recent study of several tools to encourage medication adherence in older adults, a major area of focus of mHealth developers, found that the most common descriptors participants used to describe their experience with the devices were “frustrating” and “challenging” (352). In another study of the usage of a dietary app to promote healthy eating, investigators found that fewer than 3% used the app for at least one week and fewer than 10% of these individuals made positive changes in their diet (353). Users require consumer-friendly devices and apps that are self-reinforcing and enjoyable to use. These goals might be accomplished with the use of incentives, gamification, and social networks to promote managed competition among peers or family members. This review demonstrates that there are a plethora of feedback attributes enabling users to customise their experience by choosing the device with best works for them.

In order for the promise of wearable technology to be fully realised, consumers, providers, and health care systems must be able to trust the reliability, privacy and security of their data as well as the devices that collect and share it. Although regulatory oversight is often considered to be an impediment to the rapid dissemination of innovative technologies, the existence of potential scams which could harm the end user necessitates some level of oversight. Globally, there is a great deal of uncertainty around wearable technology regulation; there are numerous countries that have no regulatory framework, whereas the others that do have a framework are still in their infancy and being actively refined (354,355).

Wearable technology users are also concerned about the privacy and ownership of their health data. In the era of big data, it is critical that the terms of ownership of personal data, most especially medical data, be unambiguously stated – not buried in the universally unread and then accepted terms of use agreements – with users required to explicitly consent whenever their data are sold or transmitted to others (356).

One of the benefits of mHealth is easier accessibility to pertinent health care data, but this increased availability to both consumers and providers creates the potential for substantial security risks. Because of the small size of the device it becomes easier to inadvertently lose or be easier to steal, which may mean that the information stored on the device becomes accessible to others. As consumer demand for wearable sensors increase, health care providers will face the possibility of being inundated by a torrent of patient data. This will create a number of difficult challenges, including the potential requirement for 24/7 oversight, the need to summarize multi-parameter, continuously collected data into a usable and clinically meaningful format, and liability challenges (357).

The strengths of this review are the systematic approach taken and the comprehensive range of technologies that have been found. However, there are some limitations. Due to the nature of papers included, it was not possible to present data on the validity and reliability of the devices in their ability to measure sedentary behaviour. Similarly, due to the fact that objectively self-monitoring is in its infancy, there are gaps in the literature as to whether these devices truly work as self-monitors, consequently, we cannot comment on how useful or valid they are in these settings. However, validity data are important. Users of self-monitoring technologies must be able to trust in the feedback that is being returned to them; otherwise they may become disenfranchised with the tool and the behaviour change tool. Therefore, incorporating important valid data with the feedback tools means additional value can be added to the consumers and potentially more potent behaviour change.

3.5 Conclusion

In conclusion, the authors believe that this review is the first of its kind to systematically describe the wide plethora of devices that self-monitor and provide feedback on physical activity and sedentary behaviour. There has been an explosion in the number of devices that measure physical activity and there is a greater need for the development of tools that specifically measure sitting time. Co-operative work between engineers, computer scientists and academics in relevant fields is needed to develop these technologies that provide real time, personalised, context aware feedback to aid in the reduction in sitting time, and its detrimental effect on cardio-metabolic health independent of physical activity. This could potentially lead to the use of these devices in a healthcare setting; both as part of the increasing value-based care systems that are starting to arise in the United States or as a diagnostic tool in which is beginning to be implemented in the National Health Service in the UK.

The plethora of devices and differing feedback attributes allows the user to choose which device and which attribute works best for them. However, there is not currently a “one size fits all devices" which means individuals may have to choose more than one device to measure different parameters of the behaviour or to determine the most resonating feedback attribute for them.

This scoping review provides a record of a large breadth of devices with information on their capabilities both in terms of their ability to measure behaviour and to provide feedback to the user, therefore providing a foundation for clinical, research, and public health use. These self-monitoring tools are becoming ever more present in daily life as well as becoming integrated into health systems throughout the world. Future studies are needed to further investigate the validity of these devices and their feasibility to in increasing physical activity and/or decreasing sedentary behaviour and the public health impact this may produce.

From this review, it was determined that the LumoBack was the device which contained the highest volume of attributes as well as the ability to measure sedentary behaviour to the definition. Therefore in chapter 4, the LumoBack will be validated for measuring sedentary behaviour.

Chapter 4 - The validity of the LumoBack Posture Sensor as an objective measure of sedentary behaviour in adults

4.1 Introduction

Sedentary behaviour (measured by posture sensors and questionnaires), is a distinct risk factor for cardio-metabolic health, which may be additional to the risks associated with lack of moderate-vigorous physical activity (MVPA (28,29,59,60,358). However, the optimal amount, frequency and distribution of sedentary behaviour are still a matter for debate. Reliable and valid measurements of sedentary behaviour are therefore essential to draw appropriate conclusions about their influences on health. Early studies measuring sedentary behaviour predominantly used self-report tools (52,59,104). However, self-reported measurement tools are prone to recall and response bias, social desirability, and under- or over-reporting (104). Additionally the reproducibility and validity of self-reported sedentary behaviour are variable (107,359).

Accelerometry has been proposed as a method to objectively quantify sedentary time (measured by accelerometry) in addition to physical activity (360). Briefly, activity monitoring using accelerometers measures the intensity of the behaviour based on acceleration at the point the accelerometer is attached to the body. Accelerometers, which measure activity using accelerometric counts determine sedentary time as less than 100 CPM (48); however, the most accurate cut-point is yet to be universally agreed upon and may vary between different population groups (361). A problem with this approach is the inability to discriminate between differing postures (a key component of the sedentary behaviour definition (43)). In other words, if a person is sitting or standing still, these could both be interpreted as sedentary time using the accelerometer cut-point method. This will cause measurement problems for interventions where participants are encouraged to replace sitting with standing (134).

In one study (52), 86 participants (87% women; mean age 52.7 years, SD 8.6 years) simultaneously wore an ActiGraph (ActiGraph, LLC, Pensacola, FL, USA) activity monitor and activPAL (PAL Technologies Ltd, Glasgow, UK) for 7 consecutive days (52). For this analysis, only valid days that had similar estimated wear times for both devices (±30 minutes) were considered. Sedentary time derived from the ActiGraph activity monitor (<100 CPM) was compared to sedentary behaviour from the activPAL (sitting and lying down) over an average of 4.5 observed days per person, and an average wear time of 14.3 ± 1.5 hours per day for each device. On average, recorded sedentary time was lower for the ActiGraph activity monitor (8.7 [SD=1.6] hours/day, or 60.9%) than for the activPAL (99 [SD=1.8] hours/day, or 63.4%; both p=0.01), but the correlation between the measures was relatively high (ρ = 0.76, p<0.01). Interestingly, Bland-Altman analysis showed a small mean difference (-0.34 hours) and wide 95% limits of agreement (2.11 to -2.79 hours (52). In another study, 32 participants wore an ActiGraph GT1M and activPAL for one day (136). For similar amount of wear time (15.1 ± 1.9 vs 15.0 ± 2.0 for ActiGraph and activPAL respectively) the ActiGraph (sedentary time defined as <100 CPM) had statistically higher levels of sedentary time (650.6 ± 111.8 minutes/day) compared to the activPAL (518.5 ± 147.8 minutes/day). This indicates that the ActiGraph activity monitor has minimal bias overall, but can both substantially over- and under-estimate sedentary time compared with the activPAL (136). These two validity studies imply that ActiGraph activity monitors provide useful estimates of sedentary time and that are sufficiently accurate to rank individuals by their level of sedentary time. However, given the limitations of accelerometry, development and testing of new measures of sedentary behaviour are required. The activPAL, an inclinometer enabled monitor, is able to measure different postures, such as lying, sitting, and upright postures, which has been shown to be a valid measure of behaviour in both laboratory and free-living settings (151–153,255,256,362,363). Additionally, posture sensors are emerging in the commercial market aimed at measuring various behaviours, some of which have the ability to measure posture, one such device is the LumoBack posture sensor (338).

The LumoBack (LumoBody Tech, Inc, Palo Alto, CA) is a small (4.15 x 10 x 0.8cm, 25g) and flexible posture sensor, worn on the lower back. The LumoBack and other newer consumer electronic (CE) technologies in this area, has the ability to empower the wearer to self-monitor their behaviour. Furthermore, the systematic scoping review in Chapter Three (page 46) identified that there is currently a lack of sedentary behaviour self-monitoring devices compared to their physical activity self-monitoring counterparts. Of the nine sedentary behaviour self-monitoring devices, the LumoBack was seen as one of the more promising tools with its ability to measure body posture (as opposed to the absence of activity like accelerometers, or being seat based), to provide real-time feedback of behaviour to a mobile application, to utilise a vibratory functionality to provide prompt/cues for immediate feedback, and open source Software Development Kit (SDK) and Application Programming Interfaces (API), along with being relatively inexpensive compared to its research grade counterparts, makes the LumoBack worthy of validating for use as a sedentary behaviour measurement self-monitoring tool.

Therefore the aim of this study was to examine the criterion and convergent validity of the LumoBack in measuring sedentary behaviour, by comparing the validity of the LumoBack to direct observation, the ActiGraph wGT3X+ and the activPAL under laboratory conditions as well as examining the convergent validity of sitting time, standing time and stepping time of the LumoBack compared to the activPAL3 and ActiGraph wGT3X+ in a sub-sample of healthy adults in a free-living setting.

4.2 Methods

4.2.1 Design

Data were collected in a controlled, laboratory environment. Data from the LumoBack were compared to direct observation (as the gold standard) as well as activPAL (worn on the thigh: hereafter referred to as activPAL) and ActiGraph wGT3X+ (worn on the waist: hereafter referred to as ActiGraph). In the laboratory measurement, the participants were instructed to follow a strict activity and posture protocol in a fixed setting. A sub-sample of participants wore the LumoBack, activPAL and ActiGraph for a period of seven days as part of the free-living component of this study.

4.2.2 Participants

A convenience sample of 34 apparently healthy adults (45% male, mean age 27.1 ± 5.5 years, mean BMI = 23.8 ± 3.5 kg/m^2) participated in the laboratory study. A sub-sample of 12 healthy adults who participated in the laboratory study participated in the free-living study (58.3% male, mean age 26.8 ± 4.6 years old, mean BMI = 24.2 ± 3.2 kg/m^2). This sub-sample was chosen based on which of the individuals in the laboratory study had an iOS compatible device. The participants read an information sheet and completed a Health Screening Questionnaire, and Informed Consent form before measurements took place. Study documentation can be found in Appendix 2 (page 213).

4.2.3 Procedures

In the laboratory experiment, preliminary data were collected from the participants including their age, weight, standing height (enabling BMI to be calculated), and sex. For standing height, the participants were asked to stand upright, barefoot, with their back to the vertical backboard of the stadiometer (Leicester Portable health measure). The heels of the feet were placed together with both heels touching the back of the vertical board. The participant’s feet were pointed slightly outward at approximately a 60 degree angle. The participants head was maintained in the Frankfort Horizontal Plane position (the head is in the Frankfort plane when the horizontal line from the ear canal to the lower border of the orbit of the eye is parallel to the floor and perpendicular to the vertical backboard) while the investigator lowered the horizontal bar snugly to the crown of the head with sufficient pressure to compress the hair. The participants were asked to inhale deeply and to stand fully upright without altering the position of their heels. The act of taking a deep breath helps straighten the spine to yield a more consistent and reproducible stature measurement. The measurement was recorded to the nearest 0.1 cm (364). For measurement relating to weight and BMI, the Tanita Body Composition Analyser BC-418 (Tanita, West Drayton, UK) was used. Participants were asked to remove all footwear and any extra weight (heavy jumpers, coins in pockets, belts etc.). Participants were asked to step on the weight platform, making sure to place their heels on the posterior electrodes, and the front part of their feet in contact with the anterior electrodes. The participants were then asked to hold onto the grips of the analyser until the measuring process had completed. Body weight was measured to the nearest 0.1kg.

Following these anthropometric measurements, the devices were fitted to the participants. The activPAL was fitted on the midline anterior aspect of the participant's right thigh affixed with medical dressing, whilst the ActiGraph was worn on the right hip. The LumoBack was fitted to the lower back with the Lumo logo facing outward, and in the centre of the back. Exact position was not necessary due to the calibration feature of the LumoBack. As such, each participant was asked to go through this calibration process before the commencement of the study protocol. The LumoBack was connected to the mobile application (app) via low energy Bluetooth (BLE). The mobile application possesses an avatar which assumes the posture of the wearer. Calibration of the device takes place by having the participant assume the posture shown by the avatar. Participants would hold this position while the mobile application calibration functions were enabled, signified by five mild vibrations from the LumoBack. Calibration was indicated to be completed by a push notification (see Table 3.3 and 3.5) as part of the app. Once calibration was complete, the participant was asked to walk for a distance of approximately 20 metres and then to sit down on a chair (which was used for all sitting activities) so as to ascertain whether the calibration process had been performed correctly. This was determined by the avatar on the mobile application displaying in real time the postures and activities of the participants. Due to the lack of download feature from the device or the mobile application at the time of testing, data were recorded during the laboratory experiment on customised data recording sheets (See Appendix 2.4 page 221).

Once the device had been fitted and the LumoBack had been calibrated, the participants were instructed to undergo seven different seated activities (Table 4.1). Each of these activities lasted for five minutes with between 30-60 seconds in between activities. Time spent in each activity was recorded on the activity log sheet. At the time of data collection, study investigators were not aware of a method to download LumoBack data; therefore, a methodology of direct observation of the sitting time minimum card (min card; see Chapter 5 page 120) on the LumoBack app via a secondary investigator was used to record the data from the LumoBack. A sub sample of this group was asked to wear the LumoBack, ActiGraph and activPAL for a period of seven days. Traditionally, in validation studies, participants would be provided with a diary log for participants to document when they removed the ActiGraph and activPAL so as to remove non-wear time from the analysis. However, when a LumoBack is removed and placed on charge or laid horizontally on a flat surface with the Lumo logo facing up, this is recorded in the data as non-wear. Therefore, participants were instructed to remove all devices at the same time and place the LumoBack on charge to create an electronic log of wear time.

4.2.4 Activity Monitors

The LumoBack is a small (4.15 x 10 x 0.8cm, 25g) and flexible posture sensor, worn on the lower back. Designed to measure an individual’s posture, the LumoBack has personalised built in calibration algorithms which adapt to each person’s body shape and movement behaviour. These are used to create a recommended optimal back posture model. The embedded posture sensors feed data to machine learning algorithms that continuously track the amount of time spent lying (used to infer sleeping), sitting, standing and stepping. The monitor connects wirelessly via BLE to an app, which includes an avatar that mimics the postures and daily activities of the wearer in real time. The LumoBack was worn on the lower back just above the waist using an elastic belt. The LumoBack measures posture based on the waist angle of the wearer, the device must be calibrated to each individual before use as the tilt is different from individual to individual.

Table 4.1 - A description of the sitting activities carried out

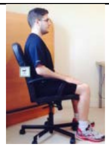
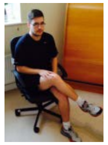
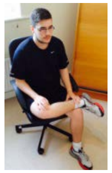
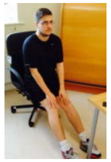
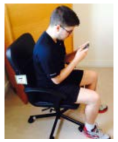
Activity	Picture	Description
1. Sitting on chair with feet flat on floor		Sitting upright in a chair with trunk at approximate right angles to upper legs as well as approximate 90º right angles at the knees, with hands placed on the anterior aspect of the upper legs. Feet flat on floor.
2. Sitting on chair with legs crossed (right over left)		Sitting upright with trunk at approximate right angles to upper legs with knee of the right leg resting on the anterior aspect of the left knee, with hands resting on top of right knee. Left foot flat on floor.
3. Sitting on chair with right foot resting on left thigh		Sitting upright with trunk at approximate right angles to upper legs with the left knee at a right angle, with the lateral side of the right ankle resting on the left knee with the anterior aspect of the hands resting on the anterior aspect of the left leg and the medial aspect of the right thigh.
4. Sitting on chair with legs stretched out forwards		Sitting upright at the edge of a chair with legs stretched out straight, and feet flat on floor with the anterior aspect of the hands resting on the anterior aspect of the upper leg.
5. Sitting with feet backwards underneath chair		Sitting upright in a chair with trunk at approximate right angles to upper legs as well as approximate acute angle of less than 90º at the knees, with hands placed on the anterior aspect of the upper legs.
6. Sitting with upper body movement (computer)		Sitting upright in a chair with trunk at approximate right angles to upper legs as well as approximate right angles at the knees whilst typing on a computer, copying from a passage.
7. Sitting playing games on a phone		Sitting upright in a chair with trunk at approximate right angles to upper legs as well as approximate right angles at the knees whilst playing the same mobile game application.

Table 4.2 - Characteristics of the activity monitors used

	LumoBack	ActiGraph	activPAL3
Manufacturer	LUMObody Tech Inc,	ActiGraph LLC	PAL Technologies Ltd
Size (cm)	4.15 x 10 x 0.8	4.6 x 3.3 x 1.5	5 x 3.5 x 0.7
Weight (g)	25	19	15
Placement	Lower Back	Wrist, Waist, Thigh	One third down midline of the anterior aspect of the thigh
Sample Frequency (Hz) *	25	100	20
Epoch Length [+]	5minutes	15 seconds	15 seconds
Sensor	Posture Sensors, Triaxial Accelerometers	Triaxial Accelerometer, Ambient Light Photodiode	Capacitative Accelerometer
Waterproof	Unknown	1m, 30mins	Splash Proof[++]
Interface	Bluetooth Low Energy	USB	Micro USB
Software	LumoBack App	ActiLife	ActivPAL3 7.2.32
Outcomes – Measured	Lying, Sit time, Standing time, Stepping time Number of Stand up, Step counts	Counts, Inclinometer determined posture	Time Spent in Sedentary, Upright, and stepping activities
Price	$69.99	£225	£380

*sample frequency – the number of times the raw acceleration is sampled. Hz is a measure of frequency – defined as one cycle per second. (i.e. 100Hz = 100 samples per second) [+]Device offers more options; the options selected in this study is presented [++]Can be fully water proofed using supplementary materials.

The ActiGraph (ActiGraph, LLC, Pensacola, FL, USA) is a small lightweight and rechargeable activity monitor. It uses a triaxial accelerometer to collect motion data on three axes. The ActiGraph measures and records time-varying acceleration in the range of 0.05-2.5Gs. The accelerometer output is digitised by a twelve-bit analog to digital converter at a rate of 100Hz. Once digitised, the signal passes through a digital filter that band-limit the accelerometer to the frequency range of 0.25–2.5Hz. Each sample is summed over an ‘epoch’, that is, a specific interval of time which typically corresponds to 60s, however, in the case of this study it was 15s. The output of the ActiGraph is given in ‘counts’. The counts obtained in a given time period are linearly related to the intensity of the participants physical activity during a given period. The ActiGraph was worn on the right in line with midline of the thigh, were initialised to measure acceleration at 100Hz, and the data were processed using ActiLife Software (version 6.11.8). A cut point of less than 100 CPM was used as a measure of sedentary time.

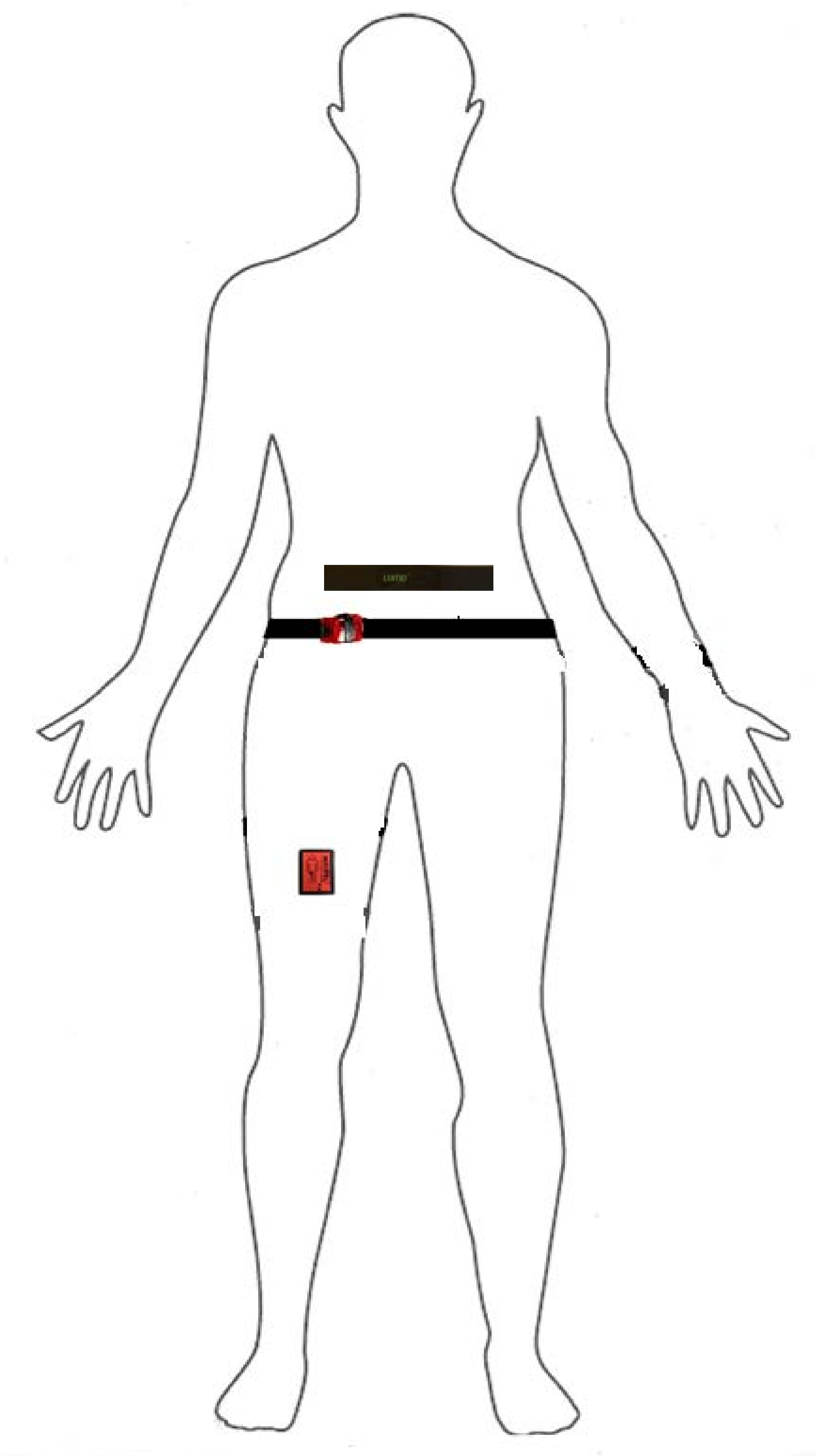


Figure 4 1- Anterior view of how the devices were worn.
*LumoBack worn on the lower back the waist using an elastic belt.

The activPAL is a lightweight activity monitor that is worn on the thigh, attached by medical dressing. The activPAL uses a triaxial accelerometer sampling at 20Hz to produce signals reflecting thigh inclination and movement. The activPAL software uses proprietary algorithms to classify an individual's free-living activity into periods spent lying/sitting, standing and walking. This information can be used to estimate daily energy expenditure and changes in free-living activity. The activPAL was taped to the anterior aspect of the thigh, approximately a third of the way down from the waist. It was attached using the medical dressing ((PAL Technologies Ltd, Glasgow, UK). See Table 4.2 for summary of the characteristics of the activity monitors and Figure 4.1 for wear sites of each of the devices.

4.2.5 Statistical Analysis

Data from the activity log sheet was transcribed into both Microsoft Excel 2010 (Microsoft Excel, Redmond, Washington) and SPSS version 22 (IBM SPSS Inc, Chicago, IL) for data analysis. Total sitting time was computed from the sum of the seven individual sitting conditions. Total Sitting Time (minus sitting with feet under chair) was also computed. Total sitting time (minus sitting with feet under chair) was calculated because the LumoBack measures sitting time via, pelvic tilt/waist angle and alignment, therefore when sitting with feet under chair the waist angle is closer to 180º, similar to that of standing. This will lead to a systematic under-estimation of sitting time by the LumoBack during this condition and consequently has been removed from a selection of analyses.

Validity was calculated using Bland-Altman plots to test for criterion validity of the LumoBack, ActiGraph and activPAL against direct observation, as well as convergent validity of the LumoBack against ActiGraph and activPAL. Bland Altman plots are conducted by plotting the difference (Y axis) between the methods calculated by:

$$Difference \ = Reference\ Method\ Mean - New\ Method\ Mean$$

plotted against (X axis) the mean of both methods calculated by:

$$Mean = \frac{Reference\ Method\ Mean + New\ Method\ Mean}{2}$$

Limits of agreement were calculated as:

$$95\%\ Limits\ of\ agreement = Mean\ Difference\ \pm (1.96\ \times SD\ of\ the\ Difference)$$

Reproducibility was assessed using Two-Way Mixed Intraclass Correlation (ICC). There was a lack of sufficient spread of data when performing interclass correlations on the individual activities and direct observation therefore interclass correlations were only performed on the total sitting time measured by the LumoBack, ActiGraph and activPAL during the lab study.

In addition mean absolute percentage error (MAPE), a measure of reproducibility of a method by comparing to a standardised method was calculated using the following equation:

$$\text{MAPE} = \frac{|Reference\ Method\ \ Mean - New\ Method\ Mean\ |}{Reference\ Method} \times 100$$

Repeated Measures Analysis of Variance (ANOVA) with pairwise comparisons were used to determine whether there were any statistical differences in the amount of sitting time recorded by the LumoBack and direct observation. It was also used to determine any differences between the amounts of time spent sitting measured by the LumoBack and the ActiGraph and activPAL. Statistical significance level was set at 0.05.

4.3 Results

A convenience sample of 34 healthy adults participated in the laboratory study. A sub-sample of 12 healthy adults who participated in the laboratory study participated in the free-living study. Descriptive statistics of both samples can be found in table 4.3. Thirty one out of the 34 participants who took part in the laboratory study were included in the analyses with three participant's data were removed from the analysis, due to preliminary data mining suggesting a systematic device malfunction of one of the three devices.

Table 4.3- Laboratory and Free-living Participants descriptive statistics*

	Laboratory Mean (SD) – N=31	**Free-Living Mean (SD) N=12**
Age (Years)	27.1 (5.5)	26.8 (4.6)
Male (%)	45.2	58.3
Height (m)	1.7 (0.1)	1.8 (0.1)
Weight (Kg)	69.2 (15.4)	76.1 (10.3)
BMI (kg/m^2)	23.8 (3.5)	24.2 (3.2)
% Body Fat	28.0 (8.2)	28.2 (7.9)

*There were no significant differences in participant characteristics between those taking part in the Laboratory validation only and those participants in both study components (P>0.05)

4.3.1 Laboratory Assessment: Criterion- and Convergent- Validity

Table 4.4 and Appendix figures 4.2-4.10 shows the Bland-Altman data and plots respectively for the LumoBack, ActiGraph and activPAL against direct observation to assess criterion validity. During the first three conditions (feet flat on floor, legs crossed (right over left) and right foot resting on left thigh) the LumoBack, ActiGraph and activPAL undercounted by

<1.1 seconds per five minute condition, with 95% CI of <±11 seconds compared to direct observation.

During the legs stretched out forward condition, the LumoBack and ActiGraph under-reported sitting time compared to direct observation. The activPAL also under-reported sitting time but to a greater extent than the LumoBack and ActiGraph.

The LumoBack, ActiGraph and activPAL all under reported sitting time during the Sitting with Feet Back Under the Chair condition, with the LumoBack having the greatest mean difference of the three measurements. Furthermore, during the Sitting with Upper Body Movement (Computer) the LumoBack, ActiGraph and activPAL under reported sitting time. And finally, the LumoBack, ActiGraph and activPAL under reported sitting time during the Sitting Playing a Game on a Phone condition.

Grouping all sitting activities together into a total sitting time condition, the LumoBack, ActiGraph and activPAL under-reported total sitting time. When the sitting with feet back under the chair was removed from the analysis, the LumoBack ActiGraph and activPAL all under-reported sitting time.

Table 4.5 and appendix 4.7-4.14 shows the Bland-Altman data and plots respectively for the LumoBack vs ActiGraph and activPAL In general, during the first three conditions (feet flat on floor, legs crossed (right over left) and right foot resting on left thigh) the LumoBack had a mean difference of <1 seconds per five minute condition, with 95% CI of <±11.1 seconds compared to ActiGraph and activPAL.

During the legs stretched out forward condition the LumoBack has a mean difference of 5.0 (SD 17.3) seconds per 5 minute condition with upper limits of 39 seconds and lower limits of -29 seconds when comparing the LumoBack to the ActiGraph during this condition. However, compared to the activPAL the LumoBack has a mean difference of -153.54 with 95% CI of -448.8, 141.7. Additionally, the LumoBack had a mean difference of 61.8 seconds compared to the ActiGraph, and mean difference of 54.2 seconds in the Sitting with Feet Back under chair condition. Furthermore, the LumoBack had a mean difference of 40.5 seconds compared to the ActiGraph, and mean difference of 43.4 seconds in the Sitting with Upper Body Movement (Computer) condition. In the final task, the LumoBack had a mean difference of 11.1 seconds compared to the ActiGraph, and mean difference of 0.7 seconds in the Sitting with Playing a Game on Phone. Finally, the LumoBack in total when accounting for all activities had a mean difference 133.9 seconds when compared to the ActiGraph and mean difference of -38.1 seconds. However, when feet underneath chair was removed from the analysis the mean difference reduced to 72.1 seconds when compared to the ActiGraph, and a mean difference of -92.3 when compared to the activPAL.

Table 4.4 - Bland-Altman data assessing the criterion validity of the LumoBack, ActiGraph and activPAL to direct observation

Sitting Posture (Seconds)	LumoBack				ActiGraph				activPAL			
	Mean Difference	Standard Deviation	95% Limits of Agreement		Mean Difference	Standard Deviation	95% Limits of Agreement		Mean Difference	Standard Deviation	95% Limits of Agreement	
			Lower Limit	Upper Limit			Lower Limit	Upper Limit			Lower Limit	Upper Limit
Feet Flat on Floor (300)	0.86	4.1	-7.2	8.9	1.1	3.9	-6.6	8.8	0.0	0.0	0.0	0.0
Legs Crossed (Right over Left) (300)	0.1	3.08	-5.9	6.1	0.6	2.9	-5.1	6.2	0.0	0.0	0.0	0.0
Right Foot Resting on Left Thigh (300)	0.9	4.9	-9.51	10.4	0.0	0.0	0.0	0.0	0.5	1.8	-3.0	3.9
Legs Stretched out Forward (300)	5.5	17.8	-29.4	40.4	0.5	2.8	-4.9	6.0	159.3	151.1	-136.9	455.4
Feet Underneath Chair (300)	60.9	130.5	-194.8	316.6	1.0	3.9	-6.5	8.6	10.9	56.7	-100.2	122.0
Upper Body Movement (Computer) (300)	42.1	100.2	-154.3	238.4	1.6	6.1	-10.5	13.6	0.2	1.1	-2.0	2.4
Playing game on phone (300)	10.9	51.0	-89.1	110.9	0.5	2.8	-4.9	6.0	11.3	56.6	-99.7	122.3
Total Sitting Time (2100)	139.0	208.0	-268.7	546.8	5.3	9.2	-12.7	23.4	180.1	206.2	-222.0	586.2
Total Sitting Time (-Feet Underneath Chair) (1800)	76.2	138.3	-194.9	347.3	4.1	8.9	-13.2	21.5	171.2	172.0	-165.9	508.4

Table 4.5 - Bland-Altman data assessing the convergent validity of the LumoBack, to the ActiGraph and activPAL

Sitting Posture (Seconds)	ActiGraph				activPAL			
	Mean Difference	Standard Deviation	95% Limits of Agreement		Mean Difference	Standard Deviation	95% Limits of Agreement	
			Lower Limit	Upper Limit			Lower Limit	Upper Limit
Feet Flat on Floor (300)	0.2	5.6	-11.1	10.7	0.9	4.2	-7.2	9.1
Legs Crossed (Right over Left) (300)	-0.4	3.65	-7.6	6.7	0.1	3.1	-6.0	6.3
Right Foot Resting on Left Thigh (300)	0.9	4.9	-8.6	10.4	0.5	3.8	-6.9	7.9
Legs Stretched out Forward (300)	5.0	17.3	-29.0	39.0	-153.5	150.6	-448.8	141.7
Feet Underneath Chair (300)	61.8	131.0	-195.0	318.6	54.2	126.0	-192.7	301.1
Upper Body Movement (Computer) (300)	40.5	99.4	-154.3	235.4	43.4	101.8	-156.1	242.8
Playing game on phone (300)	11.1	53.0	-92.7	114.9	0.7	79.8	-155.7	155.1
Total Sitting Time (2100)	133.9	209.2	-276.2	543.9	-38.1	280.4	-587.6	511.4
Total Sitting Time (- Feet Underneath Chair) (1800)	72.1	137.1	-196.5	340.8	-92.3	222.2	-527.8	343.2

Table 4.6 provides the mean time and ICC from the laboratory experiment. Intraclass correlations comparing the total sitting time of the LumoBack and ActiGraph was 0.82 (95% CI: 0.63, 0.91) and 0.73 (95% CI: 0.47, 0.87) for the activPAL.

Table 4.6 - Mean time measured by each device for Total Sitting time and the Intraclass Correlation Coefficients (ICC)

Task	LumoBack Seconds Mean(SD)	ActiGraph Seconds Mean(SD)	activPAL Seconds Mean(SD)	ICC (Lower Bound, Upper Bound) LumoBack and ActiGraph	LumoBack and activPAL
Total Sitting Time	1721.7(139.6)	1794.2(10.7)	1776.6(111.3)	0.82 (0.63,0.91)	0.73 (0.47,0.87)

Total Sitting Time is the sum of all seven sitting conditions in the laboratory setting of the validation.

The mean absolute percentage errors of the LumoBack, relative to the actual time spent sitting, at each of the conditions during the laboratory study are shown in table 4.7. The MAPE was <4% for all conditions except for, feet underneath chair (MAPE: 24.3) and upper body movement (MAPE: 16.3). The MAPE for total sitting time was 7.0 and when the feet underneath the chair condition was removed the MAPE decreased to 4.3. The MAPE for the ActiGraph and activPAL are also presented in Table 4.7.

Table 4.7 - Mean Absolute Percent Error of the LumoBack during each condition compared to direct observation, Mean (SD)

Sitting Condition	Mean Absolute Percentage Error of the LumoBack	Mean Absolute Percentage Error of the ActiGraph	Mean Absolute Percentage Error of the activPAL
Feet Flat on Floor	1.0 (0.9)	0.4 (1.3)	0.0(0.0)
Legs Crossed (Right over Left)	0.6 (0.8)	0.2 (0.9)	0.0(0.0)
Right Foot Resting on Left Thigh	0.7 (1.5)	0.0 (0.0)	0.2 (0.6)
Legs Stretched out Forward	2.3 (5.6)	0.2 (0.9)	53.1 (50.4)
Feet Underneath Chair	24.3 (40.7)	0.3 (1.3)	3.6 (18.9)
Upper Body Movement (Computer)	16.3 (35.5)	0.5 (2.0)	0.1 (0.4)
Playing game on phone	3.8 (17)	0.2 (0.9)	3.5 (18.2)
Total Sitting Time	7.0 (9.7)	0.3 (0.4)	12.0 (18.9)
Total Sitting Time (minus Feet Underneath Chair)	4.3 (7.7)	0.2 (0.5)	10.0 (9.4)

Repeated measures ANOVA were conducted to determine if there were any statistical differences in LumoBack measured time spent in sitting and the activPAL and ActiGraph during the laboratory conditions. The assumptions of sphericity were violated therefore this was corrected using the Greenhouse-Geisser estimates of sphericity. The results shows that there were no significant differences between sitting time measured by the LumoBack compared to the actual time spent sitting, ActiGraph and activPAL during the following conditions; Sitting on a Chair with Feet Flat on Floor, ($F_{(1.84,47.72)} = 1.16$ $p = 0.32$), Sitting on a Chair with Legs Crossed (Right over Left), ($F_{(1.78,49.80)} = 0.50$ $p = 0.589$), Sitting on a Chair with Right Foot resting on Left Thigh, ($F_{(1.03,28.95)} = 0.92$ $p = 0.35$), Sitting playing on game on phone, ($F_{(1.59, 47.75)} = 1.338$, $p = 0.27$).

A one way within measure ANOVA indicated that measured sitting time was different during Sitting on Chair with Legs stretched out in front, ($F_{(1.02,29.69)} = 36.613$, $p <0.0005$). Post-hoc Bonferroni analysis revealed that sitting time measured by the LumoBack was significantly higher than that of the activPAL ($p<0.0005$; 294.8 vs 141.4 seconds). There was also a significant difference in measured sitting time during the sitting with feet back under the chair, ($F_{(1.58,45.912)} = 4.52$ $p = 0.02$). Post-hoc analysis revealed that sitting time measured by LumoBack was significantly lower than actual sitting time ($p=0.02$ 239.1 vs 300.0 seconds) and ActiGraph measured time ($p=0.02$ 239.1 vs 298.5 seconds respectively). In addition, the ANOVA analysis of the sitting with upper body movement conditions showed a significant difference in measured sitting time ($F_{(1.38,41.49)} = 4.45$ $p = 0.03$). Post-hoc analysis indicated that sitting time measured by the LumoBack was significantly lower than the actual sitting ($p = 0.02$ 257.9 vs 300.0 seconds respectively) and sitting time measured by the ActiGraph ($p = 0.02$, 257.9 vs 297.58 seconds respectively).

4.3.2 Free-Living Assessment: Convergent- Validity

Table 4.8 displays the mean time and intraclass correlations from the free living experiment. Intraclass correlations comparing behaviours measured by the LumoBack and activPAL were 0.87 (95 CI: 0.55, 0.96), 0.91 (95% CI: 0.70, 0.98), and 0.78 (95% CI: 0.24, 0.94) for sedentary behaviour, standing behaviour and stepping behaviour respectively. Furthermore, ICC comparing sedentary behaviour measured by the LumoBack and sedentary time measured by the ActiGraph were 0.80 (95%CI: 0.11, 0.95).

Table 4.8 - Mean time, Standard Deviation (SD) and Intra-class Correlations Coefficients (ICC) for Sedentary, Standing, and Stepping time and steps for the LumoBack compared to the activPAL and ActiGraph

Behaviour	LumoBack Minutes Mean/ SD	activPAL Minutes Mean/ SD	ActiGraph Minutes Mean/ SD	ICC (95% CI)	
				LumoBack and activPAL	LumoBack and ActiGraph
Sedentary	524.1 (70.4)	530.5 (54.2)	562.6 (57.1)	0.87 (0.55, 0.96)	0.80 (0.11, 0.95)
Standing	232.2 (85.3)	229.7 (63.6)	N/A	0.91 (0.70, 0.98)	N/A
Stepping	83.3 (29.1)	79.6 (22.9)	N/A	0.78 (0.24, 0.94)	N/A
Steps	8780.3 (1096.6)	8179.0 (951.1)	N/A	0.84 (0.44, 0.95)	N/A

N/A – ActiGraph does not measure these variables therefore they were not included in these analyses.

Table 4.9 shows the results of the mean absolute percent error for the LumoBack as a measure of sedentary behaviour, standing, stepping and steps taken compared to the activPAL and ActiGraph during the free-living study. The MAPE for all condition ranged between 2.38 and 8.08 when comparing the LumoBack to the activPAL and was 5.07 when comparing the LumoBack and the ActiGraph.

Table 4.9 - Mean Absolute Percent Error of the LumoBack compared to activPAL for each measurable behaviour, Mean(SD)

Behaviour	Mean Absolute Percentage Error	
	LumoBack and activPAL	**LumoBack and ActiGraph**
Sedentary	2.38(3.23)	5.07 (1.81)
Standing	6.88(12.32)	N/A
Stepping	8.54(14.81)	N/A
Steps Taken	8.08(15.33)	N/A

N/A – ActiGraph does not measure these variables therefore they were not included in these analyses.

Repeated measures ANOVA was conducted to determine any significant differences in measured behaviours between the LumoBack, ActiGraph and activPAL for sedentary behaviour. The assumption of sphrecity was violated, therefore this was corrected using the Greenhouse Geisser estimates of sphercity. The results showed that there were significant differences between sedentary behaviour measured by the three devices, ($F_{(2,12.109)}$ = 8.0, p=0.014). Follow up bonferroni pairwise comparison indicated that the differences occurred when comparing the LumoBack to the ActiGraph (524.1 vs 562.6 mins, p=0.03) and the ActiGraph and the activPAL (562.6 vs 530.5mins p<0.005). In both comparisons, the ActiGraph over reported time spent sedentary in compared to the LumoBack and activPAL.

There were no significant differences in time spent sedentary when measured by the LumoBack and activPAL (524.1 vs 530.5mins, $p>0.05$). Paired sample T-test comparing behaviours measured by the LumoBack and activPAL in the free-living setting showed that there were non-significant difference in upright time [232.2 vs 229.7mins, $t_{(11)} = 0.2$, p=0.85], stepping time [83.3, 79.55 mins, $t_{(11)} = 0.57$, p=0.58] and steps taken [8780 vs 8179 steps, $t_{(11)} = 0.77$, p=0.46].

Table 4.10 and Figures 4.11-4.12 are the Bland-Altman data and plots for the LumoBack and activPAL during the free-living component of the study. On average the LumoBack over reported sitting time by 4.6 mins (SD 21.8 95% CI; - 47.7, 38.4), under reported standing time by 8.9 mins (SD 20.3; 95% CI; -31.3, 49.1) and under reported stepping time by 2.3 mins. Additionally the LumoBack under reported steps taken by 153 steps (SD 712; 95% CI -1258, 1564). Furthermore, compared to the ActiGraph, the LumoBack under-reported sedentary time by 38.4 minutes (95% CI: -46.0, 122.7).

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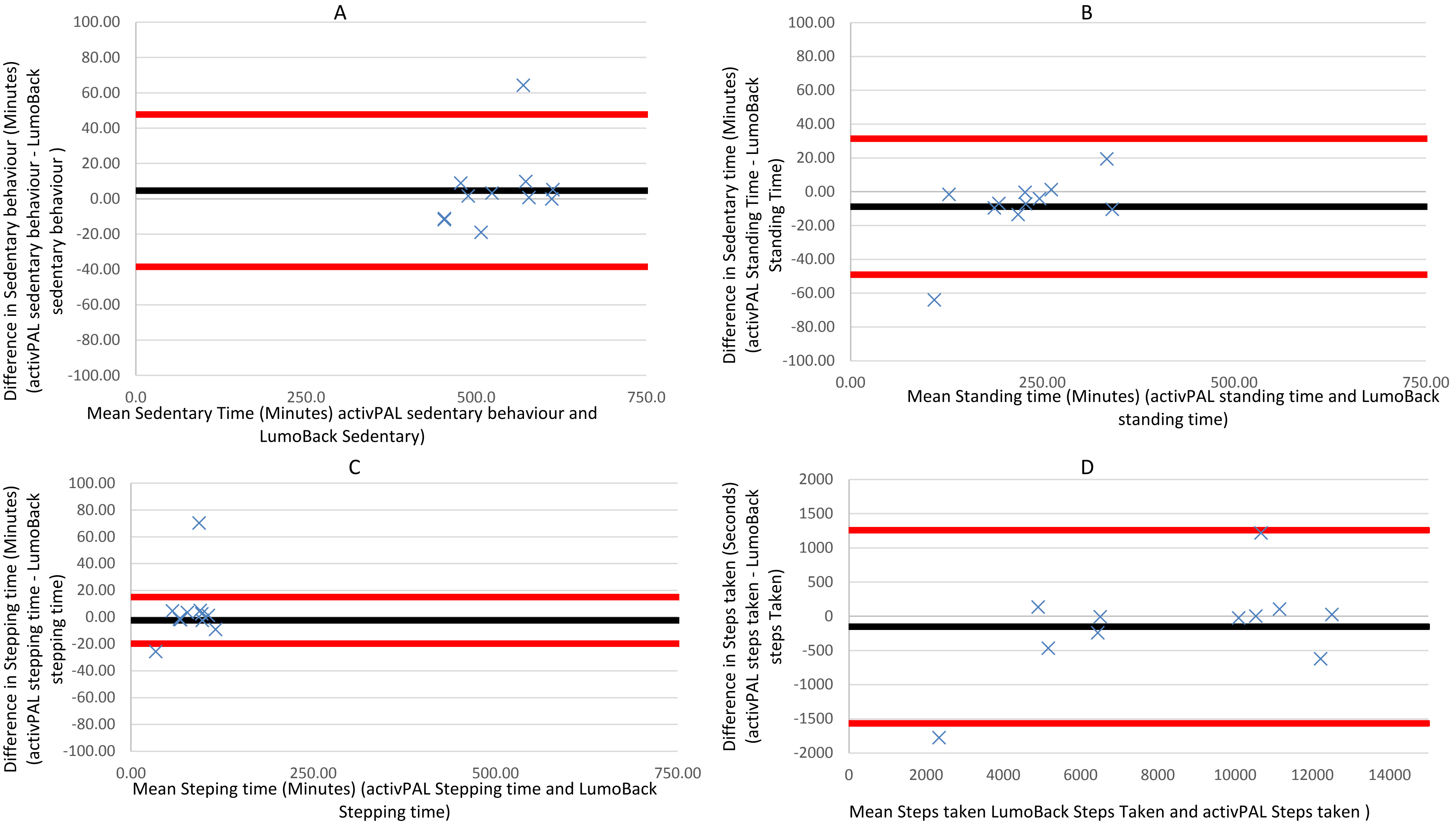

Figure 4.1 - Bland-Altman plot comparing the LumoBack and the activPAL as a measure of Sedentary, Standing and Stepping time and Steps Taken

Note: A: Bland-Altman of LumoBack vs activPAL for Total Sedentary Behaviour, B: Bland-Altman of LumoBack vs activPAL for Total Standing time, C: Bland-Altman plot of LumoBack vs activPAL fot Total Stepping time; D: Bland-Altman plot of LumoBack vs activPAL for Steps Takens, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.

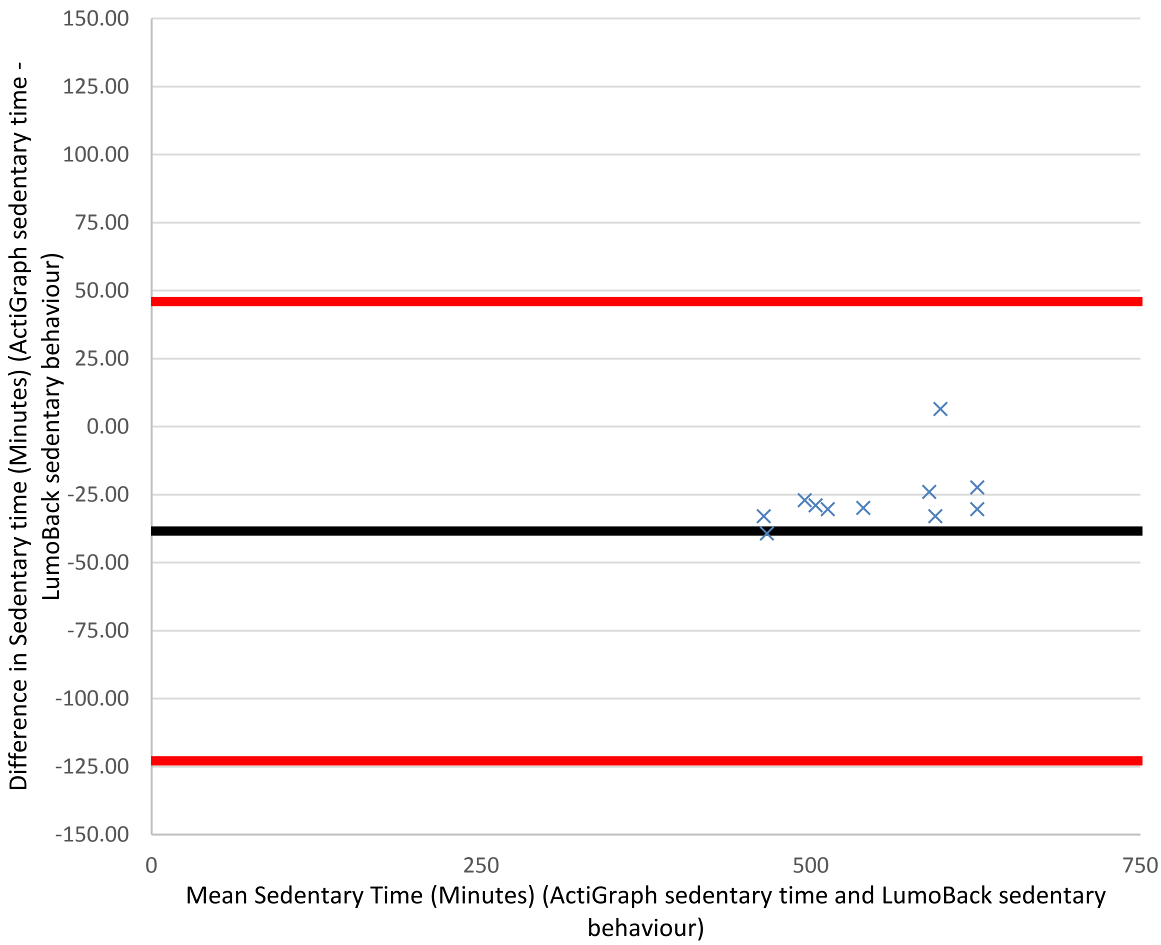

Figure 4.2 - Bland-Altman plot of total sedentary time of the LumoBack compared to the ActiGraph

Note: Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.

Table 4.10 - Bland-Altman plots data comparing measured behaviour in minutes of the LumoBack to, ActiGraph and the activPAL in the free-Living setting

Behaviour (Seconds)	activPAL				ActiGraph			
	Mean Difference	Standard Deviation	95% Limits of Agreement		Mean Difference	Standard Deviation	95% Limits of Agreement	
			Lower Limit	Upper Limit			Lower Limit	Upper Limit
Sedentary	-4.6	21.8	-47.7	38.4	38.4	42.6	-46.0	122.7
Standing	8.9	20.3	-31.3	49.1				
Stepping	2.3	8.8	-15.0	19.7				
Steps	152.9	712.8	-1258.6	1564.4				

4.4 Discussion

The aim of this study was to investigate the criterion- (direct observation) and convergent- (ActiGraph and activPAL) validity of the LumoBack as a measure of sedentary behaviour in a laboratory and free-living setting. The results from the laboratory study suggests that during the first four conditions, the LumoBack has acceptable criterion validity, with mean bias of <6 seconds per five minute condition. The tight confidence intervals of these conditions indicate that the LumoBack may be a reliable measure of sedentary behaviours during these conditions. The LumoBack, however, did significantly under-reported the time spent sitting during the feet underneath the chair condition and the upper body movement condition, by nearly 60 seconds. The feet underneath the chair condition discrepancy can be explained by the way in which the LumoBack measures postures. Briefly, the LumoBack measures posture by measuring the lower back (anterior pelvic tilt) angle of the wearer. This could be related to the participants anterior pelvic tilt angle deviating greater than 25 degrees from the calibrated seated angle therefore the LumoBack decision algorithms decided that the participant is standing (365). There is also a significant under-reporting occurring during the conditions following on from sitting with upper body movement which, could be a result of, anecdotally, participants tending to sit whilst typing on the computer with their legs behind the chair. This might be a result of there not being a ‘wash-out’ non-sedentary activity after the sitting with feet back under the chair condition. This would lead to the erroneous results for similar reasons as the previous condition. It is important to acknowledge that the extent to which this would affect misclassification of sitting time during a typical seven day period would depend on the prevalence of this type of sitting posture in daily life.

The total sitting time mean bias showed that the LumoBack under reported across all the conditions by over 2 minutes when assessing its criterion validity. However, this is perhaps unsurprising because of the two conditions previously discussed. When the condition that had the most error was removed from the analysis (i.e. feet behind the chair), the mean bias decreased by almost a minute. However, the 95% confidence interval indicates that there is still variability in the measurements.

When assessing convergent validity of the LumoBack compared to the ActiGraph, apart from the two conditions already discussed (sitting with feet back under the chair and upper body movement) the LumoBack showed acceptable convergent validity. When assessing the convergent validity of the LumoBack compared to the activPAL, during the condition of sitting with legs stretched out forward, the LumoBack over-reported compared to the activPAL. However, the results of assessing the criterion validity of the activPAL suggest that it was the activPAL which was the erroneous measurement during this condition. Indeed, during this sitting position the angle of the thigh changes slightly (i.e. knee angle increases above 90 degrees and the front of the thigh dips), which causes a misclassification by the activPAL suggesting that the activPAL proprietary angular parameters for the classification of sitting require the thigh to be close to being parallel to the ground (138). It can be considered, therefore, that the activPAL was the device that was erroneous in this condition not the LumoBack.

Apart from the two conditions previously discussed, there is MAPE, of less than 10%. Within the field of pedometry and accelerometry a MAPE of <10% is an acceptable cut off point for determining the accuracy of a device (366–369), and in the current laboratory study, when comparing the LumoBack as a measure of sedentary behaviour compared to the activPAL and the ActiGraph the LumoBack had a MAPE <10%.

The LumoBack had acceptable convergent validity in the Free-Living component of the study, with a mean bias of -4.6mins for sedentary time, 8.9mins for standing time, and 2.3mins for stepping time, with a mean bias of 152 steps compared to the activPAL. Furthermore the MAPE for the LumoBack for all behaviours were <10% indicating acceptable agreement between the LumoBack and the activPAL as measures of sedentary, standing and stepping. The ICC further corroborate the agreement between the LumoBack compared to the other devices by displaying good to excellent (as defined in (370)) correlations coefficients (ICC Total sitting time during laboratory study 0.73 and 0.87, 0.91, 0.78 for sedentary, standing and stepping time respectively during the free-living component of the study).

When comparing the LumoBack to the ActiGraph in the free-living setting, the LumoBack under-reported time spent sedentary; however, it could be said that the ActiGraph in this instance is actually over-reporting as is the case with accelerometers when measuring sedentary time (104). Furthermore, the ICC showed acceptable agreement between the LumoBack and ActiGraph (ICC: 0.8), as well as a MAPE of 5.07, which is within the guidelines of <10%.

The large discrepancy between the two LumoBack measurements in the laboratory and in the free-living can be accounted for by the error in the measurement induced in the laboratory permutations both for the LumoBack and the activPAL (e.g. the sitting with feet under the chair for the LumoBack and the feet stretched out straight for the activPAL). Both of these permutations caused error in the measurement of LumoBack and activPAL and these two behaviours might not be as prevalent in the free-living setting.

The results from the study presented in this chapter are corroborated by the findings from Rosenberger et al. (259). Briefly this study compared the output from commercially available wearable devices to the current standards for objective measurement of sleep, sedentary behaviour, light physical activity and moderate to vigorous physical activity (MVPA) over a 24 hour period in a free-living setting. Adults wore nine devices for 24 hours: ActiGraph GT3X+, activPAL, Fitbit One, GENEActiv, Jawbone Up, LumoBack, Nike Fuelband, Omron Pedometer, and Z-machine. Comparisons to standards were made for sedentary behaviour using the activPAL. Mean error for sedentary behaviour was 9.5% for the LumoBack. Equivalence testing suggested that the LumoBack can accurately measure sedentary behaviour. Bland-Altman plots had a mean difference of 18 minutes for the LumoBack over the course of a 24 hour period, with the LumoBack also having the smallest standard deviation of all the devices measuring sedentary behaviour. Therefore, in this study presented by Rosenberger, the LumoBack was seen to be an accurate measure of daily posture. Additionally, the mean difference for the LumoBack as a measure of steps was 1,281 compared to the Omron pedometer, with the ActiGraph being the only device to have a lower mean difference (679 steps) (259). In the present study the LumoBack performed better than in Rosenberger et al’s study (4.64mins compared to 18min respectively). The difference in sedentary behaviour mean bias may be attributable to the length of time the participants wore the device. In the study conducted by Rosenberger et al, participants only wore the LumoBack for 24 hours so any discrepancy would be greater when compared to the seven days in the current study. Additionally, the difference in sedentary time between the LumoBack and the ActiGraph in the present study, match those found in Rosenberger’s study. Furthermore, because participants only wore the device for one day in the Rosenberger study, there was less variability in the daily behaviours which could potentially be a limitation of their study. Another limitation of the Rosenberger’s study is the standards used in the study are based on common field-based measures and do not represent gold standards used in the laboratory

Additionally, the LumoBack has been examined for its reliability as a measure of step counts in laboratory and free-living conditions (177). Thirty-three healthy adults walked twice on a treadmill for 30 minutes whilst wearing the LumoBack. Additionally, 56 healthy adults wore the LumoBack for one working day. Validity was evaluated by comparing each activity tracker with the gold standard (Optogait system for laboratory and activPAL for free-living conditions). The MAPE for the LumoBack during laboratory conditions were -0.2, and -0.4 in free-living conditions. Bland-Altman plots revealed a mean difference in step counts of 8 during the laboratory study and 17 during the free-living section of the study (177) whereas the mean difference of the LumoBack compared to the activPAL as demonstrated in the present study was 152. The LumoBack in the study reported in this chapter did however, report a higher MAPE for steps taken than compared to Kooiman et al (8.08 vs 0.4 (177). Again this could be related to the length of wear of the participants between the two differing studies. Further research is needed to determine possible reasons for the discrepancy in these two studies. Despite the difference in the two studies, the LumoBack still shows acceptable validity as a measure of steps taken.

The strengths of this study are the testing of a novel consumer product which has self-monitoring and feedback-friendly attributes, including the ability to connect to an app for feedback on behaviour, goal setting, vibratory function and the open SDK and API for customisation. Additionally, this validation study has differing permutations in the sitting condition, which allowing for the determination of the validity of the LumoBack in a more ecologically-valid setting. Limitations of the current study included not having laboratory validated standing and stepping time which was not possible due to not having access to downloadable data during the laboratory portion of the study so sedentary activities had to be prioritised. Furthermore, the standards used in the free-living study are based on common field-based measures and do not represent gold standards used in the laboratory. Therefore, the test device (LumoBack) and the comparison devices (activPAL and ActiGraph) could introduce substantial error in to the comparison. Whilst this error is minimised by the activPAL being extensively validated under both field and laboratory conditions the risk is still present. Furthermore, the functions of the LumoBack and its ability to measure its target behaviours can change with software and hardware update, and consequently not every possible update can be evaluated with research at one particular point in time. Additionally, during the free-living study, participants were asked to calibrate the LumoBack sensor every time they placed the sensor back on their person, however, if participants did not perform this re-calibration, the sensors posture algorithms would still be set to their previous calibration potentially producing an erroneous measure of posture . Another limitation was that the free-living assessment contained fewer participants owing to the burden of wearing multiple sensors for a long period of time. Furthermore, the large standard deviations demonstrated the large variability within the data suggesting that further research is need to corroborate these findings.

4.5 Implications and Conclusions

The LumoBack demonstrated acceptable criterion and convergent validity when compared to direct observation, activPAL, and ActiGraph under laboratory conditions and acceptable convergent validity as a measure of sedentary behaviour, standing and stepping behaviours compared to the activPAL under free-living conditions. The results from this validation study, in combination with previous validation studies, conducted to determine the accuracy of the LumoBack ActiGraph and activPAL as measures of sedentary behaviour indicate that the LumoBack has similar validity to the activPAL and the ActiGraph may over-report sedentary time in ecologically-valid settings. The current information on its validity makes the LumoBack an attractive device, for use as a sedentary behaviour measurement tool. Additional work is warranted to determine if differing body types (e.g. longer leg lengths altering waist angles during differing sitting permutation) could influence the validity of this device. For this to occur, researchers will need to expand the analytical techniques that are currently used because of the volume and complexity of wearable data. The LumoBack should also be further validated in other age groups the sitting and gait patterns may differ and therefore alter the validity of the device.

As seen from Chapter 3 (page 46), the LumoBack is capable of providing immediate feedback on its measured behaviours, this in combination with its inexpensive cost and potentially a wear site that is more conducive to participant compliance (lower waist) may make the LumoBack a more pragmatic and practical option than other devices which require surgical dressing to attach (e.g. activPAL) or devices that are attached to a chair and therefore require multiple units (e.g. Darma) to use. Furthermore, the LumoBack appears to be a more accurate measure of sedentary behaviour than the ActiGraph in free-living situations. The results from this study, in combination with the measurement (e.g. posture monitoring) and self-monitoring (mobile application and vibratory function for real time feedback) attributes, may make the LumoBack a useful tool in interventions aimed to reduce sedentary behaviour.

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Chapter 5 - Repurposing the LumoBack Posture Sensor as a sedentary behaviour self-monitor and feedback tool

5.1 Introduction

In the systematic scoping review from Chapter Three (page 46) it was revealed that the LumoBack was one of the most promising self-monitoring tools of sedentary behaviour. Next, the validation study in Chapter Four (page 84) found the LumoBack to be a valid measure of sedentary behaviour. However, the LumoBack in its original format provided vibratory feedback on sub-optimal sitting or standing posture (e.g. slouching) and was therefore not optimised for use as a sedentary behaviour self-monitor and feedback tool. As a result, the LumoBack needed modification before it could be used as a sedentary behaviour self-monitoring device. Therefore, the purpose of this chapter is to serve as a bridge to describe the alterations made to the LumoBack device to make it suitable for use as a sedentary behaviour self-monitoring device in interventions aimed at reducing sedentary behaviour.

5.2 Repurposing of the LumoBack App

5.2.1 Original LumoBack Posture Sensor

The LumoBack (LumoBody Tech, Inc, Palo Alto, CA), which is a small (4.15 x 10 x 0.8cm, 25g) and flexible posture sensor which is worn on the lower back (see figure 5.1). Designed to measure an individual's posture, it uses inertial sensors, which collects data at a constant 25Hz (aggregated on data output to five minute proportional epochs) and is controlled through a mobile application (app) via a BLE connection that can be used by both iOS and Android operating systems. The LumoBack has personalised calibration algorithms built in which adapt to each person's body shape and movement behaviour. These are used to create a recommended optimal back posture model. The embedded posture sensors feed data to machine learning algorithms that continuously track the amount of time spent lying (used to infer sleeping), sitting (including car mode), and standing and also functions as a pedometer, tracking its wearers' number of steps. The monitor connects wirelessly via BLE to a mobile application syncing with the app, with data transferred between the LumoBack and the app at 600 bytes/sec. The LumoBack app includes an avatar that mimics the postures and daily activities of the wearer in real time. The data from the sensor, along with the on board analytics allow the app to provide visual feedback to promote good posture. The on-board sensor feedback is a vibratory pulse which alerts the wearer to the need to correct their sub-optimal back posture. There is also a push notification function within the app which can alert the user to a (user-defined) period of prolonged sitting time (371).

Figure 5.1 - The LumoBack Posture Sensor and mobile application

From Top to Bottom: the LumoBack device and associated strap. The LumoBack app with avatar and minimum cards (Left to right: Posture Card, Stand Ups, Steps, Sit Time, Sleep) that are displayed on the app.

Within the app, the data are presented on minimum (min) cards; there are five min cards each displaying a different piece of information. These min cards are:

- Posture Score - measure of how much you slouch, vs sit/stand up straight – provided as a percentage of time in straight posture.

- Sit time - amount of time spent sitting.
- Stand Ups – number of times per day that the wearer stands up.
- Steps – number of steps taken, distance travelled, and calories burned.
- Sleep – time spent sleeping (inferred from lying time).

Each of these min cards, once tapped, opens up into a maximum (max) card (figure 5.2) which provides further detail on the information that has appeared on the min card. The posture max card provides a swingometer (dial) of good or bad posture throughout the day, along with tabs for total straight time and total slouch time. In the Sit time max card, presents the wearers sit time is presented as a pie chart breaking down the day/week/month wear time into standing, stepping, sitting and driving (excluding lying time). The Stand ups max card consists of a single bar of progression towards daily stand ups goal. The Steps max card consists of an arc which shows the advancement towards daily step goals. The Sleep max card is extremely similar to the sit time max card in that it comprises a pie chart breaking the lying time into time spent lying on the back/front/left/right. In addition to the pie chart/swingometer etc on the max cards, there is a temporal bar chart of the accumulation of the behaviour of interest throughout the day/week/month. As previously alluded to, the LumoBack provides vibratory feedback when the wearer is in a slouched sitting or standing posture. This vibration can be feedback in either a one off buzz or a continuous pulse and can be feedback after a user-defined period of user-defined severity of slouching. Additionally, the LumoBack can provide a push notification which reminds the user to stand up after a period of user defined sitting.

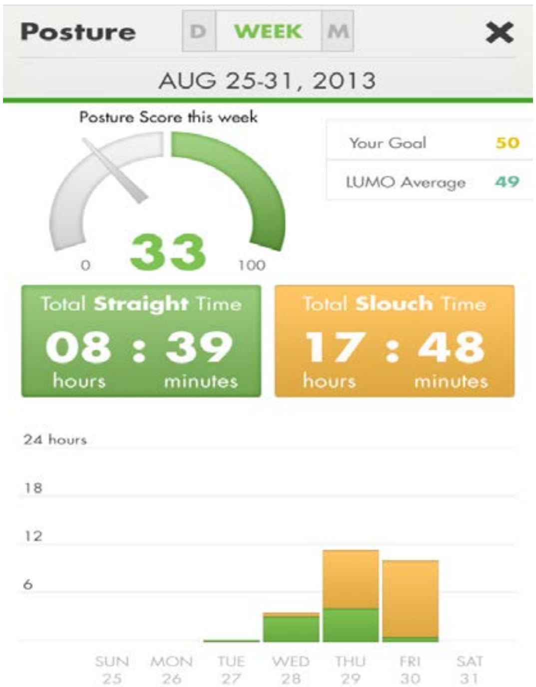
A


Sit Time
Now syncing...
Today
Day
Week
Month
TODAY
Total time spent sitting this day
06 : 43
hours minutes
Your Goal 04:00
LUMO Average 00:00
Standing 24%
Stepping 9%
Sitting 64%
Driving 1%
60 min
50
40
30
20
10
12 AM
4
8
12 PM
4
8
11 PM

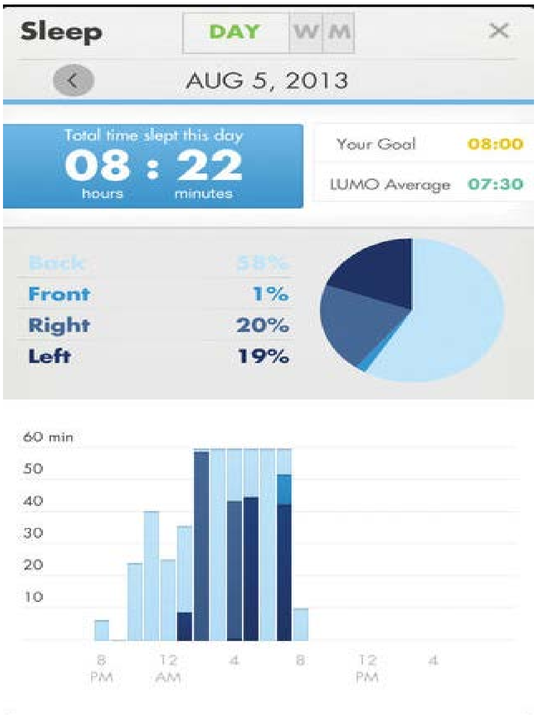
B


Steps
Last synced: Today at 8:50 pm
Today
Day
Week
Month
TODAY
Total steps taken this day
7,207 steps
0
2,500
Your Goal 2.5K
Lumo Average 5.9K
total calories 1352
total kilometers 6.26
steps
calories
kilometers
Walking 5329 230 4.27
Running 1878 142 1.99
1862 steps
1490
1117
745
372
12 AM
4
8
12 PM
4
8
11 PM

C


Posture
D
WEEK
M
AUG 25-31, 2013
Posture Score this week
33
0
100
Your Goal 50
LUMO Average 49
Total Straight Time
08 : 39
hours minutes
Total Slouch Time
17 : 48
hours minutes
24 hours
18
12
6
SUN 25
MON 26
TUE 27
WED 28
THU 29
FRI 30
SAT 31

D


Sleep
DAY
W
M
AUG 5, 2013
Total time slept this day
08 : 22
hours minutes
Your Goal 08:00
LUMO Average 07:30
Back 58%
Front 1%
Right 20%
Left 19%
60 min
50
40
30
20
10
8 PM
12 AM
4
8
12 PM
4

E

Figure 5.2 - Examples of max cards. A Sit time Max card; B: Step Max Card; C: Posture Score Max Card; D: Sleep Max Card; E: Stand Ups Max Card

Unfortunately, individuals, particularly during working hours, do not keep their phone readily available, it is usually turned off or kept out of sight so as to provide boundaries between work and non-work activities (372–374), which would negate the effect of the push notification as a feedback modality to aid in the behaviour change. Therefore, it was necessary to modify the LumoBack to create a firmware, application and device capable of repurposing the LumoBack to provide real time feedback of sedentary behaviour to the users.

5.2.2 Modification to the LumoBack Mobile application

5.2.2.1 Control Mode

The first required development commissioned was the need for a control mode within the app. Due to the feedback continually being present on the app homepage, any period of measurement of physical activity or sedentary behaviour to acquire a baseline might be influenced by the presence of the feedback. This has been shown in pedometer studies assessing reactivity (375–377). Previous research has indicated that when comparing sealed and unsealed conditions of a pedometer study, the sealed condition when participants are aware of the device may elicit some degree of reactivity (375–379), therefore, a 'control mode' of the LumoBack app was developed and created (Figure 5.3).

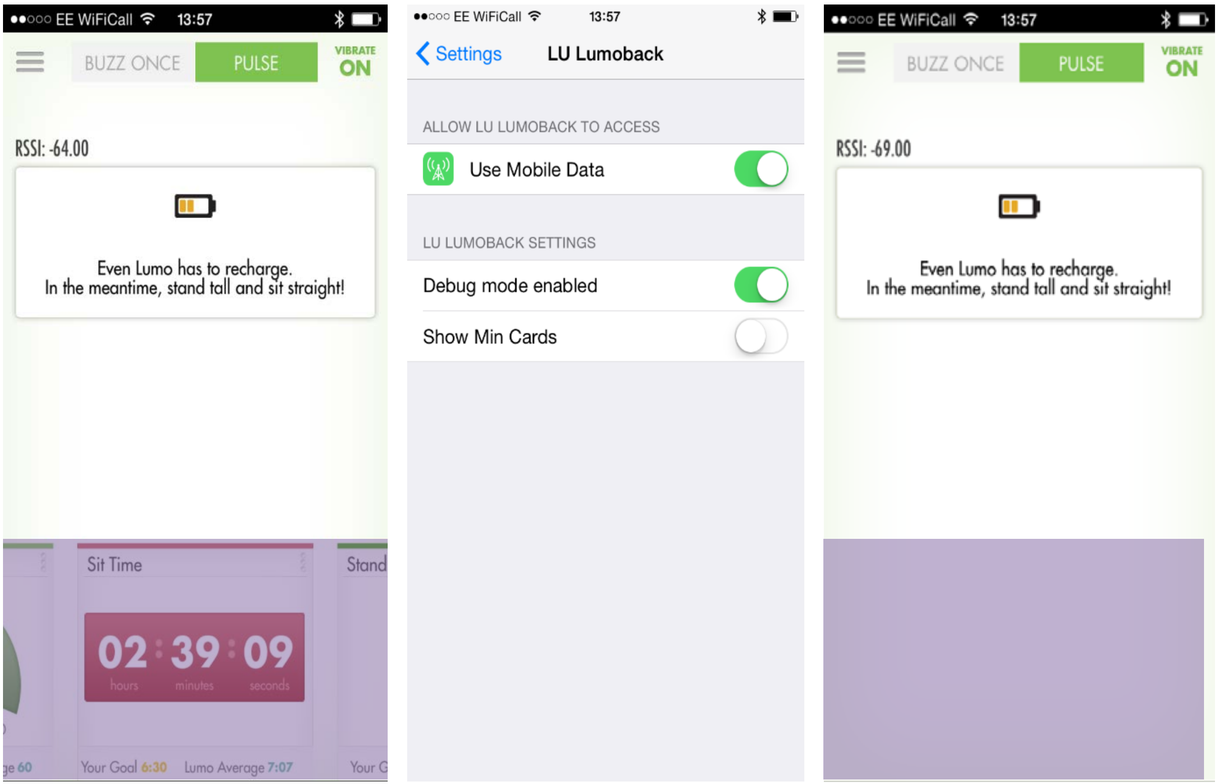


Figure 5.3 - the differences between the original mobile app and the modified control mode

From left to right, Left: normal LumoBack app, Middle: Turning off the min card in the LumoBack app settings, Right: New LU LumoBack app without control mode.

As can be seen from Figure 5.3, the invention of the control mode made the min cards for all behaviours invisible to the user. This was, fundamentally, a cosmetic change. The min cards were still present, and the device is still relaying data to the app, the change just makes the data not viewable to the user. Because the LumoBack needs to be calibrated to the wearer's body posture when it is worn and the Lumo avatar is integral in this process, the avatar was therefore not removed from the control mode.

5.2.2.2 Sedentary Buzz

In addition to the control mode, a change was made to the vibratory function of the device. Briefly, the LumoBack in its original format vibrated when the wearer was in a slouched posture, either during standing or sitting. The devices firmware was altered to allow for the posture buzz to be a sedentary buzz. Under this new firmware, the user can define the amount of sedentary behaviour (sitting and/or lying; in mins) after which a single, strong two second buzz will alert the user to their prolonged period of sedentary behaviour. The time before the sedentary buzz occurred could be set between one and 541 minutes (541 minutes was the upper time limit within the system, this time would effectively turn off the sedentary buzz. This upper limit was allowed as it is implausible to sit for 9 hours in the target population of the thesis.

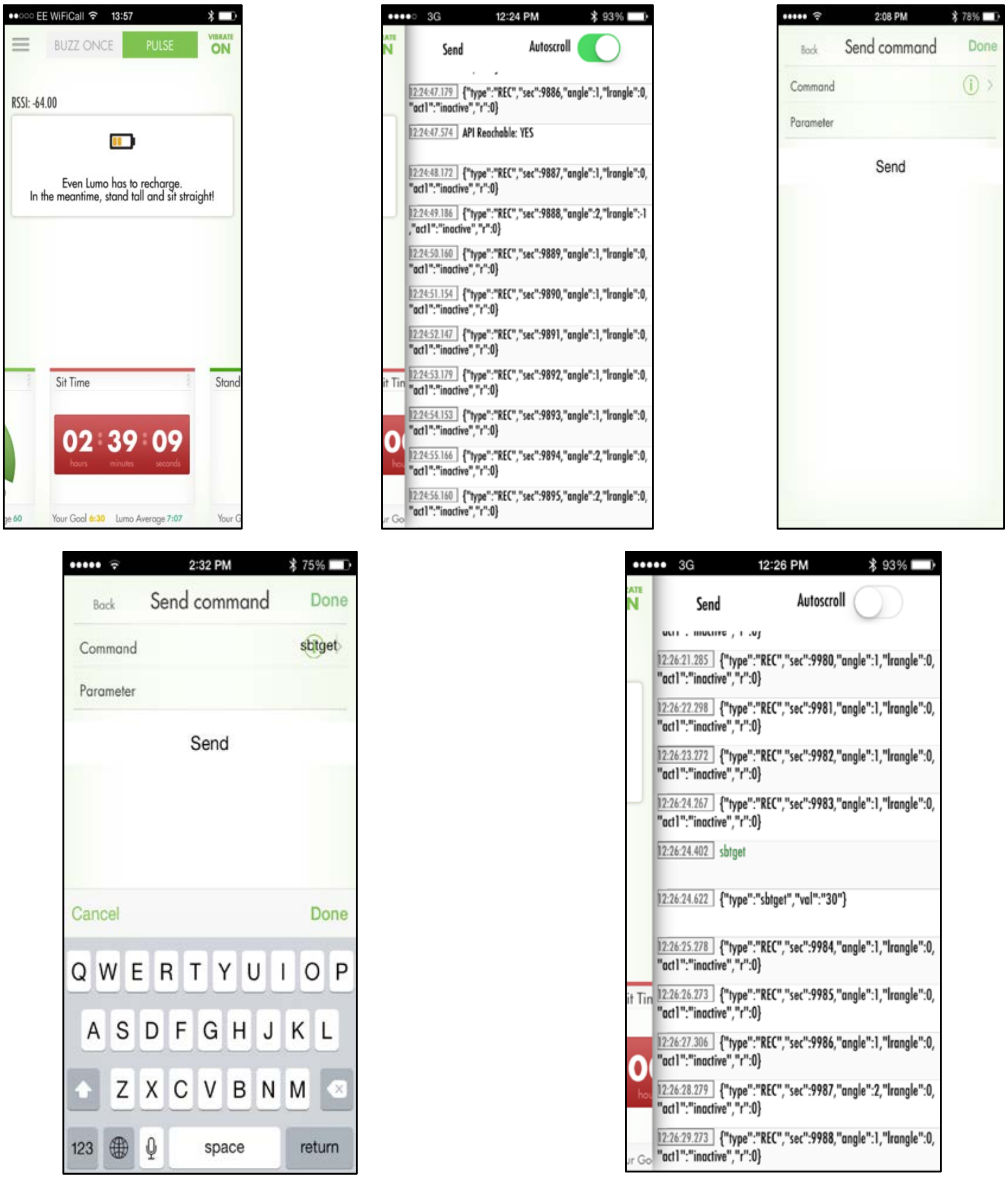


Figure 5.4 - Setting up Sedentary buzz in the LumoBack terminal

The sedentary buzz (Figure 5.4) was set up by altering small pieces of code in the mobile application terminal (coding log which is in the background of the application usually hidden from the general public). The investigator will change the time before the sedentary buzz occurred in the terminal using a simple piece of coding:

Command: <sbt>

Parameter <sedentary buzz delay in minutes>.

This would be followed up with another piece of coding:

Command: <sbtget>

Parameter <none>.

This is necessary to make sure that the first piece of coding has been implemented correctly.

The changes to the Lumo app were implemented by creating a new firmware (permanent software programmed into a read-only memory), with the new firmware connected to specific generated email addresses by Lumo BodyTech. When a specific email address is associated with a LumoBack device, the new firmware with the Sedentary Buzz supersedes the original LumoBack firmware.

5.2.2.3 Mobile App Analytics

There are three main steps to building a mobile application; firstly (and obviously) is building the mobile application, second is acquiring users for the app and finally is engaging and monetising users. To engage and monetise users mobile app developers utilise app analytics, which provide a plethora of details, including how many users have downloaded the app in total, how many of those users are active, how do users interact and engage with the app, which features do they most often use and which do they ignore and more. Mobile applications account for 89% of consumer media time on mobile devices (380). Companies investing in mobile app development use mobile app analytics to optimise their apps, without which developers risk their app reach and engagement being unclear. Using mobile app analytics companies can get insights related to three key metrics: business-related metrics (conversion, retention and engagement rates), app performance metrics (user's experience with an app, knowing which pages have been viewed the most or least, which features of the app are mostly used or rarely used) and low-level metrics (information on any crash's bugs or bad behaviour of the app). App performance metrics would be of particular interest from a public health perspective as it will provide insight into participants engagement with the intervention. One such type of mobile app analytic is Flurry Analytics. Flurry analytics enables users to analyse consumer behaviour through data observations. The platform provides features for user segmentation, consumer funnelling (describes the journey a consumer takes through an applications search system) and application portfolio analysis. In other words, Flurry analytics allows developers to see what their users are looking at on their app and for how long.

5.2.2.4 Data Aggregation and Download: Conversant Health

As with most health and wellbeing mobile apps, the downloading of data is not always possible. However, due to the freely available Application programming interface (API; a method of connecting one website/software to another) have made it possible for data aggregation services to build websites and software (fee for services) whereby users/customers can download their data from wearable devices. One such company 'Conversant Health' (https://www.conversanthealth.com/) was approached in order to facilitate the API integration from LumoBody Tech. Figure 5.5 displays the website which Conversant Health built for the intervention for the download of data.

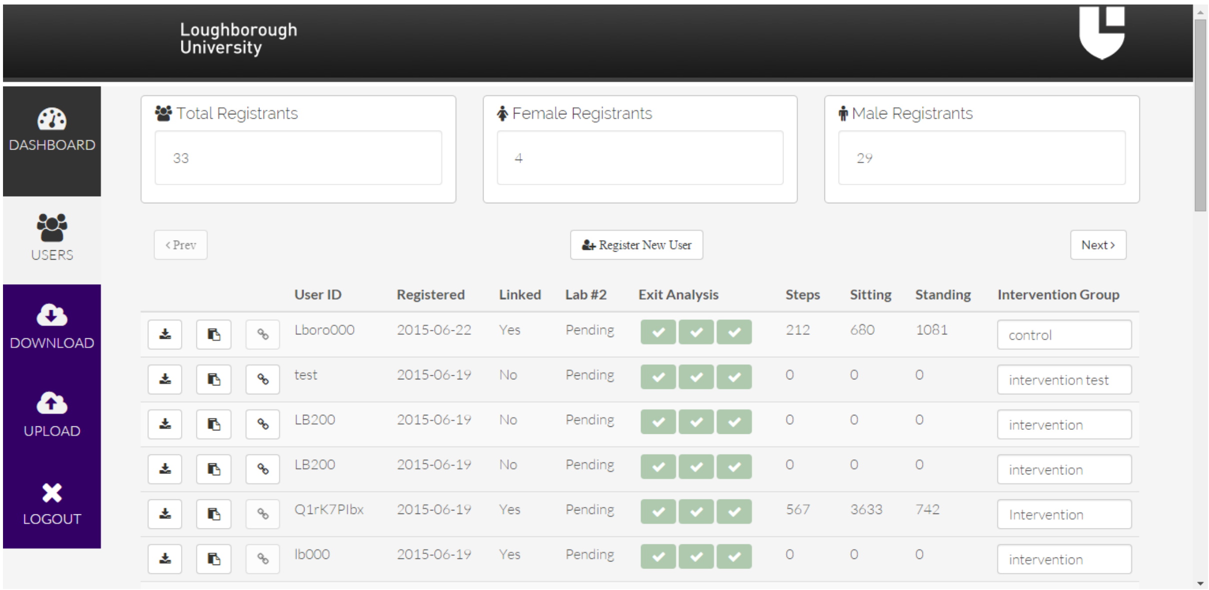


Figure 5.5 - Conversant Health platform built for the DeSIT intervention

As new participants come in to the study, the investigator would register the participant into the Conversant system. Registration information could include any information that the investigator deem necessary (e.g. User ID, DOB, study registration data etc). Subsequently, the investigator would link the LumBack posture sensor to their account (via a Lumo BodyTech provided website). Every evening, the Conversant Health platform would query the Lumo API for all data between the time of their last sync and the current time, storing it into the Conversant Health databases. If the user is new (e.g. there was no previous sync time), it would use their registration date. Additionally, participant laboratory information could be added to the system via a participant data entry form. An upload function was also compiled on the system to allow for upload of additional auxiliary information (as long as the uploaded information had the participants registered information attached to it (i.e. their user ID). Every 15 minutes, the Conversant platform would aggregate the downloaded data/uploaded data respective of each participant, as per the specification of the study protocol. These aggregations were then published and available for study investigators to download (in this instance all in CSV downloads).

5.3 Summary

In summary, the LumoBack was altered to create a control mode (no feedback on the mobile app) for baseline measurement and sedentary buzz for the intervention period. Additionally, access to mobile app analytics was also developed to measure exposure to the intervention and engagement with the app during the intervention period. Finally, data integration, aggregation and download capability was also developed to allow seamless downloading of data without further participant burden. Table 5.1 is a summary of the changes commissioned to alter and configure the LumoBack into a new sedentary behaviour self-monitoring and feedback tool. Preliminary evaluation of these commissioned changes showed that the changes were achieved, therefore making the repurposing successful.

5.4 Acknowledgements

Whilst the work conducted in this chapter was designed and conceived by the authors, implementation of the repurposing of the LumoBack app was conducted by the LumoBody Tech Inc Company, notably Cha Li and Andrew Chang. The bespoke DeSIT platform was built and programmed by Trevor Hall at Conversant Health, following the specification from the authors.

Table 5.1 – Summary table of commissioned changes to the LumoBack Mobile Application

Need	**Challenge**	**Commissioned Change**
Control Mode	Need control mode in LumoBack app to prevent salient behaviour change information being available at baseline.	Creation of a cosmetic change to the application user interface, whereby the min card removed from the user interface so that participants could access their behavioural data.
Sedentary Buzz	LumoBack, in its original format, possessed vibratory feedback based on bad posture rather than prolonged sedentary behaviour.	A new firmware was created to enable a sedentary buzz (vibratory feedback) after a user-defined period of time.
Mobile Application Analytics	To assess the feasibility of the interventions using the LumoBack, engagement with the mobile app was necessitated.	Flurry app analytics were integrated into the new Loughborough University LumoBack app allowing data to be collected on how often participants engaged with the LumoBack app (e.g. how often do they tap on the sit time min card, how long they spend on the sit time max card).
Data Integration Aggregation and Download	Due to the commercial device not having the extensive data analysis and downloading capability of research grade device, a service was sought for the integration, aggregation and download capability for LumoBack data.	Conversant Health created a platform with the ability to integrate LumoBack data for download and analysis, as well as study management and flurry analytics data aggregation.

Chapter 6 - DeSIT: Decreasing Sedentary Time using Innovative Technology: A Proof of Principle Intervention

6.1 Introduction

As an increasing body of evidence suggests that sedentary behaviours are associated with poor health outcomes (28), increased attention is being paid to the development of intervention methods that focus on reducing sedentary behaviour and increasing physical activity levels (34,35). Self-monitoring has been proposed as a promising avenue by which behaviour change can occur (41) and its use in interventions is on the rise. Furthermore, evidence from meta-regression studies (42,210) revealed that interventions aimed at increasing physical activity self-monitoring with one or more of four other self-regulation techniques, were significantly more effective than interventions not including self-monitoring (41,42,210).

Along with the rise in self-monitoring, there has been a rise in commercial wearables and activity trackers. The rise in commercial activity trackers comes through their ability to create data and generate information on behaviour as well as being able to easily make meaning and take action from these devices (234,381). Research also suggests that individual self-monitoring devices, such as pedometers, are a common element of successful physical activity interventions (211,382,383), and can increase physical activity (384–386) and decrease sedentary time (384,385). Recent advances in technology have seen the emergence of more sophisticated commercial activity trackers that go beyond just simple step counting to incorporate many of the strategies known to support behaviour change (387). Such strategies, including the provision of detailed, real-time feedback, long-term tracking, prompts/cues, and goal setting, as well as the measurement of multiple behaviours, give commercial trackers the potential to be effective behaviour change tools (244,387). Their potential as low cost behaviour change support tools has been recognised by workplace wellness programs in the US, where activity trackers are distributed to encourage employees to increase physical activity with the aim of getting healthy and therefore reducing their insurance premiums (388,389). However, as seen in Chapter Three (page 48), there is a lack of sedentary behaviour based commercial trackers.

There is minimal research on the feasibility, acceptability and effectiveness of commercial activity trackers as intervention tools, traditionally interventions utilise research grade pedometers. A recent review aiming to synthesise the efficacy and feasibility results of electronic activity monitoring systems (pedometers were not included in this review as it did not meet the authors' definition of an electronic activity monitoring systems) within published physical activity interventions, highlighted the large heterogeneity in the small group of research studies and the mixed quality of research (239). Five of the 11 studies included in the review showed significant improvements in physical activity, and three of the studies found significant improvements in sedentary behaviour in the activity monitoring system (239) suggesting that interventions utilising wearable technology may be an effective intervention modality to decrease sedentary behaviour and increase physical activity.

The mixed picture of intervention success of commercial activity trackers may be due to the fact that some cannot adequately measure exposure to the intervention. There is a need to accurately and objectively measure the exposure to the intervention modality to better understand the intervention effect on the study population. For example, in office-based standing desk interventions, self-reported log diaries would be provided to participants to document when they are at work as a means of measuring their exposure to the intervention. However, this methodology is open to bias, potentially diluting the intervention effect, subsequently, making the finding potentially invalid. Objective measurement of the exposure is therefore important to accurately quantify treatment effects.

As already alluded to, there is little evidence investigating the use of activity trackers to target sitting and standing. Furthermore interventions focusing on increasing physical activity do not necessarily result in changes in sitting (34,35), likewise activity trackers that focus on steps and activity may not necessarily elicit changes in sitting (38). The LumoBack device was identified in Chapter 3 (page 46) as a potentially promising tool for individuals to self-monitor sedentary behaviour. Additionally, the LumoBack has been shown to be an acceptably valid measure of sedentary behaviour both in the current dissertation (see Chapter 4 page 84) as well as previously published literature (177,259). Therefore, the aims of this study were:

- To determine whether a repurposed LumoBack Posture Sensor can reduce sedentary behaviour in a sample of apparently healthy adults over the course of five weeks.
- To quantify the engagement of the participants with the technology determined by time engaging with the mobile app associated with the LumoBack.

In an attempt to understand why individuals engaged with the intervention, investigation of health outcome data were used to quantify whether those with the "most to gain" (assessed by Metabolic Syndrome risk factor levels) were more engaged.

6.2 Methods

6.2.1 Participants

A convenience sample of participants were recruited using Loughborough University (UK) departmental mailing lists, consenting participants from previous research studies, physical and online university notice boards, as well as word of mouth. In total, 42 participants (≥25 years and over) who owned and could operate an iPhone 4S or later model of Apple iPhone, who also had no underlying circumstances which would prevent them from being active were recruited into the study.

6.2.2 Procedures

Participants attended three visits at Loughborough University's, National Centre for Sport and Exercise Medicine. Procedures were approved by the Loughborough University Ethics Approval Sub-Committee. When a person expressed an interest in the study, the participant information sheet was sent to the potential participant, which included full details of what the study entailed. Upon confirmation of participation in the study an appointment for the initial visit was made. At the initial visit, participants were offered the opportunity to re-read the participant information sheet (Appendix 3.1 page 258) and additionally, written informed consent was obtained. During visit one, participants were given a LumoBack and the initialisation and calibration process was explained. The initialisation process involved the assignment of each participant to a pre-determined username and password. The new firmware was linked to these specific login credentials, thereby initiating the new sedentary buzz firmware update. After initialisation, the participants were instructed on the appropriate wear of the LumoBack (i.e. worn like a belt centred on the lower back). Following this the participants were taken through the calibration process which involved following a number of on screen instructions depicted in Figure 6.1.

Post calibration participants were asked to walk approximately 20 meters before sitting down on a chair. This allowed the investigator to assess whether the calibration process was successful by monitoring the Lumo avatar on the mobile application (app) to make sure it mimicked the participant's' behaviour. Participants were then instructed to wear the LumoBack configured in control mode (i.e. no haptic feedback), during waking hours for 7 days, whilst going about their normal routine. Each night when participants removed the LumoBack they were instructed to plug it in to a fully supplied charger. Although the battery did not require daily charging, this instruction was given because when placed on or removed from charge, the LumoBack records the act in the data log. This is noteworthy because activity monitoring studies require participants to log on/off wear times in a diary, which is burdensome and given its subjective nature, open to inaccuracies or biases (390). Additionally, if the LumoBack was removed and placed on a flat surface with the logo visible, and the unit left idle the device would go into an “inactive” data state. Therefore, in lieu of the traditional wear time log diary, participants were provided with an information sheet (Appendix 3.2) which explicitly described methods by which they should remove the LumoBack. If the participant did not place the LumoBack on charge, they were encouraged to place the LumoBack in the inactive position.

During the second visit, the LumoBack assigned to the participant was altered from control mode to intervention mode (i.e. haptic feedback via a sedentary vibration or ‘buzz’). The sedentary buzz was set so that the LumoBack would vibrate after 30 minutes of continuous sitting. The decision to use 30 minutes of continuous sitting as the trigger for the buzz was a pragmatic one. There is no consensus in the literature as to how often individuals should break up their long bouts of sedentary behaviour. However, there is both epidemiological evidence to suggest that individuals spend up to 75% of their workday sedentary, with much of this accumulated in prolonged bouts of >20-30 minutes (19,391). Furthermore, a series of experimental studies have found that there can be advantageous cardio-metabolic effects of breaking up siting time with either standing or light intensity activity (58,74,94,392). Whilst the studies differ on the frequency of the breaks (every 20 minutes or every 30 minutes), a pragmatic approach was taken to choose 30 minutes as a sit buzz of 20 minutes may be too frequent and may induce disenfranchisement from use of the LumoBack.

Furthermore, during the second visit, a series of cardio-metabolic measures were taken including, body composition, blood pressure, and a lipid and glucose profile. The participants wore the LumoBack again for another 4 weeks before returning to the lab for a third and final session where the same cardio-metabolic measures were taken. Figure 6.2 is a schematic of the study procedures.

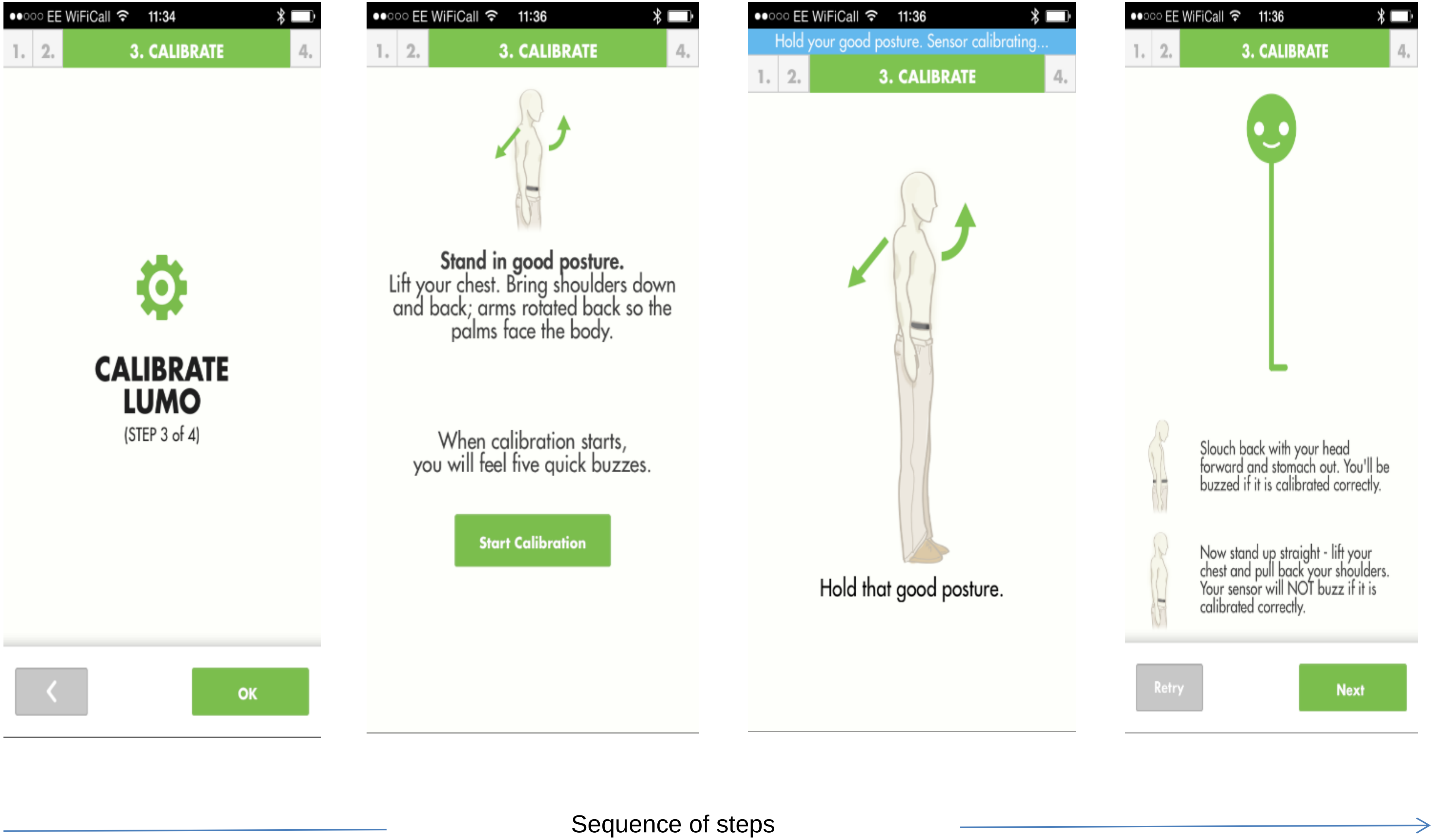


Figure 6.1 - Calibration process of the LumoBack

6.2.3 Measurements

6.2.3.1 Sedentary behaviour variables

Sedentary behaviour [comprising lying time, sitting time (including car time)], standing time, and stepping time were measured using the custom repurposed LumoBack Posture sensor.

6.2.3.2 Cardio-metabolic outcomes

Participants arrived at the lab after an overnight fast of ≥12 hours. Lipid profile and glucose was determined using the Alere Cholestech LDX analyser (Alere Inc., Waltham, MA). The LDX analyser measures total cholesterol and HDL cholesterol by an enzymatic method based on method formulation of Allain et al and Roeschlau et al (393). It measures triglycerides by an enzymatic method based on the hydrolysis of triglycerides by lipase to glycerol and free fatty acids and finally the LDX measures glucose by an enzymatic method that uses glucose to gluconolactone and hydrogen peroxide (393). The accuracy of Cholestech LDX measurements of total cholesterol (TC), calculated LDL, HDL, and triglycerides was compared to laboratory analyses, giving correlations of 0.91, 0.88, 0.77, and 0.93 respectively (all $P<0.01$). A study comparing CardioChek PA and Cholestech LDX with a standard venous blood sample tested in a laboratory, showed that the Cholestech LDX analyser demonstrated slightly better reproducibility than the CardioChek PA analyser when compared with laboratory gold standard analysis; however, the study was limited by the small sample size ($n = 34$) with no known risk factors, and did not determine superior accuracy of either device. In a comparative study of 100 samples, correlation coefficients between the Point-of-Care (POC) and laboratory methods were >0.9 for Cholestech and >0.84 CardioChek. This translates into machines that are fairly accurate. However, at levels near decision thresholds of diagnosis and treatment, the machines may over-estimate triglycerides and HDL, and under-estimate LDL (394,395). There is a growing wealth of both epidemiological and experimental evidence now that shows the deleterious effect of sedentary behaviour, and therefore beneficial effects of breaking up sedentary behaviour, on lipid profile and glucose (58,75,94,97,99,392,396–399). Finger-stick blood measurement was taken from the middle finger on the non-dominant hand of the participant, with the puncture taking place approximately 5mm from the edge of the nail bed. A blood sample of 40 µl was used for the test.

Height was measured using a stadiometer (Leicester Portable Height measure). The participants were asked to stand upright back to the vertical backboard of the stadiometer. The heels of the feet were placed together with both heels touching the back of the vertical board. The participant's feet were pointed slightly outward at approximately a 60 degree angle. The participants head was maintained in the Frankfort Horizontal Plane position (the head is in the Frankfort plane when the horizontal line from the ear canal to the lower border of the orbit of the eye is parallel to the floor and perpendicular to the vertical backboard) while the investigator lowered the horizontal bar snugly to the crown of the head with sufficient pressure to compress the hair. The participants were asked to inhale deeply and to stand fully upright without altering the position of their heels. The act of taking a deep breath helps straighten the spine to yield a more consistent and reproducible stature measurement. The measurement was recorded to the nearest 0.1cm (364). For measurement relating to weight and BMI, fat mass, visceral fat mass and fat free mass, the Tanita Body Composition Analyser MC-780MA (Tanita, West Drayton, UK) was used. Participants were asked to remove all footwear and any extra weight (heavy jumpers, coins in pockets, belts etc.). Participants were asked to step on the weight platform, making sure to place their heels on the posterior electrodes, and the front part of their feet in contact with the anterior electrodes. The participants were then asked to hold onto the grips of the analyser until the measuring process had completed. Body weight was measured to the nearest 0.1kg.

Before blood pressure measurement could be taken the correct sized blood pressure cuff was determined. This was conducted by measuring the arm circumference of the participants. Participants were asked to stand upright facing away from the investigator, with their weight evenly distributed on both feet and their right arm bent at 90^{o} at the elbow and their palm facing up. Holding the zero end of a measuring tape at scapula, the tape was extended to down the centre of the posterior surface of the arm to the tip of the olecranon process (elbow), making sure to mark the midpoint. The arm circumference measurement was taken at the upper arm by wrapping the measuring tape around arm perpendicular to the long axis of the upper arm. Participants were asked to sit, with both feet on the floor and to rest their right arm on a table top level with their heart, with their arm stretched out and palm facing upwards. The cuff was placed on the bare upper arm approximately one inch above the bend in the elbow, with the tubing falling over the front centre of the arm. The cuff was tightened evenly around the arm. The participant was then given five minutes to sit quietly. Three measures of systolic and diastolic blood pressure were taken using an Omron blood pressure monitor, with one minute of rest between each reading to get a stable and accurate average reading.

Three waist and hip measurements were taken, again in an attempt to get a stable reading. Waist circumference was measured in a horizontal plane, midway between the inferior margin of the ribs and the superior border of the iliac crest. The hip measurement was taken at the widest lateral extension of the hips. Waist and hip measurement was taken to the nearest 0.1cm. A health report was provided to the participant upon exit from the study (see Appendix 3.3).

6.2.3.3 Mobile Application Analytics Flurry App Analytics

App analytics allow for real-time data on user engagement with the app, and importantly for the use in interventions, there is no additional burden on the participant. The downloading of customised LumoBack app was already connected to app analytics software which meant the investigators could tunnel directly into the app use data. A mobile app analytics platform was used to determine user engagement by quantifying the number of bouts and time spent on the five min/max cards (the tiles present on the app during the sedentary buzz phase of the trial see chapter 5 120) within the app. App analytics were determined using Flurry App analytics (Flurry, Yahoo, San Francisco, US).

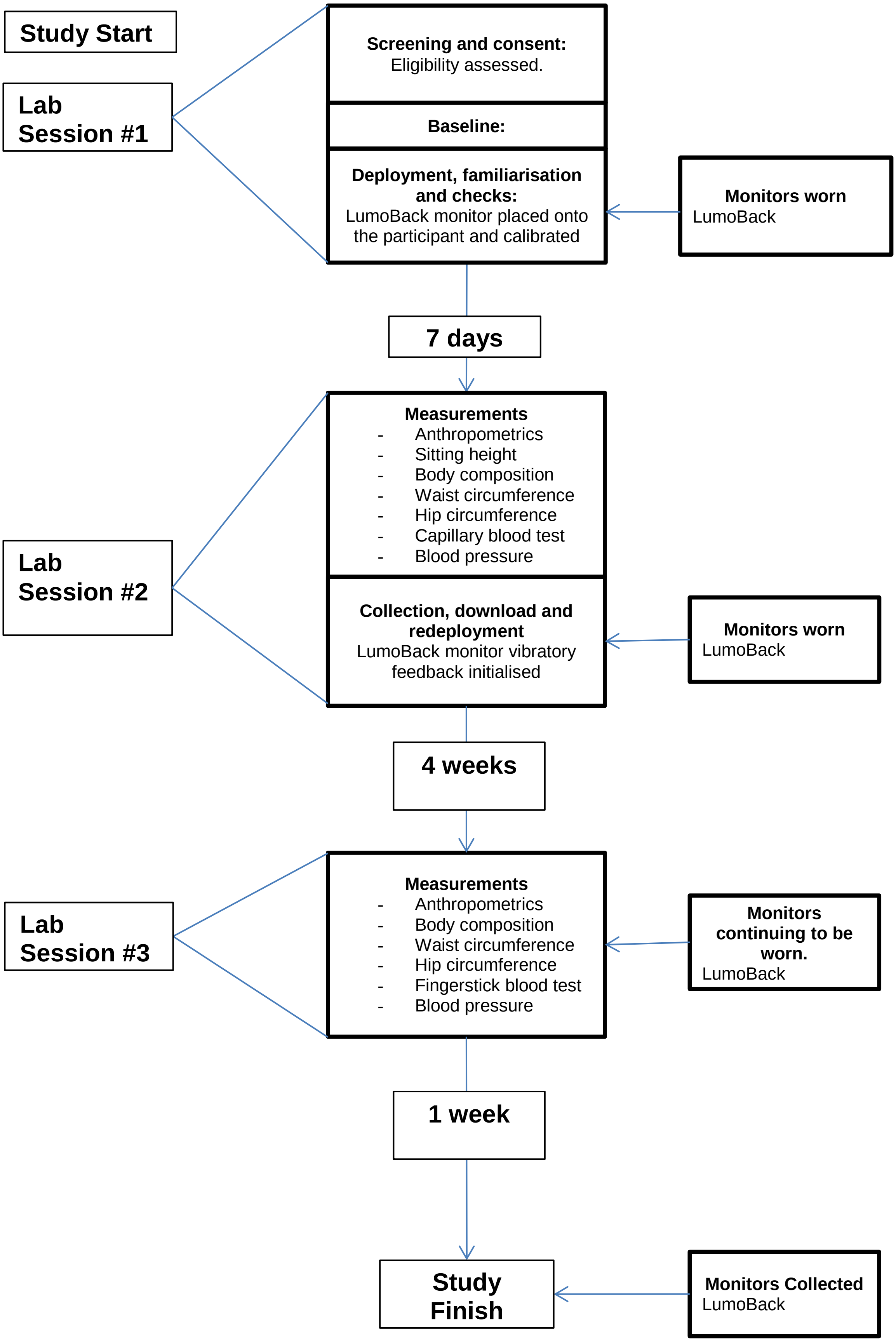


Figure 6.2 - DeSIT study procedure schematic

6.2.3.4 Data Treatment and Analysis

LumoBack data were aggregated by the customised platform designed by Conversant Health under the specification of the study investigators. The DeSIT platform was able to provide three real-time interrogative analyses. These interrogative analyses included a flag in the system if a participant had >10 hours per day of non-wear/inactive time, the expectation of data for all expected time-points from the start of the study to the end point, and a biological implausibility notification to alert the study investigators if the LumoBack has been recording a behaviour for a prolonged period of time (i.e. >10 hours on one day). These were used as a method to signal to the investigator that there may be an issue with the participants involvement in the study and may require further attention. The minimum wear-time criteria for a participants data to be considered viable for analyse was set at $\geq$1 valid day of data, whereby a valid day was deemed to be achieved by >10 hours per day (i.e., 600 minutes) of wear time was recorded for the LumoBack. These wear time criteria were selected based on the wear time criteria typically applied in ActiGraph studies (20).

Repeated Measures ANCOVA were used to determine if there were any significant differences in sedentary behaviour, standing time and stepping time as measured by the LumoBack, across the three time points (control period, week 1, week 5), when controlling for the global average wear time of the device. Participant mobile app analytics data were used to determine the number of bouts and duration of time spent per week on the specific tiles in the LumoBack app. From this a tap engagement ratio:

$$\frac{Specific\ Tile\ Bouts}{Total\ Bout\ for\ all\ tiles}$$

and time engagement ratio:

$$\frac{Specific\ Tile\ Time}{Total\ time\ spent\ on\ all\ tiles}$$

were calculated. Furthermore, using the SPSS visual binning tool, participant’s engagement, determined by total tile taps from the mobile app analytics tool, into equal quartiles based on the scanned cases. Using these groupings mixed measures ANOVA on a sub-sample of participants (those in the highest quartile against those in the lowest quartile) was used to determine if there were any significant interactions between behaviour and engagement group.

In an attempt to determine why individuals engaged with the LumoBack, health outcome data were used to determine the number of Metabolic Syndrome (MetS) risk factors, using the

International Diabetes Federation (IDF) classification (see table 6.1) each participant had. Participants were dichotomized into whether they had ≤1 MetS risk factor or ≥2 MetS risk factors. Level of engagement between the two groups was compared.

Statistical data analysis was conducted using IBM SPSS 22.0 (IBM SPSS Inc, Chicago, IL) with alpha level set at 0.05. LumoBack data aggregation was performed by Conversant Health, with wearable activity data were processed using KineSoft 3.3.80 (KineSoft, Loughborough, UK).

Table 6.1 - International Diabetes Federation (IDF) metabolic syndrome definition

Central Obesity	Waist Circumference: Ethnicity – specific values, plus any two for the following:
Raised Triglycerides	≥ 1.7 mmol/l (150 mg/dl) or specific treatment for this lipid abnormality
Reduced HDL - Cholesterol	< 1.03 mmol/l (40mg/dl) in males <1.29 mmol/l (50mg/dl) in females Or specific treatment for this lipid abnormality
Raised Blood Pressure	Systolic: ≥ 130 mmHg Or Diastolic: ≥ 85mmHg Or treatment of previously diagnosed hypertension
Raised Fasting Plasma Glucose	Fasting plasma glucose ⩾ 5.6 mmol/l (100 mg/dl) or previously diagnosed Type 2 diabetes If > 5.6 mmol/l or 100 mg/dl, oral glucose tolerance test is strongly recommended but is not necessary to define presence of the syndrome

6.3 Results

6.3.1 Participants

Forty-one participants (53.7% female, 44.1 ± 11.3 years, BMI: 25.7 ± 3.7 kg/m^2) took part in the study. 94.6% of the study population were White British, with all participants educated to at least A-level, with 83.8% completing an undergraduate university degree, and all in full time employment.

6.3.2 Sedentary Behaviour and Physical Activity

Table 6.2 shows the mean wear time of the LumoBack (min/day) at baseline, week 1 and week 5.

Table 6.2 - Mean Wear time (mins/day) for the LumoBack at baseline, week 1 and week 5

	Baseline	*Week 1*	*Week 5*
Wear Time [mins/day (SD)]	887 (46)	867 (61)	853 (64)

Table 6.3 shows the sedentary behaviour, standing time and stepping time as measured by the LumoBack at baseline, week 1 and week 5 for the study population. Sedentary behaviour, as measured by the LumoBack, was highest at baseline, which decreased at week 1 after the sedentary buzz was activated, and was decreased again at week 5. At baseline, standing time was 197.2 mins/day, 195.3 mins/day at week 1 and 194.8 min/day at week 5. Furthermore, stepping time at baseline was 93.9min/day at week 1 this decreased to 89.2mins/day and increased at week 5 to 107.0 mins/day. When controlling for LumoBack wear time, the results of the repeated measures ANOVA revealed that sedentary behaviour was not significantly different between baseline, week 1 and week 5 [$F_{(2,56)}=0.212$, $p=0.809$]. Furthermore, there were no significant differences in standing time [$F_{(2,56)}=1.036$, $p=0.362$] and stepping time [$F_{(2,56)}=2.714$, $p=0.075$] among the three time points.

Table 6.3 – LumoBack measured behaviours at Baseline, week 1 and week 5 [Estimated Marginal Mean Minutes (SE)]

Behaviour	*Baseline*	*Week 1*	*Week 5*	*P Value*$^{+}$
Sedentary Behaviour	595.9 (17.2)	584.1 (16.2)	550.7 (17.3)	.809
Standing Time	197.2 (12.2)	195.3 (13.9)	194.8 (12.4)	.362
Stepping Time	93.9 (6.9)	89.2 (5.9)	107.0 (8.9)	.075

+ Repeated Measures ANOVA controlled for Global Average Wear Time of LumoBack.

6.3.3 Mobile App Analytics

Table 6.4 shows the temporal trend of participants LumoBack app usage. During week 1, the frequency of sit time card taps was 4.5 with a total duration of 2 minutes of time spent on the sit time card. Compared to week 1, there was a reduction in frequency of sit time card taps by 36.2%, 30.0%, and 28.8% in weeks 2, 3, and 4 respectively. With total time spent on the Sit time tile reducing by 10.5%, 8.5%, and 15.9% compared to week 1 in weeks 2, 3 and 4 respectively. Week 5 saw the frequency of sit time tile tap return to the level of week 1 with 4.3 taps per week, however compared to week 1 the total time spent on the sit time tile increased by 17.9%, spending 2.3 minutes on the sit time tile.

Compared to week 1, where the average number of taps on the Posture score card was 3.4, and the total duration was 0.9 minutes, frequency and time on spent on the Posture score tile decreased steadily during week 2, 3, and 4 to an average tile tap of 1 tap per week, and 0.3 minutes spent on the posture score. Similar to the sit time tile, there was a slight increase in week 5 compared to the preceding weeks in terms of frequency of taps on the Posture Card; however total times decreased to 0.2 minutes.

In week 1, participants on average tapped on the Step tile 7.5 times, and spent on average a total of 3.9 minutes on the tile. Following a similar pattern to the previous two tiles, in that, frequency decreases in weeks 2, 3, 4, and 5 respectively. Participants on average tapped on the Stand Ups tile 3.1 times and spent on average a total of 0.9 minutes on the tile in week 1. Engagement with the stand ups tile decreased from week 1 in weeks 2, 3, 4, and 5 respectively. Finally, in week 1, participants on average tapped on the sleep tile 1.5 times and spent on average a total of 0.4 minutes on the tile per week. Compared to week 1, in week 2, 3, 4 and 5 respectively. Furthermore, total time spent on the sleep tile decreased, compared to week 1, in weeks 2, 3, 4 and 5.

Table 6.4 shows the number of time participants swiped on the Lumo avatar on the app. Briefly, a person would swipe up or down on the LumoBack app if the avatar was not displaying correctly what the participant was doing. This would in turn feed into the machine learning algorithms to enable the LumoBack to correct its biomechanical model. Participants swiped up on the app 2.8, 1.1, 1.1, 0.9, 1.3 times and swiped down on the app, 1.4, 0.9, 0.6, 0.5, and 0.4 times in weeks 1, 2, 3, 4, and 5.

Table 6.4 - Average time spent on min/max card and average number of bouts on each min/max card [minutes spent (number of bouts)]

Min/Max Card	*Week 1*	*Week 2*	*Week 3*	*Week 4*	*Week 5*
Sit Time	2.0 (4.5)	1.8 (2.9)	1.8 (3.1)	1.7 (3.2)	2.3 (4.3)
Posture Score	0.9 (3.4)	0.4 (1.8)	0.3 (1.3)	0.3 (1.0)	0.2 (1.4)
Steps	3.9 (7.5)	2.6 (5.1)	2.4 (4.8)	3.7 (5.4)	3.8 (5.7)
Stand Ups	0.9 (3.1)	0.4 (1.8)	0.5 (2.0)	0.5 (1.6)	0.4 (1.3)
Sleep	0.4 (1.5)	0.1 (0.8)	0.1 (0.6)	0.1 (0.5)	0.1 (0.6)
*Swipe Up to Stand **	2.8	1.1	1.1	0.9	1.3
*Swipe down to Sit **	1.4	0.9	0.6	0.5	0.4

*Swipe Up to Stand and Swipe down to Sit only have bout information as it is an event monitoring metric

Figure 6.3 shows the tap engagement ratio and time engagement ratio. This ratio analysis will allow for the interpretation of time spent on a particular tile relative to total time on app. Tap engagement ratio shows that participant spent proportionally greater bouts and time on the steps tile than any other tile. However, the greatest increase in engagement with the app was in the sit time card with tap engagement starting in week 1 at 0.225 and increasing to 0.320 in week 5, whilst time engagement ratio increased from 0.272 in week 1 to 0.348 in week 5.

A mixed measures ANOVA was used to determine whether there were any interaction effects between engagement group and sedentary behaviour, standing time and stepping time. When a sub-sample of participants were placed into engagement groups, when controlling for LumoBack wear time, the ANCOVA revealed no significant interaction effects between engagement groups and sedentary behaviour [$F_{(2,28)}$=1.883, p=0.1], standing time [$F_{(2,28)}$=0.286, p=0.753], and stepping time [$F_{(2,28)}$=0.347, p=0.71] See Table 6.5).

Table 6.5 – Sub-sample (n=20) of LumoBack measured behaviours at Baseline, week 1 and week 5 grouped by level of engagement [Estimated Marginal Mean Minutes (SE)]

	Low Engagement			*High Engagement*			
Behaviour	*Baseline*	*Week 1*	*Week 5*	*Baseline*	*Week 1*	*Week 5*	*P Value*+
Sedentary Behaviour	640.2 (30)	617.3 (30.1)	558.6 (35.8)	562.4 (28.3)	588.5 (28.4)	561.2 (33.7)	.171
Standing Time	181.5 (22.9)	169.7 (26.3)	178.5 (14.8)	208.3 (21.7)	190.7 (24.9)	186.6 (13.9)	.753
Stepping Time	84.9 (10.1)	65.7 (9.7)	108.7 (20.6)	98.2 (10.1)	82.2 (9.2)	117.0 (19.4)	.710

+ Mixed Measures ANOVA controlled for Global Average Wear Time of LumoBack.

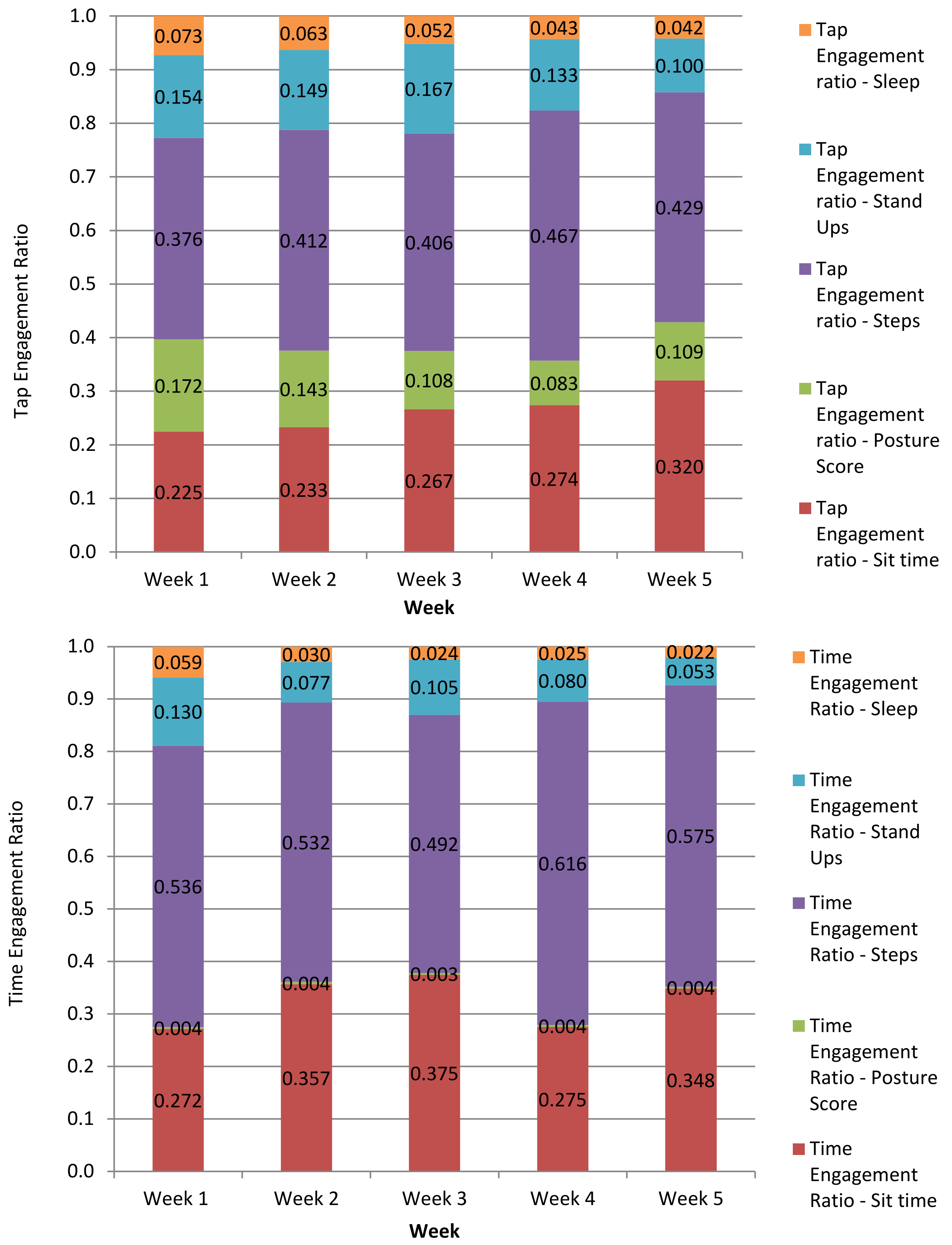


Figure 6.3 – Tap and Time Engagement ratio during the intervention for all five min/max cards on the LumoBack app

Tap Engagement Ratio = ($Specific\ Tile\ Bouts$) / ($Total\ Bout\ for$), Time Engagement ratio = $Specific\ Tile\ Time$) / ($Total\ time\ spent\ on\ all\ tiles$)

6.3.4 Cardio-metabolic risk factors.

Table 6.6 shows the cardio-metabolic risk factors at baseline and week 5 of the study. A two way, repeated measures ANOVA, controlling for age and sex, revealed no significant differences in number of risk factors when comparing baseline to week 5.

Table 6.6 – Participant characteristics and cardio-metabolic health outcomes at baseline and week 5

Characteristics	Baseline	Week 5	P-Value
Female [n (%)]	22 (53.7)		
Age (years)	44.1 (11.3)[1]		
Anthropometric Measures			
Height (cm)	172.9 (8.2)		
Weight (kg)	80.2 (2.4)	78.5 (2.5)	0.332
BMI (kg/m^2)	26.2 (0.6)	25.7 (0.7)	0.311
Fat Free Mass (kg)	55.3 (1.4)	53.7 (1.2)	0.215
Fat Mass (kg)	23.9 (1.6)	23.4 (1.5)	0.568
Visceral Fat %	28.3 (1.4)	29.0 (1.2)	0.208
Waist Circumference (cm)	87.4 (1.7)	85.9 (1.8)	0.344
Hip Circumference (cm)	96.4 (2.0)	96.0 (1.7)	0.607
Waist – Hip Ratio	0.9 (0.1)	0.9 (0.1)	0.306
Cardio-metabolic risk factors (mmol/L)			
Glucose	5.0 (0.1)	4.9 (0.1)	0.770
HDL	1.3 (0.1)	1.3 (0.1)	0.140
LDL	2.7 (0.1)	2.7 (0.1)	0.122
Non-hdl	3.3 (0.2)	3.1 (0.2)	0.503
TC/HDL	3.7 (0.3)	3.6 (0.2)	0.666
Total Cholesterol	4.6 (0.2)	4.4 (0.2)	0.190
Triglycerides	1.3 (0.2)	1.1 (0.1)	0.254
Blood Pressure (mmHg)			
Systolic blood pressure	120.5 (1.7)	117.8 (1.4)	0.529
Diastolic blood pressure	73.3 (1.1)	72.1 (1.1)	0.863

[1] Estimated Marginal Means (Standard Error) – controlled for age and sex

6.3.5 Metabolic Syndrome by Engagement

In terms of engagement with the Sit time card (see Table 6.6), those with ≥2 MetS risk factors, in general, had more engagement apps and spent more time per week compared to their ≤1 MetS risk factor counterparts. Indeed, those with ≥2 MetS risk factors spent more on the app compared to their ≤1 MetS risk factor counterparts at weeks 2, 3, 4, and 5 of the intervention period. In week 1, those in the lowest MetS group accrued slightly longer time on the app card compared to those in the highest group. A similar pattern occurs in the Posture Score card. Those with ≥2 MetS risk factors had more time and taps on Posture Score card in weeks 2, 3, and 5. Indeed, participants in the ≥2 MetS spent approximately 30 seconds more on the Posture Score Card with up to one extra tap on the Posture Score Card.

Again, those with ≥2 MetS risk factor had similar taps but longer time spent on the Steps card that those in the ≤1 MetS group. Those in the ≥2 MetS spent 35, 46, 68, and 158 seconds more on the Steps card than the ≤1 MetS group in weeks 1, 2, 3, and 4, indicating that the higher MetS group engaged to a greater degree than the lower MetS group.

With regards to the Stand ups card those in the ≤1 MetS group had increased taps on the Stand Ups card in weeks 1 and 4, whilst accruing more time on the Stand Ups card in weeks 1, 3, 4, and 5. Indeed, in weeks 3, 4 and 5, those in the lowest MetS groups spent 31, 17, and 11 seconds more time on the Stand ups card, respectively.

Table 6.7 - Average time spent (mins/week) on min/max card and average number of bouts (bouts/week) on each min/max card [minutes spent on min/max card (number of bouts)] dichotomised into ≤1 MetS risk factor and ≥2 MetS risk factors

Min/Max Card	≤1 MetS risk factor					≥2 MetS risk factors				
	Week 1	*Week 2*	*Week 3*	*Week 4*	*Week 5*	*Week 1*	*Week 2*	*Week 3*	*Week 4*	*Week 5*
Sit Time	2.0	1.4	1.3	1.4	1.9	1.8	2.4	2.5	2.0	3.0
	(4.8)	(2.7)	(3.0)	(3.0)	(4.2)	(4.0)	(3.1)	(3.4)	(3.4)	(4.3)
Posture Score	1.1	0.3	0.2	0.3	0.3	0.7	0.5	0.4	0.2	0.2
	(3.6)	(1.4)	(1.1)	(1.0)	(1.4)	(3.2)	(2.3)	(1.5)	(0.9)	(1.6)
Steps	3.6	2.3	1.9	2.7	3.8	4.2	3.1	3.1	5.3	3.9
	(7.3)	(4.8)	(4.6)	(5.0)	(6.1)	(7.8)	(5.4)	(5.0)	(6.1)	(5.1)
Stand Ups	1.3	0.3	0.7	0.6	0.4	0.5	0.5	0.2	0.3	0.2
	(3.7)	(1.7)	(2.6)	(1.5)	(1.3)	(2.3)	(2.1)	(1.0)	(1.6)	(1.4)
Sleep	0.2	0.2	0.2	0.3	0.3	0.3	0.3	0.2	0.3	0.3
	(1.3)	(0.6)	(0.5)	(0.4)	(0.6)	(1.6)	(1.0)	(0.7)	(0.6)	(0.4)

6.4 Discussion

The aims of the current study were to assess whether there is any change in sedentary behaviour and/or physical activity when wearing the repurposed LumoBack posture monitor. Furthermore, in an attempt to understand why individuals engaged with the intervention, health outcome data were also used to quantify whether those with the "most to gain" (health-wise, determined by assessing cardio-metabolic health) were more engaged.

To the investigators' knowledge there have been no previous studies investigating or examining the use of this device alone as a method of reducing sedentary behaviour or increasing physical activity. The goal behind the design and development of the LumoBack was to create a wearable device that could quantify posture with a view of correcting poor posture more efficiently and effectively than current alternatives (371). Due to the LumoBack application programming interface (API) and software development kit (SDK) being openly sourced and therefore making customisation readily possible, the LumoBack may offer valuable assistance with the goal to simply self-monitor sitting and physical activity behaviour during an intervention. However, the findings from the current study suggest that the customised LumoBack did not elicit a change in sedentary behaviour over a 5 week intervention. Although there are reductions in sedentary behaviour (measured by LumoBack) by almost 45 minutes between baseline and week 5, these changes were not statistically significant and may be explained by the reductions in wear time reported by the two devices. Furthermore, the LumoBack-measured behaviour showed no significant changes in standing time or stepping time, although stepping time did increase from ~94 mins/day at baseline to 107 mins/day at week 5. The poor compliance may indeed be the reason for not finding an intervention effect.

The finding that self-monitoring of sedentary behaviour did not elicit a behavioural change is corroborated with other studies in this area (400,401). For example, Project STAND, an educational intervention where participants were provided with a Gruve device (GruveTechnology, Inc, Anoka, MN), showed no significant differences in accelerometer determined sedentary time, nor any statistically significant findings in sedentary behaviour determined by the activPAL (400). More recently, an intervention by Ellingson et al. (401) used the activPAL VT (abbreviation for vibrotactile) with a sedentary buzz of 30 minutes (similar to the current study) in a population of thirty young adults and found no significant within- or between-group differences in total minutes of objectively-measured sedentary behaviour or physical activity (401). However, Barwais et al. (402) conducted a four-week randomised control trial to reduce sedentary behaviour and increase physical activity levels in sedentary adults. This study by Barwais and colleagues found that an online self-monitoring system [Gruve (GruveTechnology Inc)] (386) lead to greater than 20% reductions in self-reported sedentary behaviour over a four week period. However, as these findings were based on self-reported sedentary behaviour, rather than the objective data, conclusions need to be interpreted cautiously.

In the present study, engagement with the app was measured to determine if participant exposure to the intervention and those who engaged more with the app would also decrease their sedentary behaviour to a greater degree. Sedentary behaviour, when measured by the LumoBack, was lower in the high engagement group, and corroboratively, there was higher standing time and stepping time in the higher engagement group than the lower engagement group, with decreased sedentary behaviour seemingly displaced by stepping time. This is not surprising when findings from the app analytics showed that people were most engaged with the steps min card rather than the stand ups or sit time (which has information on standing time). Participants had the greatest number of engagement bouts and time spent on the steps min card, whilst also spending proportionally more time on steps each week compared to any other min card. However, the largest increases in proportional engagement were seen in the sit time min card, suggesting that there may be a delay in learning/participants educating themselves about the importance of reducing sedentary behaviour and what the important metrics are in determining sedentary behaviour. Furthermore, those with the 'most-to-gain' (i.e. those in the highest MetS risk factor group) appeared to engage generally more with both engagement bouts and time spent on cards, suggesting that those who were in the unhealthiest category engaged more with the intervention than those who were in the healthier category.

There are a number of possible explanations for the non-significant results of this study. Firstly, due to this study being a proof of principle/feasibility study, it was challenging to appropriately determine the power necessary to detect a statistically significant difference. Nonetheless, these data can be used to suitably power future research. Secondly, sedentary behaviour is a highly variable behaviour. Indeed, data suggest that anywhere from 55-70% of the day can be spent sedentary (31,96). Furthermore, due to large proportions of the day being spent sedentary, small changes (relative to the total time) will make it difficult to achieve statistical significance. Thirdly, sedentary behaviour is an inherently insidious behaviour, which may be difficult to shift. Unlike physical activity, which is infrequent, short in bout length and usually requires planning, sedentary behaviour is a regular activity lasting potentially several hours in length, and ubiquitous in nature. Our environment is queued up to facilitate sedentary behaviour (403). Living and office spaces are constructed in such a way to make sitting the dominant behaviour. Given this, sedentary behaviour may be a difficult behaviour to displace due to its permeating presence. Environmental changes may be useful in aiding this displacement (39,404). Indeed, a systematic review of behaviour change strategies used within interventions that sought to reduce sedentary behaviour in adults found that interventions based on environmental restructuring were the most promising (41). Furthermore, provision of sit-stand desks has been shown to be effective in reducing sitting time in adults (37). In addition, motivation to change will involve conscious decision making as well as less conscious 'automatic' processes. The latter involve acting in accordance with basic likes and dislikes and with rather little deliberation. Automatic processing will involve habitual reactions to the environment and acting out of habit (405). This is highly likely for sedentary behaviours where chairs are provided and sitting is the norm. Whether it is possible to create a situation where not sitting is seen as 'enjoyable', and hence the default option, has not been tested.

Likewise, in the systematic review of behaviour change strategies, self-monitoring was the behaviour change technique that was shown to be particularly promising (41). Behaviour change theory is now suggesting that self-monitoring is just one (albeit an important one) of many ways that could change behaviour (42,187,209,210). Whilst the current study gave participants a small but better understanding about sedentary behaviour, and the adverse health effects associated with it, as well as the ability to explore the behaviour change technique of self-monitoring, when they leave contact with the investigator, they were essentially on their own to embed the strategies in to their lives. Without environmental restructuring or other behaviour change strategies, it may be difficult to incorporate and embed self-monitoring into individual lifestyles. There is also a need to assess how self-monitoring in accordance with overt changes in the environment may change the outcomes of interventions. Combinations of multiple behaviour change techniques and strategies might be particularly important in individuals who do not see themselves as being at risk of the deleterious health effects of prolonged sitting. A recent cluster randomised control trial study by Healy and colleagues (40) implemented a multicomponent intervention employing organisational, physical environmental and individual behaviour change methods to reduce sedentary behaviour. The workplace-delivered multicomponent intervention was successful at reducing workplace and overall daily sitting time in both the short and long-term (40).

Consequently, interventions may be better constructed when using a combination of environmental restructuring and self-regulatory techniques.

Fourthly, the LumoBack is a wearable outlier, in so far as, many wearable devices currently on the market are worn on the wrist (approximately 55% of wearables are worn on the wrist and approximately 60% of wearables are worn on the wrist hand or arm), it might therefore be the case that devices which are worn around the waist (which make up approximately 3% of the market (406), might not be suitable for behaviour change. Whilst the wrist might not be the best location for activity recognition (407,408), the large number of wearables worn on the wrist, in accordance with scientific literature, seems to suggest that this is the best place for user adherence (409), therefore, the LumoBack (worn around the waist on the lower back) might not be a wear-site conducive to participant adherence or engagement. Indeed, exit questionnaire data from this study revealed that 59.5% of participant found that a wear site at the waist was not an important contributing factor in whether or not they chose a wearable, compared to the 67.6% who indicated that using a wearable that can be worn at the wrist was important, of which 56.8% indicated that wearing a device at the wrist was very important.

Fifthly, results from the mobile app analytics demonstrate that individuals were most engaged with the Steps card on the LumoBack app. Indeed, over half the time in each week spent on the LumoBack was spent engaging with the steps min card. This is not surprising when considering that the majority of consumer activity trackers measure physical activity, traditionally in the form of steps (see scoping review from chapter 3 page 48), and that knowledge of the potentially adverse health effect of sedentary behaviour and sedentary behaviour guidelines are low (410). Indeed most mass media campaigns and population level information has been focused on increasing MVPA (411), so it is not surprising that people's perceptions of sedentary behaviour are not in keeping with what is known in the literature. However, daily MVPA (if meeting guidelines) only accounts for approximately 2-3% of our daily behaviour (20) (which also includes sleep, sedentary and light physical activity), whilst epidemiological data show that sedentary behaviour accounts for approximately two-thirds of the day (26,31,96). Consequently, a greater focus and education on sedentary behaviour guidelines [where available e.g. new Canadian 24 hours guideline (219)] and the associated adverse health effects might be needed. Furthermore, unpublished data from the Mi-LAB at Loughborough University found that when individuals were presented with 20 feedback options (on a single A3 sheet of paper) and were requested to place four stickers on the four options that they thought would be most useful to monitor their health (no restrictions on placing a certain amount on each topic, free to pick four from a single topic e.g. MVPA if desired), steps were the most frequently selected (n=20 of 33) as one of the top four feedback options to monitor their health (Unpublished Data). A participant's greater interest in steps, combined with the low levels of knowledge around sedentary behaviour, may partially explain the lack of significant behaviour change seen in this intervention. On the other hand, the largest increases in min card bouts and time were seen with the sit time card across the weeks of the intervention. This suggests that it takes a longer period of time for participants to become engaged with the issue of reducing sedentary behaviour and with the metrics associated with sedentary behaviour (411). These might be more cognitively loading than the traditional step count metric. Therefore, more educational information might be needed from the outset of interventions; making participants knowledgeable of the detrimental effects of sedentary behaviour making feedback from the LumoBack having greater salience.

Finally, whilst the systematic scoping review in Chapter 3 (page 48) found the LumoBack to have a number of self-monitoring and feedback attributes, feedback is an inherently personalised element, and feedback should be tailored to the individual. In the current study, we took the pragmatic decision to set the sedentary buzz of the LumoBack at 30 minutes. Two other studies which have used vibrating self-monitoring tools set at 30 and 60 minutes, also found no statistically significant changes in time spent in sedentary behaviour (36,401). This might suggest two issues: firstly, that perhaps vibratory feedback is not the most powerful feedback mechanism by which to act, despite its low cognitive loading, some individuals may be better suited to auditory feedback, or to omnipresent feedback like the FitBit Flower, and secondly, that the amount of time after which the sedentary buzz occurs needs to be a personalised and tailored time (i.e. participants decide whether to have the buzz at 20 minutes or 30 minutes). Future intervention should aim to take a person centred approach in the development of feedback.

There are a number of strengths associated with this study. Firstly, this study is, to our knowledge, the first to use a novel, commercially-available piece of wearable technology, which has been validated as a measure of posture. Secondly, the usage of mobile app analytics to measure the user's engagement with the LumoBack is also a novel component to measure the exposure to the intervention and one that should be utilised and investigated further in future interventions. Thirdly, this study commissioned and deployed a scalable online platform for the aggregation and download of LumoBack data. Whilst the company behind this platform is no longer running, there are a number of alternatives available which can be used in lieu of the current system, which can be initiated and deployed in a short space of time and accessed from most devices connected to the internet. Fourthly, this study deployed the LumoBack as a continuous, pervasive intervention which is different from other intervention such as sit-stand desk which only work in their context of their deployment or educational programmes which traditionally occur in organised workshops. Finally, the LumoBack contains an objective measure of wear and non–wear time which is something that previously would have relied upon algorithms or diary logs to track. This is of particular importance when assessing sedentary behaviour given that the missing data from poor wear/non-wear recording at both the beginning and end of the day is likely to be sedentary behaviour.

There are also a number of limitations associated with this study. Firstly, the participants in this study were a sample of mostly white-British, highly educated (due to it being a broadly a sample of convenience), which therefore may make these findings non generalisable to the general population. Secondly, there was no environmental change associated with this intervention, which, as already alluded to, may have meant that individuals who are motivated to change, may have lacked the capacity to do so when the prompt occurred. Thirdly, POC testing is not the gold standard for measuring lipid profile and glucose and more clinical laboratory techniques should be utilised in the future. Finally, there was no follow up beyond the five week intervention study, which may have given us an indication of how behaviour changed after commencement of the study. Fourthly, the need for individuals to own a iPhone to participate in this study decreases the generalizability of the study, as not everybody has a iPhone in the general population. Finally the study may not be long enough to allow for an effective behaviour change to take place.

6.5 Conclusion

In conclusion, self-monitoring of sedentary behaviour using the LumoBack on its own may not be sufficient to change behaviour. Future studies should look to assess different feedback methods and modalities in an attempt to optimise the salience of the feedback and to make it more likely to be heeded by the participants. Furthermore, follow up interventions should look to assess the use of real time sedentary behaviour feedback in conjunction with other behaviour change strategies and techniques (e.g. environmental restructuring) as part of multi-faceted designs that target reductions in sedentary behaviour. Furthermore, the use of mobile app analytics to determine intervention exposure and engagement not only as a ratio of app time, but also as part of mobile use as a whole, should be further investigated. Finally, further research should look to conduct interventions over a longer period of time, longer than 5 weeks, as 5 weeks may not be long enough to instil behaviour change. Indeed small changes in behaviour may be more sustainable and prevent further increases in sedentary behaviour. These research directions show strong potential to add value to wearable technologies and increase their potency in lifestyle behaviour change interventions.

Chapter 7 – General Discussion

This thesis presents three studies and development of the user interface which each contribute novel and important components to the evidence informing the use of commercially available technologies as measurement and behaviour change tools in sedentary behaviour research in adults. The overall purpose of this three study thesis was to review, validate, develop, and apply a novel commercially available technology to generate new insights in its ability to be used as a behaviour change tool for self-monitoring sedentary behaviour with the intent of reducing such behaviour. This thesis has presented a systematic review, which scoped the current technologies that could be used to self-monitor and provide feedback on time spent in physical activity and/or sedentary behaviour, as well as quantifying the level and frequency with which self-monitoring attributes appears in these technologies. Using the information from the systematic scoping review, the LumoBack was identified as the most promising technology for monitoring and providing feedback on sedentary behaviour. Therefore, the second component of this thesis was to ensure that the LumoBack could provide accurate and reliable measures of sedentary behaviour. Having determined the validity and reliability of the LumoBack, the third and final study presented in this thesis was to determine whether a repurposed LumoBack Posture Sensor can reduce sedentary behaviour in healthy adults.

7.1 Summary of main findings

In Chapter Three, a systematic review was conducted to scope the current standing of wearable technologies that are available that can self-monitor physical activity and/or sedentary behaviour. The review identified 82 pieces of technology, 73 of which self-monitored physical activity, the majority of which originate from the consumer electronic, health and fitness market. These devices tended to consist of an accelerometer for activity measurement (steps, calories burned, distance travelled) with varying levels of secondary sensors that provide additional metrics for behavioural and physiological measurement. Fortuitously, a greater number of these devices are now providing not just feedback on activity time, but also time spent in periods of inactivity which is now the fourth leading risk factor for chronic disease (23). Unfortunately, there is a dearth of monitors that measure sedentary behaviour, with only nine having been identified in the scoping review. However, unlike activity monitors that measure activity traditionally using one methodology (i.e. accelerometry), the commercially available postural allocation monitors utilise a variety of methods to determine sedentary behaviour, including inclinometry and pressure sensors. Both these types of devices usually utilise proprietary algorithms to convert the raw signals from the sensors to provide metrics of use. They also provide feedback, the majority of the time, either via vibratory feedback (e.g. LumoBack) or via an omnipresent display on the device (e.g. Garmin Vivofit). These devices tend to, but not exclusively, connect to an app for feedback on physical activity and sedentary behaviour. For physical activity, this usually takes the form of energy expenditure or proprietary company points (e.g. Nike Fuel). For sedentary behaviour, this usually takes the form of time spent sitting/lying (e.g. LumoBack) These mobile apps allow the wearer to receive real-time continuous feedback along with goal-setting capabilities and customization of type and timing of feedback; this is an aspect not traditionally offered by research devices.

From the systematic review, the LumoBack was identified as the most promising sedentary behaviour self-monitor due to its numerous feedback attributes and its ability to measure sedentary to the current definition and therefore warranted further investigation into its validity. In Chapter Four, an experiment was conducted to determine the validity of the LumoBack Posture Sensor compared to direct observation, ActiGraph and the activPAL in the laboratory and ActiGraph and activPAL in free-living settings. In both the laboratory and free-living setting the LumoBack was seen to be acceptably valid as a measure of sedentary behaviour, standing behaviour or stepping behaviour when compared to the activPAL and ActiGraph. Given the feedback attributes and immediacy of the self-monitoring capabilities of the LumoBack, it may be a potentially useful tool for behaviour change with a view to reducing sedentary behaviour.

In its original format the LumoBack was not optimised to provide feedback on sedentary behaviour. Therefore the LumoBack was repurposed to provide vibratory feedback on sedentary behaviour. This included collaborating with Lumo BodyTech Inc. to repurpose the vibratory function of the LumoBack, originally used to signal sub-optimal posture, and use it as a feedback modality for prolonged user-defined sedentary behaviour. Other alterations included creation of a control mode for the app, which meant that the user did not have access to the feedback on the device, as well as the ability to track user LumoBack app usage.

Now that the LumoBack had been repurposed, Chapter Five describes a proof of principle intervention whereby 42 participants were asked to wear the LumoBack for a period of six weeks, (one week of control period, five weeks of intervention) in an attempt to determine whether self-monitoring sedentary behaviour could change behaviour. The results indicated that the LumoBack as a sedentary behaviour self-monitor may not be sufficient on its own as a behaviour change modality to change behaviour. Furthermore, user engagement analysis showed that individuals were mostly interested in the steps card of the LumoBack app with peaks in interest displayed around the time of the laboratory visits. Furthermore, those with the ‘most-to-gain’ (i.e. high Metabolic Syndrome risk factor group) engaged to a greater degree than those in the low Metabolic Syndrome risk factor group. This chapter suggests that there is a need for multi-faceted interventions employing multiple behaviour change strategies and techniques to change the insidious behaviour that is sedentary behaviour.

7.2 General Discussion

Despite almost six decades of research showing clear evidence that engagement in moderate to vigorous physical activity (MVPA) reduces the likelihood of developing an array of non-communicable diseases, and the decade of work that shows increasing sedentary behaviour is detrimental to your health, surveillance studies have shown that population levels of sedentary behaviour are high (48,51,54,127,412) and the levels of guideline fulfilling MVPA are low (19,20,31,48). It is therefore apparent that current interventions are not creating the substantial changes that are needed to improve population level health and new intervention modalities are required. Self-monitoring as a behavioural modality for beneficially altering a range of behaviours and health outcomes is increasing (247,353,413–417), including its use in physical activity and sedentary behaviour interventions (38,41,42,210).

Wearable technology offers potential for continuous and personalised real-time feedback, which has not been possible up until now. Indeed, new research finds that over 3 million wrist-worn wearable devices such as fitness trackers and smartwatches are estimated to have been sold in the UK in 2015, which is up 118% from unit sales in 2014. Furthermore, 1 in 5 people plan on purchasing a piece of wearable technology in the next 12 months (231). Moreover, an estimated 48 million devices were sold worldwide (418), which is expected to rise in the coming years. Partner these figures with figures now showing that 76% of adults own a smartphone, there is a real sense that wearable technology might be the pervasive entity which can have a real influence on behaviour, certainly given the breadth of devices that are available in the current market which is apparent in Chapter Two. Wearables are inherently tied into the behaviour change technique of self-monitoring, with the majority of wearable also able to providing feedback on behaviour, able to allow for goal-setting, and importantly, able to provide feedback in light of these goals all of which, in combination have been shown to provide greater behaviour control (42,185,210,212).

Previous reviews have sought to provide an overview of research grade devices (104,123,419–421), or discussion on a particular commercial tracker (422,423) and how useful they are at measuring aspects of physical activity. This is presumably because of the sheer size of the consumer activity tracker market. There is also a dearth of reviews into the measurement tools of sedentary behaviour (52,104). Chapter Three took on the ambitious project of attempting to review both the research grade and commercial activity monitors that could be used to self-monitor physical activity and/or sedentary behaviour. The over whelming outcome from the review was the large number of devices that self-monitor and provide feedback on physical activity and there is a scarcity of devices that measure and self-monitor sedentary behaviour in the current definition. Indeed, no current device measures all three aspects of the current sedentary behaviour definition, however there are some promising devices.

There is a logical explanation for the absence of sedentary behaviour devices and a flourishing of physical activity devices. The majority of mass media campaigns that are currently used by health promoters are used to disseminate physical activity messages (411). Couple this with the well-published 10,000 steps goal (424–426), it is unsurprising that most commercial activity trackers are based around measuring physical activity, traditionally in the form of steps, as this is a metric that is easily understood and of low cognitive bearing to the public. Sedentary behaviour is less well understood by the public despite the growing media interest and often gets confused with physical inactivity (44). This is apparent in certain physical activity monitoring devices (e.g. Apple Watch) that claim to measure sitting time but it is expected that this is to be time spent inactive as only accelerometers are present in these devices. It may be more appropriate therefore to increase the educating of populations around sedentary behaviour as well as increasing the “popularity” or salience of sedentary behaviour in the same way that mass media campaigns such as ‘*Change4Life*’ have done for physical activity.

It should also be noted that this fast-paced innovation of commercial trackers provides an obstacle to researchers, as the speed with which research can be conceptualised, developed, investigated and disseminated is of a slower pace. Although the review in Chapter Three was published in a peer-reviewed journal in Q1 2016, in the time between publication and this thesis going to print there have been a slew of new devices which may be of interest to researchers, which can monitor a wide variety of behavioural and physiological outcomes.

This will necessitate researchers and commercial sector entities working in partnership in this ever evolving area to make sure research can remain as up to date and relevant as possible.

With the increase in these commercial activity trackers, there has been an increase in the number of validation studies assessing their ability to measure a multitude of metrics (168,170–173,175–178,181,422) with some showing encouraging results for their validity to measure physical activity (168,181), whilst others have shown to over-estimate or under-estimate certain metrics (174,179). Undeniably, Rennie and Wareham (33,106) determined that for the currency of use in behavioural research to matter to both researchers and the public, accurate measurement of behaviour is necessary. Furthermore, accuracy and precision is imperative if consumer devices are to be used in research aiming to determine dose-response relationships between behaviour and disease outcomes (427). Ttherefore, robust validations to determine the validity and reliability of these novel commercial devices is of paramount importance. The study presented in Chapter Four showed that the LumoBack has acceptable validity as a measure of sedentary behaviour, standing behaviour, stepping behaviour, as well as steps taken in adults. These findings are corroborated by previous studies (175,177); however, the validation in this thesis was the first to validate the LumoBack over the course of the traditional seven day free-living validation protocol. Commercial activity trackers are likely to be used more frequently for research purposes given their low cost, wear acceptability, immediate feedback capacity, and ease of syncing wirelessly with smartphones or smart devices for data retention. Therefore, free-living evaluations of these devices with robust comparative measures are imperative to better understand the accuracy and precision of these devices in estimating behaviours.

With commercial devices becoming progressively more user-friendly, further work is needed before broad use in intervention studies can be realised. Behavioural lifestyle interventions that are delivered face-to-face and incorporate behavioural change strategies have been successful in interventions aimed at increasing physical activity behaviours (428). However, these types of interventions are labour intensive, expensive and require behaviour change experts. It is possible that consumer devices that allow for self-monitoring and the incorporation of previously-determined successful behaviour change strategies, could replace the high study burden of face-to-face interventions.

Previous research has been focused on increasing MVPA, however as epidemiological evidence suggests the levels of guideline fulfilling MVPA in the population are still low

(19,21,22,49). Interventions aimed at reducing sedentary behaviour may provide the ‘biggest bang-for-our-buck’ in terms of a public health strategy, as decreasing sedentary behaviour is likely lead to increases in light physical activity (due to these two being highly and inversely correlated (50)) which can be a gateway to more beneficial MVPA. Self-monitoring of behaviour and outcomes have been shown to be effective in a number of behavioural and health-related interventions (211,246,413,415–417,429,430) and may be a useful intervention modality to reduce sedentary behaviour. At the time of this thesis, to the authors knowledge, there were only three other interventions utilising activity trackers to reduce sedentary behaviour (400–402), and in fact, one of the devices used was the activPAL VT (a research grade device), whilst the other two studies used the Gruve. Only one of these studies showed pre-post reductions in sedentary behaviour; however, these were self-reported reduction in sedentary behaviour, therefore, these results should be taken with caution. The results of the study found in Chapter Five corroborate the findings of these studies suggesting that self-monitoring on its own did not induce a behaviour change in the study population. The result of the engagement analysis showed that individual were more engaged with steps on the LumoBack app which is not surprising given the level of information that is disseminated nationally on increasing steps. Further strategies may need to be incorporated into interventions along with self-monitoring, which also aim to increase the level of knowledge surrounding sedentary behaviour making feedback metrics less cognitively loading.

At the same time as commercial activity trackers increasing in popularity, there is preponderance of other ‘ables’ coming on to the market. These include, Nearables (smart everyday items with small, wireless computing devices attached to them), Hearables (smart headphones designed for a range of purposes including wireless transmission to communication, medical monitoring and fitness tracking), Ingestibles (small pill size pieces of technology which mainly serve the two primary functions of wireless patient monitoring and diagnostic imaging), Embeddables (consisting of microchips that can be implanted into or onto the human body for the purpose of monitoring or affecting the body’s biometrics), Adhearable (which are usually used for sports, drug-delivery or patient monitoring), and Trainables (an adjunct of wearables designed to provide accurate real time feedback to allow individual to take an active role in their monitoring with the aim of maximizing behaviour change). Despite all these devices having differing applications and measuring different biometrics the one thing all of these types of ‘ables have in common is that they are designed to have the ability to self-monitor. In addition, given the plethora of ‘ables, which measure an array of both behavioural and physiological metrics, individuals will have the ability to monitor the acute health benefits or disadvantages to positive or negative health behaviours respectively. This inter-connectivity of such a range of devices means that citizens are coming upon a time where they can become an active rather than passive nexus of their health.

Furthermore, this increase in availability of electronic self-monitoring technologies provides an opportunity for researchers to utilise them on a large scale for behaviour change by integrating them into corporate wellness programmes and health care systems. Recent reports from the National Information Board in a review of the National Health Service (NHS) in the United Kingdom (UK) indicated the need for “citizens” to start playing a more active role in their health care by accessing, entering, and uploading data into their own online medical record. Under these new plans, citizens will be able to access and download their detailed medical records as well as contribute to it with information from their personal wearable technology or biosensors (248,249). And more recently still, the current UK Secretary for Health has announced that data from approved health apps will feed directly into personal health records, NHS England publishing a library of apps and devices in areas related to mental health and other chronic diseases by March 2017 (431). In addition, as more health care providers in the United States move to a value-based care system (i.e., “reward points” for positive lifestyle alterations that can be redeemed for discounts on a range of products and/or activities), mobile technologies that promote health and well-being by engaging in important health behaviours (e.g., decreased sedentary behaviours) will continue to grow and have the potential to be an integral piece of future health care systems.

Other advantages of wearable technologies are their relatively low cost compared to their research grade counterparts, being compatible with a smart phone, and having an array of behaviour change techniques. Lyons et al (387)conducted a content analysis to determine the number of behaviour change techniques implemented in 13 consumer devices (387). The most common strategies implemented were self-monitoring, feedback provision, adding objects to the environment, and goal setting. Furthermore, the industry is developing at such a fast pace that very quickly the current wearables will be obsolete and there will be new and innovative ways of measuring behavioural and physiological parameters of health.

There are some concerns with the increased use of commercial activity trackers. The innovation and development of these technologies now form part of the Internet of Things, a development of the internet in which everyday objects have network connectivity, allowing them to send and receive data. This will mean that current fitness trackers now have the ability to double as a smart watch which can also be used to monitor home energy, put favourite TV shows on record, or turn a coffee machine on in the morning. All of these developments can be seen as ways to engineer activity out of our lives. This is part of the Megatrend (pattern or a movement which has a major impact on business and society as a whole) of de-industrialisation which is exemplified by the fact that in the 60's 36% were employed in manufacturing and 49% were employed in services whereas as of 2011, 8% were employed in manufacturing and 81% were employed in services (432). This shows that the increase in modern technological advances has led to a services based economy which is epitomised by sedentary lifestyles. It may therefore seem counter intuitive that a portion of the Internet of Things which is part of the problem can also be a part of the solution.

Furthermore, the 'dirty secret of wearables' is that a third of users stopped utilising their wearable technology six months after purchase (433). A possible reason for this is that habit formations may have taken place (research suggest the average time for habits to form is 66 days (405)) so it may be the case that individuals no longer need the devices for behaviour change as it has already occurred. This is unlikely though as population levels of sedentary behaviours are high, and levels of MVPA are still low. Another option could be that the information provided by some activity monitors are inaccurate as can be seen with the recent lawsuit filed against Fitbit (434) for the inaccuracy of their heart rate function in their Fitbit Charge HR. Inaccuracy in the measurement may lead individuals to become disenfranchised with the device and stop using it; however, as self-monitoring theory (213) tells us that as long as a device is relatively accurate with good reliability it can still be a useful self-monitor. One other option is that there needs to be improvements in the fundamental consumer value proposition. After a period of usage, information from wearables which have remained the same from the beginning can make users either get jaded of the stagnated information, or they find the information adds nothing as they are already familiar with it and therefore participants may require newer layers of information. Whichever the reason, it is clear that developments need to be implemented in order to keep people from disregarding wearables after a period of time and making there persuasive and pervasive behaviour change tools.

7.3 Future direction

There are essential research priorities that are apparent to build upon the findings in this thesis. There is a greater need for collaborative work between computer scientists, behavioural scientists, engineers and public health researchers in order to create technologies that may have a better uptake. A cursory search of Fitbit, Jawbone, Misfit, Garmin, Hexoskin and Withings advertised career opportunities has indicated that there is only one position between all of these companies that currently advertise looking for a behavioural scientist to help advance the salience of wearables to their users. Furthermore, the co-operative work between commercial companies and researchers should look to design methods of measuring all aspects of the sedentary behaviour definition, not just postural allocation, but also the energy expenditure and whether the individual is awake in order to obtain the most accurate estimate of sedentary behaviour possible.

One of the limitations of current commercial activity trackers is the trade-off between raw data measurement and availability of the data for other feedback and battery life related requirements. If researchers are going to continue to increase their use of commercial trackers, they will require access to greater granularity of data that researchers are accustomed to in research grade devices, for data processing and analysis. It is difficult to see how this might occur as to accommodate raw data storage and feedback greater than seven day battery life would require an increase in the size of the device, and the main customer of commercial activity trackers (the general public) has no appetite of the acuity of data which researchers require.

A major issue with current activity tracker use is the problem around stickiness. This is the concept describing the ability of the tracker to remain useful and therefore be used for a prolonged period without being discarded as is currently the case for a lot of wearable users. There are two ways this might occur. Firstly, to integrate activity trackers into other smart wearable systems. This would mean that when there is a trough in the practice of positive health behaviours the activity tracker remains useful for other reasons and will continue to be used, so that when there is a peak in the practice of positive health behaviours, their device is already being used and can be engaged with easily. Secondly, activity tracker developers should look for a means to evolve data feedback over time so users remain engaged with the device because they are receiving new pieces of information, thereby keeping their attention. However, it is unlikely this is to occur from the activity tracker company side as there are few ways to monetise this, so there is little incentive for the wearable company to pursue this avenue.

Likewise, work should look to focus on creating personalised feedback that are relevant to the individuals (i.e. real-time feedback of information must resonate with the individual and not be information that has been presupposed for them, as well as being aware of the environment in which the person is in so that the feedback can be acted upon). In a review of personal health technology for cardiovascular disease prevention, Franklin et al (435)reported that studies using self-monitoring tool are most effective for health behaviour change when they are combined with personalised feedback (435). This type of intervention has been coined as 'lifestyle medicine' by making individuals the centre of their health (436). Evidence suggests that personalised feedback following objective measurement may increase their awareness of physical activity levels (437,438), which may in turn stimulate intention to increase physical activity, which ultimately may lead to positive changes in behaviour (439,440) and may be part of the mechanism underlying the effectiveness of pedometers (211). Furthermore, research using fMRI to examine neural processes associated with affirmation effects during exposure to health messages and feedback, found self-affirmation (affirming core values of the individual) may exert its effect by allowing individuals to see the self-relevance and value in the message. In other words, for a health-message to be heeded by the individual, it must be presented in the method that resonates with individuals beliefs on what is important to them (441).

Personalised feedback, however, may elicit negative effects on participant's behaviours, if the behaviour is seen to be acceptable it may lead to false assurances and a subsequent deviation from appropriate behaviour. Furthermore, interventions utilising personalised strategies and feedback may cause heterogeneity within the data making it harder to determine the effectiveness of interventions. Despite these limitations, further investigation should look into combining self-monitoring with context aware personalised feedback.

There is also an additional need for feedback to become context aware. It is important that the feedback or behavioural nudge occurs in a timely manner and aware of the environment and situation to which the user is in. For example, if a participant is using the repurposed LumoBack to provide vibratory feedback on sedentary behaviour, it is important that this occurs in an environment where this advice can be heeded, and not in one where is cannot (for example a dentist chair). The increase in the number of technologies that can measure location and context is increasing and proliferating (120) and their use in combination with self-monitoring devices may provide context-aware feedback. The combination of context aware personalised feedback may increase the salience of the feedback and the likelihood of it being heeded by the user.

Historically, people have always needed to be physically activity (e.g. hunter-gatherer, preponderance of manual jobs). However, with the technological revolution there is less need to be physically active. Currently, being physically inactive and sedentary is the unconscious easy option. Work should be conducted to create a situation whereby being physically active is the easy choice to make. One option might be to use a combination of behavioural and physiological trackers which can show the acute and immediate health benefits of increasing activity and reducing sedentary behaviour. This might be a more potent message to relay because temporal discounting literature shows that we are more likely to make an immediate decision if we can see the immediate rewards, rather than making an immediate decision for a future reward (i.e. relaying the message of ‘be physically active now to reduce the post-prandial glucose excursion’ over the message of ‘be physically active to reduce the risk of developing type 2 diabetes in 20-30 years’ time’) (442–444).

Finally, interventions should look to layer behaviour change strategies and techniques in to multi-component interventions such as the organisational intervention in office workers in Australia (38) which is deploying sit-stand desk whilst also utilising the LumoBack to self-monitor sedentary behaviour. These types of multi-component interventions may have the potential to aid beneficial behaviour change.

7.4 Final Comments

This thesis presents evidence from three studies regarding the review, validation, development and implementation of a commercially available tracker for the measurement of sedentary behaviour. Whilst the results in this thesis are preliminary and require further investigation, they indicate that there is cause for concern around the lack of devices that are capable of measuring sedentary behaviour in its current definition. Those devices that can measure sedentary behaviour only do so to a certain degree of the current sedentary behaviour definition, namely the postural allocation segment. Having said that, those that do measure sedentary behaviour such as the LumoBack, by measuring postural allocation have been shown to be valid and reliable when tested and the validation conducted as part of this body of work has corroborated these past findings. As commercial trackers continue to expand, it is likely that researchers will continue to use these devices as measurement tools, and behaviour change tools. The final study in this thesis developed and implemented one such commercial device (LumoBack) as a behaviour change tool in an attempt to reduce sedentary behaviour. Whilst the results did not reach significance, self-monitoring devices should be utilised as part of a pack of behaviour change strategies and techniques which can help to facilitate changes in sedentary behaviour. However these findings may be related specifically to the LumoBack device, as previous research has demonstrated that self-monitoring in combination with other control theory components is the most robust behaviour change technique for altering physical activity and sedentary behaviour

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Appendix 1 – Devices for self-monitoring sedentary behaviour and/or physical activity: A systematic scoping review: Additional Material

Appendix 1.1 - Search Strategy example – MEDLINE (search result in brackets)

Behaviour

1. MH "sedentary lifestyle" (1,560)
2. AB "Sedent* behav*" OR TI "sedent* behav*" (1,390)
3. AB Sedent* OR TI Sedent* (15,246)
4. AB "TV View*" OR TI "TV view*" (432)
5. AB "Video games" OR TI "Video games" (683)
6. AB "screen time" OR TI "screen time" (344)
7. AB "sedentary lifestyle" OR TI "sedentary lifestyle" (1,531)
8. AB "computer use" OR TI "computer use" (953)
9. AB "couch potato" OR TI "couch potato" (24)
10. AB "light activit*" OR TI "light activit*" (186)
11. AB "physical activ*" OR TI "physical activ*" (48,221)
12. AB "physical inactiv*" OR TI "physical inactiv*" (3,371)
13. AB "physical fit*" OR TI "physical fit*" (5,022)
14. MH Exercise OR TI exercise OR AB exercise (180,875)
15. AB "moderate-vigorous physical activ*" OR AB "moderate£vigorous physical activ*" OR AB "moderate#vigorous physical activ*" (67)
16. TI "moderate-vigorous physical activ*" OR TI "moderate£vigorous physical activ*" OR TI "moderate#vigorous physical activ*" (5)
17. TI MVPA OR AB MVPA (728)
18. TI "energy expenditure" OR AB "energy expenditure" (15,039)
19. MH "motor activity" OR AB "motor activity" OR TI "motor activity" (51,841)
20. MH "activities of daily living" OR AB "activities of daily living" OR TI "activities of daily living" (51,841)
21. AB Posture OR TI Posture (18,409)
22. S1 OR S2 OR S3 OR S4 OR S5 OR S6 OR S7 OR S8 OR S9 OR S10 OR S11 OR S12 OR S13 OR S14 OR S15 OR S16 OR S17 OR S18 OR S19 OR S20 (356,020)

Measurement

1. AB Validation OR TI Validation OR MH Validation (84,533)
2. AB Reliability OR TI Reliability (87,609)
3. AB "activ* monitor*" OR TI "activ* monitor*" (2,213)
4. AB "objective measur*" OR TI "objective measur*"(8,708)

5. AB "device*" OR TI "device*" (201,464)
6. AB Sensor OR TI Sensor OR MH Sensor (40,263)
7. AB "wear* monitor*" OR TI "wear* monitor*" (45)
8. AB Methodolog* OR TI Methodolog* (161,958)
9. AB Assessment OR TI Assessment (499,305)
10. AB "Motion Sensor*" OR TI "Motion Sensor*" (334)
11. AB "Physiological Sensor*" OR TI "Physiological Sensor*" (89)
12. AB "Ambulatory monitor*" OR TI "Ambulatory monitor*" (1,933)
13. S22 OR S23 OR S24 OR S25 OR S26 OR S27 OR S28 OR S29 OR S30 OR S31 OR S32 OR S33 (1,001,341)

Together S35 AND S36 (41,991)

Limiters – English Language, Human, All Adult 19+ years

Total Number = (17,840)

Appendix 1.2 – Links to online supplementary journal material relating to systematic review

The below link directs to the online ome of the articles were there is access to online supplementary material including the search strategy and all supplementary tables.

http://www.jmir.org/2016/5/e90/

Appendix 2 – The validity of the LumoBack Posture Sensor as an objective measure of Sedentary Behaviour in adults: Additional Material

Appendix 2.1: Laboratory Setting: Participant Information Sheet

Leicester-Loughborough
Diet, Lifestyle and Physical Activity
Biomedical Research Unit

NHS
National Institute for Health Research

PARTICIPANT INFORMATION SHEET

'The validity of three devices for measuring sitting and changes in posture: A laboratory and free living study.

You are being asked to take part in a research study. Before you decide, it is important for you to understand why the research is being done and what it involves. This information sheet is designed to help you decide whether you would like to participate in this study. Please take time to read the following information carefully to decide whether or not you wish to take part and discuss it with friends, and relatives. Please ask if you would like more information.

What is the purpose of the research?

The effects of excessive sedentary behaviour (i.e., sitting with low energy expenditure) on the health of the population is an increasing concern and has become a focus of much research in recent years. Recent evidence suggests that spending high amounts of time sedentary, independent of time spent in physical activity, is associated with an increased risk of type 2 diabetes, cardiovascular disease, cancer and mortality. Recent research has also demonstrated that regularly breaking up prolonged sitting can have beneficial effects on health.

It is really important that researchers have accurate devices to measure sitting so that they can fully understand the negative effects of sitting as well as the positive effects of breaking up sitting by changing to an upright position. Over the past couple of years several new devices and device functions have become available that may be useful in measuring sitting time and changes in posture (i.e., going from a sitting position to a standing position). The aim of this study is to examine the accuracy of several objective methods (activPAL, ActiGraph, GENEActiv and LUMOback) for estimating lying, sitting and upright time and detecting changes in posture.

Do I have to take part?

It is up to you to decide; participation is voluntary. We will describe the study and go through the information sheet with you. We will then ask you to sign a consent form to show that you have agreed to take part. You will be given a copy of the signed consent form. You are free to withdraw at any time without giving a reason.

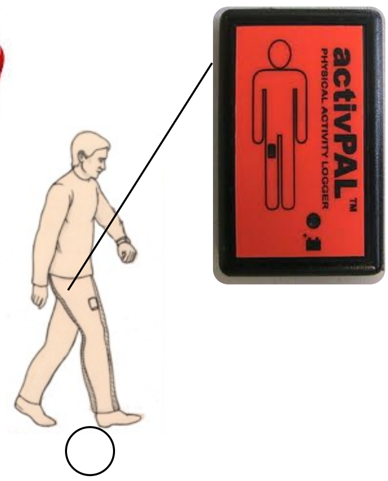
What will happen to me if I take part?

Visit 1: At the first visit you will have the opportunity to discuss the study with us and ask any questions you may have before being asked to sign our consent form. We will then measure your height, weight, body fat percentage and waist circumference and ask you to answer some questions about yourself, for example your date of birth, your postcode and ethnicity. You will then get to try out some of the activities that you will be asked to do during the experiment. This first visit should take no longer than 30 minutes. At the end of this visit we will arrange your full study visit (at a time and date convenient for you).

Visit 2: We will again explain the procedure for the experiment and then we will fit the measurement devices. You will be fitted with the following; one activPAL to wear on the thigh, three ActiGraph monitors (one on the wrist, waist and thigh), three GENEActiv monitors (one on the wrist, waist and thigh) and one LumoBack to wear on the lower back. You will then be required to complete a circuit of 16 activities in the exercise laboratory. The activities will range from lying down, watching TV, typing, standing still, washing pots, and light walking. Each activity will last for 5 minutes. This visit should last for no more than 2 hours. Once this has been completed you will be asked to wear the measurement devices (excluding the LumoBack) for two full days in your daily life and complete a log of any times that you remove the devices as well as times that you went to bed and got out of bed. After the two days you will be asked to return the monitors so that the data can be downloaded and processed.

What do the monitors look like?

ActiGraph G3TX+ activPAL GENEActiv LumoBack



What do I have to do if I want to take part in this study?

If you decide to take part in the study we will contact you to arrange a convenient time and date for you to sign a consent form and we will arrange a date for the study measures to begin.

What are the possible benefits of taking part?

You are unlikely to directly benefit from participating in the study however it will be possible for you to view your free-living data from the devices following completion of the study (this will show you how long you spend sitting, standing and walking).

Will my taking part in the study be kept confidential?

All information that is collected about you during the course of the research will be kept strictly confidential. Data will be stored either in locked filing cabinets or in password protected databases which are only accessible by members of the research team. Any information about you which is disseminated will have your name and address removed so that you cannot be recognised from it. Information collected will not be used for any other purpose than that explained here.

What are the risks of taking part?

Taking part involves minimal risk for you, just the inconvenience of taking the time to participate in the study.

What will happen to the results of the research study?

The results of the study may be published in a professional journal, but you will not be identified by name in any publications. You will be informed about the results of the study when it has finished.

Who is organising and funding the research?

This study is being organised and co-ordinated by the Leicester-Loughborough Diet, Lifestyle and Physical Activity Biomedical Research Unit.

Who has reviewed the study?

This study was reviewed by the Loughborough University ethics committee.

Contact for Further information:

Thank you for taking the time to read this information sheet. We will be pleased to discuss any questions or concerns that you may have.

If you have any further questions about this research or would like to take part please contact the team on 0116 258 8929 (Sarah Bunnewell)/01509 228173 (Myanna Duncan) or email us at sarah.bunnewell@uhl-tr.nhs.uk / M.Duncan@lboro.ac.uk

Appendix 2.2 Informed Consent

Leicester-Loughborough Diet, Lifestyle and Physical Activity Biomedical Research Unit

NHS National Institute for Health Research

Study ID Label

Principal Investigator: Dr Charlotte Edwardson
Contact: Diabetes Research Centre, University of Leicester, Leicester General Hospital, LE5 4P2

CONSENT FORM version 1 27/08/2013

Title of project: Assessing the validity of three objective measures of sedentary behaviour in laboratory and free living environments.

Please Initial Every Box

I confirm that I have read and understand the participant information sheet dated 27/8/2013 (Version 1) for the above study and have had the opportunity to ask questions. ☐

I understand that my participation is voluntary and that I am free to withdraw at any time, without giving any reason, without my medical care or legal rights being affected. ☐

Name of participant	Date	Signature
Researcher	Date	Signature

Appendix 2.3 Health Screening Questionnaire

Leicester-Loughborough
Diet, Lifestyle and Physical Activity
Biomedical Research Unit

NHS
National Institute for
Health Research

Participant ID:

The validity of three devices for measuring sitting and changes in posture: A laboratory and free living study.

Health screening questionnaire

Principal Investigator: Dr Charlotte Edwardson

It is important that volunteers participating in this study are currently in good health and have no significant medical problems. This is to ensure (i) your own continuing wellbeing and (ii) to avoid the possibility of individual issues affecting the research outcomes. Please complete this brief questionnaire to confirm your fitness to participate.

1. At present, do you have any health problem for which you are:

(a)	on medication, prescribed or otherwise...........	Yes	☐	No	☐
(b)	attending your general practitioner..................	Yes	☐	No	☐
(c)	on a hospital waiting list	Yes	☐	No	☐

2. Have you ever had any of the following:

(a)	Asthma	Yes	☐	No	☐
(b)	Diabetes	Yes	☐	No	☐
(b)	Heart problems	Yes	☐	No	☐
(c)	Problems with bones, joints or muscles	Yes	☐	No	☐
(d)	Disturbance of balance/ coordination	Yes	☐	No	☐
(e)	Severe memory problems	Yes	☐	No	☐

3. Do you have a **heart pacemaker** fitted? Yes ☐ No ☐

4. Has **any,** otherwise healthy, member of your family under the age of 35 died suddenly during or soon after exercise? Yes ☐ No ☐

Appendix 2.4: Activity Log Sheet

Activity Log Sheet

ID: **Gender:** **DOB: / /** **Study Date: / /**

Height (m): **Weight (kg):** **BMI:**

Activity	Start Time	End Time	Time taken for Activity	Baseline sitting LumoBack	Post LumoBack sitting time
Lying completely flat on back					
Lying on back with legs bent					
Lying on side with legs straight					
Lying on side with legs bent					
Sitting on chair with feet flat on floor (TV)					
Sitting on chair with legs crossed (TV)					

Sitting on chair with right foot resting on left thigh (TV)					
Sitting on chair with legs stretched out forwards (TV)					
Sitting on chair with feet backwards under chair (TV)					
Sitting with upper body movement (computer)					
Sitting playing games on tablet/smart phone					
Standing still					
Washing pots					
Cleaning/dusting					
Hoovering /sweeping					
Self-paced free living walk					

Appendix 2.4 Free Living Setting: Participants Information Sheet

Leicester-Loughborough
Diet, Lifestyle and Physical Activity
Biomedical Research Unit

NHS
National Institute for
Health Research

PARTICIPANT INFORMATION SHEET

'The validity of LumoBack posture sensor for measuring sitting and changes in posture: A free living study.

You are being asked to take part in a research study. Before you decide, it is important for you to understand why the research is being done and what it involves. This information sheet is designed to help you decide whether you would like to participate in this study. Please take time to read the following information carefully to decide whether or not you wish to take part and discuss it with friends, and relatives. Please ask if you would like more information.

What is the purpose of the research?

The effects of excessive sedentary behaviour (i.e., sitting with low energy expenditure) on the health of the population is an increasing concern and has become a focus of much research in recent years. Recent evidence suggests that spending high amounts of time sedentary, independent of time spent in physical activity, is associated with an increased risk of type 2 diabetes, cardiovascular disease, cancer and mortality. Recent research has also demonstrated that regularly breaking up prolonged sitting can have beneficial effects on health.

It is really important that researchers have accurate devices to measure sitting so that they can fully understand the negative effects of sitting as well as the positive effects of breaking up sitting by changing to an upright position. Over the past couple of years several new devices and device functions have become available that may be useful in measuring sitting time and changes in posture (i.e., going from a sitting position to a standing position). The aim of this study is to examine the accuracy of LumoBack for estimating lying, sitting and upright time and detecting changes in posture.

Do I have to take part?

It is up to you to decide; participation is voluntary. We will describe the study and go through the information sheet with you. We will then ask you to sign a consent form to show that you have agreed to take part. You will be given a copy of the signed consent form. You are free to withdraw at any time without giving a reason.

What will happen to me if I take part?

If you decide to take part in this study, you will be asked to come to physical activity and sedentary behaviour measurement lab in the new NCSEM building. In the first instance you will have the opportunity to discuss the study and ask any questions that you may have before being asked to sign the consent form.

A series of anthropometric measurement will then be taken including height, weight, BMI and body fat percentage.

You will be asked to wear the three devices; one activPAL to wear on the thigh, one ActiGraph monitors one on the waist, and one LumoBack to wear on the lower back for a period of 7 days. You will be asked to completer the a log of any times that you remove the devices as well as time that you went to bed and got out of bed. After the seven days, you will be asked to return the monitors so that the data can be downloaded and processed.

What do the monitors look like?

ActiGraph G3TX+ activPAL LumoBack

What do I have to do if I want to take part in this study?

If you decide to take part in the study we will contact you to arrange a convenient time and date for you to sign a consent form and we will arrange a date for the study measures to begin.

What are the possible benefits of taking part?

You are unlikely to directly benefit from participating in the study however it will be possible for you to view your free-living data from the devices following completion of the study (this will show you how long you spend sitting, standing and walking).

Will my taking part in the study be kept confidential?

All information that is collected about you during the course of the research will be kept strictly confidential. Data will be stored either in locked filing cabinets or in password protected databases which are only accessible by members of the research team. Any information about you which is disseminated will have your name and address removed so that you cannot be recognised from it. Information collected will not be used for any other purpose than that explained here.

What are the risks of taking part?

Taking part involves minimal risk for you, just the inconvenience of taking the time to participate in the study.

What will happen to the results of the research study?

The results of the study may be published in a professional journal, but you will not be identified by name in any publications. You will be informed about the results of the study when it has finished.

Who is organising and funding the research?

This study is being organised and co-ordinated by the Loughborough-Leicester Diet, Lifestyle and Physical Activity Biomedical Research Unit.

Who has reviewed the study?

This study was reviewed by the Loughborough University ethics committee.

Contact for Further information:

Thank you for taking the time to read this information sheet. We will be pleased to discuss any questions or concerns that you may have.

If you have any further questions about this research or would like to take part please contact James Sanders (J.Sanders2@lboro.ac.uk)

Appendix 2.5 Activity Monitors Logbook for iOS users

Participant ID: _______________

ActiGraph Numbers:

____

activPAL Number:

____

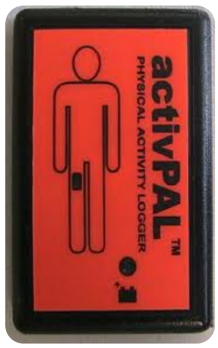
LUMOback:

The validity of three devices for measuring sitting and changes in posture: A free living study'.

Activity monitor instructions

&

Daily logbook



Please keep this booklet in a safe place so that you can return it to us at the end of the two day monitoring period when you come back the laboratory.

If you have any questions or concerns, please contact:

James Sanders
J.Sanders2@lboro.ac.uk
07538330734

1. General Information

<u>How long do I wear the monitors for?</u>

- Please wear all monitors **for 7 full days** removing them on the morning of day 7
- Please wear the monitors **continuously** (i.e. for 24 hours/day)
- If you wish to remove the monitors before you go to bed please **put them on as soon as you wake up in the morning**

WARNING:

Please **do not** wear the devices when showering, bathing, or performing water-based activities.

<u>What else do I need to do?</u>

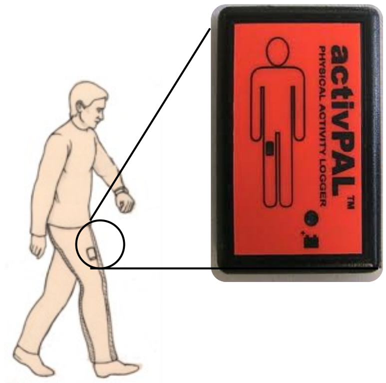
- It is important that you fill in this logbook for all 7 days that you are wearing the monitors
- This helps us match the monitor data to your waking hours and patterns during the day

<u>Returning your activity monitors and logbook</u>

Please return the activity monitors (and any unused adhesive patches) and completed logbook to James Sanders (NCSEM PhD area)

2. How to wear the activPAL thigh monitor

The activPAL is to be worn midline on the anterior aspect of the right thigh using medical dressing.



The monitor should be positioned so that the man on the monitor is standing upright.

3. How to wear the ActiGraph monitors

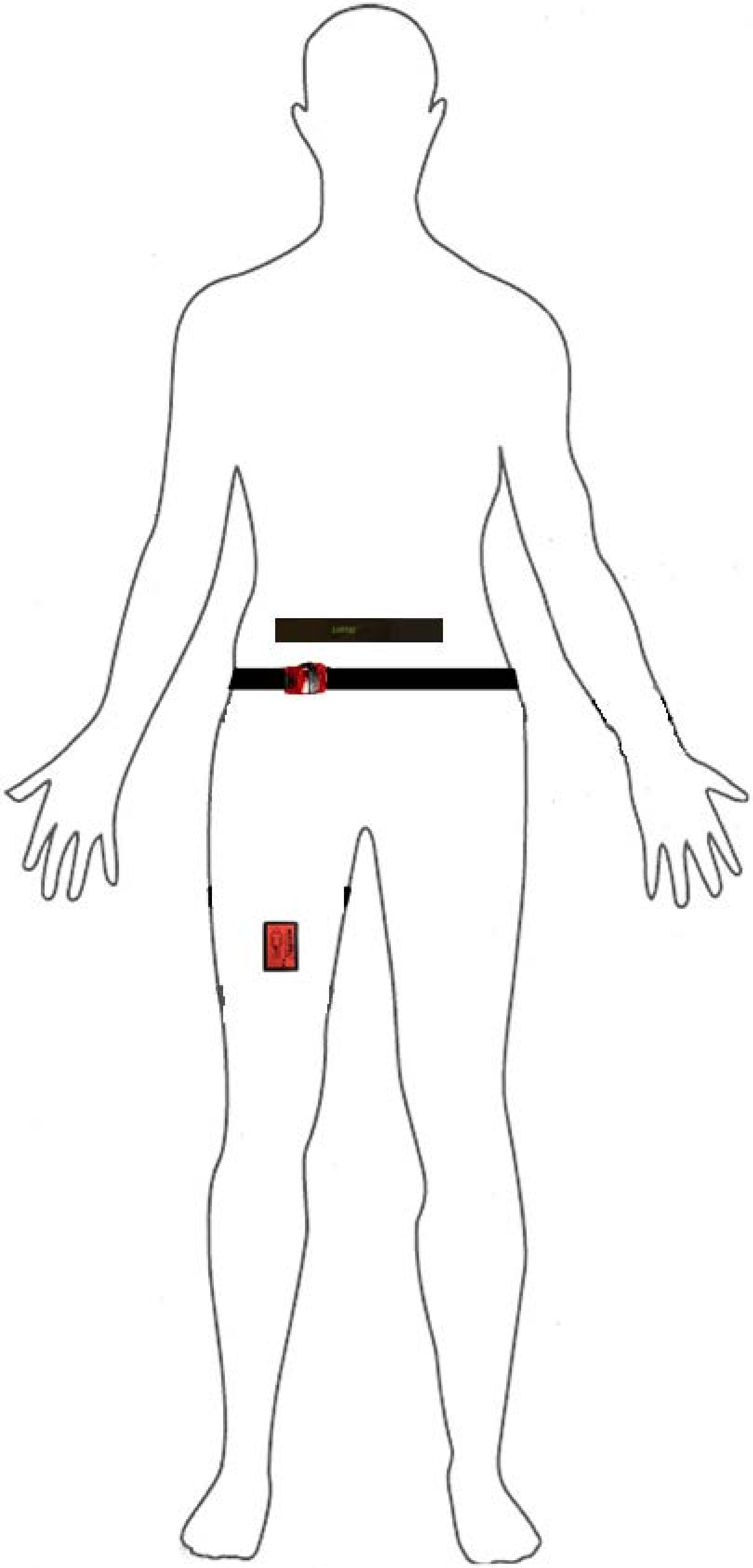
The ActiGraph will be attached using adjustable elastic straps and should be positioned so that the small black

cap is facing upwards. The hip monitor is to be worn on the right hand side of the body on the midaxillary line of the hip.

4. How to wear the LumoBack

The LumoBack will be attached using adjustable plastic straps. The LumoBack should we worn on base of the back with the logo outward facing, and readable.

5. Placement of the activity monitors



4. How to fill in the daily logbook

- The logbook is divided into 7 days. Please complete each day's questions as accurately as possible.

- Record the exact times if you can - or to the **nearest 5 minutes**.

- Start by writing the date in the top row.

- Then record the time that you woke up, and the time that you put the monitors on for the first time that day (only if you removed it to go to bed). Tick which monitors you wore overnight and if you did not wear one of them overnight then records what time you put it back on at in the morning. If you did not put on one of the monitors at all that day then please cross the corresponding box instead of recording a time.

- Next, record any times you **removed** the monitors **for more than 15 minutes**. Record removal time in 'Off' columns and the time that you put back on the monitors in the 'On' column. Also mark whether this time was 'am' or 'pm' in the row below and your reason for removal. Please DO NOT include removal times related to night time sleeping here – **only record removal times during waking hours**.

- If you have any other comments, please note them down.

NOTES:

- Midnight = **12am**; midday = **12pm**
- Sleep and awake times are very important.

5. LumoBack FAQ's

Wearing the sensor

1. Place the LUMO on your lower back, either directly on your skin or over a thin layer of clothing. The LUMO logo and circular Touch button should be facing out.
2. Wrap the belt around your waist directly above your hip bones, and secure the Velcro near your belly button.
3. If your belt doesn't fit snuggly around your waist, take it off and adjust the Velcro straps inside the belt.

Checking the LumoBack charge.
Tap the Touch Button to view charge level:
Green - The sensor has more than one day of charge remaining.
Orange - The sensor has one day or less of charge remaining. Recharge soon

Charging the LumoBack

1. Plug the sensor into a USB power source using the included cable.
2. It takes about 2 hours to charge the sensor completely.
3. A complete charge will last for about 5 days of continuous use

When to calibrate your sensor.
The LumoBack sensor works for everybody, but only if it is calibrated correctly. This process stores your good posture position on the sensor and determines when the sensor will vibrate, indicating bad posture.

When should you calibrate?

1. When you first setup your sensor.
2. When your sensor is vibrating, but you are in good posture.
3. When you put the sensor on a little bit differently than when you calibrated previously.

How do I clean my Lumo? Is it water resistant?
You can simply take a damp cloth or a wipe and wipe the sensor down. Also, if needed you can remove the Velcro straps from the actual sensor moulding and you can hand wash the belt straps and line dry.

LumoBack is not completely water resistant. While it is ok to have moisture and sweat from normal use and activities, you can NOT submerge the Lumo Back sensor in water or shower with it, etc. It has a Lithium battery and other hardware components that can be damaged if it gets wet.

Removal of the LumoBack.
Night Removal
When removing the LumoBack at night please take it off immediately before you go to sleep and place it on charge using the charging plug and cord provided in your pack. It is best to place this on your bed side table so as a reminder to put it on the when you wake up in the morning
It is important that you place the device on charge every night so that we can have a data stream to note removal time.

Removal for water-based activities
Please remove the device immediately before and immediately after the water based activities – making sure to place the device horizontal on a flat surface with Lumo sign facing upwards.

Connectivity issues. What do I do?
Please try the following:

1. Turn the Bluetooth on your iOS device off and then on again through the iOS Settings icon. Go to Settings>Bluetooth>On/Off in your iOS device.
2. Kill the app: first double-click on the home screen of your iOS device, then hold down the LumoBack icon in the tray for 3 seconds, then press the red delete button.

3. Restart the LumoBack app.
4. If this doesn't work, try turning off your iOS device completely, and then turn it back on.

   Please make sure your battery is charged as the app works best when it is charged.

   The LumoBack will still be collecting data during this time even if it isn’t connected to the app.

   Any other problems please contact me. The details can be found on the title page.

	Example	Day 1	Day 2	Day 3
Date	DD/MM	DD/MM	DD/MM	DD/MM
Did you **WEAR THE MONITORS TO BED** last night? • LumoBack • ActiGraph • ActivPAL	☒ **Yes** ☐ **No** ☒ **Yes** ☐ **No** ☒ **Yes** ☐ **No**	☐ **Yes** ☐ **No** ☐ **Yes** ☐ **No** ☐ **Yes** ☐ **No**	☐ **Yes** ☐ **No** ☐ **Yes** ☐ **No** ☐ **Yes** ☐ **No**	☐ **Yes** ☐ **No** ☐ **Yes** ☐ **No** ☐ **Yes** ☐ **No**
What time did you **WAKE UP** today?	**7 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
What time did you put the monitors on?	**7:15 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
What time did you **go to bed** today?	**10 ~~am~~ / pm**	**am / pm**	**am / pm**	**am / pm**
If you **remove the monitor for more than 15 mins please report below:**				
The reason for removing the LumoBack	Showering			
What time did you **remove** the **LumoBack?**	**7:30 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
What time did you **put the LumoBack back on?**	**7:45 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
The reason for removing the ActiGraph	Showering			
What time did you **remove** the **ActiGraph?**	**7:30 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
What time did you **put the ActiGraph back on?**	**7:45 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
The reason for removing the activPAL	Showering			
What time did you **remove** the **activPAL?**	**7:30 am /**	**am /**	**am /**	**am /**

	~~pm~~	pm	pm	pm
What time did you **put the activPAL back on?**	7:45 am / ~~pm~~	am / pm	am / pm	am / pm
The reason for removing the LumoBack	Showering			
What time did you **remove** the **LumoBack?**	7:30 am / ~~pm~~	am / pm	am / pm	am / pm
What time did you **put the LumoBack back on?**	7:45 am / ~~pm~~	am / pm	am / pm	am / pm
The reason for removing the ActiGraph	Showering			
What time did you **remove** the **ActiGraph?**	7:30 am / ~~pm~~	am / pm	am / pm	am / pm
What time did you **put the ActiGraph back on?**	7:45 am / ~~pm~~	am / pm	am / pm	am / pm
The reason for removing the activPAL	Showering			
What time did you **remove** the **activPAL?**	7:30 am / ~~pm~~	am / pm	am / pm	am / pm
What time did you **put the activPAL back on?**	7:45 am / ~~pm~~	am / pm	am / pm	am / pm

	Day 4	Day 5	Day 6	Day 7
Date	DD/MM	DD/MM	DD/MM	DD/MM

Did you **WEAR THE MONITOR TO BED** last night? • LumoBack • ActiGraph • ActivPAL	☒ **Yes** ☐ **No** ☒ **Yes** ☐ **No** ☒ **Yes** ☐ **No**	☐ **Yes** ☐ **No** ☐ **Yes** ☐ **No** ☐ **Yes** ☐ **No**	☐ **Yes** ☐ **No** ☐ **Yes** ☐ **No** ☐ **Yes** ☐ **No**	☐ **Yes** ☐ **No** ☐ **Yes** ☐ **No** ☐ **Yes** ☐ **No**
What time did you **WAKE UP** today?	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
What time did you put the monitor on?	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
What time did you **go to bed** today?	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
If you **remove the monitor for more than 15 mins please report below:**				
The reason for removing the LumoBack				
What time did you **remove** the **LumoBack?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
What time did you **put the LumoBack back on?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
The reason for removing the ActiGraph				
What time did you **remove** the **ActiGraph?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
What time did you **put the ActiGraph back on?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
The reason for removing the activPAL				
What time did you **remove** the **activPAL?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
What time did you **put the activPAL back on?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**

The reason for removing the LumoBack				
What time did you **remove** the **LumoBack?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
What time did you **put the LumoBack back on?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
The reason for removing the ActiGraph				
What time did you **remove** the **ActiGraph?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
What time did you **put the ActiGraph back on?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
The reason for removing the activPAL				
What time did you **remove** the **activPAL?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
What time did you **put the activPAL back on?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**

If you have any other comments please note them here.

Appendix 2.6 Activity Monitors Logbook for Android users

Participant ID: ______________

ActiGraph Numbers:

____

activPAL Number:

____

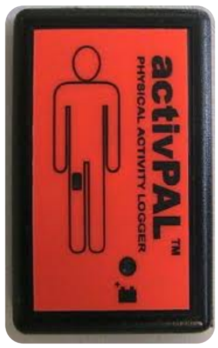
LUMOback:

The validity of three devices for measuring sitting and changes in posture: A free living study'.

Activity monitor instructions

&

Daily logbook



Please keep this booklet in a safe place so that you can return it to us at the end of the two day monitoring period when you come back the laboratory.

If you have any questions or concerns, please contact:

James Sanders
J.Sanders2@lboro.ac.uk
07538330734

2. General Information

How long do I wear the monitors for?

- Please wear all monitors **for 7 full days** removing them on the morning of day 7
- Please wear the monitors **continuously** (i.e. for 24 hours/day)
- If you wish to remove the monitors before you go to bed please **put them on as soon as you wake up in the morning**

WARNING: Please **do not** wear the devices when showering, bathing, or performing water-based activities.

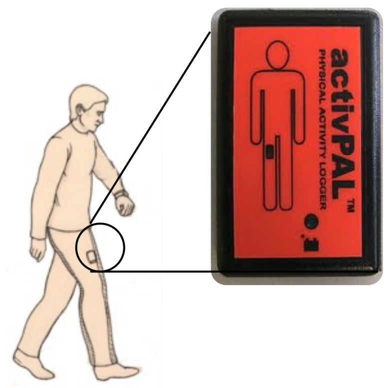
What else do I need to do?

- It is important that you fill in this logbook for all 7 days that you are wearing the monitors
- This helps us match the monitor data to your waking hours and patterns during the day

Returning your activity monitors and logbook

Please return the activity monitors (and any unused adhesive patches) and completed logbook to James Sanders (NCSEM PhD area)

2. How to wear the activPAL thigh monitor



The activPAL is to be worn midline on the anterior aspect of the right thigh using medical dressing.

The monitor should be positioned so that the man on the monitor is standing upright.

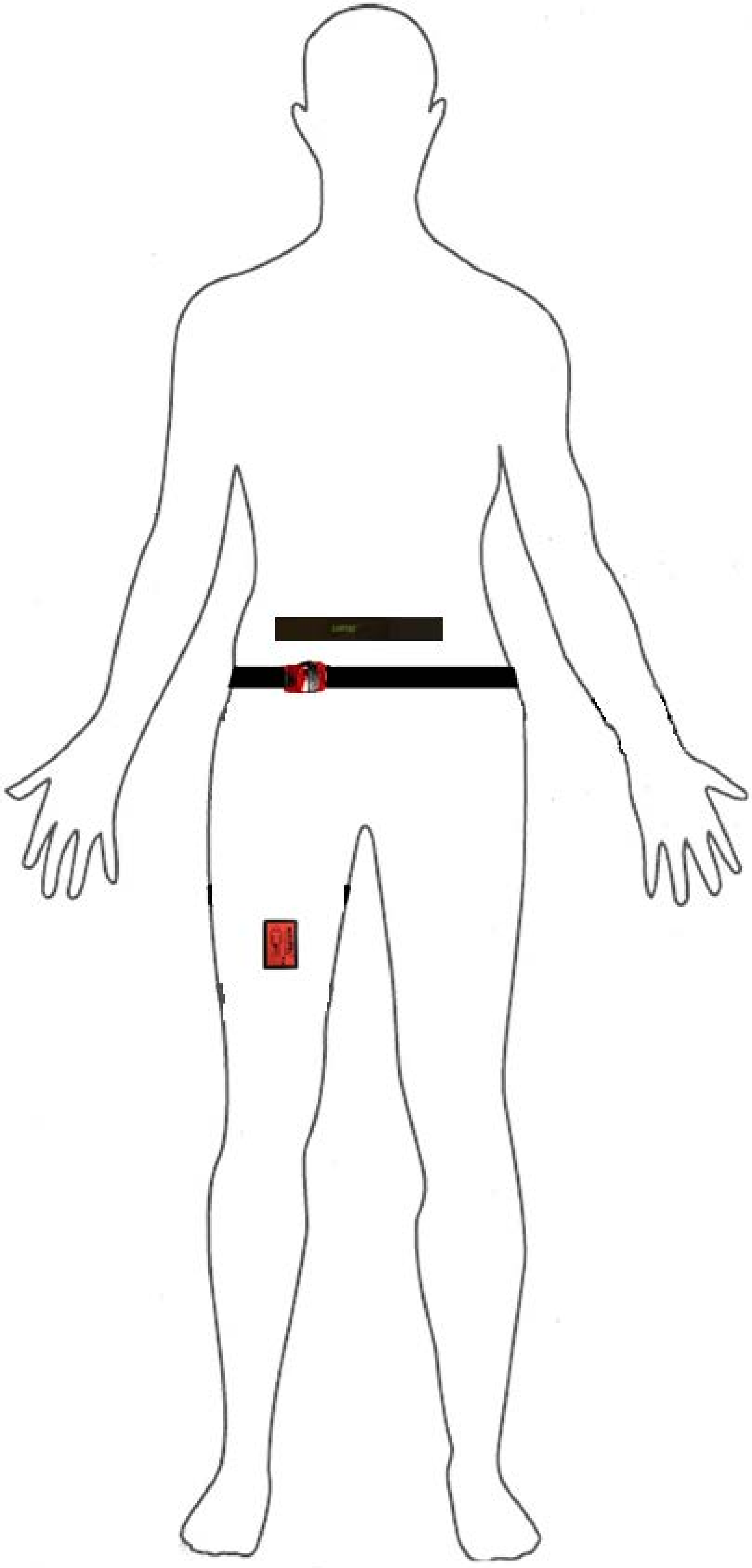
3. How to wear the ActiGraph monitors

The ActiGraph will be attached using adjustable elastic straps and should be positioned so that the small black cap is facing upwards. The hip monitor is to be worn on the right hand side of the body on the maxillary line of the hip.

4. How to wear the LumoBack

The LumoBack will be attached using adjustable plastic straps. The LumoBack should we worn on base of the back with the logo outward facing, and readable.

5. Placement of the activity monitors



4. How to fill in the daily logbook

- The logbook is divided into 7 days. Please complete each day's questions as accurately as possible.

- Record the exact times if you can - or to the **nearest 5 minutes**.

- Start by writing the date in the top row.

- Then record the time that you woke up, the time you got out of bed and the time that you put the monitors on for the first time that day (only if you removed it to go to bed). Tick which monitors you wore overnight and if you did not wear one of them overnight then record what time you put it back on at in the morning. If you did not put on one of the monitors at all that day then please cross the corresponding box instead of recording a time.

- Next, record any times you **removed** the monitors **for more than 15 minutes**. Record removal time in 'Off' columns and the time that you put back on the monitors in the 'On' column. Also mark whether this time was 'am' or 'pm' in the row below and your reason for removal. Please DO NOT include removal times related to night time sleeping here – **only record removal times during waking hours**.

- If you have any other comments, please note them down.

NOTES:

- Midnight = **12am**; midday = **12pm**
- Sleep and awake times are very important.

5. LumoBack FAQ's

Wearing the sensor

4. Place the LUMO on your lower back, either directly on your skin or over a thin layer of clothing. The LUMO logo and circular Touch button should be facing out.
5. Wrap the belt around your waist directly above your hip bones, and secure the Velcro near your belly button.
6. If your belt doesn't fit snuggly around your waist, take it off and adjust the Velcro straps inside the belt.

Checking the LumoBack charge.

Tap the Touch Button to view charge level:
Green - The sensor has more than one day of charge remaining.
Orange - The sensor has one day or less of charge remaining. Recharge soon

Charging the LumoBack

4. Plug the sensor into a USB power source using the included cable.
5. It takes about 2 hours to charge the sensor completely.
6. A complete charge will last for about 5 days of continuous use

When to calibrate your sensor.

The LumoBack sensor works for everybody, but only if it is calibrated correctly. This process stores your good posture position on the sensor and determines when the sensor will vibrate, indicating bad posture.

When should you calibrate?

4. When you first setup your sensor.
5. When your sensor is vibrating, but you are in good posture.
6. When you put the sensor on a little bit differently than when you calibrated previously.

How do I clean my Lumo? Is it water resistant?

You can simply take a damp cloth or a wipe and wipe the sensor down. Also, if needed you can remove the Velcro straps from the actual sensor moulding and you can hand wash the belt straps and line dry.

LumoBack is not completely water resistant. While it is ok to have moisture and sweat from normal use and activities, you can NOT submerge the LumoBack sensor in water or shower with it, etc. It has a Lithium battery and other hardware components that can be damaged if it gets wet.

Removal of the LumoBack.

Night Removal

When removing the LumoBack at night please take it off immediately before you go to sleep and place it on charge using the charging plug and cord provided in your pack. It is best to place this on your bed side table so as a reminder to put it on the when you wake up in the morning
It is important that you place the device on charge every night so that we can have a data stream to note removal time.

Removal for water-based activities
Please remove the device immediately before and immediately after the water based activities – making sure to place the device horizontal on a flat surface with Lumo sign facing upwards.

Known Android Issues and advice.
If you experience an issue in discovering your LumoBack Sensor or connecting to your LumoBack Sensor, it is recommended that you apply the following suggestion on your android device:

- Turn off Wi-Fi
- Turn off Bluetooth
- Turn on Bluetooth
- Turning off Wi-Fi is key to getting a clean connection on your android device.

To avoid reconnecting to your sensor often, when leaving the app, we advise you to press the "Home" button on your Android phone. This will keep the application running in the background while you continue to use other features of your phone. While you can also exit from the app by pressing the "Back" button on your android phone, your sensor will be disconnected from the application in that case.

Your sensor will continue to function entirely on its own (giving posture feedback and collecting activity data) even when it is not connected to the app.

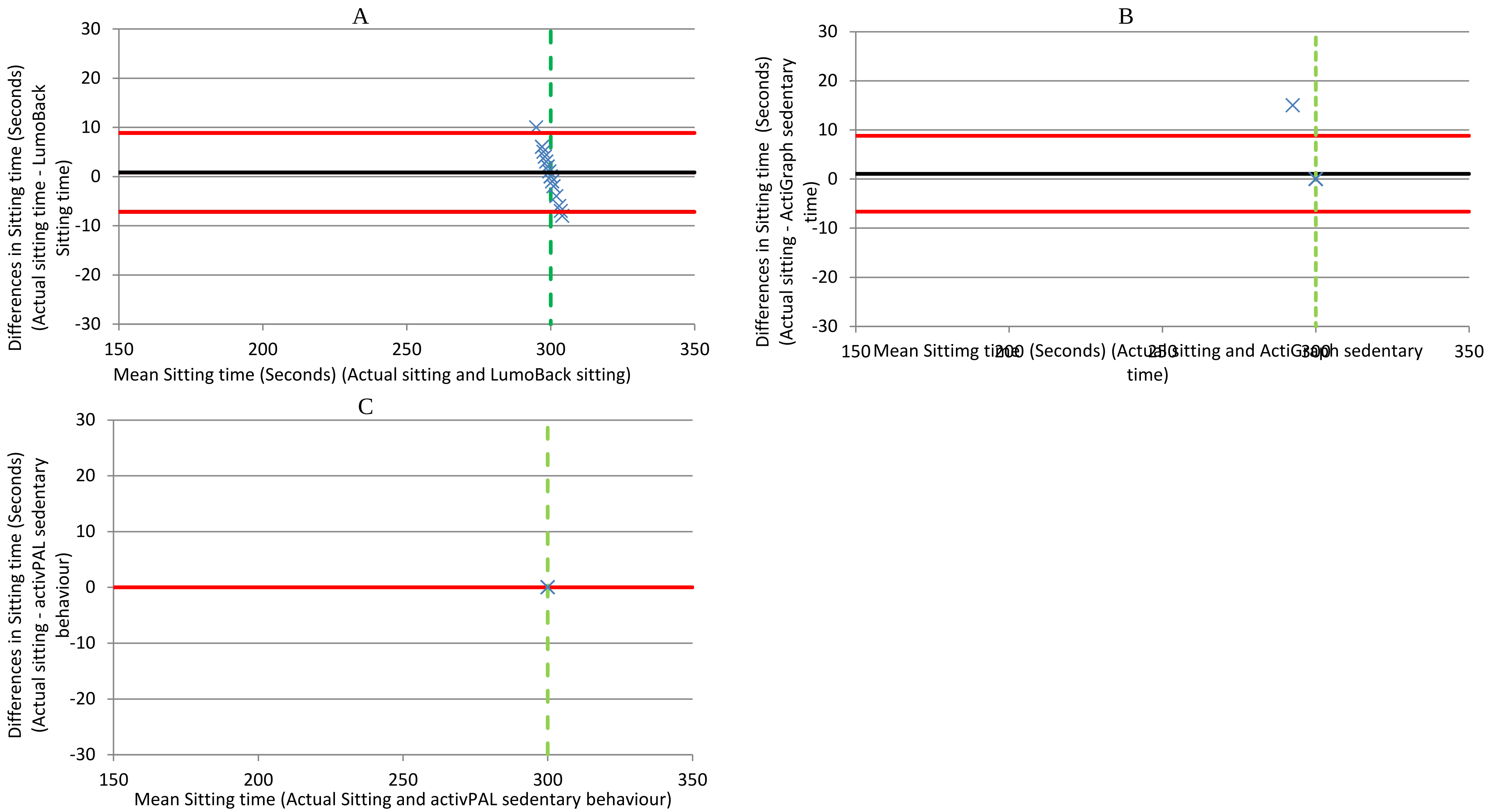
	Example	Day 1	Day 2	Day 3
Date	DD/MM	DD/MM	DD/MM	DD/MM
Did you **WEAR THE MONITOR TO BED** last night?	☒ **Yes** ☐ **No**	☐ **Yes** ☐ **No**	☐ **Yes** ☐ **No**	☐ **Yes** ☐ **No**
What time did you **WAKE UP** today?	**7 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
What time did you put the monitor on?	**7:15 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
What time did you **go to bed** today?	**10 ~~am~~ / pm**	**am / pm**	**am / pm**	**am / pm**
If you **remove the monitor for more than 15 mins please report below:**				
The reason for removing the LumoBack	Showering			
What time did you **remove** the **LumoBack?**	**7:30 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
What time did you **put the LumoBack back on?**	**7:45 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
The reason for removing the ActiGraph	Showering			
What time did you **remove** the **ActiGraph?**	**7:30 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
What time did you **put the ActiGraph back on?**	**7:45 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
The reason for removing the activPAL	Showering			
What time did you **remove** the **activPAL?**	**7:30 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
What time did you **put the activPAL back on?**	**7:45 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**

The reason for removing the LumoBack	Showering			
What time did you **remove** the **LumoBack?**	**7:30 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
What time did you **put the LumoBack back on?**	**7:45 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
	Example	Day 1	Day 2	Day 3
Date	**DD/MM**	**DD/MM**	**DD/MM**	**DD/MM**
The reason for removing the ActiGraph	Showering			
What time did you **remove** the **ActiGraph?**	**7:30 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
What time did you **put the ActiGraph back on?**	**7:45 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
The reason for removing the activPAL	Showering			
What time did you **remove** the **activPAL?**	**7:30 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**
What time did you **put the activPAL back on?**	**7:45 am / ~~pm~~**	**am / pm**	**am / pm**	**am / pm**

	Day 4	Day 5	Day 6	Day 7
Date	**DD/MM**	**DD/MM**	**DD/MM**	**DD/MM**
Did you **WEAR THE MONITOR TO BED** last night?	☐ **Yes** ☐ **No**	☐ **Yes** ☐ **No**	☐ **Yes** ☐ **No**	☐ **Yes** ☐ **No**

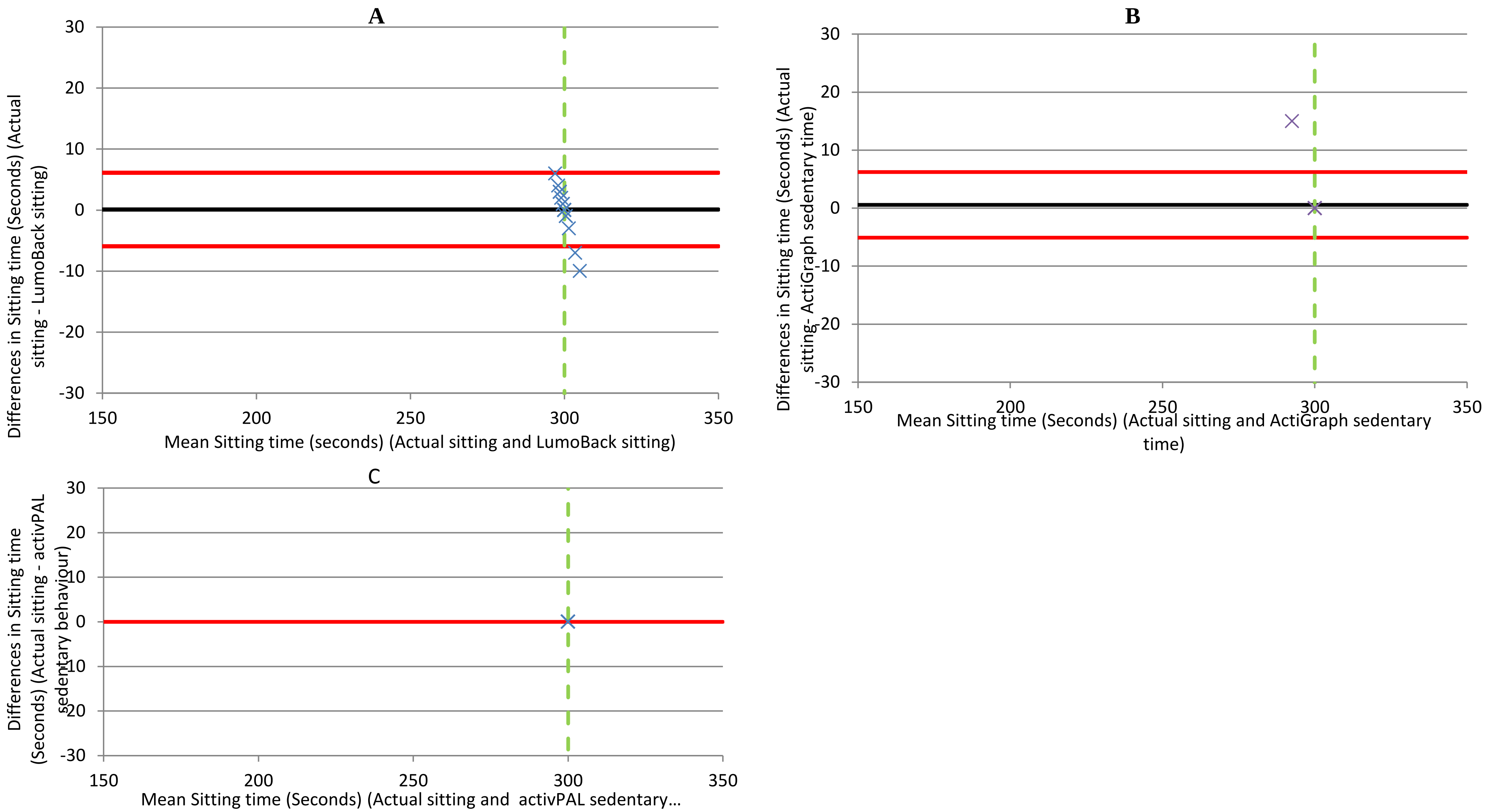
What time did you **WAKE UP** today?	**____ am / pm**	**____ am / pm**	**____ am / pm**	**____ am / pm**
What time did you put the monitor on?	**____ am / pm**	**____ am / pm**	**____ am / pm**	**____ am / pm**
What time did you **go to bed** today?	**____ am / pm**	**____ am / pm**	**____ am / pm**	**____ am / pm**
If you **remove the monitor for more than 15 mins please report below:**				
The reason for removing the LumoBack				
What time did you **remove** the **LumoBack?**	**____ am / pm**	**____ am / pm**	**____ am / pm**	**____ am / pm**
What time did you **put the LumoBack back on?**	**____ am / pm**	**____ am / pm**	**____ am / pm**	**____ am / pm**
The reason for removing the ActiGraph				
What time did you **remove** the **ActiGraph?**	**____ am / pm**	**____ am / pm**	**____ am / pm**	**____ am / pm**
What time did you **put the ActiGraph back on?**	**____ am / pm**	**____ am / pm**	**____ am / pm**	**____ am / pm**
The reason for removing the activPAL				
What time did you **remove** the **activPAL?**	**____ am / pm**	**____ am / pm**	**____ am / pm**	**____ am / pm**
What time did you **put the activPAL back on?**	**____ am / pm**	**____ am / pm**	**____ am / pm**	**____ am / pm**
The reason for removing the LumoBack				
What time did you **remove** the **LumoBack?**	**____ am / pm**	**____ am / pm**	**____ am / pm**	**____ am / pm**
What time did you **put the LumoBack back**	**____ am /**	**____ am /**	**____ am /**	**____ am /**

on?	**pm**	**pm**	**pm**	**pm**
	Day 4	Day 5	Day 6	Day 7
Date	DD/MM	DD/MM	DD/MM	DD/MM
The reason for removing the ActiGraph				
What time did you **remove** the **ActiGraph?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
What time did you **put the ActiGraph back on?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
The reason for removing the activPAL				
What time did you **remove** the **activPAL?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**
What time did you **put the activPAL back on?**	______ **am / pm**	______ **am / pm**	______ **am / pm**	______ **am / pm**



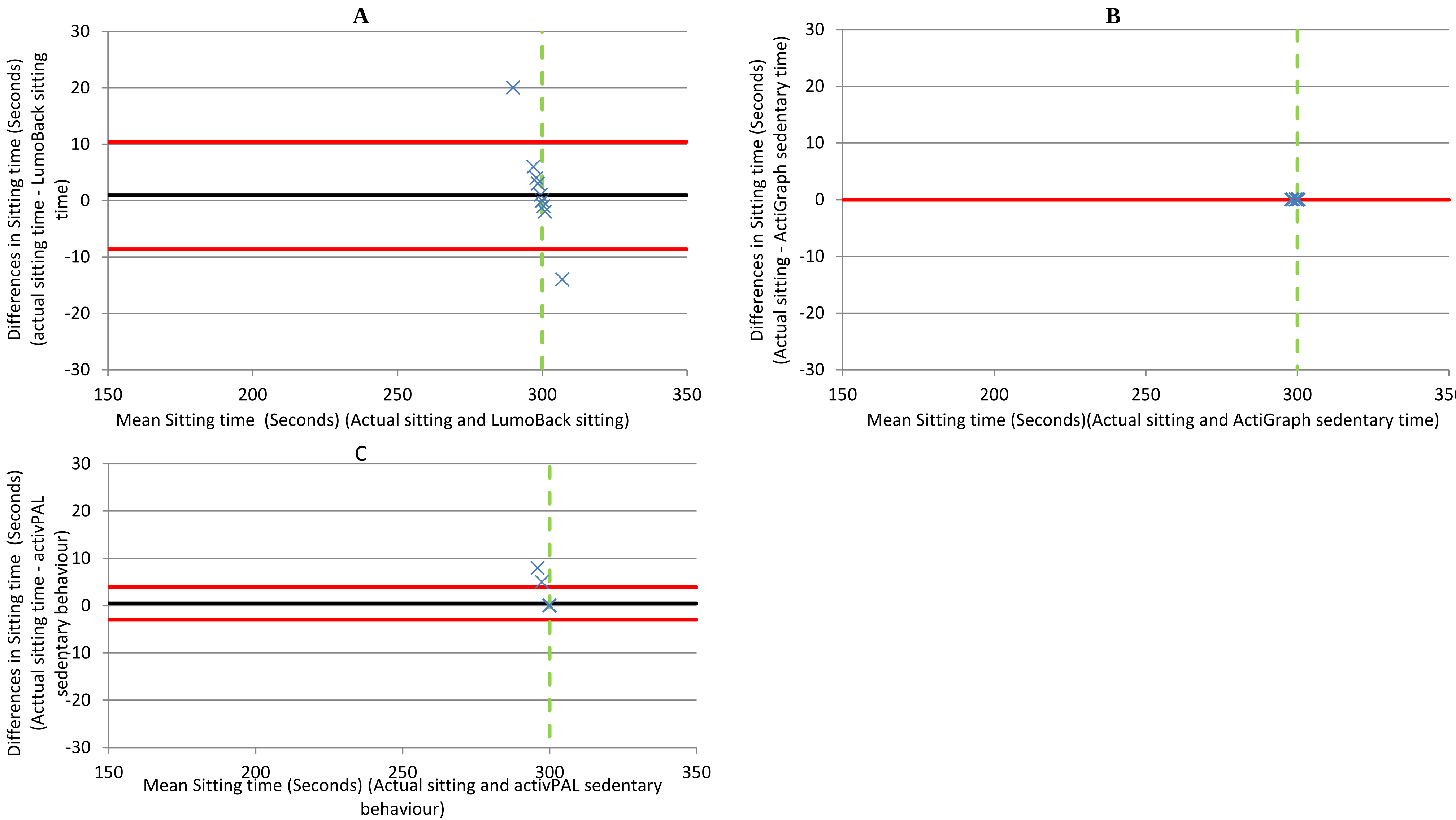
Appendix 2.7 - Sitting on chair with feet flat on floor (Actual sitting vs devices)

Note: A: Bland-Altman of LumoBack vs Direct Observation, B: Bland-Altman of ActiGraph vs Direction Observation, C: Bland-Altman plot of activPAL vs Direction Observation; Intersection between Green dotted line and 0 on Y axis denotes the desired point of the data, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.



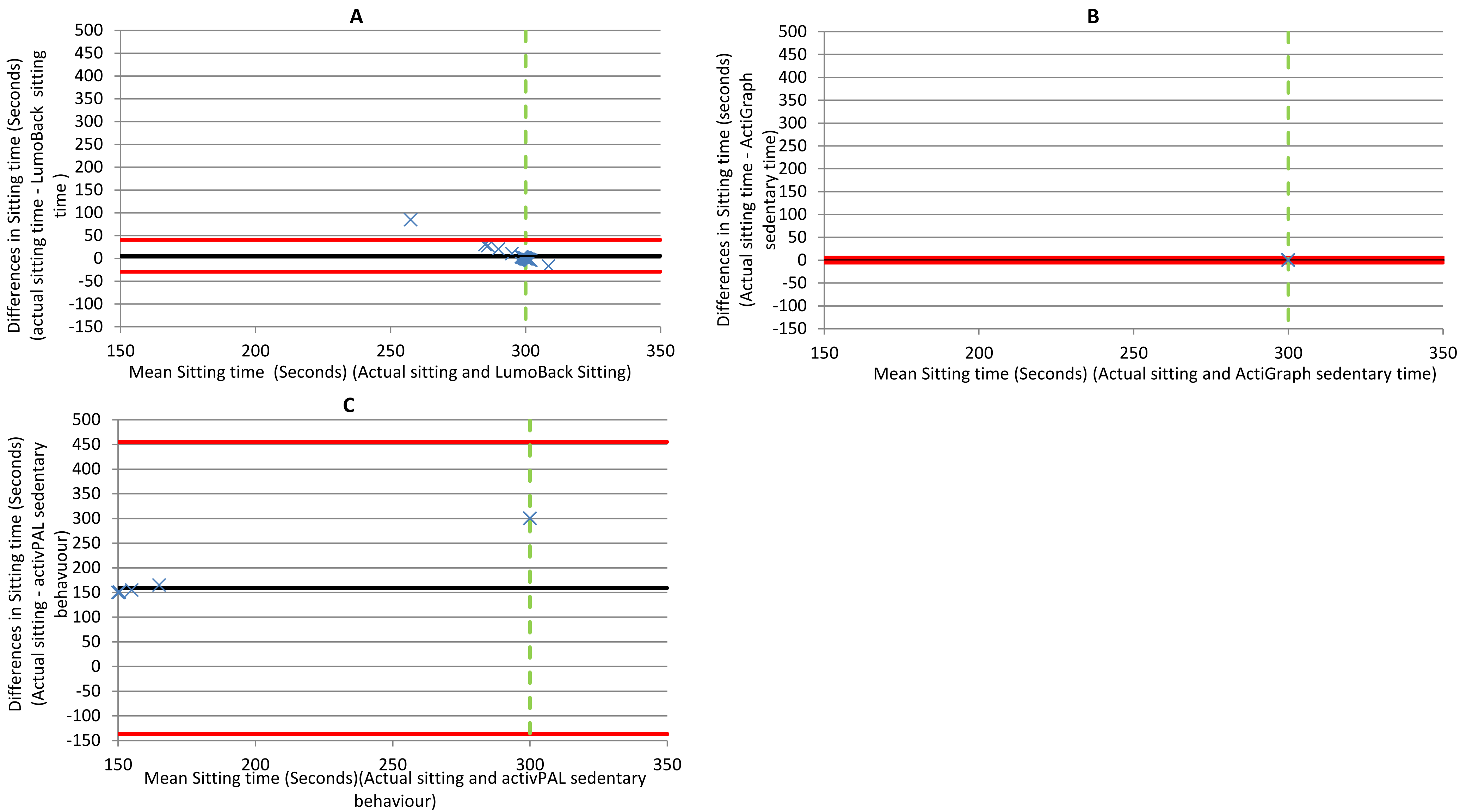
Appendix 2.8 - Sitting on chair with legs crossed (right over left) (Actual sitting vs devices)

Note: A: Bland-Altman of LumoBack vs Direct Observation, B: Bland-Altman of ActiGraph vs Direction Observation, C: Bland-Altman plot of activPAL vs Direction Observation; Intersection between Green dotted line and 0 on Y axis denotes the desired point of the data, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.



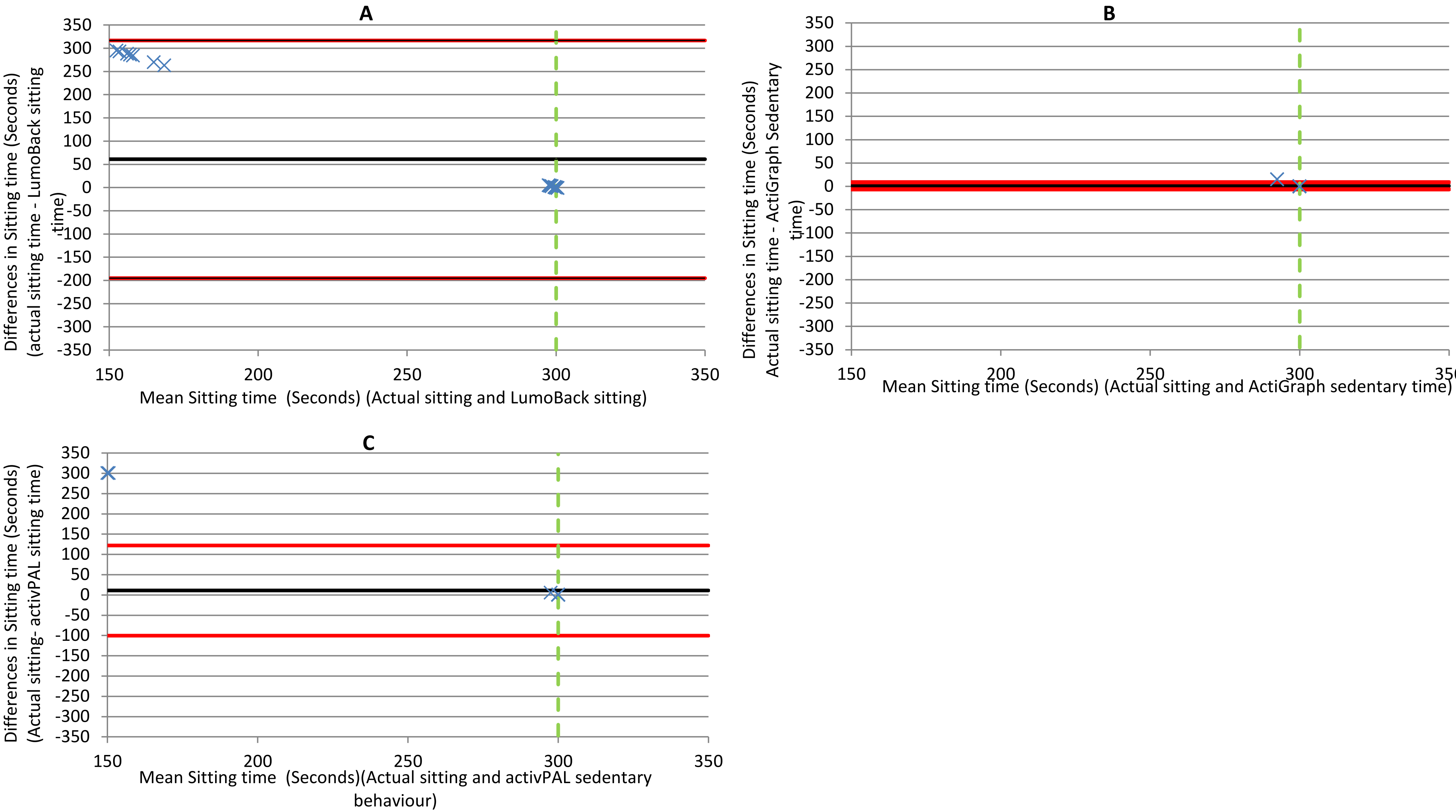
Appendix 2.9 : Sitting on chair with right foot resting on left thigh (Actual sitting vs devices)

Note: A: Bland-Altman of LumoBack vs Direct Observation, B: Bland-Altman of ActiGraph vs Direction Observation, C: Bland-Altman plot of activPAL vs Direction Observation; Intersection between Green dotted line and 0 on Y axis denotes the desired point of the data Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.



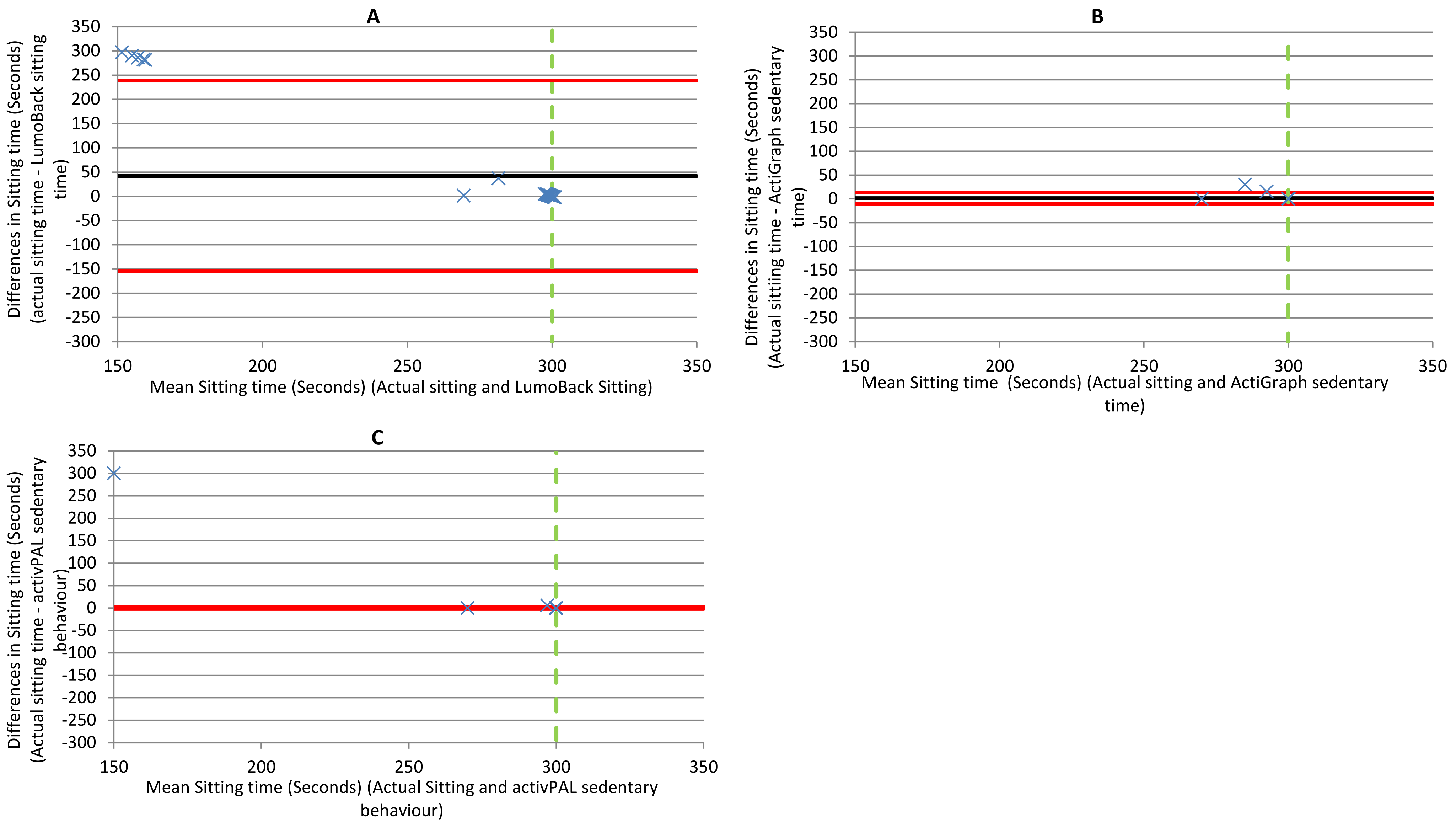
Appendix 2.10 - Sitting on chair with legs straight out in front (Actual sitting vs devices)

Note: A: Bland-Altman of LumoBack vs Direct Observation, B: Bland-Altman of ActiGraph vs Direction Observation, C: Bland-Altman plot of activPAL vs Direction Observation; Intersection between Green dotted line and 0 on Y axis denotes the desired point of the data, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.



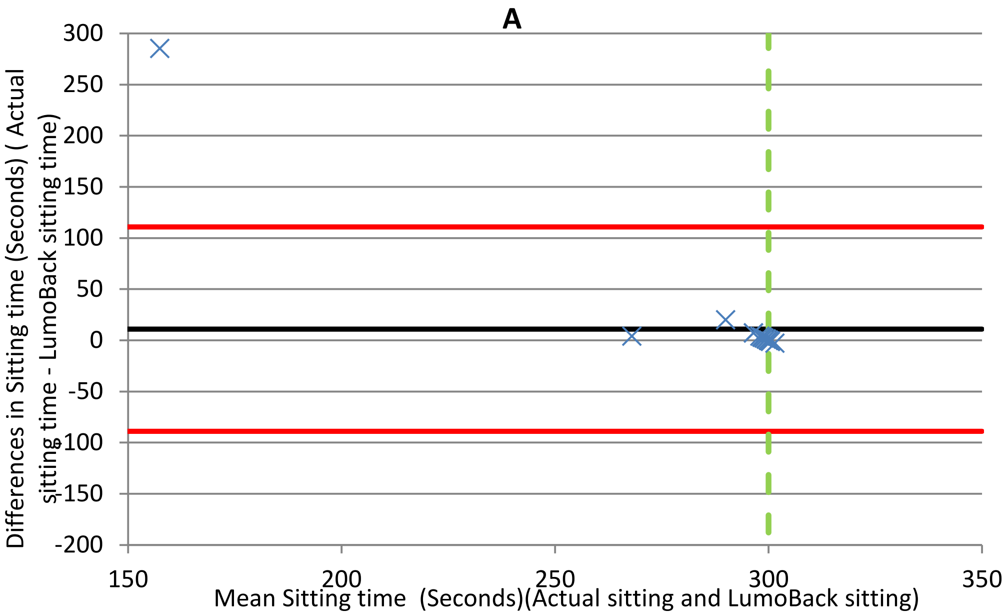
Appendix 2.11 - Sitting with feet back under chair (Actual sitting vs devices)

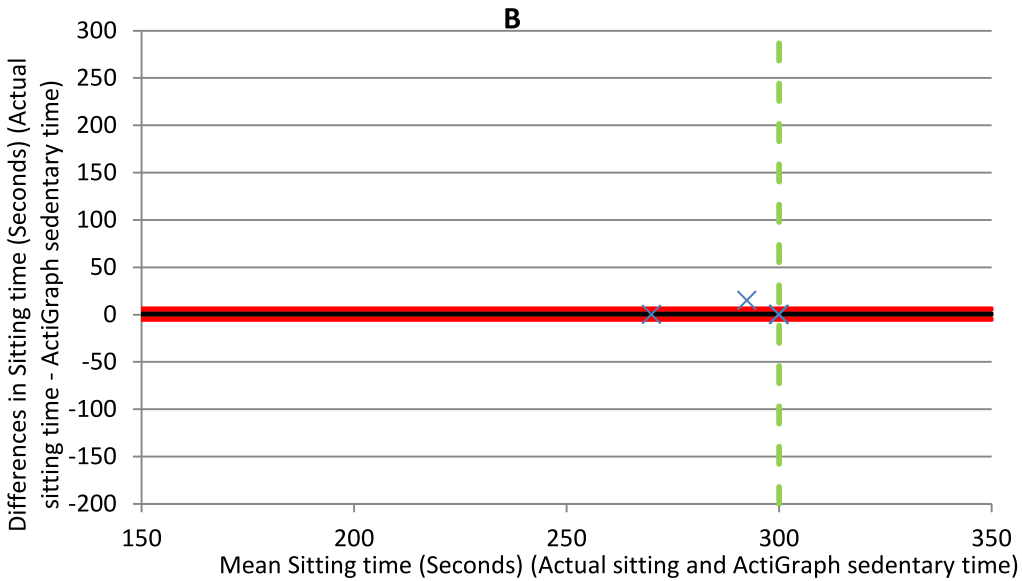
Note: A: Bland-Altman of LumoBack vs Direct Observation, B: Bland-Altman of ActiGraph vs Direction Observation, C: Bland-Altman plot of activPAL vs Direction Observation; Intersection between Green dotted line and 0 on Y axis denotes the desired point of the data, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.

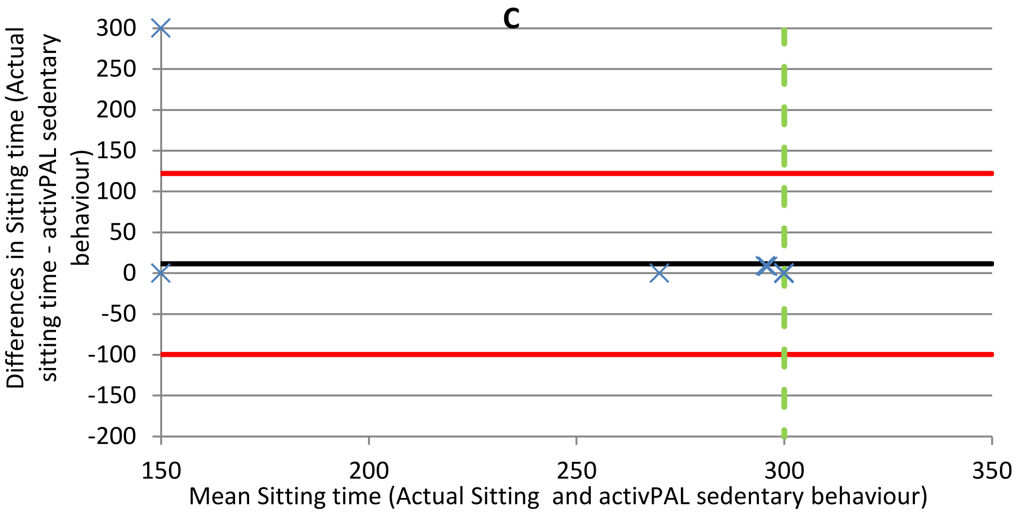


Appendix 2.12 - Sitting with upper body movement (computer) (Actual sitting vs devices)

Note: A: Bland-Altman of LumoBack vs Direct Observation, B: Bland-Altman of ActiGraph vs Direction Observation, C: Bland-Altman plot of activPAL vs Direction Observation; Intersection between Green dotted line and 0 on Y axis denotes the desired point of the data, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.

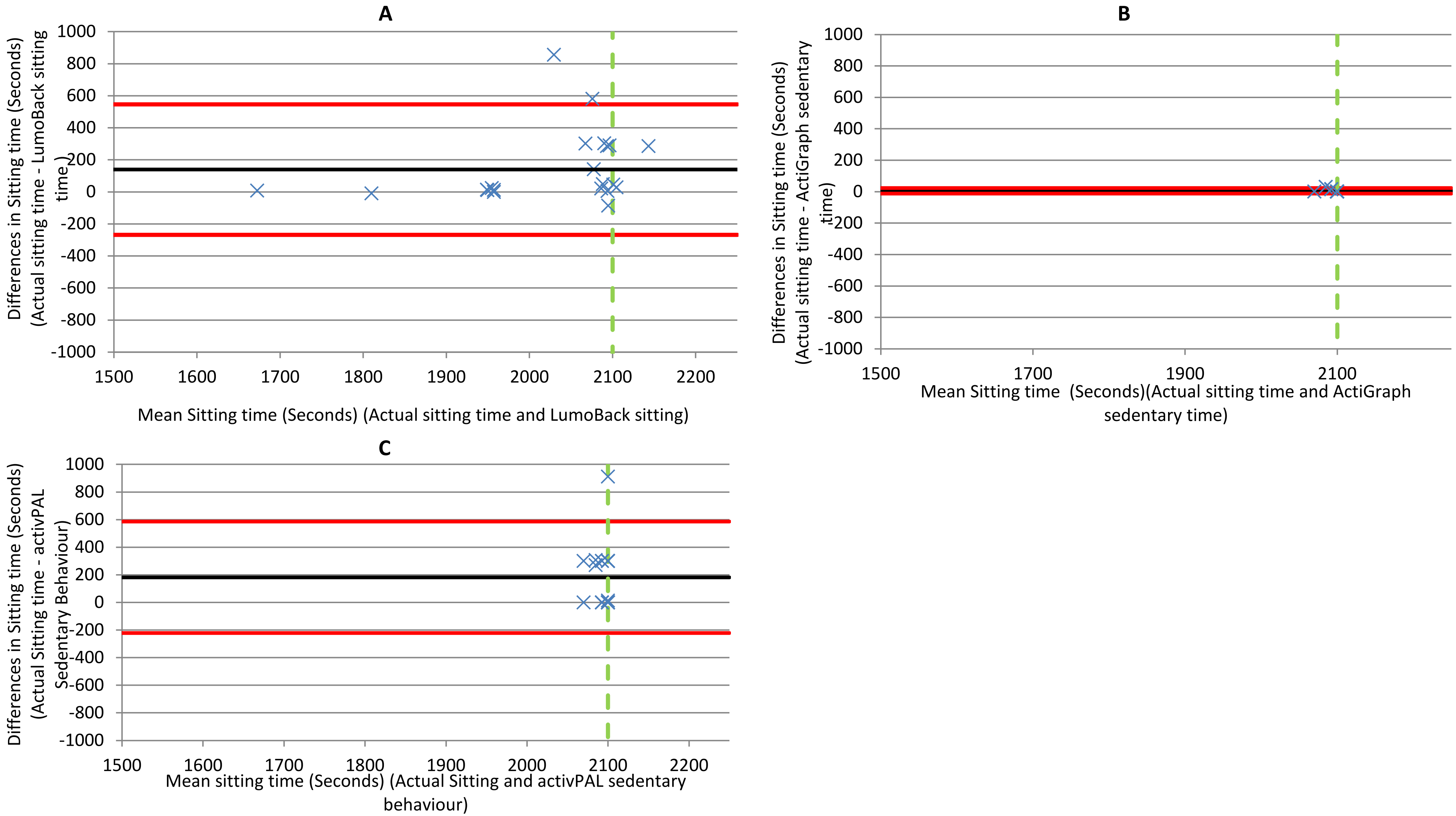






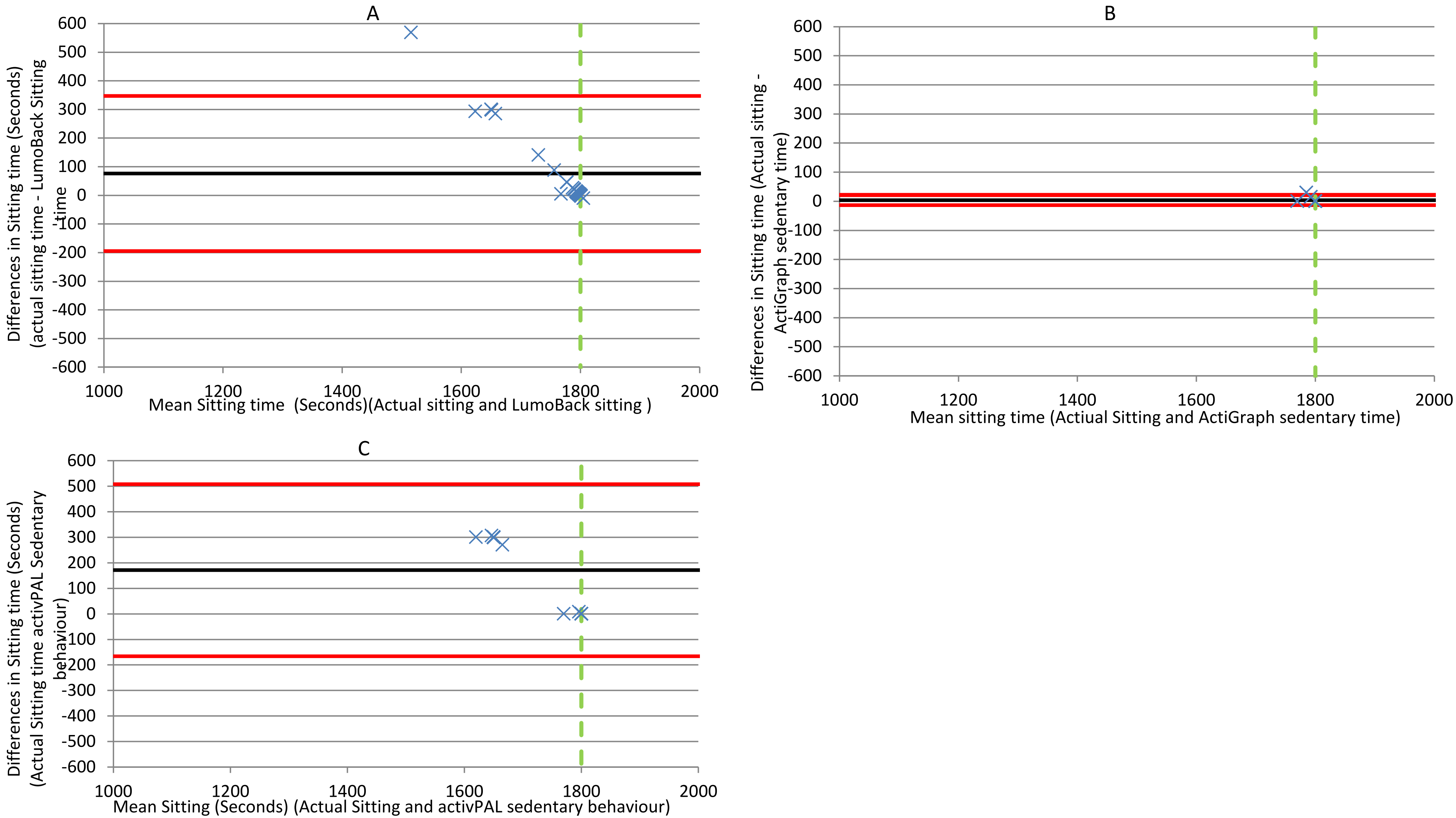
Appendix 2.13 - Sitting playing game on phone (Actual sitting vs devices)

Note: A: Bland-Altman of LumoBack vs Direct Observation, B: Bland-Altman of ActiGraph vs Direction Observation, C: Bland-Altman plot of activPAL vs Direction Observation Intersection between Green dotted line and 0 on Y axis denotes the desired point of the data, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.



Appendix 2.14 – Total Sitting time (All Activities) (Actual sitting vs devices)

Note: A: Bland-Altman of LumoBack vs Direct Observation, B: Bland-Altman of ActiGraph vs Direction Observation, C: Bland-Altman plot of activPAL vs Direction Observation; Intersection between Green dotted line and 0 on Y axis denotes the desired point of the data, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.

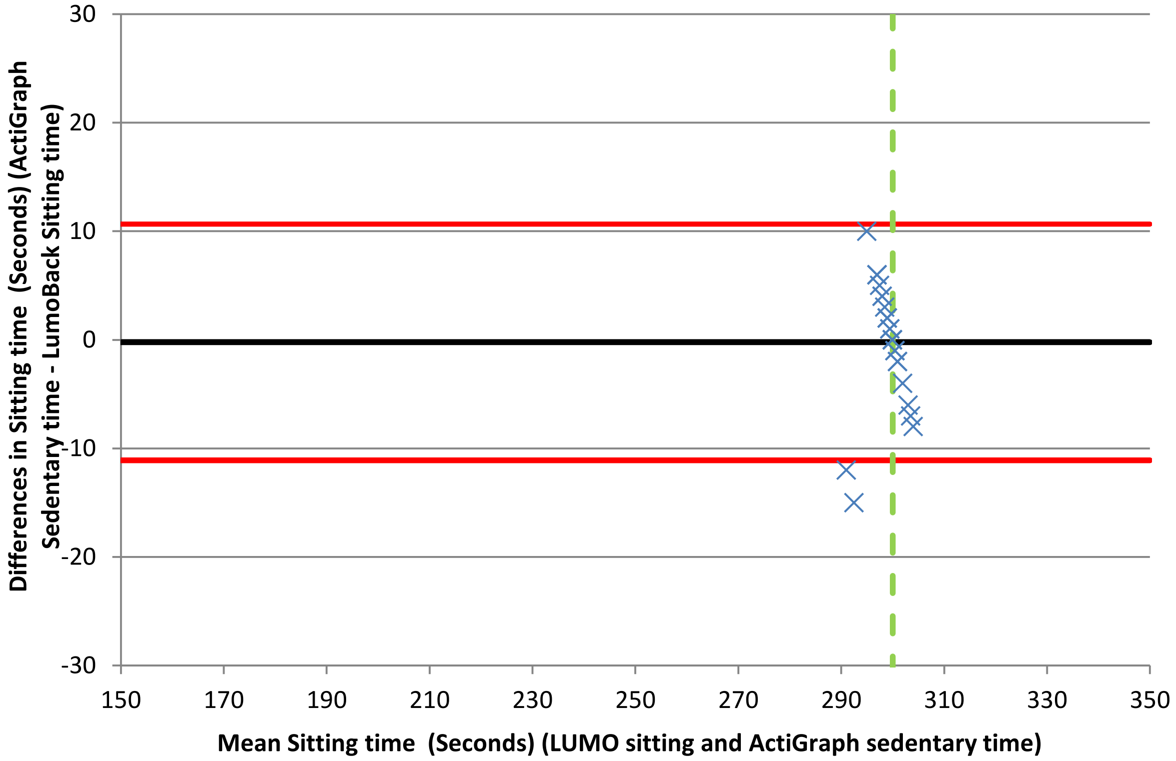


Appendix 2.15 – Total sitting time (All activities – Sitting with feet back under chair removed) (Actual sitting vs devices)

Note: A: Bland-Altman of LumoBack vs Direct Observation, B: Bland-Altman of ActiGraph vs Direction Observation, C: Bland-Altman plot of activPAL vs Direction Observation; Intersection between Green dotted line and 0 on Y axis denotes the desired point of the data, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement

Appendix 2.16 – Bland-Altman plot: Sitting on Chair with Feet Flat on Floor (LumoBack vs activPAL/ActiGraph)

A



B

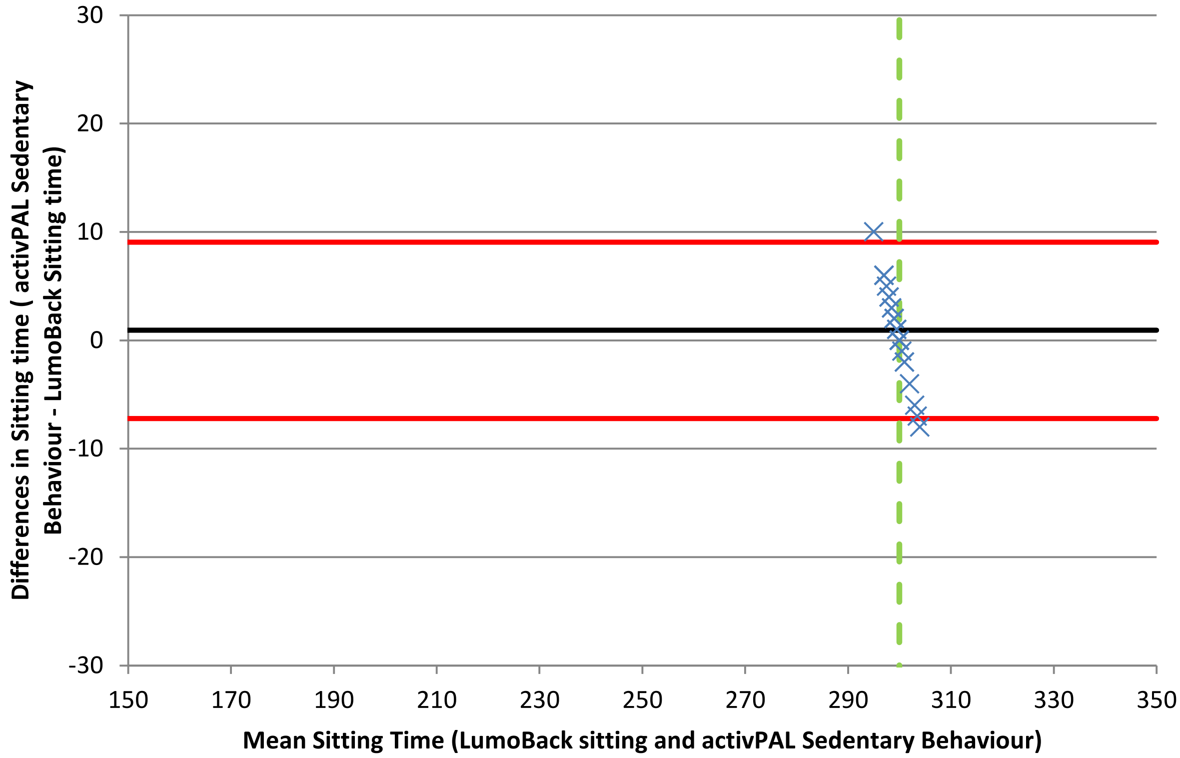
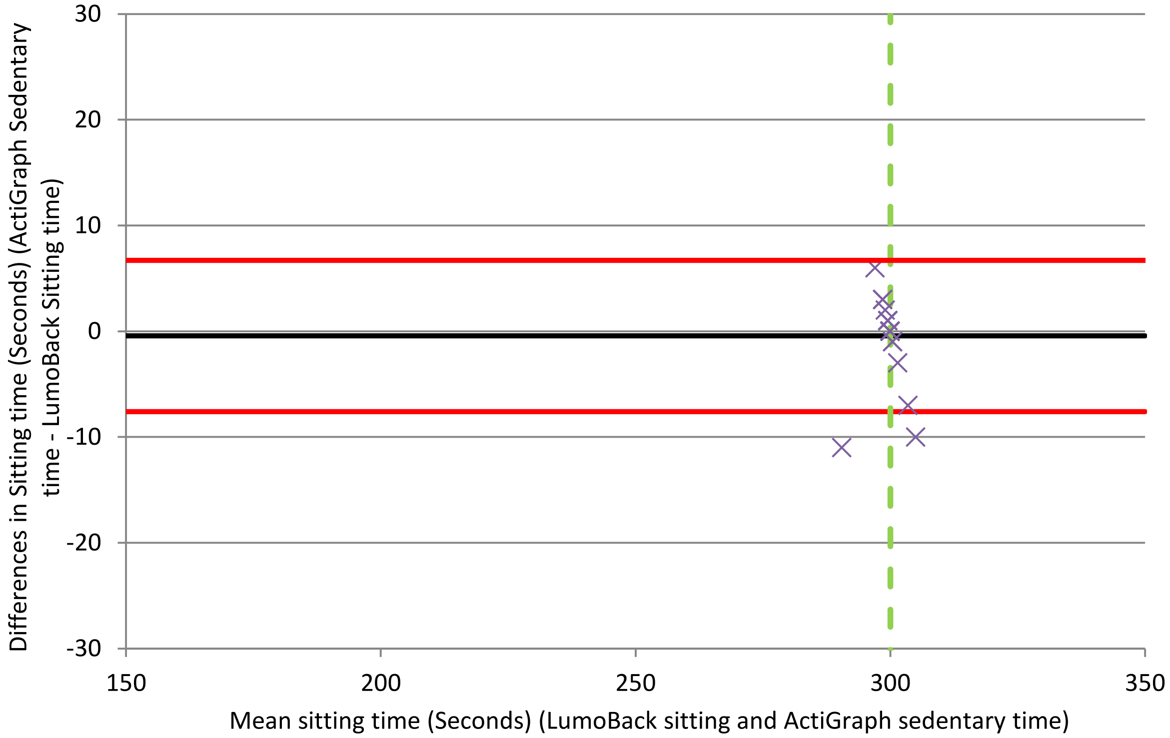


Figure 6.1. - Sitting on Chair with Feet Flat on Floor

Note: A: Bland-Altman of LumoBack vs ActiGraph, B: Bland-Altman plot of LumoBack vs activPAL; Green dotted line denotes the desired line of data points, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.

Appendix 2.17 – Bland-Altman plot: Sitting on chair with Legs Crossed (Right over Left) (LumoBack vs activPAL/ActiGraph)

A



B

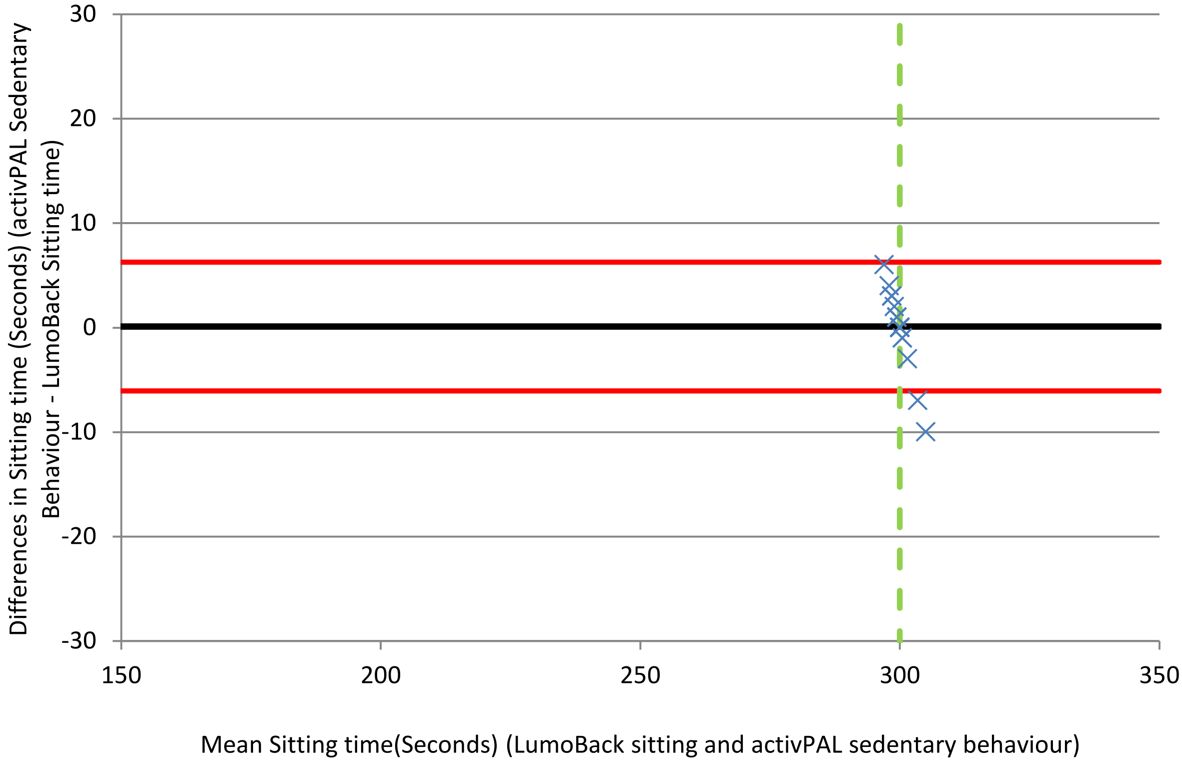
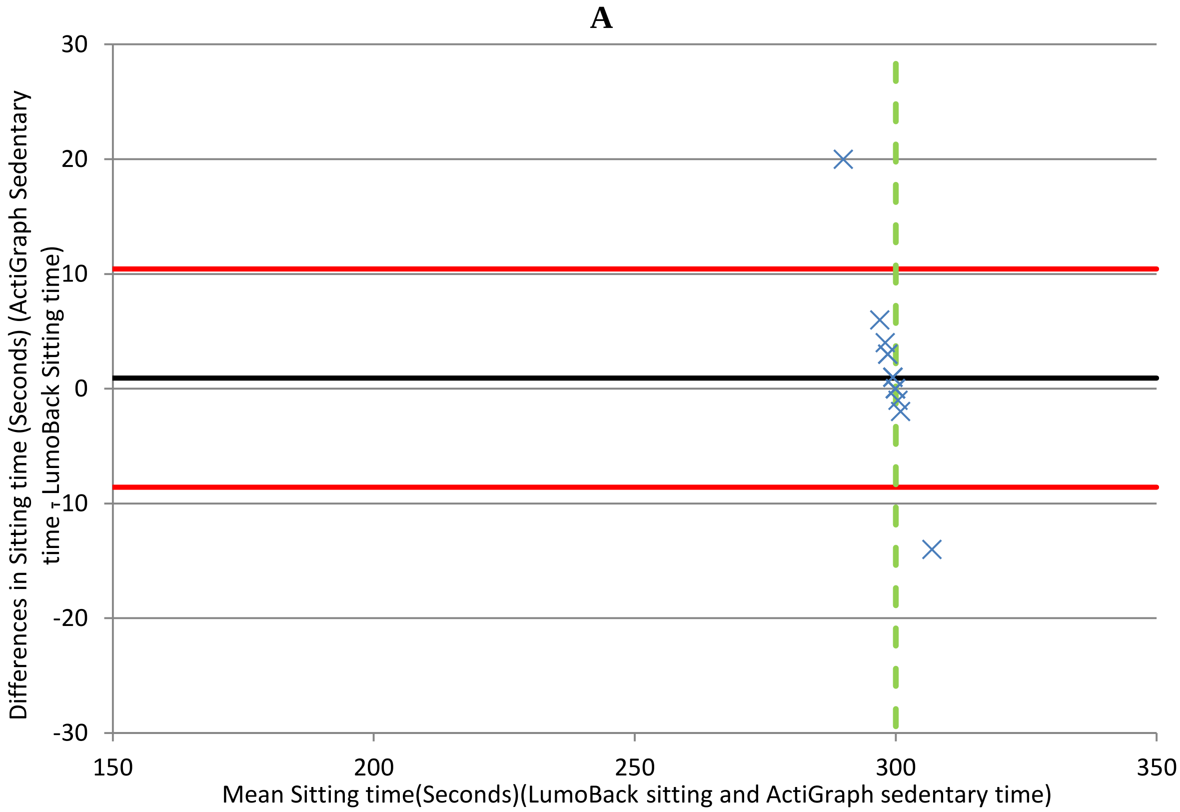


Figure 6.2 - Sitting on Chair with Legs Crossed (Right over Left)

Note: A: Bland-Altman of LumoBack vs ActiGraph, B: Bland-Altman plot of LumoBack vs activPAL; Green dotted line denotes the desired line of data points, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.

Appendix 2.18 – Bland-Altman plot: Sitting on Chair with Right Foot resting on Left Thigh (LumoBack vs activPAL/ActiGraph)



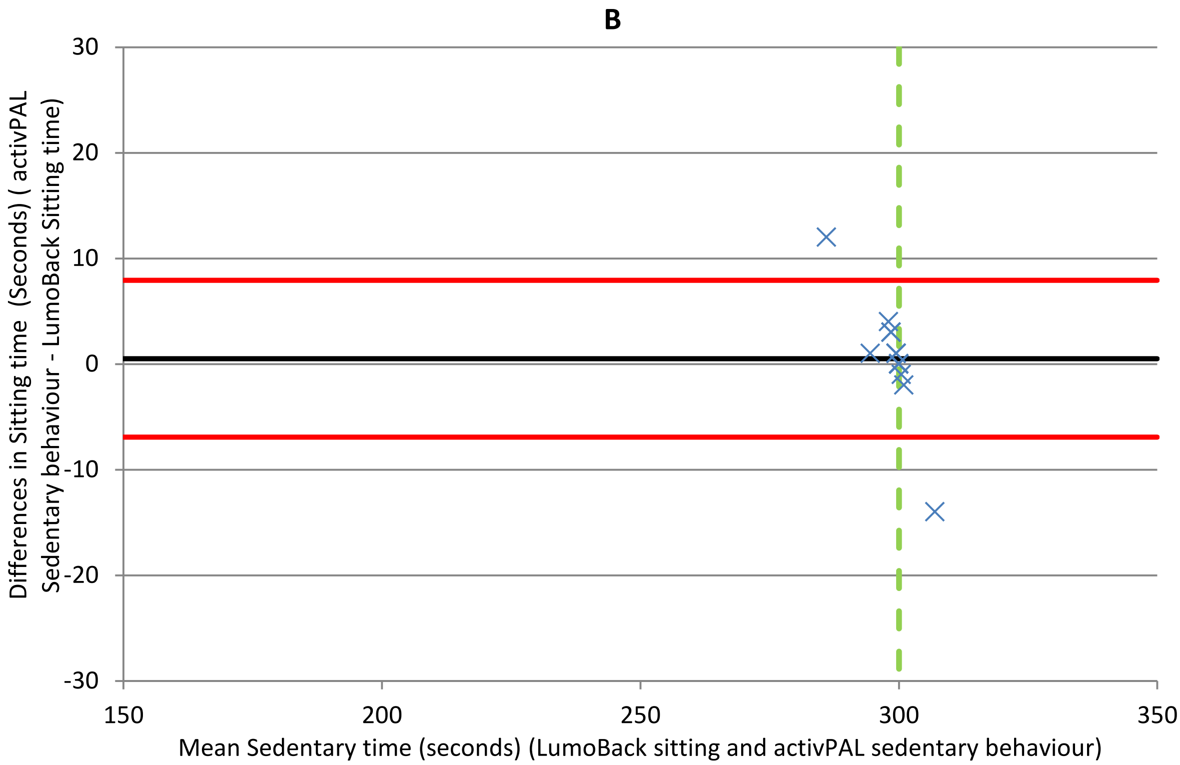


Figure 6.3 - Sitting on Chair with Right Foot resting on Left Thigh

Note: A: Bland-Altman of LumoBack vs ActiGraph, B: Bland-Altman plot of LumoBack vs activPAL; Green dotted line denotes the desired line of data points, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.

Appendix 2.19 – Bland-Altman plot: Sitting on Chair with Legs Straight out in Front (LumoBack vs activPAL/ActiGraph)

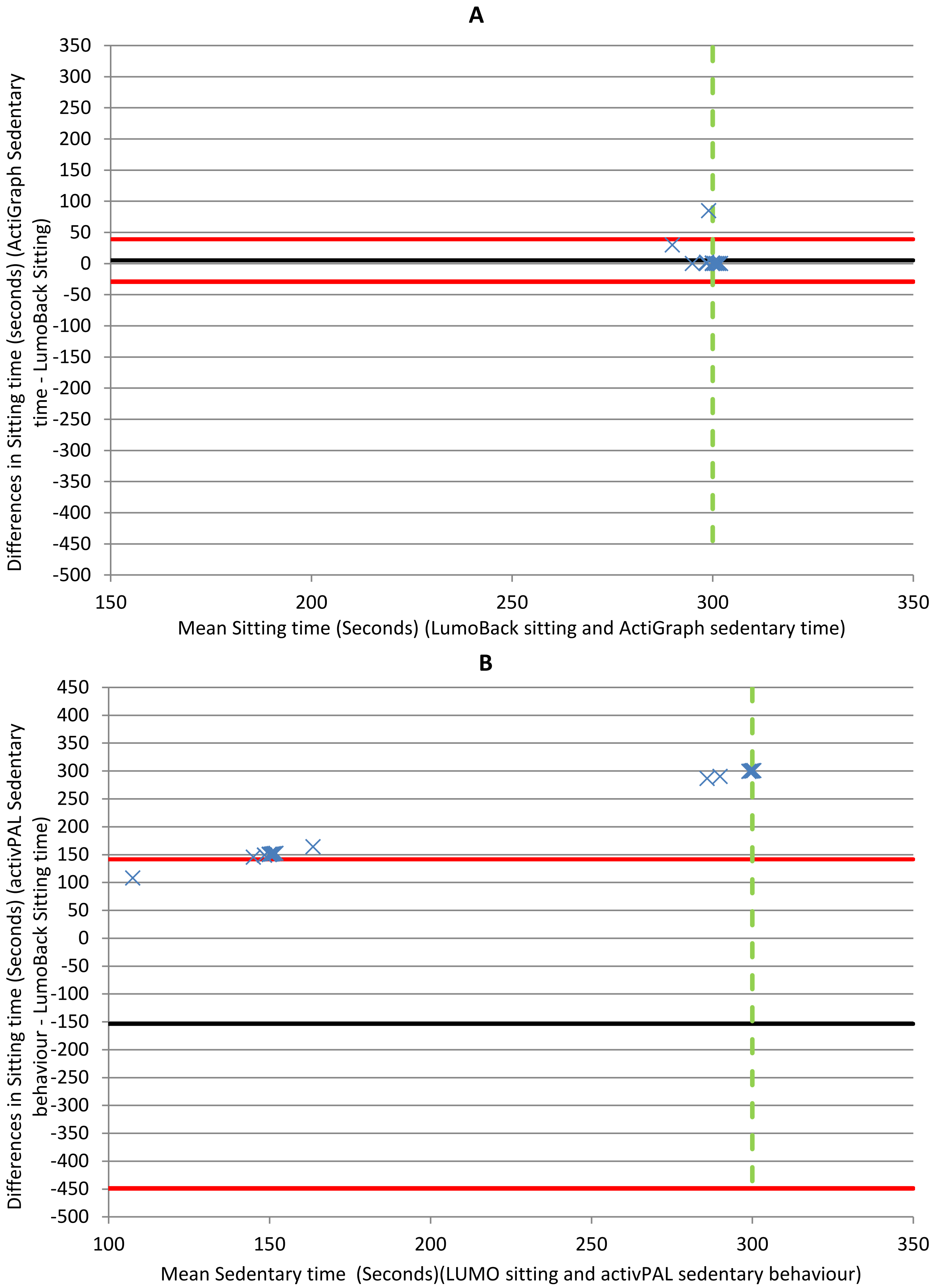
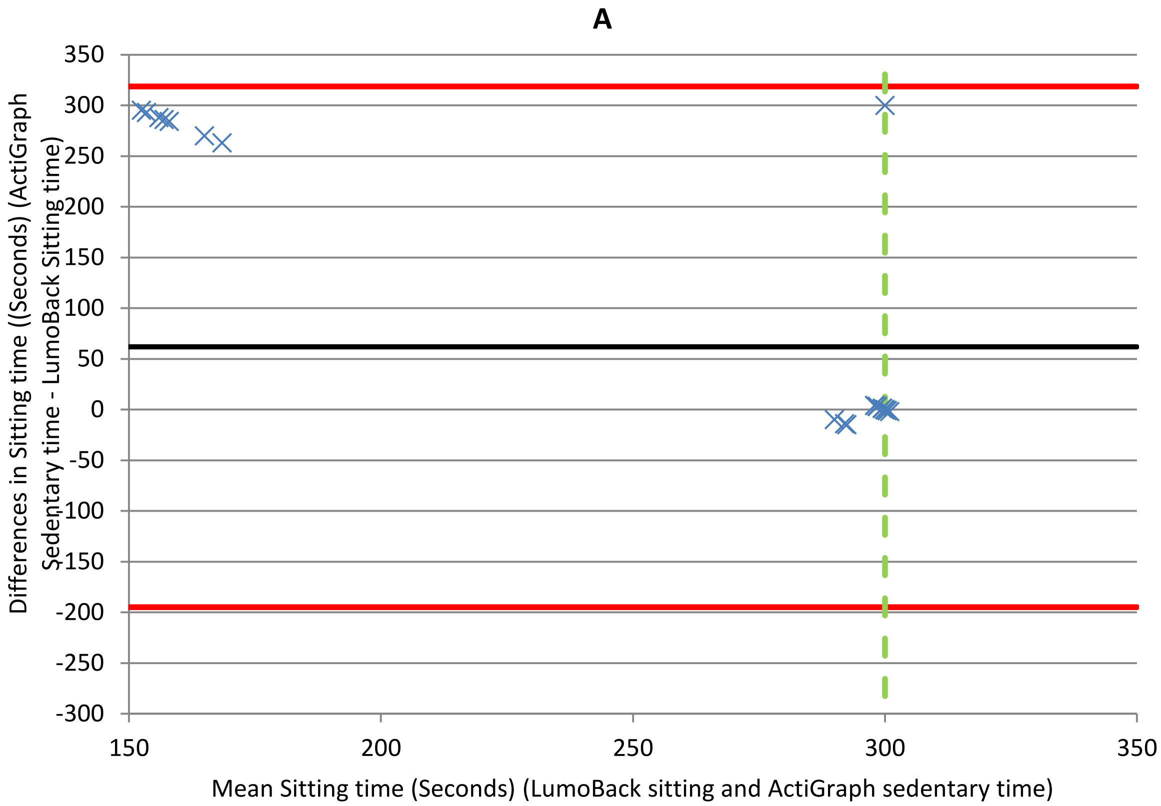


Figure 6.4 - Sitting on Chair with Legs Straight out in Front

Note: A: Bland-Altman of LumoBack vs ActiGraph, B: Bland-Altman plot of LumoBack vs activPAL; Green dotted line denotes the desired line of data points, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.

Appendix 2.20 – Bland-Altman plot: Sitting on Chair with Feet Back under Chair (LumoBack vs activPAL/ActiGraph)



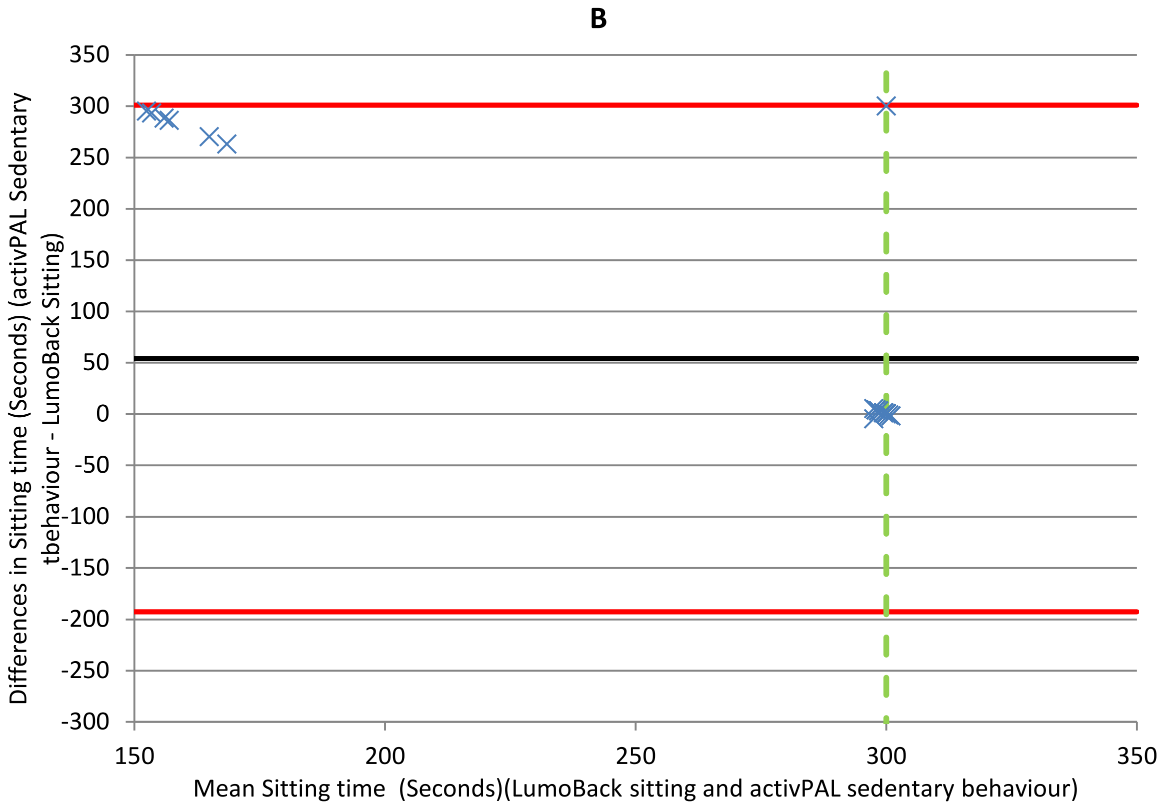
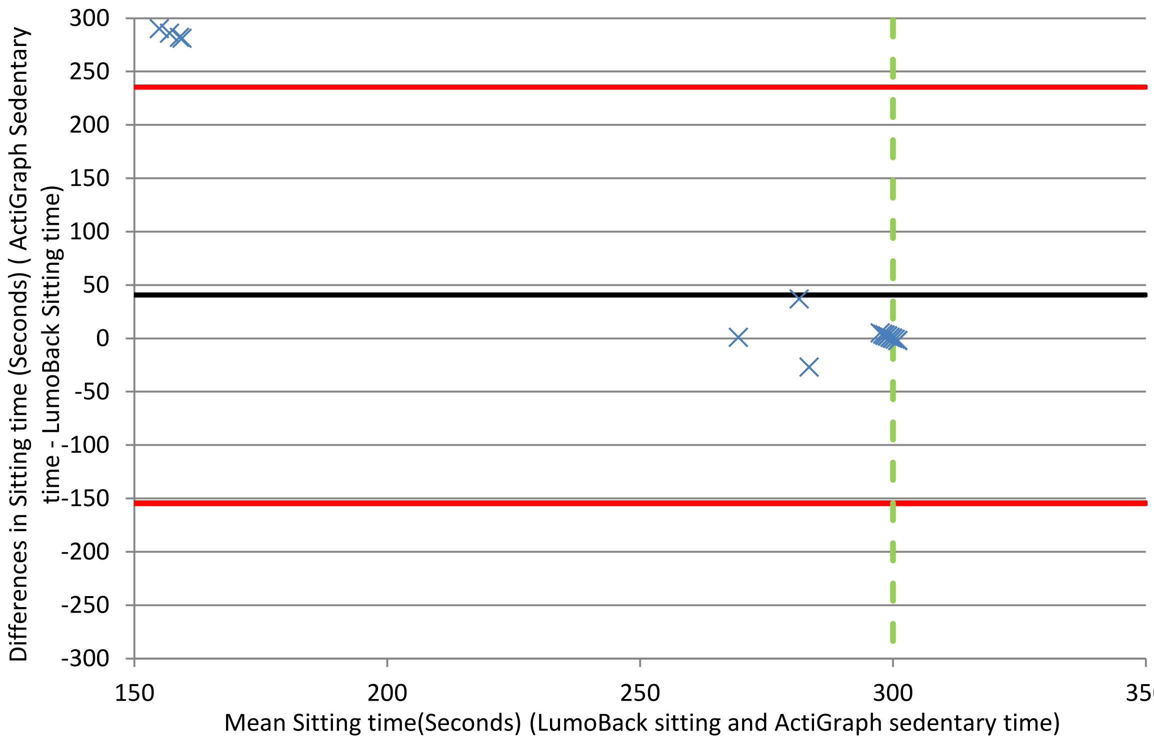


Figure 6.5 - Sitting on Chair with Feet Back under Chair

Note: A: Bland-Altman of LumoBack vs ActiGraph, B: Bland-Altman plot of LumoBack vs activPAL; Green dotted line denotes the desired line of data points, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.

Appendix 2.21 – Bland-Altman plot: Sitting on Chair with Upper Body Movement (Computer) (LumoBack vs activPAL/ActiGraph)

A



B

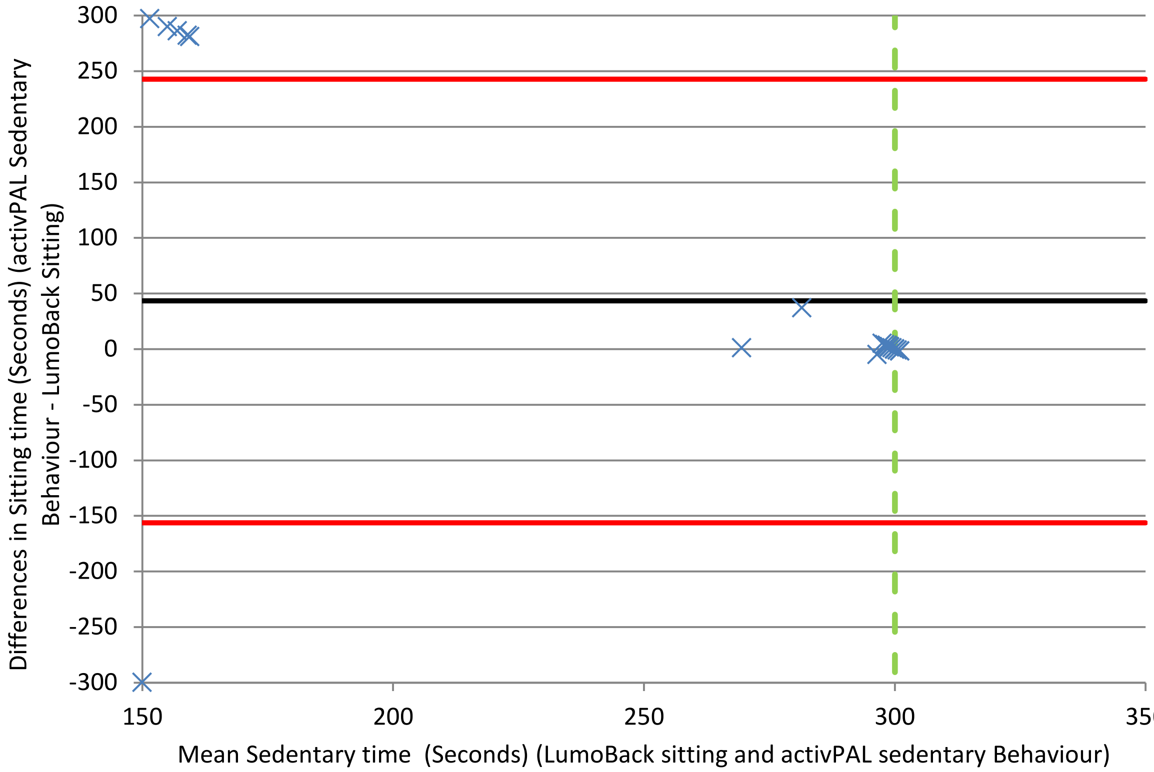
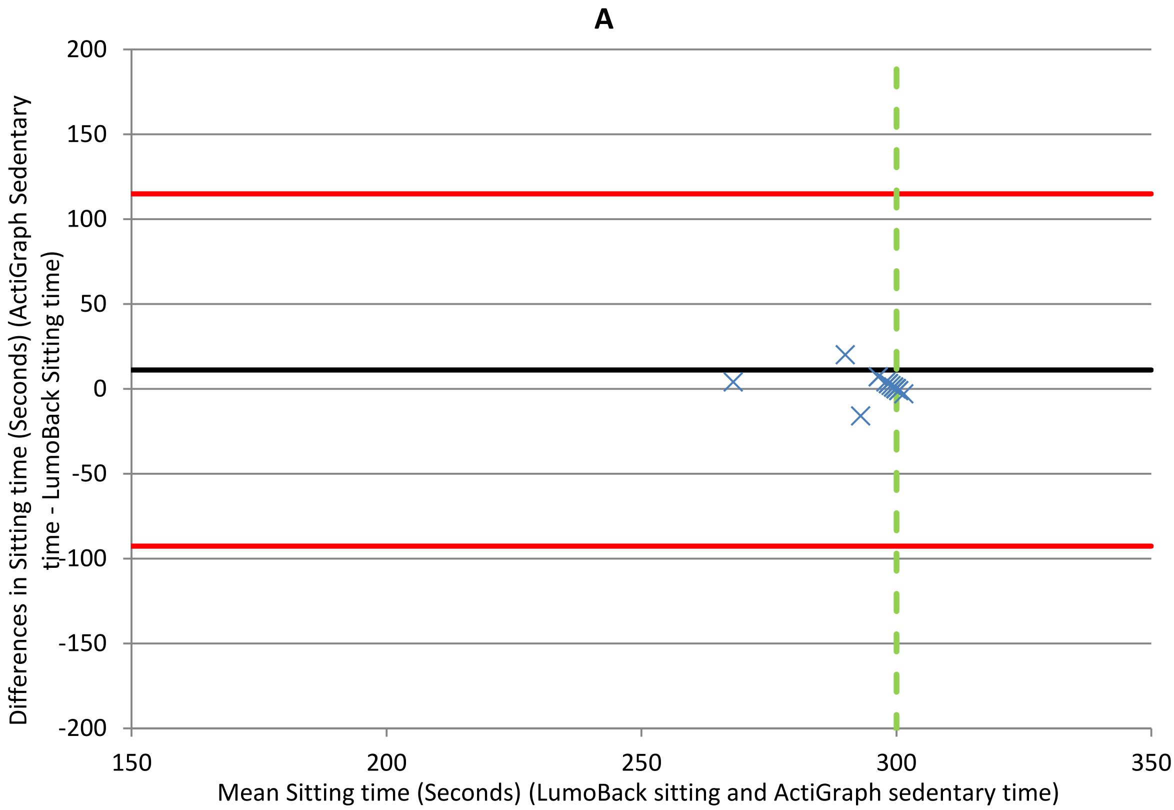


Figure 6.6 - Sitting on Chair with Upper Body Movement (Computer)

Note: A: Bland-Altman of LumoBack vs ActiGraph, B: Bland-Altman plot of LumoBack vs activPAL; Green dotted line denotes the desired line of data points, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.

Appendix 2.22 – Bland-Altman plot: Sitting on Chair Playing Game on Phone (LumoBack vs activPAL/ActiGraph)



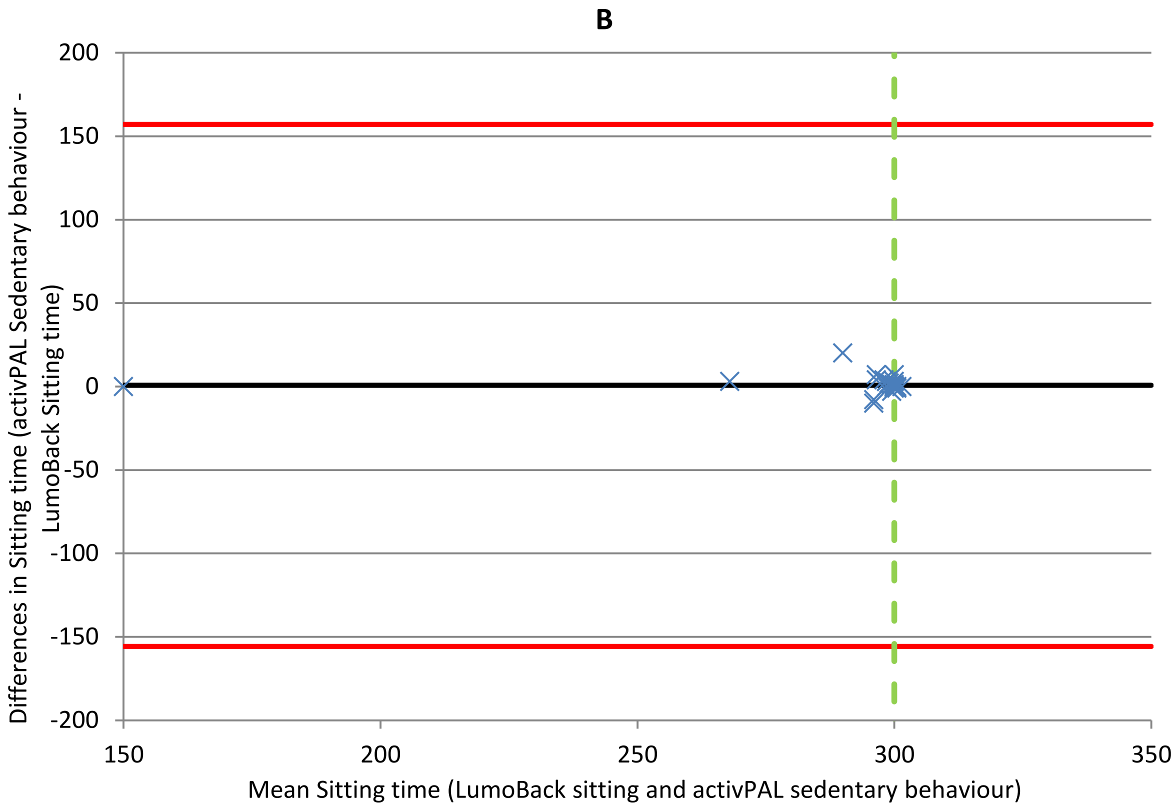
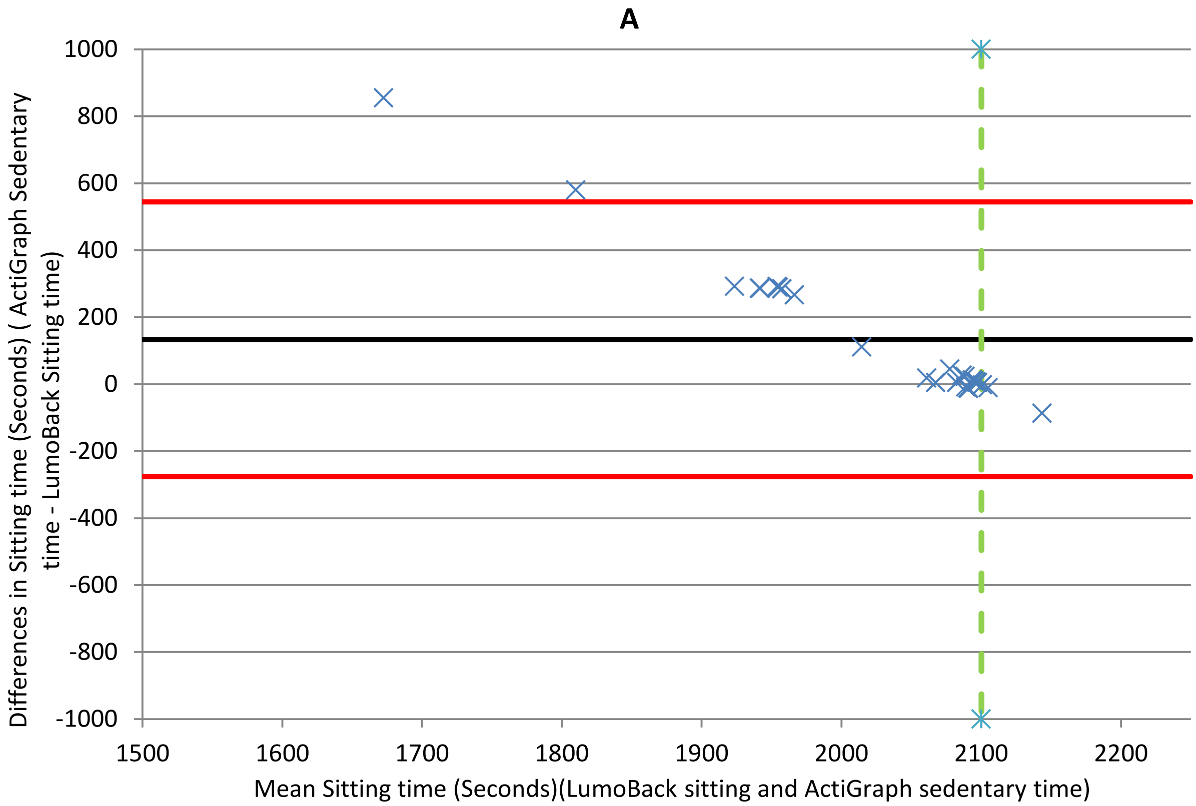


Figure 6.7 - Sitting on Chair Playing Game on Phone

Note: A: Bland-Altman of LumoBack vs ActiGraph, B: Bland-Altman plot of LumoBack vs activPAL; Green dotted line denotes the desired line of data points, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.

Appendix 2.23– Bland-Altman plot: Total Sitting time (All Activities) (LumoBack vs activPAL/ActiGraph)



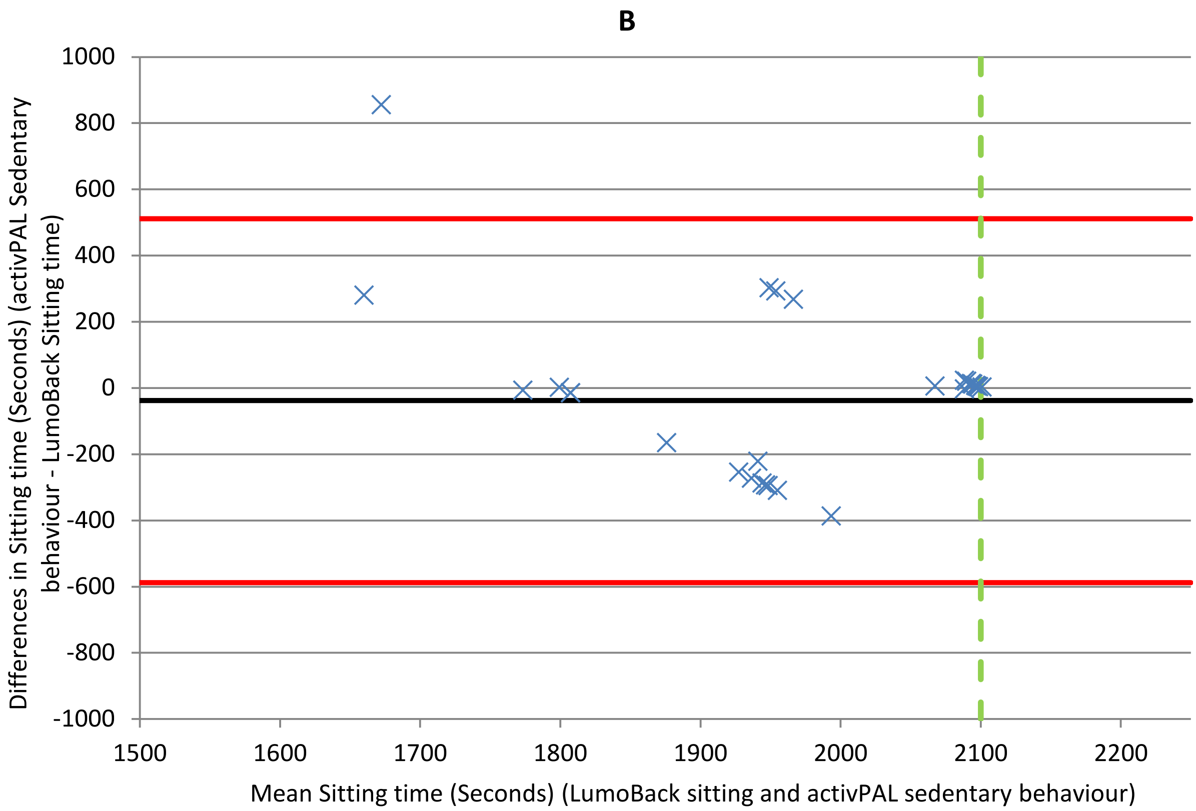
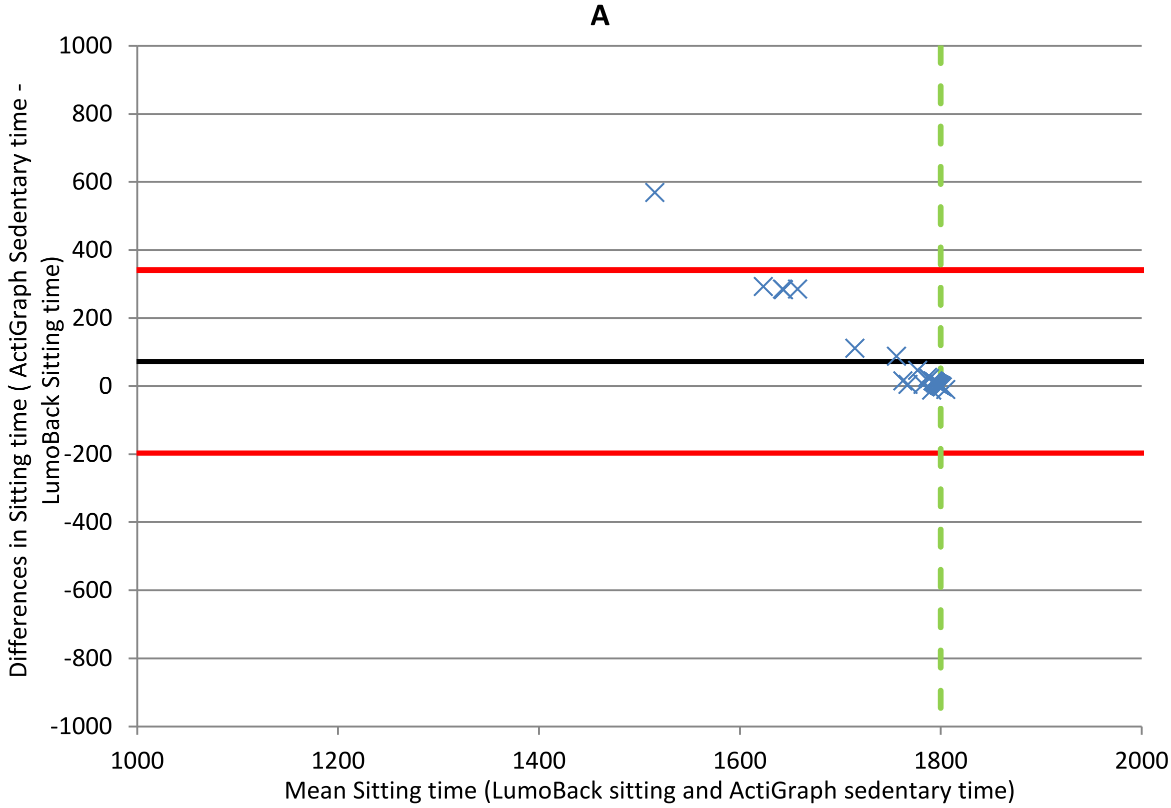


Figure 6.8 – Total Sitting Time (All Activities)

Note: A: Bland-Altman of LumoBack vs ActiGraph, B: Bland-Altman plot of LumoBack vs activPAL; Green dotted line denotes the desired line of data points, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.

Appendix 2.24 – Bland-Altman plot: Total Sitting time (All Activities – Sitting with Feet Back under Chair) (LumoBack vs activPAL/ActiGraph)



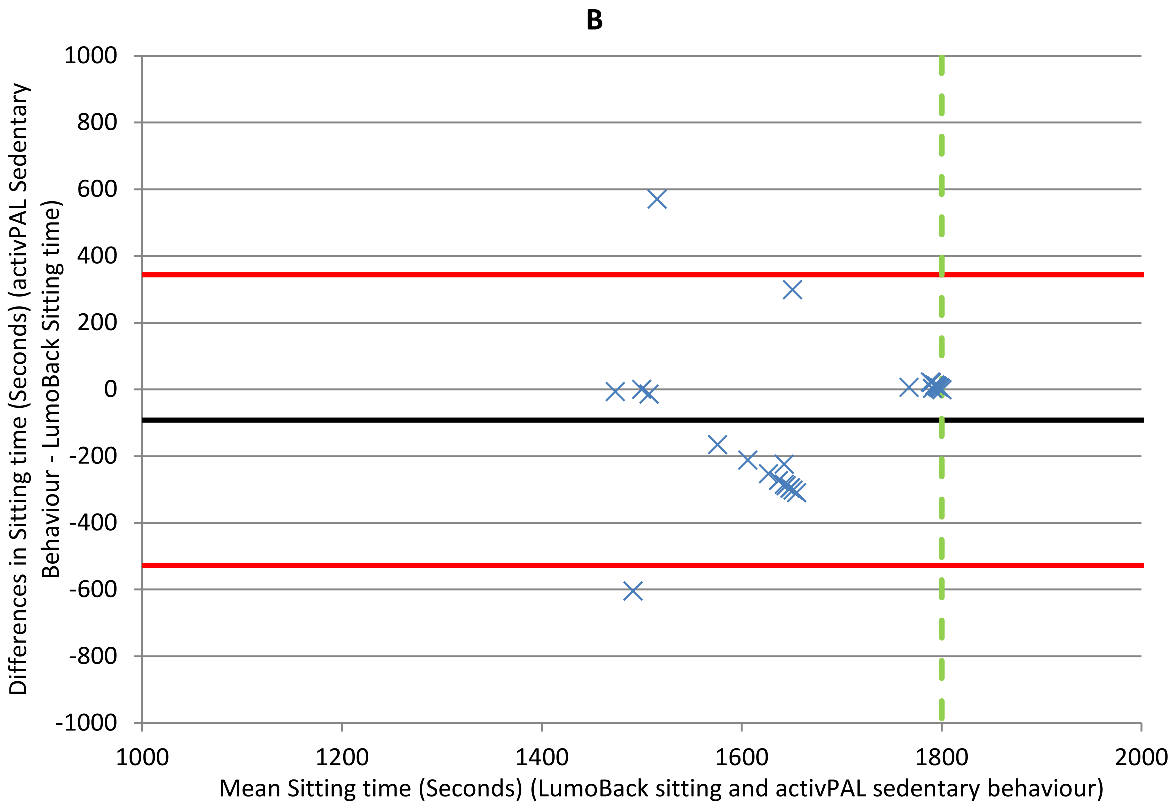


Figure 6.9 – Total Sitting Time (All Activities – Sitting with Feet Back under Chair)

Note: A: Bland-Altman of LumoBack vs ActiGraph, B: Bland-Altman plot of LumoBack vs activPAL; Green dotted line denotes the desired line of data points, Black solid line shows the mean difference, Red lines denotes the upper and lower 95% Limits of Agreement.

Appendix 3 – DeSIT: Decreasing Sedentary Time using Innovative Technology: A Proof of Principle Intervention: Additional Material

Appendix 3.1: DeSIT Participant Information Sheet

DeSIT: Decreasing Sedentary Time using Innovative Technology: A Proof of Principle Intervention

Participant Information Sheet

Main Investigator

Name: James Sanders (PhD Student),

Address: Sir John Beckwith Building, SSEHS, Loughborough University, Loughborough, LE11 3TU

Email Address: J.Sanders2@lboro.ac.uk

Contact number: 01509 226452

Other Investigators

Name: Dr Dale Esliger

Sir John Beckwith Building, SSEHS, Loughborough University, Loughborough, LE11 3TU

Email Address: D.Esliger@lboro.ac.uk

Contact number: +44 (0) 1509 223280

What is the purpose of the study?

Modern environments and technological advancements have radically altered the way we live our lives. The need to undertake purposeful physical activity has all but disappeared and sedentary behaviour, defined as 'any waking behaviour in a sitting or reclining posture with an energy expenditure ≤1.5metabolic equivalent' is now the main behaviour.

There is mounting evidence that the amount of time spent sedentary is an important determinant of health status independent of physical activity levels. Additionally, it is estimated that 60-70% of the average waking day is spent in sedentary pursuits and as little as 3-5% of the population achieve the recommended levels of moderate-to-vigorous physical activity.

Over the last decade, there has been a plethora of wearable technologies that have been developed to support physical activity and sedentary behaviour behaviour change, of which the greatest growth has been seen in self-monitoring tools. Self-monitoring for behaviour change has a strong theoretical foundation and as such, when used in interventions, self-monitoring in conjunction with feedback, has been proven to be an effective behaviour change strategy across a variety of behaviours including smoking, diet and physical activity and is considered a foundation of lifestyle behaviour change interventions. With the increasing amount of wearable technology, it has been suggested that use of electronic approaches might lessen the burden of traditional methods (diaries, and questionnaires etc.) and may improve adherence to self-monitoring and thus result in greater achievement towards behavioural goals.

Therefore, the purpose of this study is to assess the potential beneficial effects of using wearable technology to reduce sedentary behaviour

Who is doing this research and why?

This study is being conducted by as part of JS's PhD research, supervised by Dr Dale Esliger. This study is part of a Student research project supported by Loughborough University.

Are there any exclusion criteria?

You will not be able to take part in the study if you are in one of the following criteria:

- Younger than 30 or older than 69
- Are pregnant
- Not willing to give signed consent
- Cannot adhere to the study protocol
- Do not have an iPhone 4S or later smartphone

Will I be required to attend any sessions and where will these be?

Yes. Should you agree to participate in the study, we will book your appointment in a time of your choosing before 12pm (midday). You will be required to attend in total four laboratory based sessions. The first lasting approximate 10-20mins and 3 more lasting approximately 30-45mins. These sessions will take place in the Physical Activity and Sedentary Behaviour Measurement Lab in the National Centre for Sport and Exercise Medicine.

Is there anything I need to do before the sessions?

Participants are asked to be over-night fasted and asked to please drink a glass of water at least 1 hour before your allocated laboratory session. This will help with us acquiring an accurate measurement from the finger stick blood test.

For Lab sessions 1-4 you will also be required to bring with you, your iPhone 4S or later smartphone

What will I be asked to do?

If you decide to take part within the study then you will be asked to attend 4 laboratory appointments at Loughborough University over a 9 week period. These appointments will be held in the Physical Activity and Sedentary Behaviour Measurement lab in the National Centre for Sport and Exercise Medicine.

Lab session #1

At the first testing session, we will explain the study procedures and answer any question you may have before asking you to sign an informed consent form and a health screening questionnaire. You will then be fitted and set-up with your wearable technology. See fig 1.

Figure 1 – ActiGraph wGT3X+BT (Red) LumoBack Posture Sensor (Black).

The red device (ActiGraph accelerometer) is a small instrument (4.6cm x 3.3cm x 1.5cm, 19g) that sits on a provided elastic belt around your waist and can be worn discretely under clothing and will be used to measure you physical activity throughout the week.

The black device (LumoBack Posture sensor) is also a small instrument (4.15 x 10 x 0.8cm, 25g) also using a provided elasticated belt, will be worn on the lower back either on the skin or over a thin layer of clothing and will be used to measure your sitting time of the measurement period. The LumoBack connects to the LumoBack mobile app which will be provided to you should you agree to participate in the study.

You will be required to wear these devices for a period of 7 days, only removing them during sleep, bathing and water based activities.

At the end of this first visit we will arrange for your next lab visit for the following week.

Lab Session #2

Pre-testing requirements (lab 2-4)

Participants are asked to be over-night fasted and asked to please drink a glass of water at least 1 hour before your allocated laboratory session. This will help with us acquiring an accurate measurement from the finger stick blood test.

We will again run through the study test procedures. A series of screening measurements will be taken. These will consist of height, weight, BMI, body fat%, waist circumference, grip strength and blood pressure as well as a finger stick blood test. This will consist of a small finger prick blood sample (0.04ml) which will be analysed for blood cholesterol, lipid concentrations and blood glucose levels.

The activity monitors you had worn previously will be collected and downloaded. The black device will be reinitialised to provide vibratory (short buzz) feedback to you after prolonged sedentary behaviour. The black device will then be returned to you.

You will be asked to wear the black device for the following 4 weeks, only removing it during sleep, bathing and water based activities. A diary will be provided to document the removal/replacement of the device.

Lab Session #3

Lab sessions 3 will follow an identical format to lab session 2.

Lab Session #4

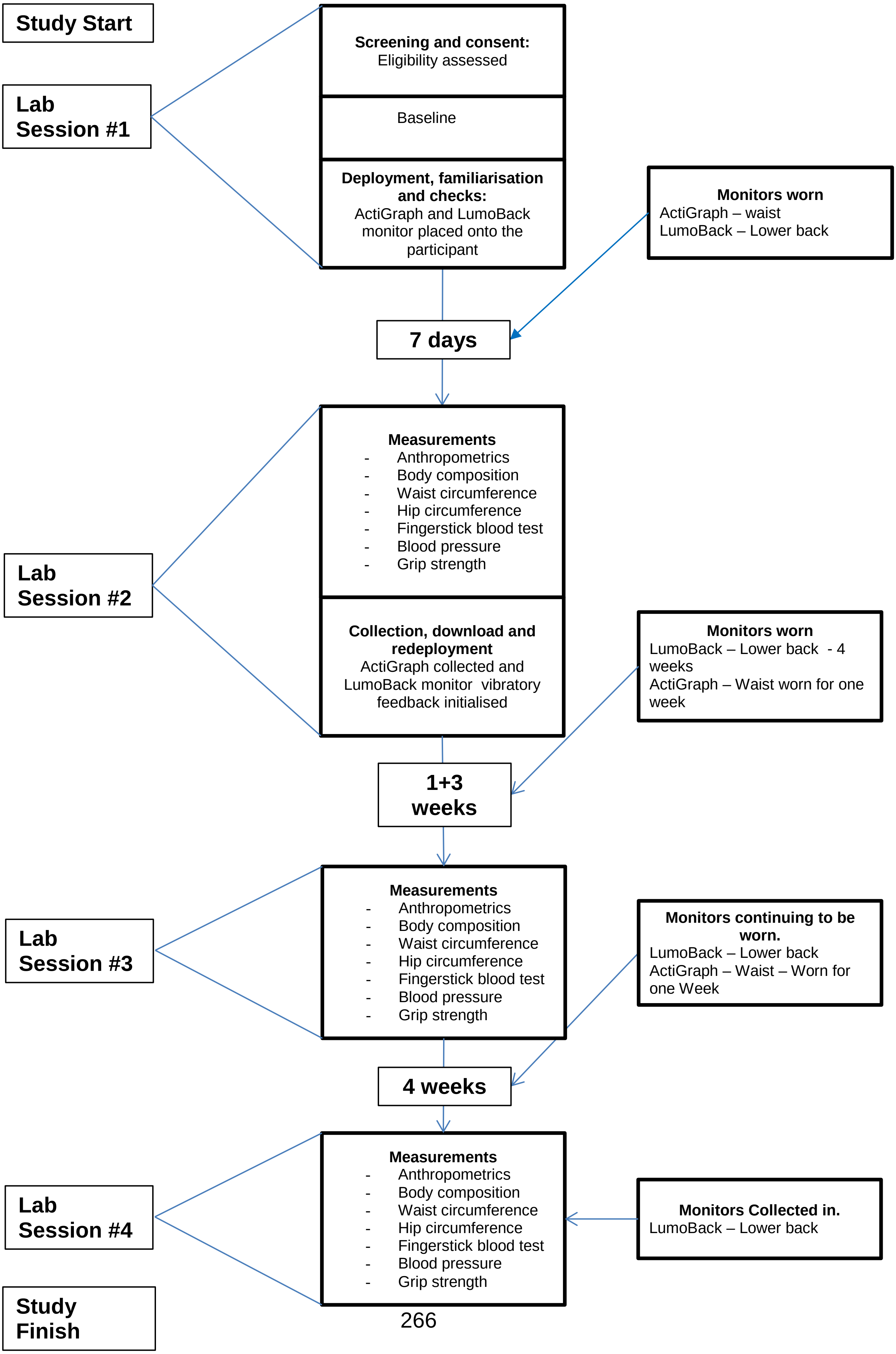
Lab session 4 will follow an identical format to lab sessions 2 and 3. The only exception is that as this will be the final session the black device will be collected in by the research team and not returned to you. A series of questions will be asked about you experiences whilst using and wearing the device.

How long will it take?

Lab session #1 will take 10-20mins. Each lab session thereafter will take approximately 30-45mins. And the total time of the study will be 9 weeks. Please see figure 2.

Once I take part, can I change my mind?

Yes. After you have read this information and asked any questions you may have we will ask you to complete an Informed Consent Form, however if at any time, before, during or after the sessions you wish to withdraw from the study please just contact the main investigator. You can withdraw at any time, for any reason and you will not be asked to explain your reasons for withdrawing.


Study Start
Lab Session #1
Screening and consent:
Eligibility assessed
Baseline
Deployment, familiarisation and checks:
ActiGraph and LumoBack monitor placed onto the participant
Monitors worn
ActiGraph – waist
LumoBack – Lower back
7 days
Lab Session #2
Measurements
- Anthropometrics
- Body composition
- Waist circumference
- Hip circumference
- Fingerstick blood test
- Blood pressure
- Grip strength
Collection, download and redeployment
ActiGraph collected and LumoBack monitor vibratory feedback initialised
Monitors worn
LumoBack – Lower back - 4 weeks
ActiGraph – Waist worn for one week
1+3 weeks
Lab Session #3
Measurements
- Anthropometrics
- Body composition
- Waist circumference
- Hip circumference
- Fingerstick blood test
- Blood pressure
- Grip strength
Monitors continuing to be worn.
LumoBack – Lower back
ActiGraph – Waist – Worn for one Week
4 weeks
Lab Session #4
Measurements
- Anthropometrics
- Body composition
- Waist circumference
- Hip circumference
- Fingerstick blood test
- Blood pressure
- Grip strength
Monitors Collected in.
LumoBack – Lower back
Study Finish

Are there any risks in participating?

There is a small, single finger prick to one finger on your non-dominant hand. As this will cause a small puncture just below the skin, there is a very small chance that you will experience a small amount of discomfort. However, the discomfort should only be momentary, and will *Figure 2 – Study outline*

Will my taking part in this study be kept confidential?

All information that is collected about you during the course of the research will be kept strictly confidential. Data will be stored either in locked filing cabinets or in password protected university managed PC's which are only accessible by members of the research team. Any information about you which is disseminated will have any identifiable information removed so that you cannot be recognised from it. Information collected will not be used for any other purpose than that explained here. The data from this study will be kept for a maximum period of 6 years. Once the blood sample has been analysed it will be disposed of immediately. However, once the results of the study are published or a dissertation has been submitted (expected to be by December 2015), it will not be possible to withdraw your individual data from the research.

What will happen to the results of the study?

The results will be coded (for anonymity) and analysed by the research team. The results may be published in scientific journals and/or presented at relevant conferences. Furthermore, the results will be written up as part of JS's PhD thesis.

What if I am not happy with how the research was conducted?

If you are not happy with how the research was conducted, please contact Ms Jackie Green, the Secretary for the University's Ethics Approvals (Human Participants) Sub-Committee:

Ms J Green, Research Office, Hazlerigg Building, Loughborough University, Epinal Way, Loughborough, LE11 3TU. Tel: 01509 222423. Email: J.A.Green@lboro.ac.uk

The University also has a policy relating to Research Misconduct and Whistle Blowing which is available online at http://www.lboro.ac.uk/committees/ethics-approvals-human-participants/additionalinformation/codesofpractice/ .

I have some more questions; who should I contact?

For any further questions please contact James Sanders and/or Dr Dale Esliger, whose contact details are shown at the top of this information sheet.

Appendix 3.2: LumoBack information sheet and FAQ

Participant ID: ______________

ActiGraph Numbers:

____

LUMOback:

______________.

DeSIT: Decreasing Sitting using Innovative Technology

Activity monitor instructions Manual

If you have any questions or concerns, please contact:

James Sanders
J.Sanders2@lboro.ac.uk
07538330734

3. General Information

- Please wear the LumoBack for the duration of the study period
- Please wear the ActiGraph for the next 7 day period
- Please wear the monitors **continuously** only removing for sleep and water based activities.
- If you wish to remove the monitors before you go to bed please put the LumoBack on charge, preferably in a place where you will remember to put it on in the morning (e.g. your bedside table) and remember to **put them on as soon as you wake up in the morning.**
- If you decide not to put it on charge overnight – please place the LumoBack down horizontally on a flat surface with the Lumo logo facing upward – this will put the Lumo into Inactive mode after 5 mins and will allow the research team to determine wear and non-wear times.

WARNING: Please **do not** wear the devices when showering, bathing, or performing water-based activities.

<u>Returning your activity monitors and logbook</u>

Please return the activity monitors (and any unused adhesive patches) and completed logbook to James Sanders (NCSEM PhD area)

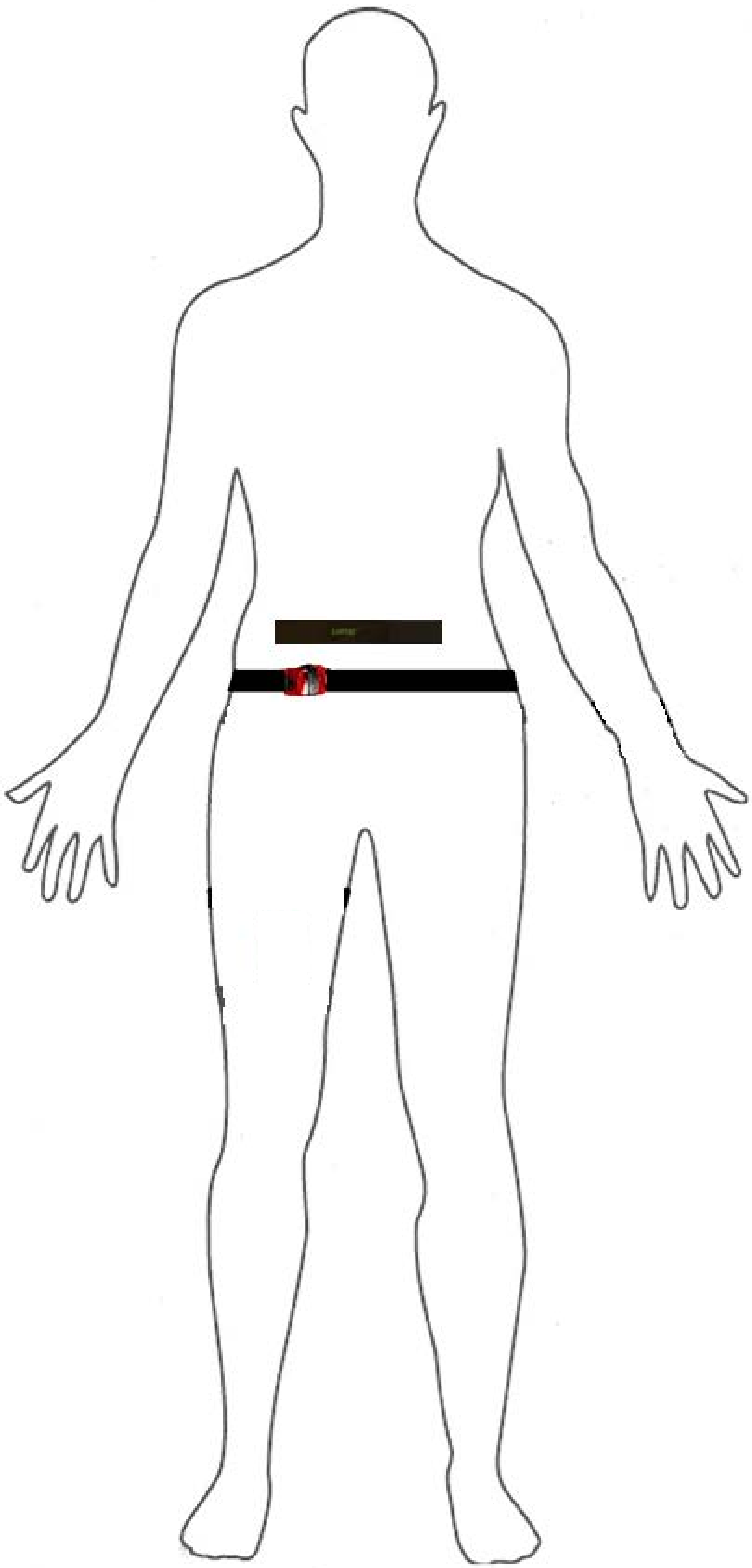
2. How to wear the ActiGraph monitors

The ActiGraph will be attached using adjustable elastic straps and should be positioned so that the small black cap is facing upwards. The hip monitor is to be worn on the right hand side of the body on the midaxillary line of the hip.

3. How to wear the LumoBack

The LumoBack will be attached using adjustable plastic straps. The LumoBack should we worn on base of the back with the logo outward facing, and in a readable orientation.

4. Placement of the activity monitors



5. Removal of the LumoBack.

Night Removal

When removing the LumoBack at night please take it off immediately before you go to sleep and place it on charge using the charging plug and cord provided in your pack. It is best to place this on your bed side table so as a reminder to put it on the when you wake up in the morning

It is important that you place the device on charge every night so that we can have a data stream to note removal time.

Removal for water-based activities

Please remove the device immediately before and immediately after the water based activities – making sure to place the device horizontal on a flat surface with Lumo sign facing upwards.

6. LumoBack FAQ's

Wearing the sensor

7. Place the LUMO on your lower back, either directly on your skin or over a thin layer of clothing. The LUMO logo and circular Touch button should be facing out.
8. Wrap the belt around your waist directly above your hip bones, and secure the Velcro near your belly button.
9. If your belt doesn't fit snuggly around your waist, take it off and adjust the Velcro straps inside the belt.

Checking the LumoBack charge.

Tap the Touch Button to view charge level:

Green - The sensor has more than one day of charge remaining.

Orange - The sensor has one day or less of charge remaining. Recharge soon

Alternatively – touch the three horizontal bars on the top left corner of the app which will display the side menu will display the battery charge next to the Lumo tab.

Charging the LumoBack

7. Plug the sensor into a USB power source using the included cable.
8. It takes about 2 hours to charge the sensor completely.
9. A complete charge will last for about 5 days of continuous use

When to calibrate your sensor.

The LumoBack sensor works for everybody, but only if it is calibrated correctly. This process stores your good posture position on the sensor and determines when the sensor will vibrate, indicating bad posture.

When should you calibrate?

7. When you first setup your sensor.
8. Everytime you put the sensor back on after any period of removal.

How do I clean my Lumo? Is it water resistant?

You can simply take a damp cloth or a wipe and wipe the sensor down. Also, if needed you can remove the Velcro straps from the actual sensor moulding and you can hand wash the belt straps and line dry.

Lumo Back is not completely water resistant. While it is ok to have moisture and sweat from normal use and activities, you can NOT submerge the LumoBack sensor in water or shower with it, etc. It has a Lithium battery and other hardware components that can be damaged if it gets wet.

Connectivity issues. What do I do?

Please try the following:

5. Turn the Bluetooth on your iOS device off and then on again through the iOS Settings icon. Go to Settings>Bluetooth>On/Off in your iOS device.
6. Kill the app: first double-click on the home screen of your iOS device, then hold down the LumoBack icon in the tray for 3 seconds, then press the red delete button.
7. Restart the LumoBack app.
8. If this doesn't work, try turning off your iOS device completely, and then turn it back on.
9. Alternatively – try turning the LumoBack on and off again – this can be achieve by touching the button on the device for a period of 5 seconds until the red light flashes. Perform the same action again to turn it back on. A green light should flash to let you know it is turned on again.

Please make sure your battery is charged as the app works best when it is charged.

The LumoBack will still be collecting data during this time even if it isn’t connected to the app.

Any other problems please contact me. The details can be found on the title page.

Appendix 3.3 Participant Health report

ID Number: ____________________

Lab Session: ____________________

Date: ____________________________

DeSIT

DeSIT: Decreasing Sedentary Time using Innovative Technology

If you have any questions or concerns, please contact

James Sanders (J.Sanders2@lboro.ac.uk)

Dr Dale Esliger (D.Esliger@lboro.ac.uk)

1) **Body mass index (BMI)** is a simple index of weight-for-height that is commonly used to classify overweight and obesity in adults. It is defined as a person's weight in kilograms divided by the square of his height in meters (kg/m2).

BMI provides the most useful population-level measure of overweight and obesity as it is the same for both sexes and for all ages of adults. However, it should be considered a rough guide because it may not correspond to the same degree of fatness in different individuals.

Raised BMI is a major risk factor for non-communicable diseases such as:

- cardiovascular diseases (mainly heart disease and stroke), which were the leading cause of death in 2012;
- diabetes;
- musculoskeletal disorders (especially osteoarthritis - a highly disabling degenerative disease of the joints);
- some cancers (endometrial, breast, and colon).

The risk for these non-communicable diseases increases, with an increase in BMI.

BMI (Kg/m^2)

Body Mass Index (BMI)

Weight in Pounds (lbs) and Kilograms (kg)

Height in Feet and Inches and in Meters (m)

	100 lbs 45 kg	110 lbs 50 kg	120 lbs 54 kg	130 lbs 59 kg	140 lbs 63 kg	150 lbs 68 kg	160 lbs 73 kg	170 lbs 77 kg	180 lbs 82 kg	190 lbs 86 kg	200 lbs 91 kg	210 lbs 95 kg	220 lbs 100 kg	230 lbs 104 kg	240 lbs 109 kg	250 lbs 113 kg
4'8" 1.46 m	22	25	26	29	31	34	36	38	40	43	45	47	49	52	54	56
4'9" 1.47 m	22	24	26	28	30	33	35	37	39	41	43	45	48	50	52	54
4'10" 1.49 m	21	23	25	27	29	31	34	36	38	40	42	44	46	48	50	52
4'11" 1.50 m	20	22	24	26	28	30	32	34	36	38	40	42	44	46	49	51
5'0" 1.52 m	20	22	23	25	27	29	31	33	35	37	39	41	43	45	47	49
5'1" 1.55 m	19	21	23	25	26	28	30	32	34	36	38	40	42	44	45	47
5'2" 1.57 m	18	20	22	24	26	27	29	31	33	35	37	38	40	42	44	46
5'3" 1.60 m	18	20	21	23	25	27	28	30	32	34	35	37	39	41	43	44
5'4" 1.63 m		19	21	22	24	26	28	29	31	33	34	36	38	40	41	43
5'5" 1.65 m		18	20	22	23	25	27	28	30	32	33	35	37	38	40	42
5'6" 1.67 m		18	19	21	23	24	26	27	29	31	32	34	36	37	39	40
5'7" 1.70 m			19	20	22	24	25	27	28	30	31	33	35	36	38	39
5'8" 1.73 m			18	20	21	23	24	26	27	29	30	32	34	35	37	38
5'9" 1.75 m			18	19	21	22	24	25	27	28	30	31	33	34	35	37
5'10" 1.78 m				19	20	22	23	24	26	27	29	30	32	33	35	36
5'11" 1.80 m				18	20	21	22	24	25	27	28	29	31	32	34	35
6'0" 1.83 m			16	18	19	20	22	23	24	26	27	28	30	31	33	34
6'1" 1.85 m			16		19	20	21	22	24	25	26	28	29	30	32	33

Healthy Weight Overweight Obese

2) Body Composition

2.1) Weight

Weight (Kg)

2.2) Body Fat percentage: Our body is composed of two types of fat:

a) Essential Body Fat: necessary to maintain correct functionality of our body. The percentage body fat is 3-5% in men and 8-12% in women.

b) Storage Fat: this is the fat accumulated in our body and used to protect internal organs as well as an energy reserve.

In general, having excess body can lead to an increase in the stiffness of artery walls, therefore increasing the risk of developing cardiovascular diseases.

Body Fat Percentage	**Body Fat Mass**

Classification	**Male**	**Female**
Unhealthy Range (too low)	5% and below	8% and below
Acceptable range (lower end)	6-15%	9-23%
Acceptable range (higher end)	16-24%	24-31%
Unhealthy Range (too high)	25% and above	32% and above

2.3) **Visceral Fat Percentage**

Visceral Fat Percentage	**Visceral Fat Mass**

Visceral fat is the fat that is in the internal abdominal cavity, surrounding the vital organs in the trunk (abdominal) area. Research shows that even if your weight and body fat remains constant, as you get older the distribution of fat changes and is more likely to shift to the trunk. Ensuring you, have healthy levels of visceral fat my reduce the risk of certain diseases such as heart disease, high blood pressure, and the onset of type 2 diabetes.

Low Risk	High risk
1-12	13-59

2.4) **Fat Free Mass Percentage**

Fat Free Mass %

This feature indicates the weight of muscle in your body. The muscle mass displayed includes the skeletal muscles, smooth muscles (such as cardiac and digestive muscles) and the water contained in these muscles. Muscles play an important role as they act as an engine in consuming energy. As your muscle mass increase, your energy consumption increases helping you reduce excess body fat levels and lose weight in a healthy way.

3) Waist Circumference (WC): This is an important indicator of how healthy we are. This is a proxy measure used to assess abdominal fat for chronic disease risk. A high waist circumference or a greater level of abdominal fat is associated with an increased risk of type 2 diabetes, high cholesterol, high bloody pressure and heart disease.

Waist Circumference (cm)

3.1) Waist-to-Hip Ratio – having a larger waist circumference (when compared to having fat around the bottom or thighs) is an indicator of greater risk of developing heart disease, high blood pressre and diabetes

Hip Circumference (cm)	Waist-to-Hip Circumference (cm)

Indicator	Cut-off points (cm)		Risk of metabolic complications
	Men	Women	
Waist Circumference	>94	>80	Increased
Waist Circumference	>102	>88	Substantially increased
Waist-to-hip ratio	≥ 0.90	≥ 0.85	Substantially increased

4) Blood Pressure

Systolic Blood Pressure	Diastolic Blood Pressure	Resting Heart Rate

When measuring blood pressure we obtain 2 reading

a) Your systolic blood pressure: the highest pressure when your heart beats pushing the blood around your body.
b) Your diastolic blood pressure: the lowest pressure when your heart relaxes between beats.

Blood Pressure Category	Systolic mm Hg (upper #)		Diastolic mm Hg (lower #)
Normal	less than **120**	and	less than **80**
Prehypertension	**120 – 139**	or	**80 – 89**
High Blood Pressure (Hypertension) Stage 1	**140 – 159**	or	**90 – 99**
High Blood Pressure (Hypertension) Stage 2	**160** or higher	or	**100** or higher
Hypertensive Crisis (Emergency care needed)	Higher than **180**	or	Higher than **110**

5) Capillary Blood Test

Blood Component	mmol/l	Desirable range
Blood Glucose		3.9-5.5
Triglycerides		<1.7
HDL Cholesterol		>1.6
LDL Cholesterol		<2.0
Total Cholesterol		<4.0

Triglycerides: It is a type of fat (lipid) fund in the blood. When you eat, your body converts any calories it doesn't need to use right away into triglycerides. The triglycerides are stored in your fat cells. Having a high level of triglycerides, a type of fat (lipid) in your blood, can increase your risk of heart disease.

Low Density Lipoproteins: These lipoproteins carry cholesterol throughout your body, delivering it to different organs and tissues. But if your body has more cholesterol than it needs, the excess keeps circulating in your blood. Over time, circulating LDL cholesterol can enter your blood vessel walls and start to build up under the vessel lining. Deposits of LDL cholesterol particles within the vessel walls are called plaques, and they begin to narrow your blood vessels. Eventually, plaques can narrow the vessels to the point of blocking blood flow, causing coronary artery disease. This is why LDL cholesterol is often referred to as "bad" cholesterol

High Density Lipoproteins (HDL) Cholesterol: Often referred to as “good” cholesterol, they act as cholesterol scavengers, picking up excess cholesterol in your blood and taking it back to your liver where it's broken down. The higher your HDL level, the less "bad" cholesterol you'll have in your blood.

Total Cholesterol: Your total blood cholesterol is a measure of the cholesterol components LDL (low-density lipoprotein) cholesterol, HDL (high-density lipoprotein) cholesterol, and VLDL (very low-density lipoprotein, which is the triglyceride-carrying component of lipids).

Blood Glucose: This is the main sugar found in the blood and the body’s main source of energy. Keeping it within normal ranges is very important to prevent future health complications.