Patterns of physical activity accumulation and their association with physical function

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I certify that all material in this thesis which is not my own work has been identified and that any material that has previously been submitted and approved for the award of a degree by this or any other University has been acknowledged.

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Abstract

This thesis investigates the relationship between patterns of physical activity (PA) accumulation and physical function, focusing on midlife populations. It begins with a systematic review of current evidence linking PA with physical function. The review finds that higher levels of PA, regardless of intensity, are generally associated with better physical function. However, significant gaps are identified, including a predominant focus on older adults and reliance on aggregate measures of PA that overlook how PA is accumulated. To address these gaps, novel metrics are employed to describe patterns of how upright and stepping events are accumulated. These include measures of the fragmentation, temporal distribution, and composition of upright, stepping, and sedentary events. These metrics aim to build on traditional aggregate measures of PA time or volume by adding new information about how a given level of activity is accumulated.

The thesis then examines how patterns of PA accumulation vary by a range of sociodemographic factors in two population cohorts: the early midlife population of the 1970 British Cohort Study and the older population of The Maastricht Study. Significant variations in activity accumulation are observed based on age, sex, Body Mass Index, self-rated health, disability, occupational activity, and smoking status—variations that are ignored if only aggregate measures are reported. Next, the thesis examines cross-sectional relationships between patterns of PA accumulation and self-reported and objective measures of physical function. Associations between patterns of accumulation and physical function outcomes are observed in both early and later midlife populations, independent of the volume of physical activity.

This thesis adds new knowledge by demonstrating that different people may accumulate the same volume of PA in very different patterns, and that these patterns are associated with physical function, independently of aggregate measures of PA volume. This suggests that future research investigating the relationship between PA and health should assess patterns of PA accumulation in addition to the amount of PA people undertake. Such measures are important not only in older adults but also in midlife, when declines in physical function start to occur. If these findings are confirmed in future longitudinal studies, the next revisions of public health guidelines, population surveillance, and intervention studies should reflect this new evidence to optimise health outcomes.

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Glossary

6MWT: refers to the 6-minute walk test.

ASTP: The Active to Sedentary Transition Probability is a measure of fragmentation of physical behaviours, defined as the probability of transitioning from an active to a sedentary state and calculated as the reciprocal of the average active bout duration.

BCS70: The 1970 British Cohort Study.

Burstiness: The inter-event time distribution (burstiness) refers to the variability and irregularity in the time between events, characterised by a non-uniform distribution of inter-event times (clustering of events followed by long intervals before the next event), versus a uniform distribution (inter-event times are equal). This concept is used to describe and analyse non-uniform distributions of inter-event times in various systems, used in this thesis to help to understand patterns of postural and activity data, with assumed mechanistic explanations discussed.

DMS: The Maastricht Study.

MVPA: refers to moderate-to-vigorous physical activity.

Patterns of physical activity: For the purpose of this thesis, pattern refers to the ways in which physical activity is accumulated and distributed through a day, including the frequency, duration, intensity, and temporal distribution of activity and inactivity events, as measured through event-based metrics.

Phenotype: refers to the observable characteristics or traits of physical activity patterns that reflect an individual's functional capacity.

SF-36: refers to the Short Form-36 survey. SF-36pf refers to the physical functioning sub-scale of the SF-36.

TCST: refers to timed chair stand test.

TUG: refers to the timed up-and-go test.

Chapter 1
Physical Activity and Physical Function: An Introduction

1.1 Physical function and health

1.1.1 An ageing population

The global population is undergoing a profound demographic shift characterised by the increasing prevalence of older individuals.[1] This demographic transformation is reshaping the landscape of healthcare and public health policy.[2] While the extension of life expectancy is celebrated as a testament to advancements in healthcare and living conditions, it is essential to acknowledge the substantial gap between life expectancy and healthy life expectancy.[3]

The concept of healthy life expectancy encapsulates the number of years an individual can expect to live in good health, free from debilitating illnesses and functional impairments.[4] This metric is a stark reminder of the challenges posed by an ageing population, as it reveals the discrepancy between the length of life and the quality of life. The consequence of this discrepancy is highlighted in the latest UK figures, which suggest 16 and 19 years of life will be lived in poor health for males and females, respectively.[5]

The years lived in poor health are influenced by a complex interplay of factors. Among the primary contributors to this phenomenon are disability and frailty, two closely related conditions that often overlap but are distinct.[6] *Disability,* defined as impairment, activity limitation, and participation restriction,[7] is considered both a social phenomenon and medical entity,[8] which can be either a

physical or mental impairment that substantially limits one or more of the major life activities.[9] *Frailty* is a multidimensional concept that overlaps with, but is distinct from, disability, defined as “a clinically recognised state of increased vulnerability”, resulting from age related declines in the body’s physical and psychological reserves.[10]

The cycle of frailty is depicted in **Error! Reference source not found.**. Evidence suggests that various exposures, chronic diseases, and ageing-related processes can trigger this cycle at any stage.[11] However, the initial signs typically include reductions in muscle strength, walking speed, and/or physical activity.[12] These early declines are predictive of the development of exhaustion and, in advanced stages, significant unintentional weight loss.

Frailty independently predicts progression of disability in older adults, in addition to falls, hospitalisation, and mortality.[8] All-cause mortality rates are higher among adults with disabilities.[13] Therefore, these conditions, individually and in concert, contribute significantly to the overall burden of years lived in poor health among the ageing population.[14,15] However, disability and frailty are preceded by impairments in physical function, and/or declines in physical activity.[16]

1.1.2 The role of physical function

A fundamental determinant of an individual's capacity to lead a healthy and independent life is their physical function. According to the World Health Organisation (WHO) International Classification of Functioning, Disability, and Health (ICF), physical function is a core component of an individual's overall functioning, encompassing both physical and psychological aspects of health.[7] The ICF framework provides a comprehensive view of health and health-related

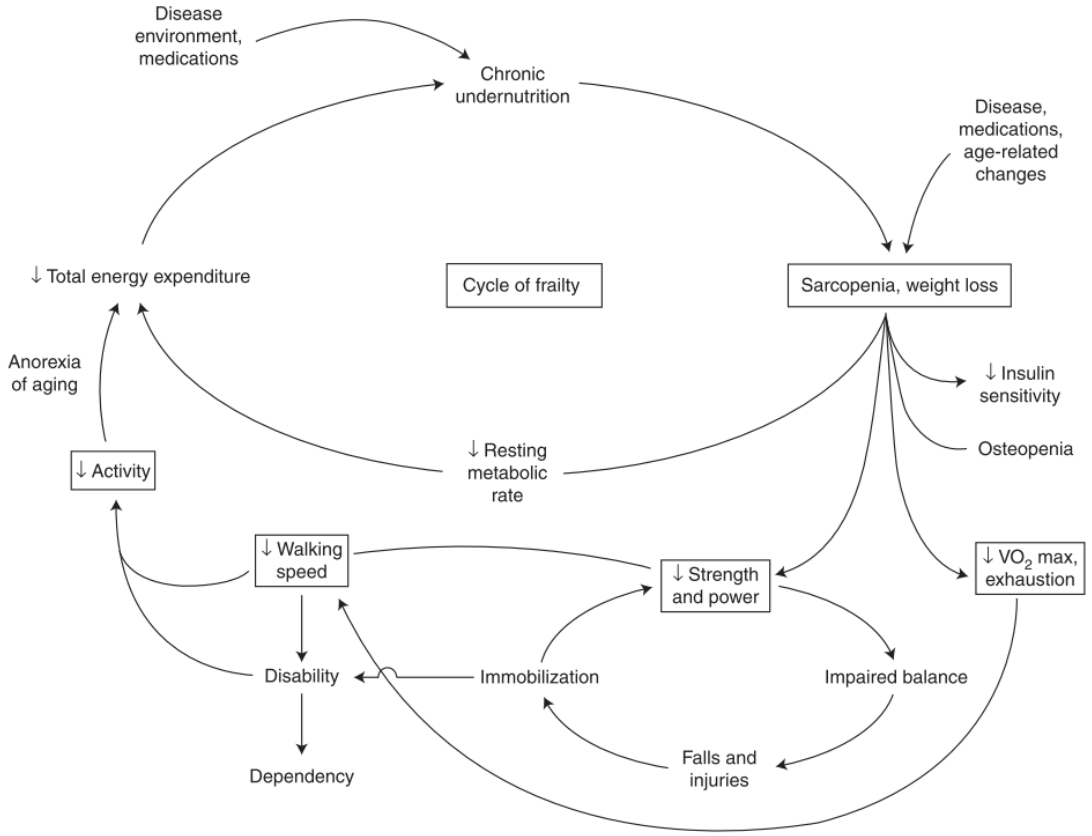


Figure 1.1. Cycle of frailty. (From Fried 2001; reprinted with permission.)

domains, considering how people with a health condition function in their daily lives rather than focusing solely on their diagnosis. This framework is particularly relevant when examining the precursors to disability and frailty, as it acknowledges the interaction between an individual's health condition, environmental factors, and personal factors.

This multidimensional concept is influenced by various factors including physical fitness components such as cardiorespiratory fitness, muscle strength, endurance, and flexibility, as well as clinical, behavioural, socioeconomic, and environmental factors.[11,17] Given its complexity, physical function is assessed through a range of measures, including physiologic impairment tests, field-based performance measures, and self-report surveys.[18,19] These assessments capture different aspects of physical function, from physiological limitations to limitations

in specific tasks and daily activities within one's social and environmental context.[20,21]

Despite the complexities involved in assessing physical function, performance-based measures emerge as a common, simple, and effective means of screening for and classifying low function.[22,23] While the multifaceted nature of physical function may present challenges, performance-based assessments offer a straightforward approach to evaluating functional capacity. By objectively assessing an individual's ability to perform specific physical tasks, these measures provide clinicians and researchers with valuable insights into functional limitations.[24]

In this thesis, physical function is primarily defined and measured using performance-based assessments, which offer objective indicators of an individual's lower extremity functional capacity and overall strength. These assessments, such as gait speed, grip strength, and chair rise tests, are employed to quantify the physical capabilities that are critical to maintaining independence and preventing the onset of frailty and disability.[11,25] In addition, these measures are associated with future health outcomes and mortality.[26–28] While the ICF provides a broad conceptual framework, this thesis focuses on these performance-based measures of function and seeks to determine if they are associated with variations in patterns of physical activity accumulation.

1.1.3 The prevalence and burden of low physical function

The prevalence of low physical function is high in general populations with 20-50% of people recording slow gait speed, and 20% with weak grip

strength.[29,30] Prevalence increases with age, co-morbid health conditions, smoking, and is higher in women.[31–33]

The burden imposed by low physical function extends beyond individual well-being. Declines in physical function precede frailty and disability;[8,34] which lead to significant economic, social, and healthcare-related consequences due to increased productivity loss and healthcare demand.[14,15] In addition to financial costs, the burden encompasses reduced quality of life, increased caregiver burden, and greater dependency on social and healthcare systems.

It is essential to recognize the role of low physical function as a precursor to frailty and disability and the associated adverse health outcomes. The ICF framework reinforces the importance of understanding physical function within the broader context of an individual's environment and personal factors. This holistic approach is critical in identifying early signs of functional decline, which can be addressed before people progress to frailty or more severe disability. Maintaining physical function as we age, particularly through proactive measures like regular physical activity, can delay or even prevent the onset of frailty and disability.[35–37] The focus of this thesis aligns with the preventive aspect emphasised by the ICF, highlighting the potential for early detection and intervention.

1.1.4 Changes in physical function across the life course

Physical function encompasses a broad range of abilities, including strength, balance, mobility, and coordination, all of which are subject to change across the life course. These changes are influenced by various factors, including ageing, physical activity levels, genetics, and the presence of chronic

conditions.[37,38] Understanding these changes is essential for surveillance of physical function and developing strategies to maintain or prevent functional decline.

As individuals age, there is a general decline in physical function, characterised by reductions in muscle mass and strength, decreased flexibility, and impaired cardiovascular and respiratory function.[39,40] These changes can lead to a decrease in overall physical performance, making everyday activities more challenging and increasing the risk of disability and dependence. The rate of decline can vary widely among individuals, depending on their lifestyle, particularly their levels of physical activity.[35]

Balance and gait are particularly susceptible to age-related decline. Balance deteriorates due to diminished sensory input, such as impaired vision, reduced proprioception, and a less responsive vestibular system.[41] Similarly, gait becomes slower and more variable, with shorter strides and increased time spent in the double-support phase.[42] This in turn leads to an increased risk of falls, which creates a cyclical effect where a fear of falling can reduce activity and further reduce function.[43] Falls are a major cause of injury and loss of independence in older adults.[44,45]

Neurological changes, including decreased motor neuron function and reduced cognitive processing speed, further exacerbate declines in physical function.[46] The ageing brain shows diminished capacity for neuroplasticity, affecting motor control and coordination. These changes can lead to slower reaction times, reduced agility, and difficulties in performing complex motor tasks, all of which contribute to the overall decline in physical function.[47]

The relationship between physical activity and physical function is bidirectional. While engaging in regular physical activity can help slow or even

reverse some aspects of functional decline, individuals with higher physical function are more likely to remain active and vice versa. This creates a positive feedback loop, where maintaining physical function through activity further promotes continued activity. However, as previously discussed, taking the approach of physical activity as the explanatory variable allows us to focus on identifying and promoting modifiable behaviours that can prevent or delay the onset of functional decline.

1.1.5 Physical function in midlife

Due to the prevalence of poor physical function, frailty, and disability in older adults, physical function is traditionally screened for in later-life;[48] therefore, the majority of research has also focussed on physical function in older adults.[28,49,50] However, impairment in physical function can arise earlier in the life course,[51,52] and evidence suggests reductions in physical function are becoming more common among those aged 55-64 years, whilst staying relatively constant among those aged 65-84 years.[53] Reports on the prevalence of physical function impairment in midlife populations range from 19% among those aged 40-55 years to 50% among those 56-66 years.[54–56]

The trajectory of age-related decline in physical function means that decrements in function occur, and are detectable, in midlife particularly in those with morbidity.[57] Moreover, transitions and reversal between states is possible;[9,58] therefore identification of physical function impairment at the earliest feasible stage is desirable, to optimise the potential benefits of intervention.[57] Rather than treating older adults reactively, it has been suggested that a proactive policy for successful ageing be promoted from midlife onward.[59,60] To identify impaired

physical function in midlife and potentially intervene, improved methods of screening are required. This first requires a sound understanding of the determinants of low function.

1.1.6 Determinates of low physical function

The onset and progression of low physical function result from a complex interplay of various determinants. Factors such as age, chronic health conditions, genetics, and lifestyle choices play crucial roles in shaping an individual's physical function.[33,61] A model of the wide range of determinants of physical functioning is presented in Figure 1.2. Some of these factors are immutable, while others offer opportunities for intervention, albeit with varying degrees of difficulty. However, one determinant emerges as particularly pivotal in shaping physical function: physical activity, or conversely, physical inactivity.

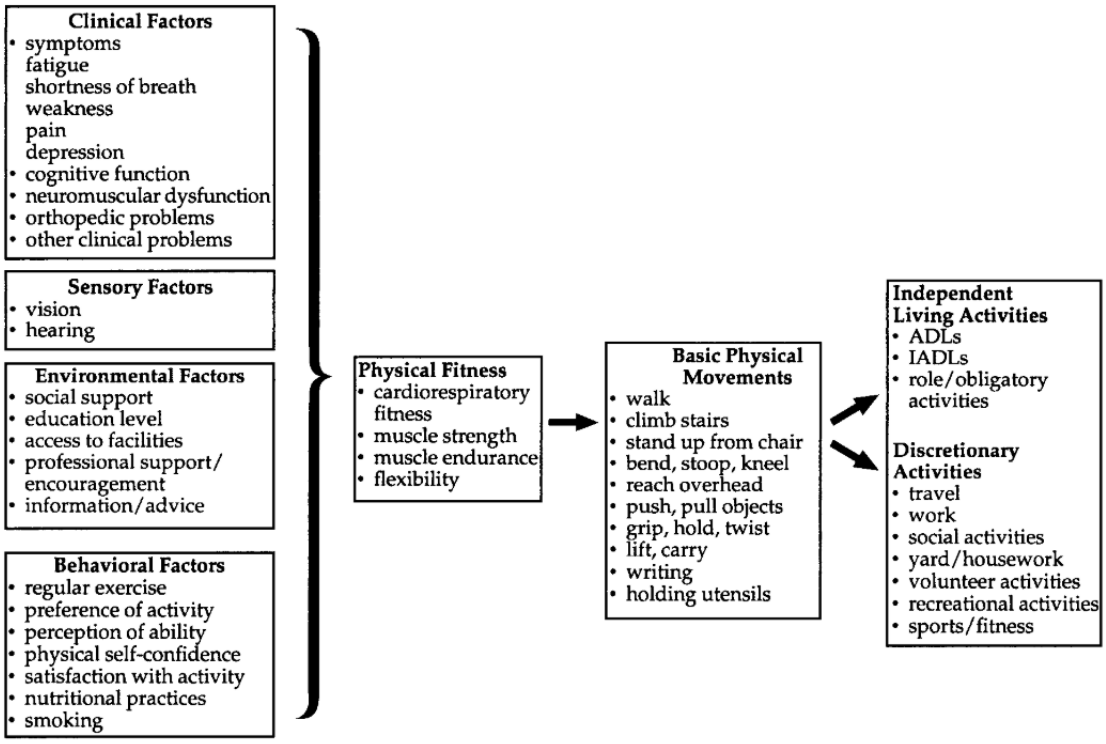


Figure 1.2. Model of the determinants of physical functioning. (From Painter et al., 1999; reproduced with permission.)

1.2 Physical activity and health

1.2.1 Benefits of physical activity for health

Physical activity is broadly defined as any bodily movement produced by skeletal muscles that results in increased energy expenditure, encompassing various domains such as occupational, domestic, travel, or leisure activities.[62] The well-documented benefits of physical activity in preventing and managing a range of health conditions underscore its importance in public health.[63] Regular physical activity offers a multitude of health benefits across the lifespan.

Engaging in physical activity is associated with a reduced risk of developing various chronic diseases, including heart disease,[64] stroke,[65] type 2 diabetes,[66] and certain cancers.[67] Moreover, physical activity plays a crucial role in managing existing health conditions and improving overall quality of life.[68] Studies have consistently shown that regular physical activity is associated with a reduced risk of premature mortality, underscoring its significance in extending lifespan and promoting longevity.[69] However, the benefits of physical activity extend beyond physical health and encompass mental well-being, cognitive function, and social connectedness.[70] Encouraging individuals to adopt and maintain active lifestyles is essential for promoting optimal health and well-being across populations.

1.2.2 Prevalence and burden of physical inactivity

Physical inactivity is defined as failing to attain the physical activity guidelines,[71] which are discussed in the following sub-section. The prevalence of physical inactivity is a significant public health concern globally. According to the WHO, worldwide around 27% of adults are considered physically inactive.[72] This trend is particularly pronounced in high-income countries, with approximately

36% of adults in the European Union,[73] and around 34% of men and 42% of women in the UK, physically inactive. These numbers highlight the need for targeted interventions to address, to promote, and to enable physically activity lifestyles.

The WHO estimate that between 2020 and 2030 almost 500 million people will develop non-communicable disease attributable to physical inactivity, at an annual cost of $27 billion.[72] However, the burden associated with physical inactivity extends beyond treating noncommunicable diseases and encompasses significant economic and societal costs. In addition to the direct healthcare costs, there are also indirect costs related to productivity loss.[74] The economic burden of physical inactivity underscores the importance of implementing effective strategies to promote regular physical activity and mitigate its adverse effects on health and society.

1.2.3 Physical activity and public health

1.2.3.1 Guidelines

The history of physical activity guidelines can be traced back to the late 20th century when national and international health organizations began recognising the importance of regular physical activity in preventing chronic diseases and promoting overall health. Early guidelines recommended ≥30 min of moderate-intensity physical activity on five days per week.[75] This was followed by an update that included the option for overall shorter durations at a higher intensity (≥20 min of vigorous-intensity physical activity on three days per week).[76] A minimum suggested bout-duration to accumulate this activity (10 minutes) was introduced, before being removed in the latest iterations.[77] This was

a result of evidence suggesting that accumulating activity in bouts of any duration confer health benefits.[78]

Current national and international guidelines recommend at least 150 minutes of moderate-intensity aerobic activity or 75 minutes of vigorous-intensity aerobic activity per week.[79,80] Further to the aerobic activity, guidelines now recommend minimising and breaking up sedentary time. Evidence suggests high levels of sedentary time are associated with greater risk of all-cause and cardiovascular mortality, independent of moderate-to-vigorous physical activity (MVPA) levels.[81] However, evidence on the dose-response relationship is lacking and therefore guidelines remain general, with insufficient evidence to support recommendations on interrupting sedentary time with standing.[77] In addition, muscle strengthening activities, on at least two days per week, have been added to the guidelines. These activities are associated with lower risk and mortality in major non-communicable diseases,[82] as well as falls prevention.[83]

Population specific guidelines have been introduced, with UK variations for early years (under 5 years), children and adolescents, adults (18 to 64 years), older adults (65+ years), pregnant and postpartum women, and disabled adults.[79] The difference between recommendations are minimal, particularly for adults and older adults. However, the WHO guidelines do differ with the conditional element that older adults should perform balance and strength training on three or more days a week, to improve functional capacity and reduce risk of falls.[79]

These guidelines were introduced, and are updated, as adherence to them is associated with significant health benefits. However, adherence to these guidelines is consistently low and has been since their introduction,[84,85] with adherence even lower in older adults, and those with multimorbidity.[85,86] Notably,

the proportion of adults meeting the muscle strengthening element of the guidelines is considerably lower than the proportion meeting the aerobic element.[87] All of which highlights the importance of continued pursuit of not only developing optimal physical activity guidelines, but improving promotion of physical activity, and intervention both at the individual and population levels.

1.2.3.2 Intervention

Interventions to promote physical activity encompass a range of strategies aimed at increasing participation in regular physical activity.[80] These interventions may include educational programs, community-based initiatives, environmental modifications, and policy changes designed to create supportive environments for physical activity.[88] There is evidence for the effectiveness of physical activity interventions for increasing levels of physical activity across a range of populations.[80,88,89] However, the lack of studies with longer follow-ups is regularly highlighted as an important limitation when evaluating the effectiveness of these interventions.[88,90]

A reliance on self-reported outcomes of physical activity limits the evaluation of many intervention studies. For example, a systematic review of inactive, but otherwise healthy, populations found interventions to be effective, even at 6-month follow-up.[91] However, sub-group analysis showed that the pooled effect was only significant for studies employing self-report measures of physical activity, and not for those utilising objective measures. Self-report measures are associated with substantial measurement error and bias, which are discussed in detail in Chapter 3. In this instance, social desirability bias may have led to an over-reporting of activity levels,[92] whereas the objective measures were

not susceptible to this bias. Further limitations to intervention evaluation, relevant to the focus of this thesis, include the reliance on only considering duration or volume of physical activity as an outcome.

This evidence, and its limitations, extend to physical activity interventions aimed at improving physical function. Review evidence suggests structured exercise interventions can improve or delay the loss of physical function in older adults.[93–95] The potential benefit of physical activity across multiple physiological systems means physical activity-based intervention may be more useful than interventions targeting a single system, e.g. pharmacological interventions.[96] However, despite showing initial increases in physical activity aimed at maintaining function, some studies showed these increases were not maintained at follow-up.[97] Effective implementation and assessment of these interventions necessitates a comprehensive understanding of physical activity behaviours. It also demands robust measures capable of detecting nuanced changes in physical activity behaviour.

1.3 Physical activity and physical function

Understanding the association between habitual physical activity and physical function is crucial for promoting healthy ageing and maintaining independence in older adults. Longitudinal evidence has shown older women who engaged in regular physical activity had higher levels of physical function (measured by the Timed Up-and-Go) at follow up, though physical activity was self-reported.[98] Systematic reviews and meta-analyses have shown positive associations between supervised physical activity interventions and indices of healthy ageing.[93–95] However, the evidence remains limited due to a reliance on

self-report measures of physical activity, that may over- or under-estimate activity levels, impacting associations, and heterogeneity in physical activity categorisation and physical function assessment methods across studies.

Emerging evidence suggests that the pattern of physical activity may play a significant role in determining health outcomes.[99] Studies have shown that patterns characterised by frequent transient or fragmented bouts of physical activity are associated with a range of health outcomes, independent of total physical activity volume.[100–103] In well-functioning older adults (65+ years), fragmented physical activity was associated with all-cause mortality, while volume of physical activity was not.[102] In addition, fragmentation metrics are associated with physical function outcomes, including gait speed, walking endurance, and the Short Physical Performance Battery (SPPB).[104,105]

The interest and evidence base in these types of pattern metrics are beginning to gain momentum, with a potential proposal for a phenotype of accelerated ageing.[106] However, there is a paucity of research on the temporal pattern of physical activity accumulation on health and physical function outcomes. Metrics that quantify the temporal distribution of clustering of activity together in short bursts followed by long periods of sedentary behaviour, may be indicative of decreased capacity and confidence in undertaking sustained periods of activity. Further research is needed to fully characterise and understand the implications of different patterns of physical activity accumulation on health outcomes.

1.3.1 Physical activity and physical function in midlife

The trajectory of age-related decline in physical function means that decrements in function occur, and are detectable, in midlife particularly in those with morbidity.[57] Moreover, transitions and reversal between states of robust, pre-frailty (low function), frailty, and disability is acheivable;[9,58] therefore, identification of physical function impairment at the earliest possible stage is desirable, to optimise the potential benefits of intervention.[57] Rather than treating older adults reactively, it has been suggested that a proactive policy for successful ageing be promoted from midlife onward.[59]

Engaging in regular physical activity has been shown to preserve physical function in midlife adults.[107,108] According to the ICF framework, maintaining physical function involves not just the prevention of disease but also the promotion of health and well-being within the context of one's environment and personal circumstances.[7] This holistic view supports the idea that interventions aimed at enhancing physical function should focus on prevention rather than reversal, with midlife representing a critical period for such proactive measures.

The performance-based measures of physical function used in this thesis are particularly relevant for early detection of functional decline. Although midlife is less likely to be targeted for intervention, as previously discussed, midlife is a key period for preserving physical function and retarding the rate of decline.[60] This approach aligns with the ICF's emphasis on early intervention to maintain and improve function, ultimately reducing the burden of frailty and disability in later life.

Acknowledging the adage "Prevention is better than cure", prioritising efforts to prevent decline or reverse early signs, would be more effective than addressing impairment once it has become a clinical issue. However, the limited

evidence available in midlife populations suffers from similar limitations as those discussed earlier; self-reported physical activity and/or physical function, and a focus on aggregate measures of duration or volume of activity. To improve our understanding of these associations, a move to objective measures which are free from the error and bias associated with self-reports, and exploration of metrics which describe day-to-day patterns of physical activity is required.

1.4 Summary

This thesis provides a comprehensive exploration of the connections between physical activity and physical function, focusing on the challenges posed by relying on self-report measures of physical activity and aggregate measures of duration or volume, while neglecting important differences in patterns of daily activity. Within the context of an ageing population, it highlights the pressing need to bridge the gap between life expectancy and healthy life expectancy. This disparity underscores the prevalence and impact of disability, frailty, and low physical function, which collectively contribute significantly to the burden of poor health among older adults. Understanding the determinants and consequences of low physical function emerges as a pivotal aspect of promoting healthy ageing, with midlife presented as a preventative window-of-opportunity for intervention.

Despite the well-documented benefits of physical activity for health, the persistent challenge of physical inactivity remains a public health imperative. The aim of this thesis is to improve our understanding of patterns of physical activity accumulation and their association with physical function.

1.5 Thesis objectives

1) **Understand the most recent evidence for the association between physical activity and physical function.**

2) **Derive a suite of physical activity pattern metrics from thigh worn accelerometer postural and stepping data.**

3) **Examine the variation in pattern metrics across sociodemographic factors in a midlife population.**

4) **Explore the associations between derived pattern metrics and a range of performance based physical function measures.**

5) **Explore these associations in an early midlife population.**

Chapter 2
Review of Current Literature

2.1 Overview

Chapter 2 aims to address the first thesis objective by providing a comprehensive review of the current literature on associations between physical activity and physical function. We identified a reliance on summary and aggregate estimates of physical activity, and a lack of research in midlife populations. The systematic review and meta-analysis within this chapter was published as a peer reviewed paper in 2023: *Associations between device-measured physical activity and performance-based physical function outcomes in adults: a systematic review and meta-analysis.*[109] The published version is available digitally using the following DOI: http://dx.doi.org/10.1136/bmjph-2023-100000.

2.2 Introduction

As described in Chapter 1, disablement models support the causal pathway from limitations in physical function to disability, and loss of independence once these limitations interfere with activities of daily living.[110,111] Relatively simple performance-based measures of physical function such as grip strength, gait speed, chair rise tests, walk tests, and balance can be strong predictors of adverse future health outcomes in older adults[50,112–114] and late midlife.[115] Weak grip strength and slow gait speed are also characteristics of Fried's frailty phenotype.[11] Chair rise tests and grip strength have been recommended as screening and diagnostic tools for sarcopenia.[39] However, physical function

assessments largely take place in clinical settings and only tend to occur when a person is attending a medical setting due to an adverse health event.

Declining physical function is a common factor of ageing and, despite impairments typically being considered in older age, they can occur much earlier in midlife (45-64 years).[60] Depending on the point of intervention, declines in physical function can potentially be prevented, retarded, or reversed.[116] However, identifying opportunities to intervene in midlife relies on the ability to detect impairments in function, prior to the point that reduced function results in presentation in medical settings. Remote health monitoring, through wearable devices, is one possible solution to early detection of pre-symptomatic and pre-clinical changes in physical function.[117] Wearable devices for monitoring health outcomes are already being employed by both individuals, to track their own health through activity levels, and by clinicians as a method of early detection.[118]

Wearable devices, such as accelerometers, have become increasingly popular for measuring physical activity in health research.[119] There is strong evidence that structured physical activity and exercise interventions can improve or delay the loss of physical function in older adults.[93,95] Therefore, it is reasonable to consider that physical activity measures may be a potential proxy for physical function. Prior to this it is necessary to know what measures of physical activity are most strongly associated with, or even predictive of, physical function. However, there is a paucity of evidence on the association between physical activity and physical function in midlife when function is likely to be high but declining.

Systematic review level evidence of the associations between free-living physical activity and physical function is limited, with reviews often focussing on

interventions in people with reduced function.[93,95] A meta-analysis has shown light intensity physical activity (LPA) and MVPA are be associated with grip strength and chair rise tests;[120] however, the focus of the meta-analysis was on the association between physical activity and strength rather than physical function. In addition, included studies were limited to older adults, preventing insight into important associations of physical activity and physical function in midlife. It also included a mix of studies of healthy populations as well as studies of specific clinical populations (e.g. chronic obstructive pulmonary disease, diabetes, osteoarthritis), where the association between physical activity and physical function might be confounded by these long-standing health conditions. No analysis of the differences in associations between studies of healthy and clinical populations was performed.

To our knowledge, there are no systematic reviews of the association between physical activity and physical function indicators such as gait speed, walk tests, balance, or the timed up-and-go test (TUG); and no reviews that examine the associations of physical activity and physical function in both midlife and older adulthood. This systematic review and meta-analysis examines associations between wearable, device-measured physical activity and a range of performance-based physical function outcomes in non-clinical adults. The findings will inform the potential of remote monitoring of early declines in physical function, that could inform the development of future screening programmes and interventions.

2.3 Methods

The review was conducted according to the COSMOS-E guidance on conducting systematic reviews and meta-analyses of observational studies[121] and the Cochrane handbook;[122] and reported according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses guidelines.[123] The protocol was registered in the International Prospective Register of Systematic Reviews – PROSPERO (CRD42021282861).

2.3.1 Search strategy

Systematic literature searches were conducted in PubMed (including Ovid MEDLINE, HMIC and Embase), EBSCOhost (including CINAHL and SPORTDiscus) and Web of Science for studies published between database inception to 15th June 2021; a top-up search was performed on 11th November 2022. The search strategy included key words related to physical activity, device-based measures of physical activity, physical function outcomes, and observational study designs (Appendix 8.1). In addition, supplementary searches were performed through bibliography screening of included papers to identify any other potentially relevant publications.

2.3.2 Study Selection

Inclusion was determined by two independent reviewers (JC + GM or RL). Disagreements were resolved by discussion with the third author (GM or RL), if required. Study selection was completed in two phases: title and abstract screening was performed to exclude clearly irrelevant studies, after which full texts were screened. If two or more studies reported similar associations for the

same cohort, we included the study with highest quality score or largest sample size, respectively.

2.3.3 Eligibility criteria

2.3.3.1 Population

Participants were adults (≥18 years old) recruited from non-clinical, community dwelling populations. Studies of adults recruited specifically due to the presence of, or expected progression to, a disease or other clinical condition were excluded. These inclusion criteria allow for generalisation to the general population, including those in midlife; these assertions cannot be made from studies of clinical populations of solely older adults.

2.3.3.2 Exposure

Studies reporting continuous wear data from remote wearable, device-based measures of physical activity were included. Depending on device, this included studies that advised participants to wear the device for 24-hours continuously, or to only remove the device during sleep and water-based activity. Studies which collapsed continuous physical activity data were contacted to try to obtain the continuous association. We excluded studies that exclusively reported estimates of sedentary behaviour.

2.3.3.3 Outcome

Studies reporting performance-based physical function instruments, adopted by clinicians and researchers, were included. These include; grip strength, gait speed, chair rise tests, walk tests, balance tests or composite assessments of these measures.[22,39,124]

The selection of functional measures for this study was guided by the need to capture objective, performance-based assessments of physical function that are both reliable and sensitive to change. First, these measures provide a direct evaluation of an individual's physical capabilities, offering an objective alternative to self-report measures of perceptions of unction that are susceptible to recall bias and subjectivity. By assessing actual performance, these tests allow for a more standardised evaluation of physical function, which is importantcrucial for accurately detecting subtle changes over time, changes resulting from intervention and for harmonising measures across studies.[125]

Performance-based measures are particularly valuable in the context of ageing and midlife populations because they can detect early signs of functional decline that may not yet be perceived by the individual. Self-report measures, while useful for capturing perceived function and quality of life, often lack the sensitivity needed to identify small, early impairments declines in physical function that indicate an accelerated pathway to loss of function and pre-frailty. In addition, performance-based assessments such as gait speed and grip strength have been shown to be strong predictors of future health outcomes, including disability, morbidity, and mortality (see Chapter 4.6).

The choice of these specific functional measures was also informed by their relevance to the study's target population, individuals in midlife, and the specific health outcomes of interest, including the prevention of disability and maintenance of independence. The research chapters of the thesis include both performance-based measures and a self-report measure of function (SF-36). However, within the scope of a systemic review and meta-analysis, including both performance-based and self-report measures was not feasible or appropriate for

evidence synthesis. The evidence for physical activity and the SF-36 is reviewed in Chapter 4.6. The measures chosen for this systematic review cover a wide range of measures of function and appear in a sufficient number of studies to permit evidence synthesis and meta-analysis, the aims of this section.

2.3.3.4 Study design

The review included observational studies (both cross-sectional and prospective designs), which reported associations between the exposures and outcomes. Experimental studies and randomised controlled trials were excluded. No restrictions were placed on country or date. Only full texts, in English, were included.

2.3.4 Data extraction

Two authors (JC + RL) independently extracted the following data from included studies: (1) author, study year and country of origin; (2) cohort and study design; (3) sample size and sex distribution; (4) age of study participants; (5) device used for physical activity measurement and metrics reported; (6) test used for assessing physical function and metrics reported; (7) statistical analyses undertaken including and covariates included; (8) key results for the association between physical activity and physical function. Discrepancies in extracted data were resolved by discussion with a third author (GB), if required.

2.3.5 Assessment of study and evidence quality

Two authors (JC + RL) independently assessed the quality of included studies using an adapted version of the National Institutes of Health *Quality Assessment Tool for Observational Cohort and Cross-Sectional Studies*

(Appendix 8.2). Scores were given ranging from 0 to 12, with higher scores indicating higher quality. Discrepancies in quality assessment were resolved by discussion with a third author (GB), if required. The continuous quality rating scores were used in sensitivity analyses.

2.3.6 Statistical analysis

The required association statistic was the standardised regression coefficient (β) and standard error (SE), see detailed explanation of β coefficient below. Using the β coefficient allowed for synthesis across different metrics and units for both physical activity and physical function variables. If only a partial correlation coefficient was obtainable, this was used as an approximation of the β coefficient, with sensitivity analysis performed to ensure these coefficients would not bias the pooled effect.[126]

Some physical function outcomes have slightly different measurement protocols, and these are grouped together in this review as follows; the chair-rise test outcome includes the 30-second and the 5-repitition variants; gait speed includes any protocol measuring normal/usual or maximal gait speed over a distance ≤10 meters; grip strength includes any protocol using a hand dynamometer to obtain maximal grip strength; walk tests included the 6-minute walk test (6MWT) and 400-meter walk test (400mWT), or any variant covering a similar time or distance in different units; the timed up-and-go test (TUG) includes both the 8-foot and 3-meter variations; and balance includes any continuous measure of tandem, semi-tandem or single-leg stance, with eyes closed or open. Where composite scores of the above measures were reported for an overall physical function score, we sought to obtain the associations for the individual components.

The adjusted β coefficients were extracted from included papers, or obtained from converting the unstandardised regression coefficient (*b*) where possible using the following equations:

$$\beta = \frac{SD_x}{SD_y}\, b \text{ and } SE(\beta) = \frac{SD_x}{SD_y}\, SE(b)$$

where SD_x is the standard deviation of the physical activity exposure and SD_y is the standard deviation of the physical function outcome.[127] If the SD_x or SD_y was reported in two sub-groups and needed to be combined the following equation was used to obtain the full sample SD:

$$\mathrm{SD}_{full\ sample} = \sqrt{\frac{(n_1 - 1)\mathrm{SD}_1^2 + (n_2 - 1)\mathrm{SD}_2^2 + \frac{n_1 n_2}{n_1 + n_2}\,(\mathrm{M}_1 - \mathrm{M}_2)^2}{n_1 + n_2 - 1}}$$

where n_1 and n_2 are the sample sizes of the two sub-groups, SD_1 and SD_2 are the sub-group SDs, and M_1 and M_2 are the subgroup means.(28) If SE was not reported, it was calculated from the 95% CIs using the following equation:

$$\mathrm{SE} = (upper\ limit - lower\ limit)/3.92$$

where the *upper limit* and *lower limit* refer to the 95% CI of the effect size.[128] In cases where the partial correlation is used, the following equation was used to calculate the SE of the partial correlation:

$$\mathrm{SE} = \frac{1 - r^2}{\sqrt{n - 1}}$$

where *r* is the partial correlation coefficient and *n* is the sample size.[128] If a study reported associations separately for two sub-groups (e.g. males and females) these were combined using the following equations to provide a composite effect size:

$$\beta_p = (W_1\beta_1 + W_2\beta_2)/(W_1 + W_2)$$

$$SE(\beta_p) = \sqrt{\frac{1}{W_1 + W_2}}$$

where β_1 and β_2 are the β coefficients for the two sub-groups, and SE(β_1) and SE(β_2) are the respective SEs. The weightings for the two sub-groups are W_1 = 1/ SE(β_1))^2 and W_2 = 1/ SE(β_2))^2.[128]

Where required, we contacted authors to request the β coefficient adjusted for age + sex, or additional unpublished data to allow us to estimate the β coefficient from the effect size published in the paper. If authors had measured additional physical activity or physical function outcomes but not reported these associations, these were also requested. β coefficients were inversed for physical function outcomes where a lower score indicated better function, so that all positive effects in this review indicate better/higher physical function.

Meta-analyses were performed to obtain a pooled estimate of individual β coefficients for associations between the reported physical activity measures and physical function outcomes, visualised as forest plots. Ideally, included effect-sizes would be adjusted for the same covariates;[128,129] however, due to varying adjustment models across papers, the included estimates were extracted from the following order of models: 1) age + sex; 2) age, sex + additional factors. We used random-effects models to account for both between and within study variance, with inverse variance as the weighting method. Statistical heterogeneity was estimated using the I-squared analysis (I^2). An I^2 (the variation across studies due to heterogeneity rather than chance) of <40% was considered low heterogeneity and an I^2 of >75% was considered high heterogeneity.[122]

Heterogeneity, along with the number of studies within each meta-analysis should be considered when interpreting the pooled effects. Where possible (≥10 studies in the meta-analysis)[122] meta-regressions were run to examine the individual effects of sex (percentage female), age, quality assessment, and study sample size (n) on the associations.

2.3.6.1 Sensitivity analyses

Leave-one-out sensitivity, the process of rerunning analyses leaving one study out at a time, was performed on each meta-analysis to explore the influence of individual studies on the overall pooled effect. In addition, for meta-analyses with ≥10 studies, a visual and statistical evaluation of publication bias was performed using funnel plots and Egger's regression tests ($p<0.05$ indicated publication bias).[130] For the purpose of quantifying the magnitude of the pooled effect size, the following values were used: 0.10-0.19 = small, 0.20-0.29 = medium, and ≥0.30 = large.[128] So as not to entirely exclude them from the review, studies for which a β coefficient was not obtained were included in a vote count summary and the directions of associations compared with those studies included in the meta-analysis via chi-square test. All analyses were performed in Stata v.17 (StataCorp. 2021. *Stata Statistical Software*: Release 17. College Station, TX: StataCorp LLC).

2.4 Results

2.4.1 Search and study selection results

The original and top-up database searches identified 2741 articles after duplicates were removed, of which 2533 were excluded based on title and

abstract screening.[123] Two hundred and eight full-text articles were reviewed, 43 of which fulfilled the inclusion criteria. Two studies, by the same author, used data from the same pool of participants,[131,132] the study with the larger sample size and greater number of reported associations was chosen for inclusion.[131] Resulting in a total of 42 included publications (Figure 2.1).

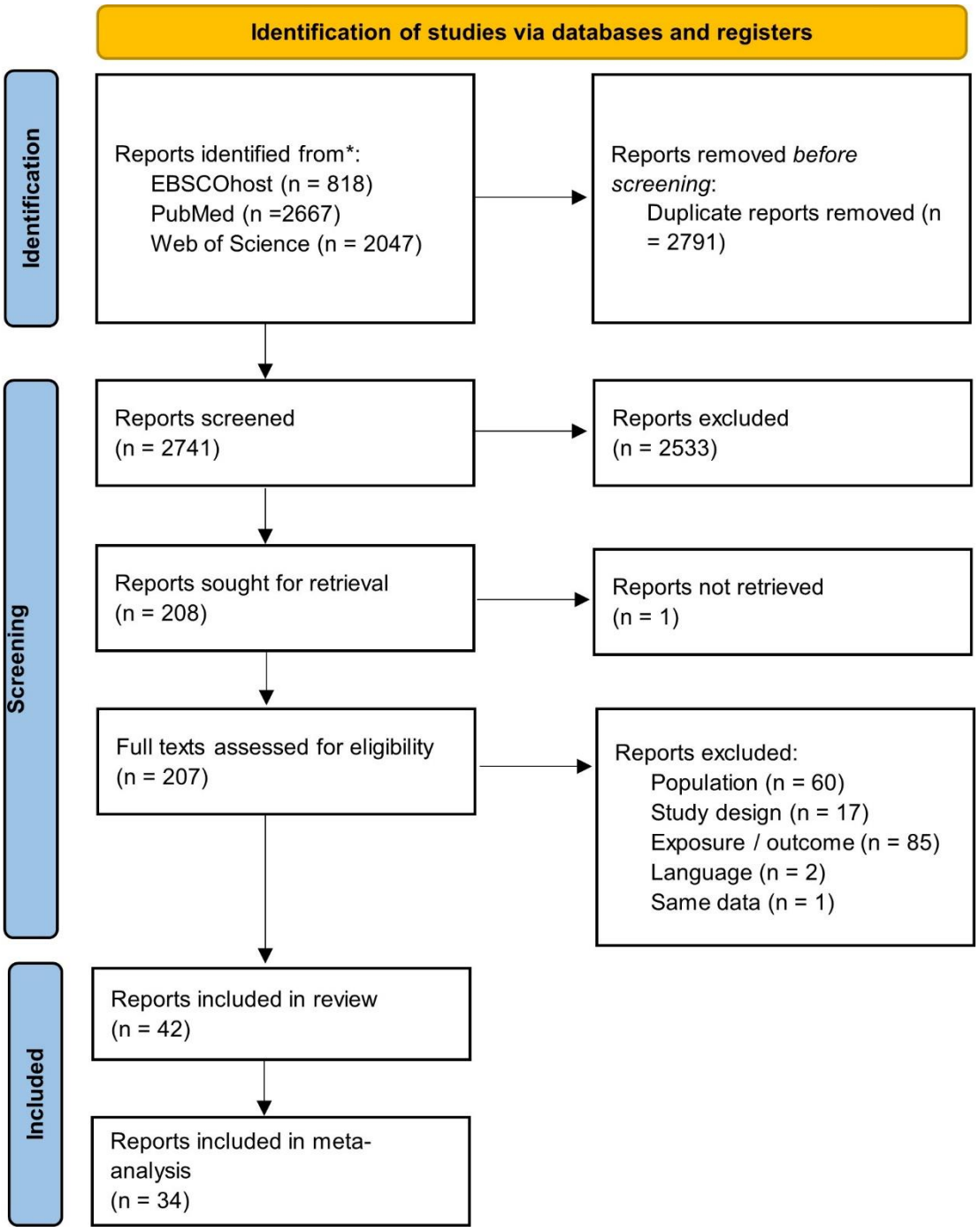


Figure 2.1. PRISMA flow diagram showing the screening process and the search results. PRISMA, Preferred Reporting Items for Systematic Reviews and Meta- Analyses.

2.4.2 Study characteristics

The 42 included studies represented N=27276 participants (range: n=64 to 4702), with an average mean sample age of 70.3 years (range: 46 to 90 years) (Appendix 8.3). Study samples were on average 63.6% female. Three studies were prospective[133–135] and the other 39 were cross-sectional.[25,104,131,136–170] Most studies used accelerometers to measure physical activity (k=39), with one study using a pedometer,[163] and two using the *Actiheart* combined accelerometer and heart rate sensor.[141,167] Device locations across studies were as follows; hip/waist (k=27), thigh (k=3), wrist (k=3), other (k=9). Studies reported the following physical activity outcomes; MVPA (k=31), LPA (k=17), TPA (k=15), and average or total step count (k=14). A range of accelerometer cut-points were used for classifying LPA and MVPA across studies, the most common non-proprietary classifications were Troiano[171] (k=6) and Freedson[172] (k=5) (Appendix 8.3).

Studies also reported the following physical function outcomes; gait speed (k=27), handgrip strength (k=24), chair rise tests (k=17), TUG (k=15), balance (k=12), endurance walk tests (k=10), and composite physical function tests (k=6) (Appendix 8.3). There were an insufficient number of studies employing composite measures of physical function for these to be pooled; only one of the four studies that did report composite measures was excluded from meta-analyses, where the associations of individual measures within the composite score were not reported or obtainable.[145]

Of the 42 studies identified for inclusion in this review, a standardised regression coefficient (β), adjusted for at least age + sex, was obtained for 34 studies and thus were included in pooled analyses. Authors of 14 of these studies provided either additional data to allow the estimation of the β coefficient, or effect

Table 2.1. Characteristics of articles assessing the association between device-measured physical activity metrics with performance-based physical function outcomes in adults.

Author (Year), Country	Cohort	Design	Sample (n)	Age	Sex (F%)	PA measures				PF measures							Adjustments		
						L	M	S	T	B	C	G	H	T	W	C	A	S	A
Adachi (2018), JP	N/R	CS	308	79.9 (3.6)	100		✓	✓				✓					✓	n/a	✓
Aggio (2016)*, GB	BRHS	CS	1286	78.2 (4.5)	0	✓	✓					✓	✓				✓	n/a	✓
Aoyagi (2009), JP	Nakanojo	CS	170	72.6 (4.6)	55.3			✓	✓	✓		✓	✓				✓	✓	
Cooper (2015), GB	NSHD	CS	1727	63.3 (1.1)	51.5		✓		✓	✓	✓		✓	✓				✓	
Cooper (2020), GB	BCS70	CS	4702	46 (0)	52.4		✓		✓				✓				n/a	✓	✓
Davis (2014), GB	Project OPAL	CS	217	78.1 (5.8)	50.2		✓			✓	✓	✓					✓	✓	✓
Duck (2019), US	N/A	CS	99	74 (6.5)	78.2	✓	✓			✓				✓			✓	✓	✓
Gobbo (2020), BR	N/A	PR	68	69.4 (6.5)	70.9		✓					✓	✓	✓			✓		✓
Hall (2017), US	MURDOCK	CS	775	62.1 (N/R)	53.2	✓	✓	✓		✓	✓	✓			✓				
Hsueh (2020), TW	N/A	CS	127	70.8 (5.3)	71.7		✓	✓	✓	✓	✓	✓	✓	✓			✓		✓
Izawa (2017), JP	N/A	CS	290	74.5 (N/R)	37.6		✓			✓		✓		✓			✓		✓
Jantunen (2017), FI	HBCS	CS	695	70.7 (2.7)	54.5	✓	✓				✓				✓	✓	✓	✓	
Johansson (2021), NO	Tromsø	CS	3653	68.5 (5.9)	51	✓	✓				✓		✓				✓		
Kim (2015), JP	N/R	CS	207	83.5 (2.6)	55.6				✓			✓	✓				✓	✓	
Kruger (2016), SA	PURE	CS	247	57.0 (10.2)	100				✓			✓	✓				✓	n/a	✓
Lai (2020), TW	N/A	CS	118	70.0 (5.0)	70.3		✓				✓	✓	✓	✓			✓	✓	✓
Lerma (2018), US	N/A	CS	91	70.7 (10.2)	60.4	✓	✓				✓	✓			✓	✓	✓	✓	✓
Lohne-Seiler (2016), NO	N/A	CS	161	72.8 (5.1)	52.8			✓		✓			✓				✓	✓	✓
Manas (2019)*, ES	TSHA	CS	771	76.8 (4.9)	54.0	✓	✓									✓	✓	✓	✓
Meier (2020), US	N/A	CS	304	72.8 (5.8)	58.2			✓				✓	✓				✓	✓	✓
Mendham (2021), SA	N/A	CS	111	*67* [*64, 71*]	100.0	✓	✓		✓			✓	✓	✓	✓		✓	n/a	
Mizumoto (2015)*, JP	PIPAOI	PR	201	79.7 (3.8)	58.7		✓	✓				✓	✓				✓	✓	✓
Nagai (2018)*, JP	N/A	CS	886	73.6 (7.0)	70	✓	✓					✓	✓						

Author (Year), Country	Cohort	Design	Sample (n)	Age	Sex (F%)	PA measures				PF measures							Adjustments		
						LPA	MVPA	Steps	TPA	Bal.	Chair	Gait	HGS	TUG	Walk	Comp.	Add.	SPPB	Add.
Oguma (2017)*, JP	TOOTH	CS	155	90.2 (1.4)	52.6			✓	✓	✓	✓		✓	✓					
Osuka (2015), JP	N/A	CS	802	72.5 (5.9)	76.7	✓	✓			✓	✓			✓			✓	✓	✓
Pina (2021), SA + GB	N/A	CS	288	68.5 (N/R)	79.9	✓	✓		✓			✓	✓				✓	✓	✓
Reid (2016)*, AU	AusDiab	CS	602	58.1 (10.0)	58.5	✓	✓	✓						✓			✓	✓	✓
Ribeiro (2020), BR	N/A	CS	230	*66* [*63, 71*]	70.4											✓	✓	✓	✓
Rojer (2018), NL	N/A	CS	236	66.9 (N/R)	64.8			✓	✓			✓	✓				✓	✓	
Sanchez-Sanchez (2019), ES	TSHA	CS	497	78.1 (5.7)	54.3	✓	✓		✓			✓	✓				✓	✓	✓
Santos (2012), PT	N/A	CS	312	74.3 (6.6)	62.5		✓				✓			✓	✓		✓	✓	✓
Savikangas (2020), FI	PASSWORD	CS	293	74.4 (3.8)	58.4	✓	✓					✓			✓	✓	✓	✓	
Schrack (2019), US	BLSA	CS	680	67.9 (13.2)	49.9				✓			✓			✓	✓	✓	✓	✓
Spartano (2019), US	FHS	CS	1352	68.6 (7.5)	54		✓	✓			✓	✓	✓				✓	✓	✓
Thiebaud (2020)*, JP	N/A	CS	86	67 (7)	100	✓	✓					✓					✓	n/a	✓
van der Velde (2017), NL	Maastricht	CS	1962	59.7 (8.2)	48.6		✓		✓		✓		✓		✓		✓	✓	✓
Ward-Ritacco (2014), US	N/A	CS	64	58.6 (3.6)	100		✓	✓			✓			✓	✓		✓	n/a	✓
Ward-Ritacco (2020), US	N/A	CS	80	52.6 (6.1)	100			✓			✓			✓	✓		✓	n/a	✓
Westbury (2018), GB	HSS	CS	131	78.8 (2.4)	75.6		✓		✓			✓	✓					✓	
Yamada (2011)*, JP	N/A	CS	515	77.0 (7.2)	67.5			✓		✓	✓	✓		✓					
Yasunaga (2017), JP	N/A	CS	287	74.4 (5.2)	37.3	✓	✓			✓		✓	✓	✓			✓	✓	✓
Yerrakalva (2022), UK	EPIC-Norfolk	PR	1488	69.9 (6.0)	54.4	✓	✓		✓		✓	✓	✓				✓	✓	✓

Age in years is presented as mean (standard deviation) or *median* [interquartile range]. Sex distribution is presented as the percentage of females within the study sample. *Asterisk denotes not included in meta-analyses. CS = cross-sectional, PR = prospective, N/R = not reported, N/A = not applicable, PA = physical activity, LPA = light intensity physical activity, MVPA = moderate-to-vigorous physical activity, Steps = average or total step count, TPA = total physical activity, PF = physical function, Bal. = balance test, Chair = chair rise test, Gait = gait speed, HGS = handgrip strength, TUG = timed up-and-go, Walk = walk tests, Comp. = composite measure, Add. = additional, SPPB = short physical performance battery. AU = Australia, BR = Brazil, ES = Spain, GB = Great Britain, FI = Finland, JP = Japan, NL = Netherlands, NO = Norway PT = Portugal, SA = South Africa, TW = Taiwan, US = United States.

sizes for additional associations that were not reported in the original paper. The variations in physical activity exposures and physical function outcomes reported across included studies prevented the computation of a single overall effect size. Instead, multiple pooled analyses (n=24) were performed for each combination of physical activity and physical function measure, as described above.

Overall, the 34 studies included in meta-analyses represent 22'774 participants (range: 64 to 4702), with a mean sample age of 69.3 (range: 46 to 83.5) and comprising 63.4% females. Two studies reported prospective associations[133,134] and 32 reported cross-sectional associations.[25,104,131,136–139,141–144,146,150,152–157,159,161,162,164,167–170,173] The limited number of studies reporting some of the associations meant that only six of the meta-analyses contained ≥10 studies, and therefore meta-regressions and Egger's test were only performed on these six. Due to an unbalanced number of studies across the device locations (27 studies adopted waist/hip), we refrained from conducting sub-group analysis on this factor. All extracted data are provided in the supplementary tables (Appendix 8.3).

2.4.3 Methodological quality

For all 42 included studies, the mean quality assessment rating was 8.1±1.2 (range: 3 to 13). For the 34 studies included in meta-analyses, the mean rating was 8.2±1.2 (range: 6 to 13). Study design (only four studies were prospective), sample size justification, and participation rate of eligible persons were the most problematic domains of study quality (Appendix 8.4).

2.4.4 Results of meta-analyses

2.4.4.1 Gait speed

There were positive associations for each of the physical activity measures with gait speed (Figure 2.2). The magnitudes of association varied between physical activity measures, with medium size associations seen in MVPA (β=0.26, p<0.001) and step count (β=0.26, p<0.001), and small associations seen with TPA (β=0.17, p<0.001) and LPA (β=0.11, p<0.001). Statistical heterogeneity was high step count, and moderate for TPA, LPA and MVPA. Meta-regressions for age, sex, sample size and quality assessment score for TPA and MVPA were non-significant (Appendix 8.5). Egger's test for TPA and MVPA were non-significant (Appendix 8.6).

2.4.4.2 Chair rise tests

All physical activity measures were positively associated with chair rise tests (Figure 2.3). The magnitudes of association varied between physical activity measures; step count was the largest but with wide confidence intervals (β=0.26 [0.09 to 0.41], p=0.003), followed by MVPA (β=0.18, p<0.001), TPA (β=0.14, p<0.001), and LPA (β=0.10, p<0.001). Heterogeneity was high for MVPA and step count, moderate for TPA, and low for LPA. Meta-regressions for MVPA were non-significant (Appendix 8.5). Egger's test for MVPA was non-significant (Appendix 8.6).

2.4.4.3 Balance

There were a limited number of studies reporting associations with balance. All measures of physical activity were positively associated with balance

(Figure 2.4). The largest associations were seen with step count (β=0.24, *p*=0.003), followed by MVPA (β=0.15, *p*<0.001) and TPA (β=0.12, *p*<0.001); the smallest association was with LPA (β=0.07, *p*=0.036). Heterogeneity was moderate for MVPA and low TPA, LPA and step count.

2.4.4.4 Walk tests

Similar to balance there were a limited number of studies reporting associations with walk tests. All measures of physical activity were positively associated with walk tests (Figure 2.5). The magnitudes were largest with step count (β=0.41, *p*=0.001) and MVPA (β=0.35, *p*<0.001); followed by LPA (β=0.19, *p*<0.001) and TPA (β=0.18, *p*<0.001). Heterogeneity was high for TPA and step count, moderate for MVPA, and low for LPA.

2.4.4.5 Timed Up-and-Go

All measures of physical activity were positively associated with the timed up-and-go test (Figure 2.6). The magnitudes were largest with MVPA (β=0.24, *p*<0.001) and step count (β=0.24, *p*<0.001); followed by TPA (β=0.19, *p*<0.001) and LPA (β=0.10, *p*<0.001). Heterogeneity was high for MVPA, and low for TPA, LPA and step count.

2.4.4.6 Handgrip strength

Handgrip strength showed small, positive associations with TPA (β=0.07, *p*<0.001), LPA (β=0.05, *p*=0.002) and MVPA (β=0.07, *p*<0.001), but had no association with step count (β=0.02, *p*=0.406) (Figure 2.7). Heterogeneity was moderate for TPA, LPA and MVPA, and low for step count. Egger's test for TPA, LPA and MVPA were non-significant (Appendix 8.6). As detailed in the methods,

effect sizes from studies reporting sub-groups were pooled, except in two instances for grip strength,[168,174] where the effects were in the opposite direction in each sub-group (Figure 2.7).

2.4.4.7 Sensitivity analyses

The results of the ’leave-one-out' sensitivity analyses suggests that, in general, our estimates of associations were robust to sensitivity analyses. The β coefficients did not change more than; -0.04 to +0.03 for balance, -0.04 to +0.08 for chair rise tests, -0.02 to +0.04 for gait speed, -0.03 to +0.03 for grip, -0.03 to +0.05 for TUG, and -0.07 to +0.12 for walk tests. Importantly, β coefficients from the ‘leave-one-out' analyses were always within the 95% confidence intervals of the original estimates derived from ‘all studies’ (Appendix 8.7). Even for the three associations that became non-significant, the magnitude of the change in the β coefficient was very small (e.g. β coefficients of 0.12, 0.07 and 0.41 fell no more than 0.04). The sample study sizes for these associations were three, three, and four, respectively, and were impacted when the studies with large sample sizes were removed; therefore, we suggest caution when interpreting the pooled associations with smaller numbers of studies.

All meta-regressions were non-significant. Bubble plots suggested that some meta-regressions might have studies with high leverage. According to Borenstein et al.[175] there are no current methods in which meta-regression deals with ‘high leverage’. Leverage was calculated for each study within each meta-regression, and the formula reported in Borenstein et al. was used to identify studies with ‘high’ leverage. In the absence of an optimal process to deal with

high leverage, analysis was re-run excluding any studies with high leverage. All meta-regressions remained non-significant.

2.4.4.8 Vote count summary

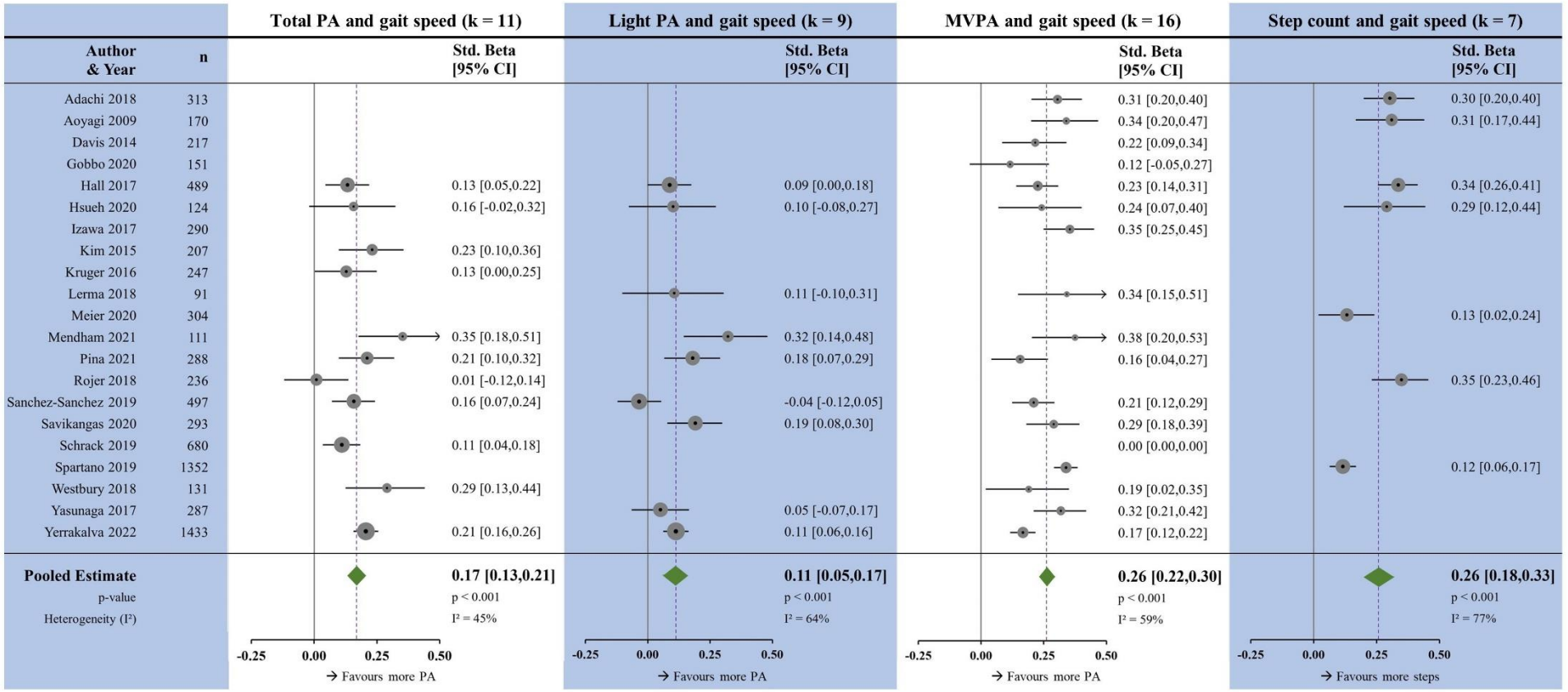
Of the 42 studies that met the inclusion criteria, β coefficients were not obtainable for eight studies; and therefore, these were not included in the meta-analysis. To avoid completely omitting these studies from the review and to acknowledge any potential bias, a vote count summary is provided with all studies and sub-group vote count comparing those studies included in the meta-analysis and those excluded (*Table 2*).

Table 2.2. Vote counting across all reported associations of included studies.

	↑ n (%)	↓ n (%)	↔ n (%)	**Total** n
All studies (n=42)	155 (65.4)	1 (0.0)	79 (32.9)	**237**
Sub-group vote count				
Included in MA (n=34)	131 (64.2)	1 (0.1)	70 (33.8)	**204**
Excluded from MA (n=8)	24 (72.7)	0 (0.0)	9 (27.3)	**33**

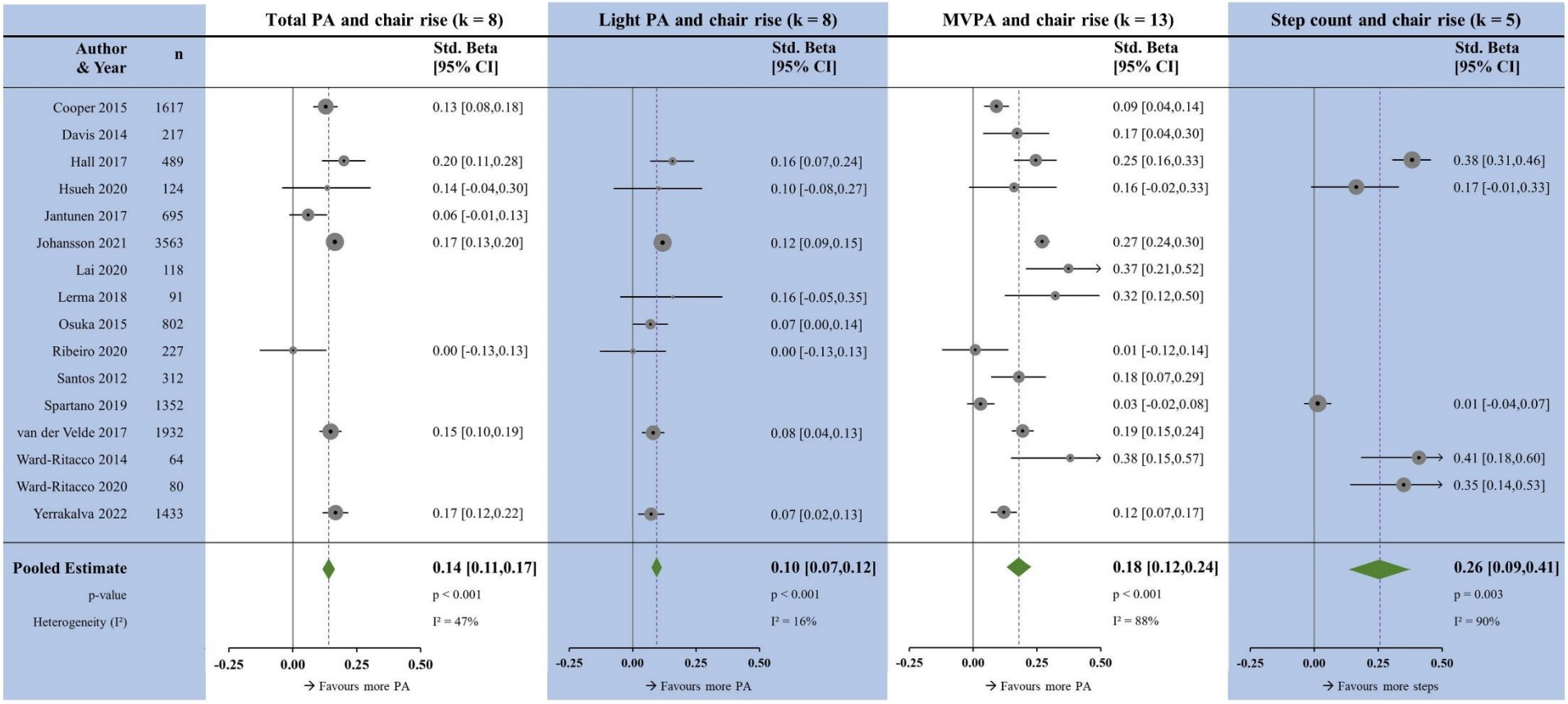
↑ = Significant positive association; ↓ = significant negative association; ↔ = no association; MA = meta-analysis.

Overall, 237 associations across 24 potential associations were reported from the 42 included studies. A higher proportion of positive (higher physical function) associations were observed in the studies not included in the meta-analyses (72.7%) compared with those included (64.2%). A chi-square test showed direction of association did not differ by included versus excluded associations, $X^2 = 1.68$, $p = 0.195$.



n = sample size; k = number of studies per meta-analysis; Std. Beta = standardised linear regression coefficients with 95% confidence intervals; PA = physical activity; MVPA = moderate-to-vigorous physical activity

Figure 2.2. Forest plots showing the associations between physical activity measures and gait speed. k, number of studies per meta-analysis; MVPA, moderate-to-vigorous physical activity; N, sample size; PA, physical activity.



n = sample size; k = number of studies per meta-analysis; Std. Beta = standardised linear regression coefficients with 95% confidence intervals; PA = physical activity; MVPA = moderate-to-vigorous physical activity

Figure 2.3. Forest plots showing the associations between physical activity measures and chair rises. k, number of studies per meta-analysis; MVPA, moderate-to-vigorous physical activity; N, sample size; PA, physical activity.

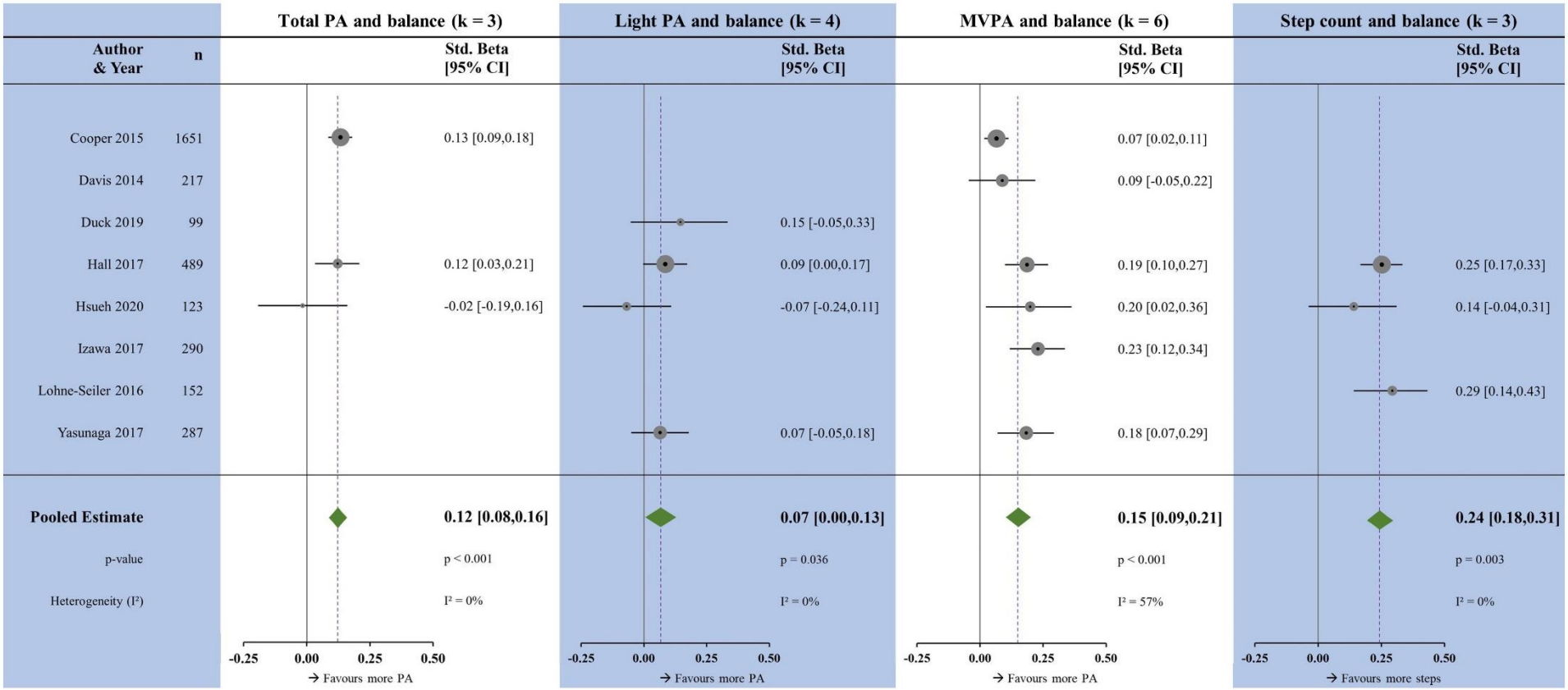
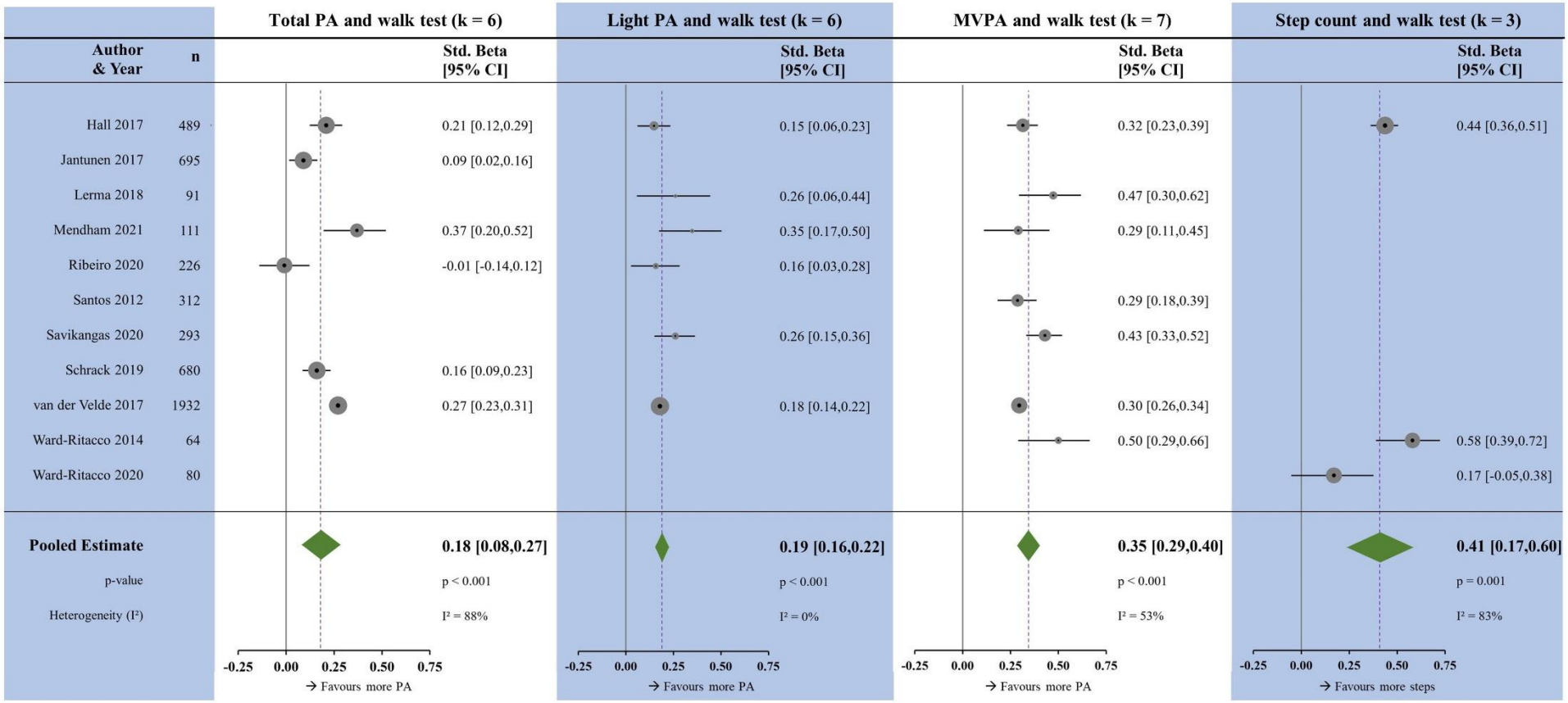


Figure 2.4. Forest plots showing the associations between physical activity measures and balance. k, number of studies per meta-analysis; MVPA, moderate-to-vigorous physical activity; N, sample size; PA, physical activity.



n = sample size; k = number of studies per meta-analysis; Std. Beta = standardised linear regression coefficients with 95% confidence intervals; PA = physical activity; MVPA = moderate-to-vigorous physical activity

Figure 2.5. Forest plots showing the associations between physical activity measures and walk tests. k, number of studies per meta-analysis; MVPA, moderate-to-vigorous physical activity; N, sample size; PA, physical activity.

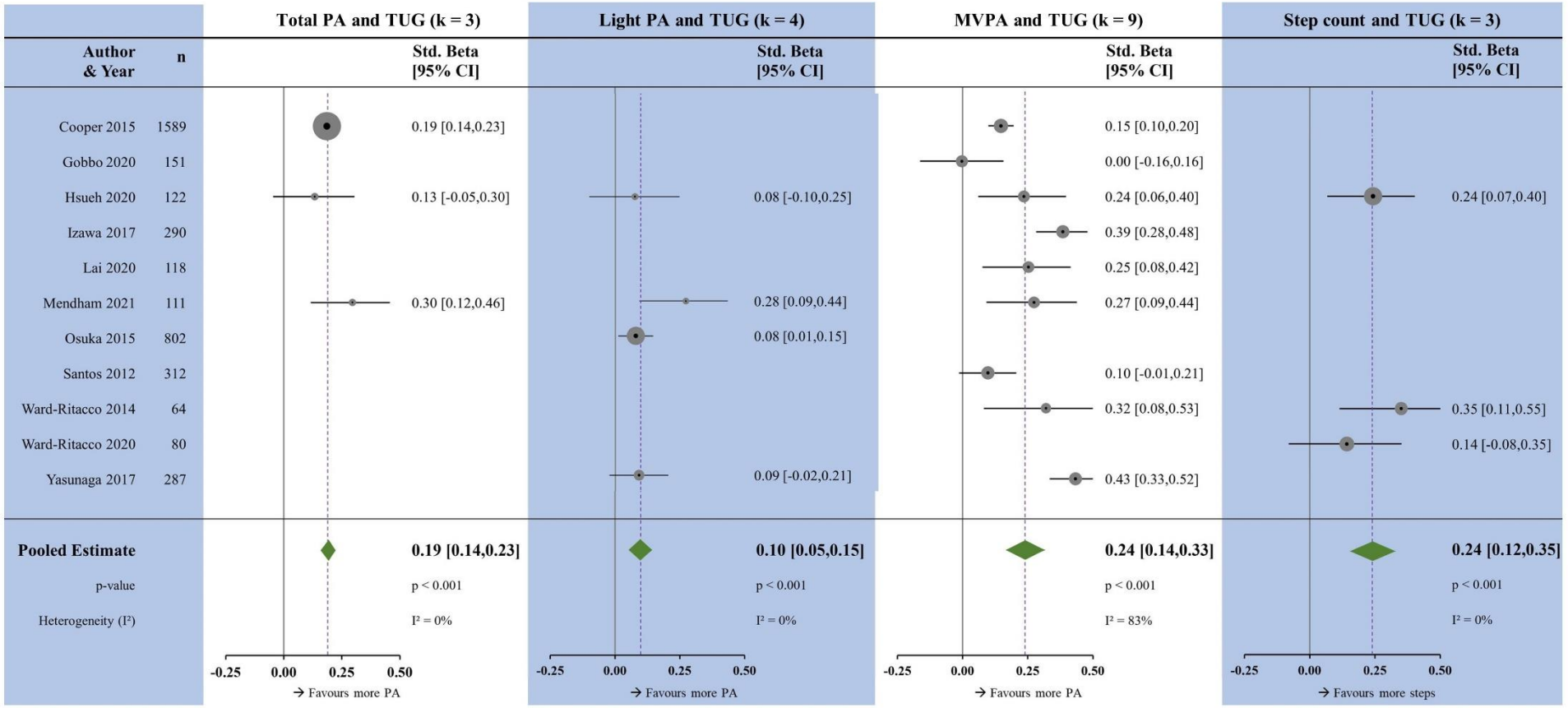


Figure 2.6. Forest plots showing the associations between physical activity measures and the timed up-and-go test. k, number of studies per meta-analysis; MVPA, moderate-to-vigorous physical activity; N, sample size; PA, physical activity.

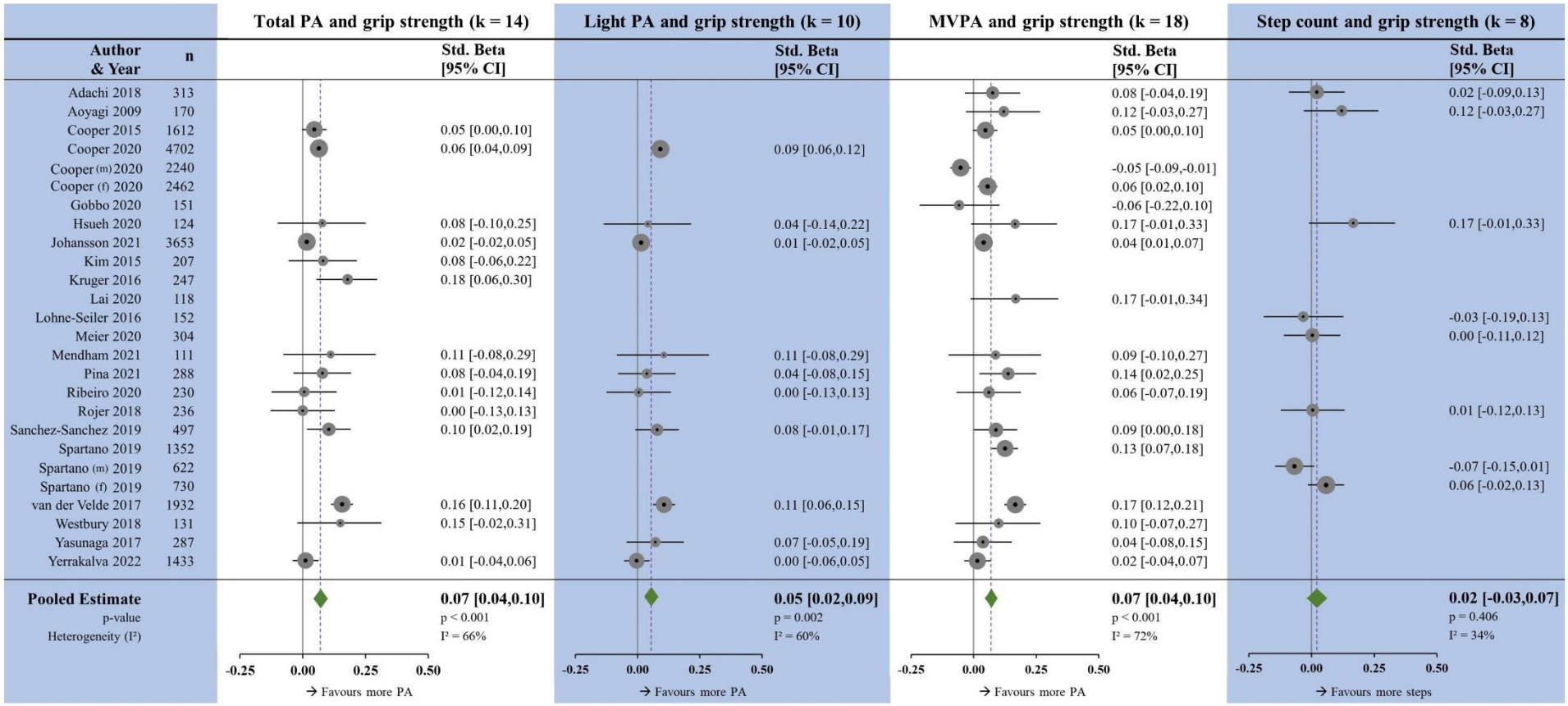


Figure 2.7. Forest plots showing the associations between physical activity measures and handgrip strength. k, number of studies per meta-analysis; MVPA, moderate-to-vigorous physical activity; N, sample size; PA, physical activity.

2.5 Discussion

The aim of this systematic review was to examine associations between wearable, device-measured physical activity, and a range of performance-based physical function outcomes in community-dwelling adults. Forty-two studies met the inclusion criteria and 34 studies provided suitable data for meta-analyses, across 24 different associations between physical activity and physical function. All measures of physical activity were positively associated with all measures of physical function, except for step count with grip strength. In general, the more physically active people were the better their physical function. Associations were generally higher with lower-body physical function tests, particularly gait speed, chair rises and walk tests.

Within each measure of physical function, the associations with either MVPA or step count were generally larger than compared to LPA or TPA. The associations of physical activity with chair-rise tests and grip strength were similar to those reported in a previous meta-analysis.[120] Direct comparisons between this review and that of Ramsey[120] are not possible due to this review excluding studies that recruited participants based on the presence of a specific clinical condition. This decision was taken to increase the external validity of the results, and because the expected association between physical activity and physical function would be condition specific. There were too few studies for each specific condition to carry out analysis separately, comparing studies in healthy populations to each clinical condition. Our inclusion of all adults (not just older adults) adds to the previous review in this area. The number of studies within many of the meta-analyses did not allow for meta-regression; though in the six which did, there was no apparent effect of sample age on the observed associations.

The differences observed in the magnitude of associations between physical activity and specific measures of physical function may be explained, at least in part, by the specificity of exercise. For example, grip strength, a general measure of muscular strength, would be expected to improve as a result of resistance type exercises rather than ambulatory activity. Therefore, measuring physical activity with devices that largely capture ambulatory behaviour, not resistance exercise, would likely underestimate the association between physical activity and grip strength, especially in participants undertaking a higher level of resistance exercise. Similarly, measures of physical function more related to ambulation (e.g. gait speed and walk tests) would be expected to produce larger associations with device-based measures of physical activity that mainly represent ambulatory activity. Although device-based measures of physical activity overcome recall and social desirability biases associated with self-report measures, they do not adequately capture strength or resistance-based activities.[176,177]

The reliance on single thresholds of acceleration to define activity intensity categories, for all study participants, can lead to the misclassification of time spent in different intensities of activity. The approach assumes that a given value of acceleration represents the same intensity of physical activity for all individuals regardless of their fitness.[178] For example, if two people (one low fit and one high fit) were walking at the same speed on a treadmill the accelerometer would record approximately the same level of acceleration assuming both people had similar stride lengths. However, the less fit person would be exercising at a higher relative intensity (% of maximum) than the fitter person. Consequently, in less fit participants the single threshold method would lead to an underestimate of time spent in MVPA – misclassified as LPA, and for fitter participants an overestimate

of time in MVPA. Further, the most common thresholds used by included studies were derived in calibration studies of young adults (<30 years old) which is unlikely to generalise to older populations with lower fitness levels.[171,172]

Our findings show that more time at higher acceleration values is associated with better function, but it is difficult to know what level of relative intensity these thresholds represent in the populations being studied, even though in general higher accelerations are correlated with higher VO^2 levels. In addition, most of the effect sizes were not adjusted for TPA, meaning associations between time spent in MVPA and physical function may be confounded by TPA if MVPA and TPA are highly correlated. Although there was some variation in the thresholds used to classify LPA an MVPA between the studies, this would not be expected to affect the pooled estimates reported. As regardless of the thresholds used, the participants who undertook more time at higher intensity physical activity would still record more minutes of accelerometer estimated MVPA, compared to participants who undertook less time at higher intensity physical activity.

The reporting of physical activity volume alone ignores other dimensions of activity and the temporal distribution, including event-based outcomes of free-living behaviour.[179] This is despite evidence that two people with the same volume of activity, accumulated in different patterns will vary in their risk of mortality,[180] and that patterns (e.g. number and duration of activity bouts) may also be associated with physical function.[105] One study included in the review looked at a measure of fragmentation, modelled as the probability of transitioning from an active to sedentary state (ASTP).[104] They found more fragmented activity is associated with poorer performance in clinical measures of physical function.

However, as this was the only study that employed a pattern metric, we were unable to include it in a meta-analysis.

Developments in data processing allow for additional physical activity metrics to be derived from accelerometers, that better reflect the frequency, duration, intensity and volume of physical activity, as well as how the physical activity was accumulated within and between days. It is also possible to estimate specific movements and postures e.g. sit-to-stand posture transitions,[181] which haven't been widely reported in this literature, but which might be more relevant to certain measures of physical function (e.g. chair rise tests and TUG).

Event-based analysis presents an avenue for investigating physical activity from a posture classification perspective.[179] Upright events start with a posture change from sitting/lying to standing, end with the reverse, and are comprised of standing or stepping events. Event-based approaches offer the opportunity to analyse distinct, contiguous postural and activity events, without the reliance on aggregate measures, uniform intensity cut-points, and a wide range of assumptions that can result in misclassification of activity behaviour and intensity.

The ability to detect postural outcomes, such as postural transitions, standing, and stepping behaviours, or even the 'quality' of these activities (e.g. duration, velocity and power),[182] holds promise for better understanding of links between specific device-measures of physical activity and physical function. This in turn raises the potential for a range of applications in research. For example, remote monitoring of physical function in free-living settings rather than being reliant on clinic-based measures. It is already documented that clinic and

laboratory measures of physical function do not capture the same broad dynamic of free-living physical function.[20,21]

Only two of the studies included in this meta-analysis reported prospective associations, meaning the direction of causation cannot be determined. It is logical that the relationship is somewhat bidirectional, given the likely cyclical relationship between impaired function, disability and reduced physical activity.[12] Prospective associations between physical activity in midlife and preserved physical function at follow-up have been demonstrated, albeit with self-report measures of the exposure and outcome.[107] Further examination of these prospective associations should be performed with device-measured physical activity, to avoid the biases associated with self-report.

The association between physical activity and physical function, or even prevalence of impairment, in midlife is poorly understood, despite the potential for early screening and intervention.[60] The WHO specifically refers to reduced gait speed and muscle strength as early markers for declines in intrinsic capacity, and emphasises the need for early detection to prevent these declines in capacity.[183] Prospective studies with measures of both physical activity and function collected in midlife are required to better understand whether device-based measures of physical activity in midlife are associated with the risk of low function later in life.

2.5.1.1 Strengths and limitations

To the our knowledge this is the first meta-analysis of the associations between device measured free-living physical activity and physical function in observational studies of adults from midlife to older adulthood. Specifically, this is

the first review to examine pooled associations of physical activity with gait speed, walk tests, balance, and TUG. We build on previous analyses of associations with grip strength and chair rise tests by focussing on non-clinical populations where associations are less likely to be confounded by the presence of health conditions. The multiple dimensions of physical activity and broad range of performance-based physical function outcomes provides a comprehensive review of the relative magnitudes of physical activity associations *between* physical function measures, and the associations of different physical activity dimensions *within* those measures.

The inclusion of studies employing device-based measures removes the impact of error and bias associated with self-report measures from pooled effects. However, we note that the number of studies within certain analyses was low, contributing to considerable heterogeneity, and an inability to explore potential effect modifiers using meta-regression. As such we interpret the reported pooled effects of these meta-analyses with a degree of caution. Adopting the standardised regression coefficient as the effect size for the pooled analysis allowed for the inclusion of studies employing different statistical inference methods, measurement methods and descriptive statistics.[128] However, only evidence of an association should be interpreted from a significant meta-analysis, as the strength of associations are not comparable across standardised regression output.

The minimum adjustment model for inclusion was age + sex, which may have meant some important confounding factors were overlooked; however, it allowed inclusion of a greater number of studies than if the criteria had been stricter. We could not include eight studies within meta-analyses, however the

proportion of these studies reporting positive associations between physical activity and physical function was similar to those included in meta-analysis.

2.6 Summary and future research

Chapter 2 has addressed the first objective of this thesis: Understand the most recent evidence for the association between physical activity and physical function. This chapter has provided an overview of the existing literature on device-measured physical activity and its associations with health outcomes, particularly focusing on physical function. In community dwelling adults, higher levels of physical activity regardless of intensity were associated with higher levels of a broad range of physical function measures. These findings provide early support for the use of device-based measures of movement being used to remotely monitor people for risk of low physical function without the need to attend a clinic or laboratory. The cross-sectional nature of all but one study and the focus on older age populations prevents generalisability of these associations to younger populations and conclusions about the direction of causality.

We identified limitations in the current literature around physical activity and physical function. In studies that have employed devices, aggregate summary values are the physical activity measures reported and used for analysis, potentially overlooking important aspects of activity accumulation and pattern. Further, there is a paucity of evidence that has looked at these associations outside of older adult populations.

Moving forward, future research should adopt a more nuanced approach to examining physical activity patterns, considering a broader range of potentially important physical activity measures, especially those that capture how physical

activity is accumulated. Specifically, there is a need to explore different ways of conceptualising and measuring patterns, such as considering the composition and temporal distribution of physical activity events. By delving into these finer details, we can gain a deeper understanding of how various activity patterns are associated with, and potentially influence, physical function outcomes.

To address these gaps in the literature, the following chapters will focus on examining upright and stepping events, their composition, and temporal distribution across diverse populations. By leveraging advanced measurement techniques and raw accelerometer data, we aim to capture the intricacies of daily activity patterns more accurately. Subsequently, we will explore the associations between these refined activity metrics and physical function outcomes, shedding light on their potential impact on health and well-being.

Chapter 3
Methodological Challenges

3.1 Introduction

The previous chapter identified limitations in current research relating to physical activity and physical function. By drawing on the limitations identified in the review chapter, Chapter 3 discusses the methodological challenges regarding the measurement of physical activity that are addressed by the original research chapters in the thesis. Firstly, we discuss traditional measurement techniques of physical activity, the dominant data processing methods, and choices of physical activity metrics. We then describe event-based analysis, an alternative analysis method that addresses limitations of traditional methods. We discuss patterns of physical activity accumulation, how they have been conceptualised and captured in previous research, and the additional measures that could provide further insights into physical activity behaviour. Finally, we describe physical function and different methods to assess this outcome.

3.1.1 Dimensions of physical activity to consider

Physical activity is a complex and multidimensional outcome. The following are sub-components of physical activity behaviour:

- **Frequency:** The number of activity events occurring within a specific time period.
- **Intensity:** The physiological or biomechanical effort per unit time associated with participating in a specific type of activity.

- **Time (duration):** The duration (measured in seconds, minutes, or hours) spent participating in a single bout of activity, or the sum of these.
- **Type:** The specific mode of activity in which a person is engaged, such as sleeping, sitting, standing, walking, cycling, or load-bearing activities.
- **Volume:** The product of frequency, duration, and intensity.

In addition to the main sub-components, physical activity can also be characterised by its domain, physical setting, and social context. Domains can include things such as occupation (job, school), transport, leisure (including exercise and hobbies), and domestic (including chores, home maintenance, self-care). Physical settings include indoors or outdoors, green/blue spaces, road network etc. The social context of physical activity includes whether the person is alone or with others, whether the activity is for pleasure etc.

The primary domains assessed using accelerometers are frequency, intensity, duration (time), and type (FITT). In the context of measurement, 'type' typically refers to postures, stepping, or a broad distinction between 'active' behaviours and sedentary behaviours.

3.2 Measurement tools for physical activity

The precise measurement of physical activity plays a pivotal role in understanding the relationship between habitual physical activity and health outcomes, including relationships between physical activity and physical function. There are a number of methods which can be used to estimate the energy expenditure of physical activity within controlled environments, such as the use of calorimetry or the doubly labelled water.[184] However, these, and similar laboratory-based methods, are not practical for assessing free-living habitual

physical activity within large scale cohort or surveillance studies, or the evaluation of interventions. In addition, physical activity behaviours are the focus of this thesis not energy expenditure. Consequently, this chapter is on remote measures, including self-report measurement methods and accelerometer measurement methods.

3.2.1 Self-reports of physical activity

Until recently, research into the association between physical activity and health outcomes has relied on self-report measures of physical activity.[185] Self-report measures offer practicality and affordability, in addition to providing contextual information such as type or domain of activity.[186] Self-report measures can be used to estimate the absolute intensity of physical activity as well as the relative intensity. However, self-report measures are also susceptible to recall error and social desirability bias along with challenges with the comprehension and interpretation of survey questions.[187]

Recall is better for intentional, structured physical activity such as sport or active commuting, compared to short duration incidental physical activity such as housework or office work.[188] The subsequent misclassification of physical activity has the potential to attenuate observed associations between physical activity and health outcomes. Consider a study examining the relationship between physical activity and physical function in older adults. Participants may underestimate their involvement in lower intensity or incidental activities such as walking around the house, which might not be as salient in memory.

Consequently, individuals who engage more in lower intensity or incidental activities might be misclassified as less active than they are. This could lead to

an attenuation of the observed association between physical activity and physical function. Similarly, if people over report their physical activity due to social desirability, they will be misclassified as more active than they are - also attenuating associations with health and physical function.[92,189]

Daily diaries and log books attempt to address recall error by recording physical activity each day or after the completion of each bout of activity.[190] With diaries and logs, there is a trade-off between the burden on participants to complete them each day versus the reduction in recall error.[191] The potential for social desirability bias remains. Further, self-report measured outcomes are generally reported per day or as an aggregate of the measurement periods. Therefore, examination of accumulation within and between days is not possible.

To address the limitations associated with self-report measures, objective device-based measures of physical activity, such as wearable accelerometers, have gained prominence.[192,193] These measures eliminate the need for recall and can capture all movement regardless of intensity or duration.

3.2.2 Accelerometer measures of physical activity

As reported in Chapter 2, device-based measures have become ubiquitous in physical activity research, particularly accelerometers. Researchers began using accelerometers to measure gait metrics in the 1950s,[194] with their potential for measuring physical activity identified in the 1970s.[195] New research devices, and widespread adoption in physical activity studies began around the mid-1990s.[196] The proliferation of these measures is evident in the exponential growth of studies employing accelerometers, from under 200 per year prior to 2007 to well over 1,300 in 2020.[197]

Technological advancements have significantly improved accelerometer capabilities, including increased storage, longer battery life, and smaller size. However, despite their increasing popularity, there is inconsistency in the reporting of key aspects of device data collection and processing.[198,199] There have been calls for improved reporting and standardised practices in order to facilitate comparability across studies and enhance collaboration.[199–201] Efforts to address these challenges include the development of reporting guidelines and tools to assess the completeness of accelerometer data reporting in observational studies.[198,202] This ongoing work seeks to enhance the transparency and standardisation of accelerometry methods, important for comparisons across studies, and harmonisation of datasets.

Despite the benefits of objective measures, and how they address the limitations of self-reports, described in the previous sub-section, there remains a risk of social desirability bias, or reactivity bias. Participants may selectively remove the device to record relatively more (or less) time in a particular activity. Reactivity bias occurs when participants are more active than usual due to the presence of the device.[203] However, when weighing the strengths and limitations of self-report and device-based measures for examining patterns of physical activity behaviour, accelerometers stand out as the most suitable method.

3.2.2.1 Step counting

The history of devices for counting steps goes back considerably further than accelerometers, with Leonardo da Vinci credited with inventing the first mechanical step counter.[204] More modern iterations have been refined since the 1990s.[205] Types of step counting device can be classified into two broad

categories, the spring-suspended lever arm and the accelerometer.[204] Whereas the simpler mechanical mechanisms of the lever arm essentially counted ‘up and down’ movement through the opening and closing of an electrical circuit, accelerometers have used more sophisticated ways of classifying steps.

Accelerometers contain an internal piezoelectric or piezo-resistive accelerometer. The sinusoidal (wave) pattern of stepping is detected by both positive and negative acceleration during different phases of the stepping cycle.[204] Alternatively, thigh mounted devices use inclinometers to measure the angle and movement of the thigh, from which posture is estimated. Stepping behaviour is further estimated based on dynamic accelerations and static orientations. However, the technological advancements in hardware, and the wide range of available devices, have outpaced the decisions and techniques employed to process accelerometer. Therefore, careful consideration is needed when making data processing decisions.

It is important to note that none of the different methods for deriving steps from devices are direct measures, they are only estimating steps. Another challenge in physical activity research, in addition to the different devices and internal algorithms, is that studies build in their own rules across protocol and data processing decisions, discussed in detail in the following sections. This variability in methodologies may contribute to the general differences found across the physical activity behaviour literature. These protocol and data processing decisions, and their potential implications, are discussed below.

3.3 Protocol and data processing decisions

Accelerometers are not a direct measure of physical activity but a proxy. Consequently, the data requires processing to convert it into behaviourally meaningful metrics. The various protocol and data processing decisions that researchers make, and the choice of algorithms, can lead to misclassification and therefore the over or underestimation of physical activity that in turn can affect associations with health outcomes.

3.3.1 Device placement

The choice of device placement on the body, a key decision in research methodology, has significant implications for data quality, accuracy, and participant adherence. Where the device is situated impacts wear instructions, data cleaning procedures, and the processing of features such as intensity and activity type. Decisions regarding device placement are not only guided by research objectives but also practical considerations including cost, device availability, and participant burden. Reviews of observational studies report that the most common placement locations have been waist (48.4 - 52.8%), followed by wrist (20.3 - 22.3%), and thigh (4.9 - 5.4%).[199,206] In early studies, waist placement was dominant, but more recently the wrist and thigh have become more common.[199]

Waist worn devices are generally attached via an elastic waistband, which needs to be removed for bathing and usually sleeping. Wrist worn devices and waterproofing enable 24-hour wear, and compliance is generally higher than the waist due to the low participant burden, and not needing to remove the device.[196,199,207] Thigh worn accelerometers are commonly affixed to the front of

the thigh using medical grade tape, and the 24-hour wear results have similar compliance to waist worn devices.[199] However, the more invasive attachment method could potentially result in a lower consent rate to wear the device compared with the wrist, especially in repeat measures. In addition, the adhesive tape could potentially cause skin irritation, resulting in removal and reduced compliance. Non-adhesive options for thigh worn devices include elastic straps, but this is less conducive to 24-hour wear.

The choice of accelerometer placement affects the assessment of physical activity and sedentary behaviour.[208] Studies comparing hip and wrist placements have shown varied results regarding accuracy. Direct comparisons of the ActiGraph GT3X+ showed that hip placement provided more accurate classification of MVPA behaviour than the wrist when performing set activities in a controlled environment, using portable calorimetry (a measure of energy expenditure) as the criterion measure.[208] However, there is evidence of better performance for wrist-worn devices in physical activity intensity classification, and for behaviours such as sitting, standing, and walking, in a similarly controlled environment.[209] Step count also varies significantly depending on device placement, with more steps counted when the accelerometer is worn on the wrist compared to the hip in free-living conditions, though no criterion was used to say which was more accurate.[210]

It is essential to recognise the absence of a universally accepted gold standard criterion measure for assessing free-living physical activity behaviours. Consequently, direct comparisons of device accuracy are inherently challenging. Compounding this issue is the fact that each device employs unique algorithms to process data, meaning comparisons are rarely like for like. Studies often

assess accuracy against lab-based or controlled environment observations, such as visually counting steps on a treadmill or using portable calorimetry to measure energy expenditure and intensity. However, these settings do not reflect real-world scenarios. Alternatively, some studies utilise uncontrolled protocols in free-living behaviour, relying on self-reported activity as a criterion. The limitations of self-report have been discussed previously.

Moreover, comparisons between devices are frequently made, with the activPAL often considered a criterion in the absence of a gold standard measure. All devices have limitations, and the absence of a gold standard criterion measure prevents us knowing the true accuracy of estimates of physical activity in all contexts.

A review that focused on the validity of wrist-worn accelerometers compared with indirect calorimetry or doubly labelled water as criterion measures, had mixed findings.[211] The included studies reported varied validity in estimating total physical activity, with correlations ranging from 0.17 to 0.93, attributable to differences in metrics, prediction models, and activity ranges. Despite this variability, wrist-worn accelerometers were found to be reliable for measuring total physical activity and categorising activity intensities. In addition, the higher compliance associated with wrist-worn devices, coupled with their capability for remote delivery and return, has prompted their widespread adoption in various cohort studies such as NHANES, UK Biobank, and the FIREA study.[211]

A systematic review encompassing studies employing lab-based, semi-structured protocols, or uncontrolled free-living designs, examined the efficacy of thigh placement for the activPAL.[212] It concluded that this placement accurately

distinguishes between sedentary and standing postures, demonstrating high validity with agreement rates exceeding 90%.

Another review, employing similar methodologies, highlighted the activPAL's capability to accurately detect stepping activity, although its ability to discern physical activity intensity was limited.[213] In laboratory protocols, the activPAL exhibited minimal mean differences in step counts, with a mean difference of fewer than 50 steps or less than 5%. Semi-structured protocols also showed negligible biases, with mean absolute percentage errors of less than 3%. However, uncontrolled free-living protocols reported no fixed biases but exhibited a mean absolute percentage error of approximately 23%.

Notably, studies reporting lower validity primarily included populations engaging in slower-paced walking or short walking distances, particularly in unhealthy populations. The apparent superior accuracy of thigh-worn devices to classify posture, and sedentary behaviour, has meant major international cohorts, including The Maastricht Study,[214] HUNT4,[215] and The 1970 British Cohort Study,[216] have recently adopted this placement location.

3.3.2 Sampling frequency

Sampling frequency refers to the rate at which acceleration data is recorded or measured within a specific timeframe, typically expressed in Hertz (Hz), indicating the number of measurements per second. The choice of sampling frequency may be constrained by the specifications of the accelerometer device itself, as some devices have fixed sampling frequencies. In other cases, researchers may have to make a deliberate choice between sampling frequency and measurement duration, as higher frequencies require more storage capacity

and may limit the duration of data collection. A recent review of observational physical activity studies in adults identified 30 Hz as the most common setting, followed by 100 Hz, with a range from 5 Hz to 100 Hz.[206] However, the review also highlighted that most studies did not report sampling frequency.

The selected sampling frequency can significantly impact the estimation of physical activity. Varied sampling frequencies introduce biases, with lower frequencies increasing the likelihood of missing rapid changes or short-duration activities. Consequently, higher sampling frequencies are more adept at capturing rapid changes in acceleration data, potentially leading to elevated estimations of physical activity levels compared with lower sampling frequencies. For instance, a study comparing two identical devices, one set at 30 Hz and the other at 100 Hz, found that the lower frequency resulted in a lower estimate of MVPA (3.6 minutes/day versus 5.4 minutes/day).[217] A limitation of higher sampling frequency, is the increased data storage required and the data processing time.

3.3.3 Measurement period

Measurement period, or days of wear, refers to the duration that participants are asked to wear the accelerometer. Considerations for the measurement period include the capacity of the device, the burden on the participant, and the reliability of the data captured. For example, if the device's battery life and/or data storage is limited, the measurement period will be restricted. Participant burden is a factor when asking people to wear the device for extended periods of time and may influence recruitment and adherence. Conversely, shorter wear periods may not provide enough data to capture typical activity patterns, affecting reliability. Therefore, a trade-off between these factors needs to be made.

3.3.4 Non-wear

Identifying when a person is or isn't wearing a device is a significant challenge in accelerometer-based physical activity measurement, as accurately identifying and handling such intervals is crucial for data integrity. One critical aspect involves the potential misclassification of sedentary behaviour as non-wear, leading to an underestimation of sedentary time, or conversely, misclassifying non-wear as sedentary behaviour, resulting in an overestimation.

Moreover, erroneously classifying sedentary behaviour as non-wear would inadvertently exclude participants with more sedentary time from the analysis, introducing bias toward less sedentary individuals in the sample. Conversely, misclassifying non-wear as sedentary behaviour would have the opposite effect. This not only compromises the sample's representativeness but would also results in the loss of valuable data, wastage of resources, and unnecessary participant burden. Additionally, the presence of proprietary algorithms and a variety of other algorithms across different accelerometer devices complicates comparability between studies.

Selective non-wear, where individuals may remove the accelerometer during specific activities, can introduce systematic bias if not properly addressed. For example, removing the device during exercise would lead to an under-estimation of physical activity. The opposite would occur if the device was intentionally removed for sedentary activities, a form of social desirability bias intended to indicate the person was more active than they actually are.

The level of non-wear per day and per person necessitates decisions to be made about how much wear time is sufficient to be included in analysis.

Therefore, it is common to classify each day of data as valid or not for inclusion in analysis.

3.3.5 Valid day classification

Valid day classification refers to the minimum duration (minutes or hours) of wear time within a day for it to be considered valid and included in the total number of wear days for analysis. The criteria for valid wear time depend on the objectives of the study and the protocol. For example, some studies are only interested in waking activity while others are concerned with the full 24-hour period. Decisions about minimum duration of hours of wear to make a day valid will alter estimates of total volume of activity and measures of the hour-by-hour (within-day) variability.

Changing the minimum wear time from 15-hours to 10-hours has been shown to underestimate time spent sedentary, and the time spent in different levels of physical activity intensity.[218] Additionally, having a lower daily minimum wear time reduces that ability to measure how physical activity is accumulated during waking hours including how it varies hour by hour.

Minimum wear time recommendations vary across studies, and consensus is lacking regarding the necessary duration of accelerometer wear to accurately represent a typical day. In observational studies, 10-hours is the most prevalent, with a range from 8-hours to 24-hours.[206] However, suggested minimums vary by population, with ≥8-hours per day for older care home residents,[219] to ≥10-hours per day for children,[220] and ≥13-hours per day in a study of adults.[221]

Whilst a higher threshold for classifying a day as valid may result in more precise estimates of physical activity and sedentary behaviour, the downside is

that there will be greater data loss. The loss of data could reduce the statistical power of the study which may alter the overall results. Once decisions have been about whether a day of wear is valid or not, the next decision is to decide what the minimum number of days of observation are for inclusion in analysis.

3.3.6 Minimum number of valid days

The minimum number of valid days required for inclusion in analysis is typically lower than the measurement period, as some days will be excluded due to valid day criteria. This often means that the first and last day of measurement are excluded as they are usually only partial days.

Recommendations for the minimum number of measurement days required to estimate habitual physical activity vary across studies. Reviews suggest that a minimum of 4-days is necessary for reliable estimation of a person's habitual physical activity.[200,208] Additionally, it has been suggested that at least one weekend day should be included to account for between-day variation that is particularly present between weekdays and weekends.[222,223] Consequently, the most common measurement period for observational research is 7-days, although studies employ periods ranging from 1 to 14-days.[206] Similarly, the most common minimum number of days required for inclusion in observational studies was 4-days, although this varies, with 3 and 5-days also being common choices.[199,206]

Setting the minimum number of valid days for inclusion high risks introducing sampling bias by excluding individuals with fewer days of wear.[208] It has been reported that participants who are younger, unhealthier, unemployed, and smokers, tend to have poorer accelerometer compliance, biasing studies

towards healthier and less diverse populations.[224,225] Excluding people from analysis due to non-wear also risks reducing the statistical power of the study. On the other hand, setting the minimum number of days too low, reduces the ability to measure between-day variability and identify the so-called weekend warrior who accumulates the majority of their physical activity on just 2-days of the week.

Too few days may also underestimate physical activity. Consider an individual who engages in a single hour-long jog on a Tuesday but remains relatively inactive on other days. The inclusion or exclusion of this specific day significantly impacts the calculated physical activity estimate, especially if metrics such as average minutes of MVPA per day are employed (discussed later in this chapter). Decisions on the minimum number of valid days for inclusion in analysis are a balance between precision and sampling bias.

3.3.7 Epochs

The segmentation of accelerometer data into discrete time intervals or epochs is used to classify each interval by some aspect of physical activity or posture. Choice of epoch duration has been shown to effect estimates of physical activity, with both under- and over-estimations of physical activity, and misclassification of intensity.[226–228]

There are proprietary and open-source algorithms for processing acceleration data into epochs. These different processing methods are complex, but essentially data processing involves summing acceleration signals within each epoch to classify activity intensity. However, this process introduces a fundamental challenge: brief changes in activity can be obscured by averaging within an epoch, leading to potential misclassification.

Misclassification occurs in epoch-based processing when the epoch duration exceeds the minimum duration of an activity state. High-frequency sampling can detect brief changes in acceleration, but compressing this data into longer epochs sacrifices granularity. Classifying epochs based on their average composition introduces misclassification. For instance, if stepping time is the behaviour of interest and data is processed into 60-second epochs, there's a risk of over- or under-estimating the behaviour.

Consider Figure 3.1, which illustrates 15-minutes of data with standing and stepping behaviour represented by two shades of blue. The grey bars indicate 1-minute epochs. Using a simplified classification rule where an epoch is classified as stepping if more than 50% of the time is spent stepping, and as standing if less than 50% is spent stepping, we can see how misclassification can occur.

In this example, the first two epochs (a) would be classified as stepping, totalling 2 minutes. However, there is only 1-minute and 20-seconds of stepping, with periods of standing at either end. Conversely, the five epochs from minute five to nine (b) would be classified as 5-minutes of standing, despite multiple intermittent stepping periods totalling 1.5-minutes. Misclassification is compounded by a ‘buffering effect’ when defining ‘bouts’ of behaviour, which sum contiguous epochs of the same type. For instance, applying this rule to minute five to nine would result in a standing bout of 5-minutes, despite the standing not being continuous. Similarly, the epochs from minutes 10 to 15 (c) would be classified as stepping, resulting in a 6-minute bout of stepping, even though the stepping is intermittent and only totals 4.3-minutes.

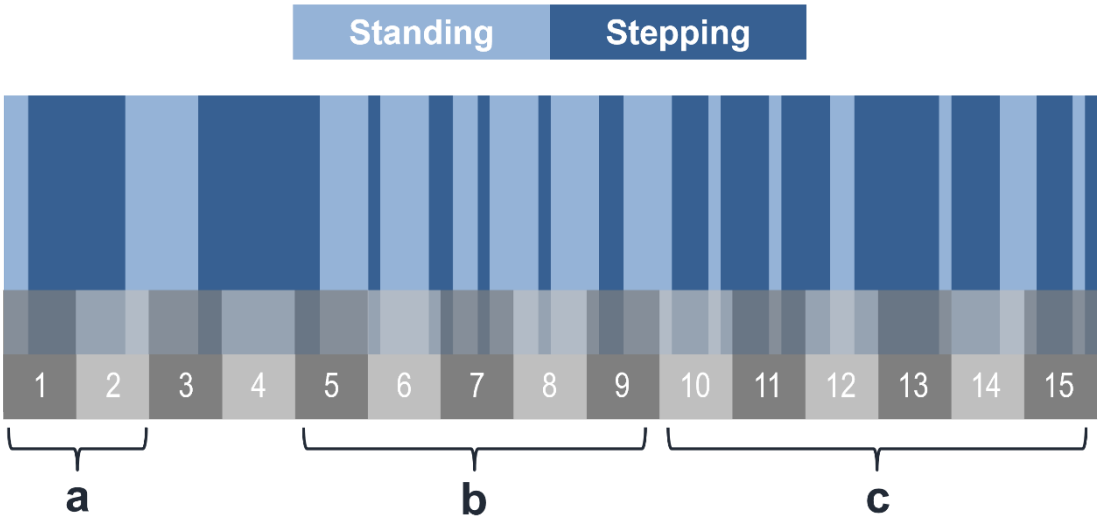


Figure 3.1. Schematic diagram of an upright event containing standing and stepping. Numbered grey bars denote 1-minute epochs.

A study comparing the number of steps in a 60-second epoch with the stepping-rate found that only 12% of minutes with stepping were walked continuously, while 69% had interruptions of less than 30-seconds.[229] Therefore, the level of misclassification when applying 1-minute epochs would be high. In addition to stepping time, researchers have used epoch-based approaches to estimate cadence. This estimation may underestimate cadence, as epochs often include periods of standing rather than continuous stepping. Calculating the true rate of stepping requires both the number of steps and the duration of stepping event.

Figure 3.2 provides an alternative representation of potential misclassifications by displaying 30 minutes of acceleration data processed with 4-second, 20-second, and 60-second epochs. Metabolic equivalent of task (METs) on the y-axis represents intensity of physical activity. In the initial 15-minute segment, the 4-second epoch time-series clearly shows intermittent acceleration (activity), with frequent transitions between high-intensity activity and periods of low-intensity, potentially sedentary behaviour. However, as the

epoch duration increases to 60-seconds, these peaks and troughs are smoothed out, giving the misleading impression of continuous moderate-intensity activity. This highlights how longer epochs can obscure the true variability in activity levels.

This misclassification can lead to potential biases in estimating physical activity. Regular intermittent behaviour can result in an underestimation of the amount of stepping or active behaviour, as brief periods of activity may be lost within longer epochs classified as inactive. Conversely, if epochs are regularly classified as active despite not containing continuous active behaviour, this will systematically overestimate physical activity levels.

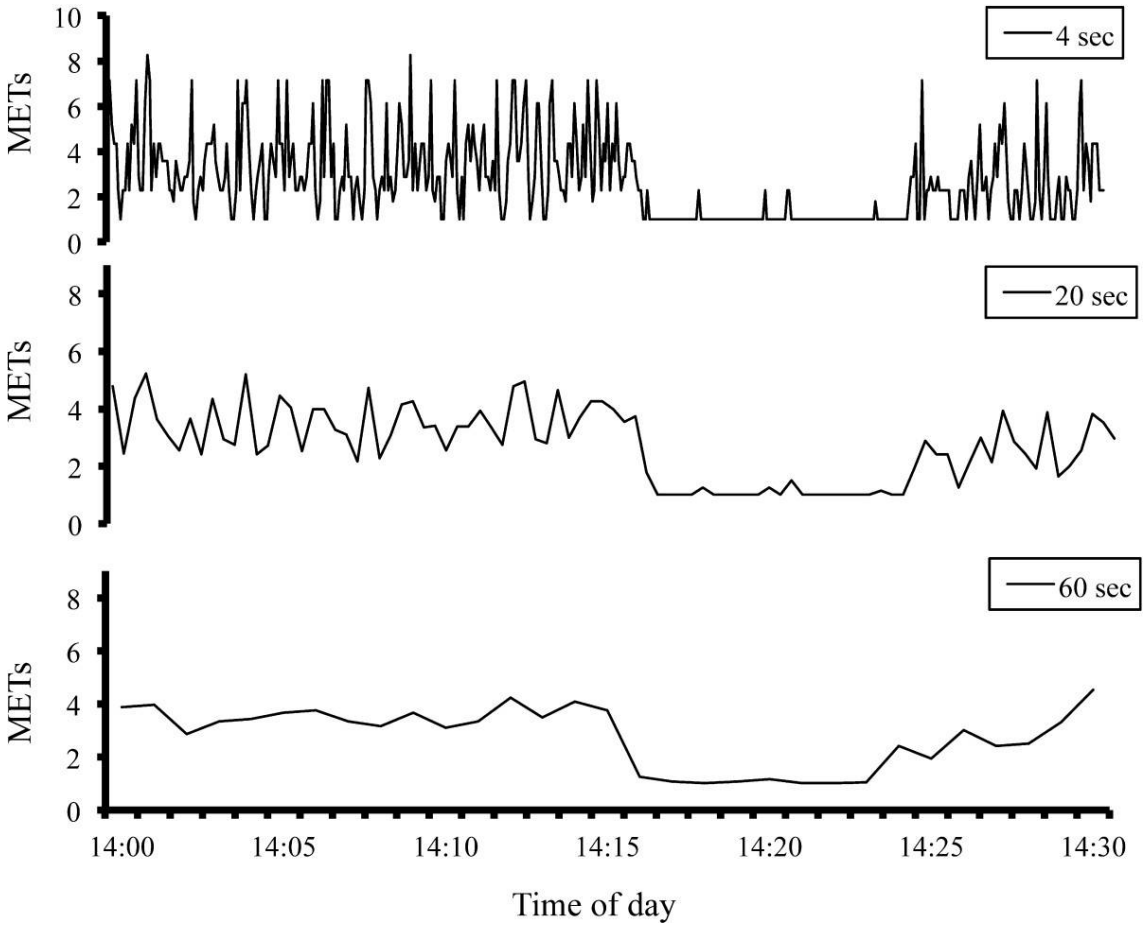


Figure 3.2. Schematic diagram of a 15-minute window of acceleration data processed using different epoch durations. METs, metabolic equivalent of task. (From Ayabe et al., 2013; reproduced under CC BY licence.)

The ‘buffering effect’ of misclassified epochs and the compounding nature of creating continuous bouts from these epochs can further obscure interruptions in activity. This limitation of epochs has been highlighted in previous research,[228,230] and is particularly significant when researchers aim to capture shorter, transient activities or when studying populations prone to brief, incidental behaviours, such as clinical populations or older adults. To mitigate this issue, shorter epochs are preferred to limit the potential for concealing rapid transitions between activity states. However, the risk is not eliminated until the epochs are as short as the minimum duration of any behaviours of interest.

3.3.8 Events

An alternative to the epoch-based approach is the event-based approach, which aims to capture discrete events.[179] An event is defined as a continuous period of time during which a person is in a singular category of event (e.g., upright, stepping, lying). In the case of this thesis, categories include postural events, sedentary or upright, with further subcategories including standing or stepping. The advantage of the event-based approach over the epoch-based approach lies in its ability to limit the misclassification of behaviours based on the average content within epochs, as discussed in the previous section. An event ‘is what it is’, either an active or inactive event or posture, without additional misclassification beyond the initial classification of the event. No rule around the average content needs to be applied.

Figure 3.3 demonstrates a 10-minute sample of (a) time-series of three-dimensional acceleration data, (b) time series of a physical activity intensity estimate converted from the acceleration data, with the dashed line indicating an

acceleration threshold for categorising active versus inactive events, and (c) time series of events where the black bars denote continuous active events, i.e., periods where the converted acceleration continuously exceeds the threshold. This figure visualises how epochs might ignore changes between event states, smoothing over short transient active events and misclassifying epochs as either active or inactive when, in truth, they would all be mixed to different degrees.

While the event-based approach assumes the algorithm that classified the behaviour for the event is accurate, there are potential misclassifications due to measurement error, incorrect definitions of the start and end of an event, or event durations being shorter than the minimum duration the device can capture or process (see sampling frequency sub-section). However, we argue that it is a more appropriate method for the outcomes of this thesis.

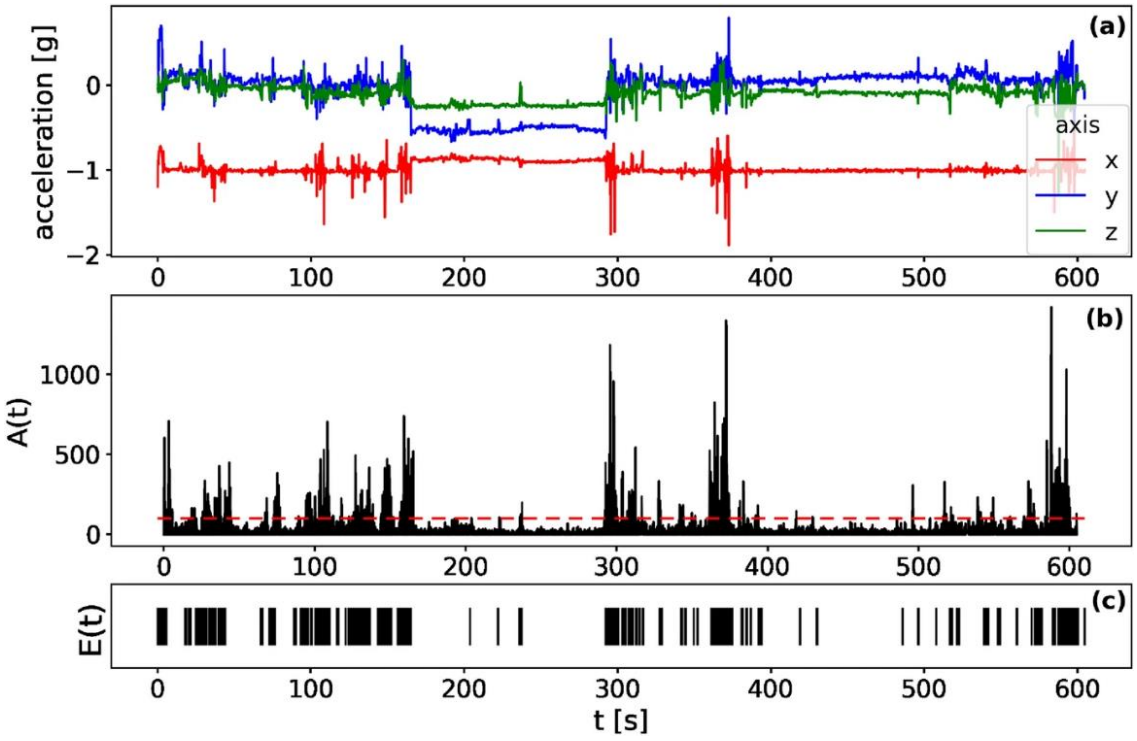


Figure 3.3. A 10-minute sample of event series data obtained from the pre-processing. (a) time-series of three-dimensional acceleration data, (b) time series of a physical activity intensity estimate converted from the acceleration data, with the dashed line indicating an acceleration threshold for categorising active versus inactive events, and (c) time series of events where the black bars denote continuous active events. (From Takeuchi et al., 2024; reproduced with permission.)

The event-based approach has several strengths, including greater precision in capturing discrete activities without averaging them, which provides a clearer picture of short, transient behaviours. It significantly reduces the risk of misclassification inherent in averaging data within epochs since events are categorised based on continuous periods. This approach allows for better detection of sporadic activities, making it particularly suitable for populations with irregular activity patterns, such as older adults or clinical populations. The inter-event times (time/events between events of interest) can also be utilised to characterise patterns of accumulation (described later in this chapter).

The event-based approach is not without limitations. Its accuracy heavily relies on the algorithm used for classifying events, and any error in determining the start or end of events can lead to misclassification of event durations, resulting in the underestimation or overestimation of these activities or postures. Additionally, very short events may be inaccurately captured if the device's resolution or processing capability is insufficient, leading to data gaps or misclassified events. Misclassifying an event not only distorts the duration of that specific behaviour but also affects adjacent events. For instance, a misclassified short active event might be erroneously added to preceding and proceeding inactive periods, artificially inflating the duration of inactivity, or vice versa. Balancing these strengths and limitations is crucial for selecting the most appropriate method for physical activity measurement in research contexts.

3.4 Accelerometer derived physical activity measures

The following sections will describe various the methods used to estimate measures of physical activity and posture that can be extracted from

accelerometer data, as well as the strengths and limitations associated with each method. Where possible reported relationships between derived measures and health outcomes will be summarised.

3.4.1 Summary outputs (frequency and duration)

The body of research employing objective physical activity assessment has largely focused on summary measures of physical activity over observation periods, such as mean step count per day or mean minutes of MVPA per day.[63] These summaries provide aggregate data but often ignore how physical activity is accumulated within and between days. For instance, summary duration measures include the average time per day people spend upright or the total number of steps per day. This is despite accelerometers providing high-resolution, time-stamped data. However, these summaries and averages cannot differentiate between different patterns of activity accumulation, which may be important for understanding health outcomes. For example, a given volume of steps could be accumulated in one continuous stepping event or in numerous shorter stepping events, which would be lost in summing or averaging steps. This distinction could be significant for health but is lost in simple aggregate measures.

Figure 3.4 presents a visual representation of this concept. It shows two upright events with the same duration, stepping duration, and step volume, (assume consistent cadence across all stepping). You can clearly see that the stepping duration was accumulated in different ways: upright event (a) contained relatively continuous stepping in just two events, while the upright event (b) was more intermittent. Simply reporting the stepping duration and/or step volume

would ignore these differences in accumulation patterns that may be important for health.

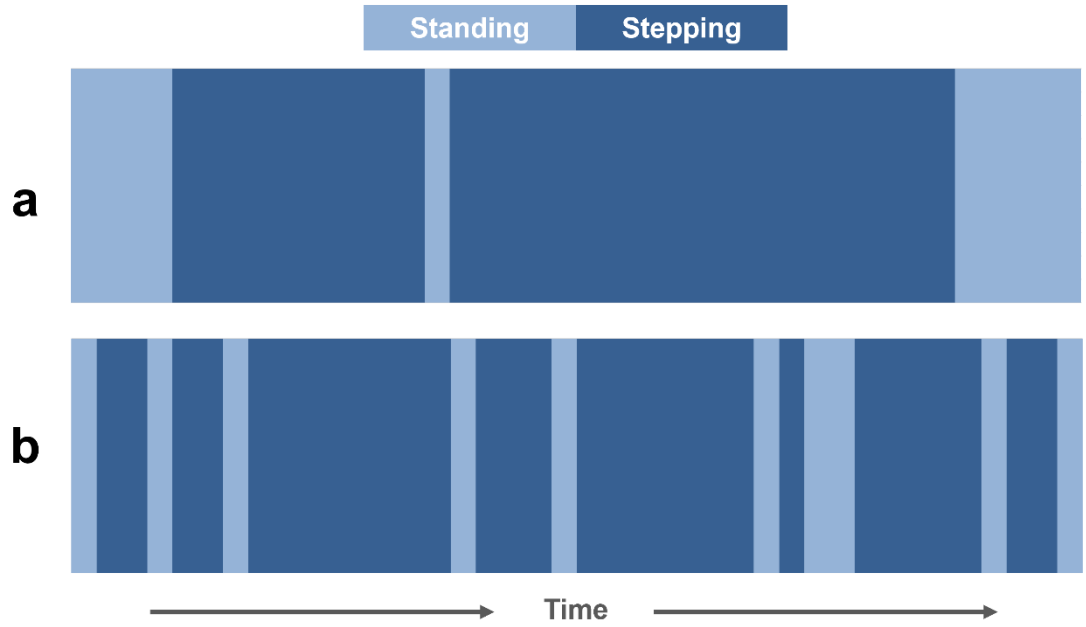


Figure 3.4. Schematic diagram of two upright events, and their standing and stepping composition.

Conversely, frequency measures count the number of events of interest. This approach has been applied to sit-to-stand transitions and sedentary interruptions (discussed later in this chapter). However, the limitation of merely counting events is that it overlooks the composition and temporal distribution of these activities. Identical event counts could represent very different patterns, with events occurring in consistent or varying durations and distributed differently throughout the measurement period. Traditional approaches are limited in accounting for these sub-components of physical activity, but event-based analysis offers a solution by allowing the nuanced patterns and distributions of these events to be quantified.

3.4.2 Intensity outputs

Estimating the intensity of physical activity from acceleration data has traditionally relied on selecting acceleration thresholds, referred to as cut-points. Laboratory based calibration studies are used to identify acceleration cut-points that correlate with MET values corresponding to light, moderate, and vigorous intensity physical activity.[171,172] Calibration studies have been undertaken in children,[231] youth,[232] older adults,[233] and clinical groups.[234] These studies typically involve small sample sizes and a limited number of activities.

As a result, extrapolating a single threshold of acceleration from a small scale calibration study to a larger population of people, likely to be more diverse than the study sample, will result in misclassification of the time spent in different intensities of activity.[235,236] For example, consider two individuals of similar stature walking on a treadmill at the same speed, wearing accelerometers on their wrists. One is a fit, 35-year-old, and the other an unfit, 60-year-old. The accelerometer will record very similar values of acceleration, and using a suitable cut-point for acceleration, both would be recorded as walking at a moderate intensity. Despite this, their relative exertion levels likely differ significantly. The fitter individual may actually be walking at an intensity that is light for them, while the less fit person will be walking at a higher intensity, more like moderate intensity for them. Hence, the accelerometer cut-point method would overestimate the time spent walking at moderate intensity for the fitter person.

Similarly, fixed single thresholds of step-rates, such as ≥100 steps/minute to classify MVPA, have been applied to stepping cadence.[237] However, associations with health outcomes do not always remain after adjusting for total volume.[238,239] Intensity inferred from step-rate is susceptible to similar

misclassification as accelerometer cut-points, as individuals with the same step-rate may experience different relative intensity levels. In addition, discrepancies may arise from the misclassification of step-rates that are calculated per epoch rather than per stepping event, as described in the earlier section on epochs.

Advanced methods have been developed to assess physical activity intensity using time-series data.[240] The intensity gradient and MX metrics are utilised to assess the distribution of activity intensities.[241,242] Their primary advantage is their independence from cut-points, addressing the issue of comparability across studies that use different cut points. The intensity gradient, when combined with average acceleration, offers a comprehensive 24-hour activity profile, allowing for the exploration of how volume and intensity distribution independently, complementarily, or interactively relate to health outcomes. The MX metric, meanwhile, maintains the continuous nature of the variable and allows post-hoc comparisons to any cut-point or standard activity level, facilitating visual comparisons within and between groups to establish data-driven norms.

However, the MX metric's effectiveness can vary depending on the wear location and device brand, which may affect comparability between studies. Additionally, there is no consensus on the key MX metrics for analysing health conditions, necessitating decisions on specific time thresholds (i.e., the most active X minutes). Both the MX metric and the intensity gradient do not account for temporal activity accumulation, suggesting that they should be used alongside physical activity accumulation indicators.

A significant issue with traditional intensity measures is the problem of co-correlation when computing time spent in different intensities, making it

challenging to adjust for total activity volume accurately. This issue arises because time spent in one intensity category is inherently dependent on time spent in others, complicating the analysis. Event-based approaches offer a solution to this problem by summing each event by its mean intensity without imposing arbitrary thresholds.

3.4.3 Accumulation and pattern measures

The Collins dictionary defines the word “pattern” as the “repeated or regular way in which something happens or is done”. However, when applied to physical activity, the term "pattern” has no consensus definition, as it can encompass a multifaceted range of concepts, reflecting the diverse nature of human movement. Pattern has been used to refer to different dimensions of physical activity. Patterns related to between-day variations in physical activity have included differences between weekdays and weekends,[243,244] seasonal variations,[245] and distinctions between term time and school holidays in children.[246]

Measures of the between day variation in physical activity require a minimum number of days of physical activity measurement for a reliable measure of a the variation in a person’s daily routine.[247] One focus has been on how many days of the week the majority of accumulated physical activity has been done on. Evidence for the concept of the “weekend warrior”, a person who accumulates the majority (>50%) of their physical activity on 1-2 days per week, has shown beneficial associations with risk for all-cause, cardiovascular disease, and cancer mortality.[248]

Within-day patterns of physical activity can include the frequency of bouts or events of physical activity, event durations, hour by hour variations and the temporal distribution of events. In addition, studies have examined the time of day when the majority of physical activity is undertaken, e.g., performing the bulk of your activity in the morning vs afternoon. A recent systematic review of such studies reported no consistent evidence that the time of day when physical activity is performed provides any impact on health.[249]

Several methods have been developed to assess how physical activity is accumulated throughout the day, often using the concept of ‘bouts.’ In this thesis, it is important to distinguish between 'bouts' and 'events,' even though the terms can sometimes be used interchangeably. An event refers to continuous periods of activity, while bouts refer to blocks of epochs classified as a single type of behaviour which, due to the previously described limitations, might not necessarily be continuous. The following methods can be applied to both types of data and provide alternative insights into patterns of activity accumulation that go beyond simple summary measures of the level of physical activity.

The power-law exponent alpha describes the relationship between the frequency and duration of activity bouts, indicating how activity is distributed across different bout lengths.[250] This metric highlights whether an individual's activity is dominated by short, frequent bouts or longer, less frequent bouts. Evidence suggests a more uniform distribution of physical activity was associated with a healthier BMI.[251] However, it is difficult to interpret alone, and is suggested to be complimented by the median bout length represents the middle value of all activity bout durations within a given period.[250]

The Gini index measures inequality in the distribution of activity bouts, similar to its use in economics to measure income inequality.[250] A higher Gini index indicates greater disparity, meaning that physical activity is concentrated in fewer bouts, while a lower Gini index suggests a more even distribution of activity across many bouts. This captures the dispersion of activity, offering insights into whether an individual's activity is evenly spread or dominated by a few intense bouts. However, it can be challenging to interpret without a clear understanding of what constitutes a healthy distribution of physical activity.

The proportion of total time accumulated in bouts longer than $\mathcal{X}$ calculates the proportion of total active time that is accumulated in bouts longer than a specified duration.[250] It highlights how much of the total physical activity is made up of sustained periods of activity, which can be particularly relevant for understanding health benefits associated with prolonged exercise. However, it may be influenced by the choice of threshold ($\mathcal{X}$) and can miss the contributions of shorter bouts that also contribute to overall physical activity levels.

3.4.3.1 Fragmentation

Fragmentation refers to the transient nature of physical activity and the extent to which periods of physical activity are interspersed with periods of inactivity throughout the day.[104] One widely examined measure of how fragmented or transient a person's physical activity is, is the active-to-sedentary transition probability (ASTP).[104] ASTP represents a probability of a transition from active to inactive, and is recorded on a scale of 0-1. Higher values represent more fragmented or transient periods of being active. Higher fragmentation typically indicates more frequent switching between activity and inactivity, which may

suggest lower overall functional capacity or greater fatigability that prevents more sustained periods of activity.

Recent studies have increasingly focused on fragmentation as a potential marker of accelerated aging and declining physical function.[106] For instance, the concept of activity fragmentation as a novel phenotype of ageing has been suggested, particularly in populations at risk for functional decline, such as older adults and cancer survivors. The evidence indicates that higher levels of fragmentation, characterised by more frequent breaks from activity, were associated with diminished physical function, increased fatigability, and a higher risk of disability. These findings underscore the potential of fragmentation metrics to serve as early indicators of physiological impairment, especially as the findings were independent of traditional summary measures of physical activity alone.

Fragmentation metrics add insights to how a given volume of physical activity is accumulated through different patterns of rest-activity cycles.[252] This is important because two individuals with the same total amount of physical activity may exhibit very different patterns of accumulation, with one person engaging in longer, sustained bouts of activity and the other in shorter, more frequent bouts interspersed with inactivity.

High ASTP has been linked to increased fatigability, suggesting that individuals who frequently switch between activity and inactivity may have lower overall endurance and higher susceptibility to fatigue. In older adults, high ASTP has been strongly associated with subjective and objective measures of fatigability, indicating that individuals with high ASTP might experience greater difficulty sustaining prolonged physical activities due to early onset of fatigue.[101,104]

The relationship between ASTP and cognitive function has also been explored. Older adults with higher ASTP were more likely to experience cognitive decline, particularly in executive function and processing speed.[100] This finding suggests that frequent transitions between activity and inactivity could reflect underlying neurological deterioration, which may contribute to cognitive impairments.

High ASTP has been associated with greater pain intensity in individuals with chronic conditions. Individuals with higher ASTP, particularly those with musculoskeletal disorders, tended to report higher levels of pain. This could be due to increased sensitivity to pain or a lack of sustained physical activity, which is often recommended for pain management in chronic conditions.[253]

High ASTP has been closely associated with frailty.[103] Older adults with higher ASTP were more likely to be classified as frail, suggesting that frequent transitions between active and sedentary states could be a marker of declining physical resilience and increased risk of adverse health outcomes.

Mortality risk has been associated with ASTP, with higher ASTP predicting greater risk of all-cause mortality.[102] Older adults with high ASTP had significantly higher mortality rates, independent of total physical activity levels. In addition, there is evidence higher ASTP is associated with incident heart failure.[254] These finding underscore the importance of activity patterns, not just the quantity of activity, in determining health outcomes. Also, much of the evidence is from prospective studies suggesting that patterns of physical activity accumulation may be a precursor to changes in health status.

Relevant to this thesis, ASTP has been shown to be associated with physical function,[104,105] Higher ASTP has been associated with poorer performance in both the 2-minute walk test, and the Short Physical Performance

Battery in older adults.[105] It appears that high ASTP reflects a reduction in endurance capacity or a pre-clinical stage of disease. However, despite the valuable insights provided by ASTP, it is important to recognise its limitations. Most studies utilising ASTP have relied on minute-epoch accelerometer data, which classifies each minute as either active or inactive. This approach, while useful, may misclassify the start and end of physical activity events, potentially leading to an underestimation of fragmentation and an attenuation of associations with health outcomes. This is because it is possible that there are postural changes occurring in less than 1-minute intervals and because the exact start time of active and inactive cycles will overlap 1-minute epochs.

The growing evidence for the associations between fragmentation/ASTP and health outcomes, and the potential for an event-based approach to address limitations in prior ASTP studies, led us to include fragmentation as a metric within this thesis.

3.4.3.2 Temporal metrics

Advanced methods have been developed to assess the temporal structure of physical activity patterns. These metrics provide insights into how activity patterns are distributed and repeated over time, which can be linked to various health outcomes.

Two measures examine the temporal correlations between activity values to find repeating patterns. Fourier analysis decomposes activity data into frequencies to identify periodic patterns, but may be limited by its assumption of stationarity.[255] This breaks down the activity data into different frequency components to see if there are any regular cycles or patterns. However, this

method assumes that these patterns stay the same over time, which might not always be true. The scaling exponent alpha measures the self-similarity of activity fluctuations over different time scale, to determine how similar activity patterns are across different time periods.[256] Higher alpha values are linked to a lower risk of cognitive impairment and Alzheimer's disease,[257] while lower values at small time scales (<1.5 hours) are associated with worse mood and social withdrawal.[258] As people age or develop conditions like Alzheimer's, their activity patterns become less consistent across different time scales.

The autocorrelation coefficient at lag k assesses the similarity between observations separated by a time lag. For example, it can check how similar your activity levels are at the same time each day. A higher 24-hour autocorrelation coefficient correlates with better sleep quality[259] but, in older adults, is associated with greater difficulty performing daily activities, suggesting higher variance in activity patterns may indicate better functional status.[260]

Other methods aim to quantify the regularity within timeseries data. Sample entropy measures the complexity and regularity of activity patterns, with lower values indicating more predictable activity.[255] Permutation Lempel-Ziv complexity evaluates the randomness of activity patterns by counting distinct patterns, with higher values indicating more varied activity.[261] Symbolic dynamics transforms activity data into sequences of symbols, identifying regularity and complexity, though some information may be lost.[262]

These measures of physical activity ‘complexity’ have been employed sporadically in physical activity research, and to a lesser degree when looking at associations with physical function outcomes. Higher fear of falling in elderly populations correlates with lower complexity in physical activity patterns, as was

lower balance and mobility.[261] This suggests cautious behaviour and/or decreased physical functioning may lead to less complex activity patterns. However, there has not been wide adoption of these metrics, potentially due to their technical nature and complexity in interpretation.

An additional pattern metric, that quantifies the inter-event time distribution of events, is burstiness.[263] In lay terms, burstiness corresponds to the degree to which events occur in clusters with longer inter-event periods between clusters, vs a more regular distribution. The burstiness parameter is measured on a scale of -1 to +1 with values nearer to 1 representing burstier events whereas values closer to -1 representing a more uniform distribution.[263] Burstiness has been employed across a range of topics, from social interactions[264] to earthquakes,[265] but very little in studies of physical activity in humans.

A study of five children with muscular dystrophy showed an increase in four out of five children in the burstiness of walking behaviour after one month of pharmacological treatment.[266] Another study with a small sample size examined the association between dynamic patterns of physical activity (including burstiness) with chronic pain, finding burstier patterns in those without pain.[267] Despite the limited research, as the first study notes, "*these findings suggest that it may be valuable to look at how physical activity is organised throughout the day*".[266]

As with fragmentation/ASTP, the interesting literature around burstiness and it's very early employment in studies of human behaviours led us to include it as a metric within this thesis. Further, the additional aspect of burstiness that looks at the temporal distribution of active and postural events, which fragmentation does not account for, further supports our interest in examining this metric.

3.4.3.3 Sedentary patterns

Sedentary behaviour has been defined as any activity with an energy expenditure of ≤1.5 METs, while sitting, reclining, or lying down.[268] Research indicates that sedentary time accumulated in long duration events correlates with adverse health effects, compared with the same total duration accumulated in shorter events and irrespective of physical activity levels.[269] Physical activity guidelines now reflect this, and recommend reducing time spent sitting or lying down and to break up long periods of sedentary behaviour.[77,79,270]

Some of the previously described metrics have been applied to sedentary behaviour, including the summary measures and some temporal metrics. The majority of literature in this area focuses on the frequency of interruptions to sedentary time, with interventions focusing on breaking up sedentary time to improve health.[271] However, the definition of "sitting interruptions" remains vague, encompassing various activities such as standing or stepping, with recent evidence suggesting that the composition of these interruptions matters.[272,273] For instance, while both standing and light-intensity walking interruptions offer health benefits, the latter appears more effective in attenuating postprandial glucose levels.[272]

A recent cross-sectional study explored the relationship between sitting interruptions, demographic factors, diabetes status, and BMI, revealing fewer interruptions and fewer steps were associated with higher BMI and diabetes prevalence.[273] However, the categorisation of interruptions as "active" or "ambulatory" seems arbitrary, overlooking the variability in activity patterns. Moreover, the study failed to consider factors like the temporal distribution of events or the composition of stepping versus standing interruptions, which may

be important for understanding their impact on health outcomes. There is scope within this area to explore different temporal metrics of sedentary behaviour and the composition of sitting interruptions.

In summary, physical activity is accumulated over continuous 24-hour periods consisting of contiguous active and inactive events.[274] The variation in how these active and inactive events are distributed throughout a day or week means that people may accumulate the same volume of physical activity in patterns that differ in their frequency, duration, intensity and temporality. Evidence suggests that the patterns in which physical activity is accumulated may play a significant role in determining health outcomes, independently of volume.[99] A range of metrics exist to quantify different aspects and domains of physical activity behaviour, each with its own strengths and limitations, and some with evidenced associations with health outcomes. There is a lack of application of temporal metrics to physical function outcomes, particularly employing event-based data. In addition, the composition of postural and activity events are underexplored in the context of health outcomes generally, and physical function outcomes.

3.5 Characterising physical function

Given its complexity, physical function is assessed through a range of measures including physiologic impairment tests, field-based performance measures, and self-report surveys.[19,275] These assessments capture different aspects of physical function, from physiological limitations to limitations in specific tasks and daily activities within one's social and environmental context.

As discussed earlier, physical function undergoes significant changes across the life course;[38] with declines in physical function occurring from mid-life.[276,277] This includes declines in muscle strength, flexibility, cardiovascular endurance, balance, and gait. These changes are influenced by both intrinsic factors, such as ageing and genetics, and extrinsic factors, like physical activity levels and environmental challenges.[94,278] Accurately assessing physical function requires an understanding of these age-related changes and the various factors that can accelerate or mitigate them.

The mechanistic pathways through which physical activity influences physical function include improvements in muscle strength, coordination, cardiovascular fitness, and neurological adaptability.[279,280] Regular physical activity can help mitigate the decline in these areas, particularly when occurring from midlife.[108,281] This thesis focuses on these mechanistic relationships to highlight the potential for physical activity to preserve physical function, thereby reducing the risk of disability and dependence in older age.

While the bidirectional relationship between physical activity and physical function is well-documented, this thesis primarily considers physical activity as the explanatory variable. This focus is driven by the need to identify modifiable behaviours that can prevent functional decline before it becomes irreversible, and the strong prospective evidence of physical activity attenuating age-related declines in physical function.[35] Although better physical function can lead to more physical activity, or adverse events impacting physical function (e.g. surgery) reduce physical activity, the primary goal here is to explore how physical activity can be leveraged as a tool to maintain or enhance physical function over time.

This approach is crucial for designing public health interventions aimed at preventing the early onset of functional impairments.

Loss of muscle strength and decline in physical performance are key indicators of age-related conditions. Muscular strength and physical function are commonly measured in the clinic or laboratory with a battery of performance measures that usually include gait speed, muscular strength/power and balance.[22] Objective, performance-based physical function assessments measure an individual's capacity to perform set tasks.

Performance-based measures like handgrip strength and gait speed are integrated into the formal diagnosis of physical frailty and sarcopenia.[11,39] They also play a crucial role in screening for low physical function, sarcopenia, and frailty, across a wide range of settings due to their practicality and simplicity.[22] These measures not only serve as targets and markers of efficacy for preventive interventions, but also demonstrate predictive capacity of future health outcomes across diverse populations, discussed in the following sub-sections.[22]

Physical function is also assessed with self-report measures, including the Activities of Daily Living (ADLs) or Instrumental ADL scales,[282] and the physical function sub-scale of the Short-Form 36 survey.[283,284] Self-report measures assess an individual's perception of their physical function limitation, taking into account their own personal, social and environmental considerations.[22,285] Therefore, the two methods of assessment capture distinct domains, and it is important to consider both.[20]

A range of physical function assessments and their associations with health are detailed below. While performance-based measures are central to the thesis, it is important to acknowledge the value of self-report measures.

Therefore, we included a self-report measure to ensure a comprehensive assessment of physical function, considering both objective performance and subjective perspectives.

3.5.1 Grip strength

Grip strength is a widely accepted measure for assessing overall muscle strength and is established as an indicator of both present and future health status, particularly among older individuals.[286,287] Grip strength generally peaks in early adult life, remains relatively consistent through midlife, but begins to decline from mid- to later life.[31] Furthermore, grip strength has demonstrated associations with future health-related outcomes, including mortality, hospital length of stay, and physical functioning, underscoring its significance as a simple but effective tool for researchers and clinicians.[27]

3.5.2 Walk tests

Walk tests, including the six-minute walk test (6MWT),[288] the 400-meter walk test (400MWT),[289] or other variations, are sub-maximal tests of aerobic capacity and endurance. The 400MWT is associated with total mortality, cardiovascular disease, mobility limitation, and mobility disability in later life.[289] The 6MWT is employed for a range of clinical uses, across a range of clinical populations.[290–293] It is associated with a range of future health outcomes, including survival after surgery,[294] decompensation in liver cirrhosis,[295] and respiratory-related outcomes after lung transplant.[296,297] This test has been less utilised than other tools for general populations, but reference values for general healthy populations are available.[298]

3.5.3 Timed Up-and-Go

The TUG is a test of dynamic balance and functional mobility (the capacity of people to move from one place to another, to participate in ADLs). It consists of standing from a chair, walking a set distance (typically 3-meters), turning around, walking back to the chair, and sitting down. It is considered a useful clinical tool, even in healthy older adults.[299] The TUG has been employed across a wide range of settings and populations,[300] and can discriminate between frail and non-frail in general older adults,[301] and clinical populations such as respiratory disease.[302] Additionally, it is associated with functional decline at 3- and 6-months post presenting at accident and emergency departments in older adults.[303]

3.5.4 Chair rise (sit-to-stand) tests

Chair rise tests are useful tools for assessing functional mobility, with test performance influenced by lower limb power, strength, dynamic balance and cardiorespiratory endurance.[304] There are a number of variations, that either count the number of repetitions over a fixed time,[305] or count the time to complete a fixed number of repetitions.[306] The test has demonstrated high reliability in both healthy adults and individuals with morbidities.[307] Poor performance has been associated with future disability,[308] and falls in older adults.[309]

3.5.5 Balance

There are a range of balance tests,[310] with balance already a component in some of the previously detailed assessment types (TUG, chair rise test). However, simple single-leg stance tests have proved popular, and predictive of a

range of outcomes, including risk of mortality in community-dwelling older adults.[311] In addition, ability to successfully complete the 10-second single leg stance balance test, in both midlife and older adults, is associated with future mortality.[312]

3.5.6 Short Form-36 (physical functioning sub-scale)

The Short-Form 36 survey (SF-36) is a self-reported health survey with 36 questions, which yields an eight-scale profile of scores as well as physical and mental health summary measures.[283] Often the overall score is erroneously employed as a general measure of health;[313] however, summary scales and subscales provide measures of different aspects of health. As well as cross-sectional associations with health, seven of the eight subscales have demonstrated associations with future health outcomes, including incident coronary heart disease.[314] The physical functioning sub-scale (SF-36pf) was the only subscale associated with future all-cause mortality.[314] In addition, the SF-36pf has been recommended as a reliable measure of physical function[315] and mobility disability.[284]

3.6 Study population

Physical function undergoes a gradual decline starting from midlife onwards, with notable changes becoming more apparent as individuals progress into older age.[60,277] This decline is multifaceted, encompassing reductions in muscle strength, aerobic capacity, balance, and agility, and may not be immediately noticeable to the individual, or clinicians. However, the assessment of physical function typically occurs in later life stages when functional limitations become more pronounced.

The WHO's Healthy Ageing Strategy underscores the importance of adopting a life course approach to healthy ageing.[2] Despite the significance of midlife in shaping long-term physical function trajectories, research and interventions targeting this life stage remain relatively sparse.

Much of the existing literature and public health initiatives tend to focus on older populations, overlooking the critical period of midlife where interventions may have the potential to delay or mitigate the onset of functional decline.[60] Figure 3.5 illustrates the impact starting and maintaining physical activity can have on attenuating the decline in physical function at different stages through the life course, highlighting the greater benefits of intervening earlier. [279]

Managing the consequences of functional loss in later life poses significant challenges, often requiring complex interventions aimed at rehabilitation and support. However, there is increasing recognition of the importance of prevention and early intervention strategies, particularly during midlife, to mitigate the downstream effects of functional decline. Midlife preservation, or retardation of early functional decline is, therefore, a public health priority.[2]

Cohort studies, which follow groups of individuals over time, provide valuable insights into how physical activity and function change across different life stages. While there are numerous cohort studies available, finding those that intersect midlife populations, include physical activity measures with accessible raw data, and incorporate performance-based physical function outcomes can be challenging. This narrow intersection influences our research decisions and the direction of the next chapters.

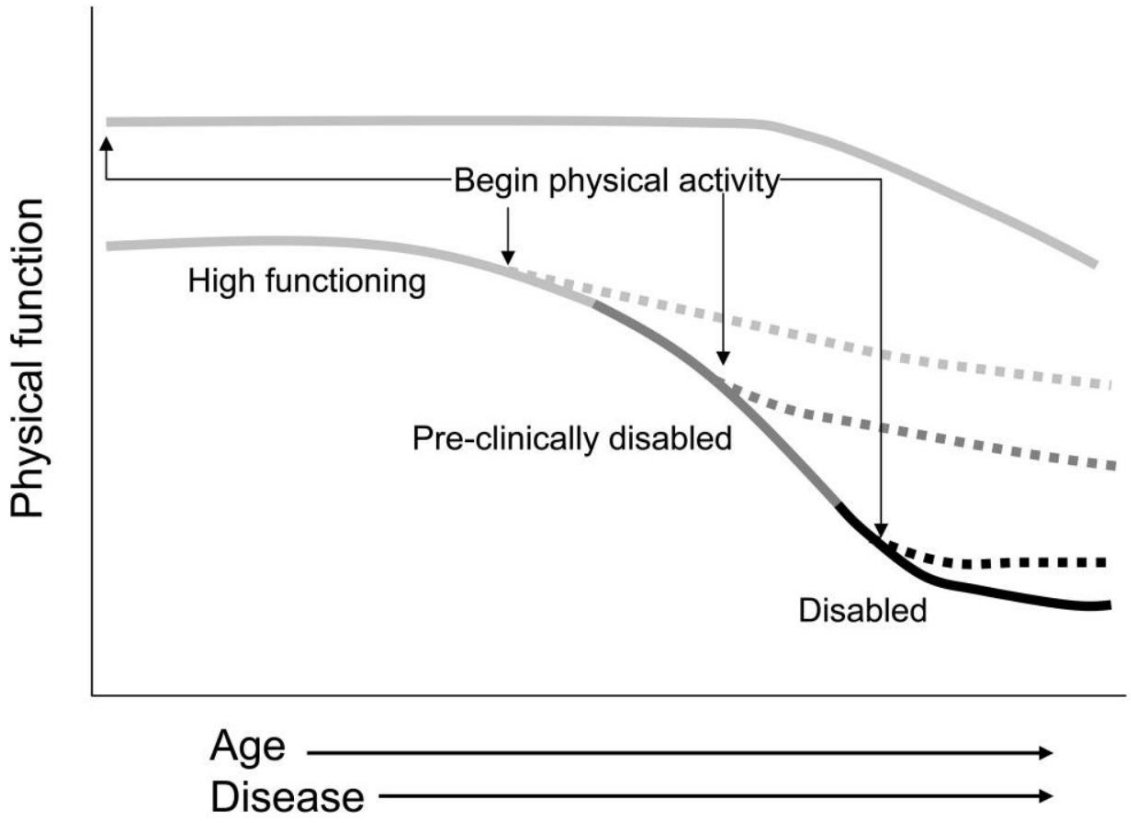


Figure 3.5. Physical function as viewed with increasing age and onset of disease. Dotted lines represent new trajectory with beginning and maintaining a physical activity programme. (From Manini et al., 2013; reproduced with permission.)

Midlife is a critical period for early detection and intervention to prevent functional decline, yet it is often underrepresented in longitudinal research. Individuals in this stage may experience diverse and fluctuating physical activity patterns due to various life circumstances, such as career demands, family responsibilities, and emerging health issues. Capturing these dynamics requires flexible and comprehensive methodological approaches. Additionally, ensuring long-term follow-up and maintaining participant engagement can be difficult given the competing priorities typical of midlife.

3.7 Summary

Chapter 3 has outlined the challenges and limitations of current research and the potential avenues to address the research aims of this thesis. Based on this information, we have chosen to focus on physical activity using an event-based approach, which allows for a more precise capture of discrete activities and reduces the misclassification issues associated with epoch-based methods. This decision was driven by the need to accurately assess the detailed patterns of physical activity and their impact on health outcomes.

We also decided to examine the associations between these detailed physical activity patterns and both performance-based and self-report measures of physical function due to their association with future health outcomes. This focus provides a more objective and comprehensive understanding of how physical activity influences physical function, beyond self-reported measures which can be prone to biases.

Additionally, we include an early midlife and older population, recognising the critical importance of the trajectory of changes in physical activity and function over the life course and the potential for early detection and intervention to prevent functional decline. Midlife represents a period where interventions can have a significant impact on maintaining or improving physical function, thus helping to mitigate the onset of age-related declines.

These methodological choices, focusing on event-based physical activity data, performance-based physical function measures, and midlife populations are detailed in the subsequent Chapter 4. This approach ensures a robust analysis of physical activity patterns and their implications for physical function, contributing valuable insights to the field.

Chapter 4
General Methods

4.1 Introduction

Chapter 3 highlighted the limitations in the current research regarding physical activity and physical function and the rationale for examining patterns of physical activity in addition to volume and in relation to physical function. This chapter provides details on the fundamental methods used for the published papers that comprise Chapters 5, 6, and 7. Each paper, and corresponding chapter has its own detailed methods section; however, here we provide a detailed description of the methods common to each study. The methodological challenges discussed in Chapter 3 are used to justify our decisions here. We describe the cohort studies utilised, and detail the device used to measure movement behaviour, the data processing, and derivation of upright and stepping metrics. Finally, we describe the physical function outcome measures.

4.2 Cohort Studies

Based on the methodological challenges and rationale outlined in the previous chapters, we sought cohort studies that met the following requirements to enable us to address our research aims. Firstly, we required the cohort to have baseline activPAL measures (discussed in the following section), with at least a 7-day measurement period. Access to the raw activPAL data was required, for us to compute the desired postural and behavioural measures. Cohort studies also needed a range of baseline performance-based physical function measures, and a self-reported physical function measure (also discussed in the following

sections). Finally, one of the cohorts need to be in an early midlife population for us to examine whether any associations between posture and stepping occur earlier in the life-course, or whether they are restricted to the later stages of the life course. Based on these criteria, we identified the following two cohort studies.

4.2.1 The 1970 British Cohort Study

The 1970 British Cohort Study (BCS70) is a long-term, multidisciplinary longitudinal cohort study of over 17’000 births in England, Scotland, and Wales.[216] The initial sample included all births in England, Scotland and Wales during a single week in 1970, with regular follow ups. During the 2016 face-to-face survey, conducted when participants reached the age of 46, a total of 8581 study members participated, offering a large sample of individuals in midlife.

The 2016 measurement phase encompassed various components, including interviews, bio-measurements administered by nurses such as physical function assessments, a digital dietary diary, and a week-long activPAL monitoring period. Physical function assessments at age 46 included grip strength, a single leg stance balance test, and a self-report of physical function, the SF-36pf. Access to BCS70 datasets is facilitated through the UK Data Service, with the raw activPAL files provided upon request. Full ethical approval for BCS70 was granted by the NRES Committee South East Coast-Brighton and Sussex.

4.2.2 De Maastricht Studie

The Maastricht Study (DMS) is a comprehensive research initiative focusing on investigating the underlying causes of type 2 diabetes (T2DM), its

traditional complications, and emerging comorbidities.[214] The study employs an extensive range of measures to assess the health status of a population-based cohort consisting of approximately 10’000 individuals. The cohort was stratified according to known T2DM status, with an oversampling of individuals with T2DM, and spans an age range of 40 to 75 years at baseline.

Enrolment for the study commenced in November 2010, and it is currently in a follow-up phase. During the baseline phase, participants underwent a week-long activPAL monitoring period. Baseline physical function assessments were conducted including, grip strength, a six-minute walk test, a timed chair-stand test, and the self-reported SF-36 survey was completed. Ethical approval for DMS was obtained from the institutional medical ethical committee (NL31329.068.10) and the Minister of Health, Welfare and Sports of the Netherlands (Permit 131088-105234-PG). All participants provided written informed consent.

Accessing DMS datasets requires researchers to submit a proposal, which undergoes a review process. External researchers seeking access must collaborate with a member of The Maastricht Study Management Team to submit a joint research proposal (Appendix 8.8). Additionally, access to the raw activPAL data was granted, with the requirement that data reprocessing is conducted at Maastricht University. To fulfil this requirement, a 10-week placement at Maastricht University was arranged to develop the proposal, reprocess the data, and generate the necessary metrics for inclusion in the dataset.

4.3 Device description: activPAL™

The activPAL™ (activPAL3 micro; PAL Technologies Ltd., Glasgow, UK) is an accelerometer that estimates posture (sitting or lying, standing, and stepping)

based on acceleration signals. It is worn on the anterior midline of the thigh, distinguishing it from other accelerometry-based activity monitors that are typically worn on the hip or wrist.

Physically, the activPAL device is compact (53 × 35 × 7 mm) and lightweight (15 g), making it comfortable for participants to wear during daily activities. Its attachment method typically involves securing the device to the thigh using medical grade, waterproof adhesive tape, ensuring stability and reliable data capture throughout the monitoring period.

The activPAL records movement data by capturing information about static and dynamic acceleration. Proprietary algorithms aim to discriminate between sitting/lying and the upright position by detecting the inclination of the thigh. It estimates stepping from the acceleration versus time wave form.[316] It classifies three different activities:

1. sitting/lying
2. standing
3. stepping

Numerous validation studies have been conducted to assess the validity and reliability of the activPAL for measuring physical activity in various settings and populations. Systematic reviews have highlighted that studies consistently demonstrate the accuracy of the device in distinguishing between different postures[212] and stepping, although at slower-paced stepping misclassification is introduced.[213] Limitations of estimates of the intensity of physical activity (e.g. MVPA) are highlighted in the latter systematic review,[213] though stepping-based

classifications of intensity are not employed in this thesis. A more relevant limitation is the difficulty in detecting slower paced stepping.

The minimum step-rate reported by the activPAL is 20 steps/min; however, the device's accuracy is compromised at slower paced stepping, with increasing underestimation of steps from 69 steps/min and slower.[317] As a result it is likely that mean step-rates are overestimated and the total daily steps underestimated. However, this limitation in detecting slower-paced stepping is a universal issue across different devices.[318] Despite these limitations, and in the absence of an alternative device better able to capture slower paced stepping, the activPAL remains the most appropriate device to address our research aims.

4.4 Data processing

The raw activPAL files (.datx) files were processed using PALbatch software v.8.11.1.63 to produce the stepping bouts output in .CSV format (https://kb.palt.com/articles/stepping-bouts-csv/). The proprietary VANE (unabbreviated term unknown) v.0.1 classification algorithm was applied to all data, using the software's 24-hour non-wear protocol and default recommended minimum durations of 10-seconds for upright and non-upright periods. Auto-correct for inverted wear was selected.

The stepping bouts output provides a time series of contiguous sit/lying (sedentary), standing, and stepping events, with a corresponding date and time stamp, duration (in seconds), and data count for each event. Stepping events had a corresponding step count (minimum 2 steps) and cadence value. Cadence was calculated as the step count divided by the duration of the stepping event, multiplied by 60, to give steps per minute. The output also provides the number

and duration of containing upright events (for contiguous standing and stepping events between to sedentary events). A screenshot of example stepping output is presented in Figure 4.1, with the columns used to derive metrics highlighted in yellow.

	A	B	C	D	E	F	G	H	I
1	Time	Time(approx)	Data Count	Event Type	Duration (s)	Upright Bout Number	Upright Bout Duration (s)	Num Steps	Cadence
2	42851.6835	26/04/2017 16:24	0	1	2.8	1	2.8	0	0
3	42851.68353	26/04/2017 16:24	28	0	1072.4	0	0	0	0
4	42851.69594	26/04/2017 16:42	10752	1	4.7	2	130.6	0	0
5	42851.69599	26/04/2017 16:42	10799	2	7.5	2	130.6	4	32
6	42851.69608	26/04/2017 16:42	10874	1	23.4	2	130.6	0	0
7	42851.69635	26/04/2017 16:42	11108	2	11.8	2	130.6	10	51
8	42851.69649	26/04/2017 16:42	11226	1	9.6	2	130.6	0	0
9	42851.6966	26/04/2017 16:43	11322	2	19.9	2	130.6	26	78
10	42851.69683	26/04/2017 16:43	11521	1	22.7	2	130.6	0	0
11	42851.69709	26/04/2017 16:43	11748	2	23.6	2	130.6	14	36
12	42851.69737	26/04/2017 16:44	11984	1	7.4	2	130.6	0	0
13	42851.69745	26/04/2017 16:44	12058	0	31.8	0	0	0	0
14	42851.69782	26/04/2017 16:44	12376	1	7.9	3	84.7	0	0
15	42851.69791	26/04/2017 16:45	12455	2	5.2	3	84.7	6	69
16	42851.69797	26/04/2017 16:45	12507	1	9.8	3	84.7	0	0
17	42851.69808	26/04/2017 16:45	12605	2	19.8	3	84.7	28	85
18	42851.69831	26/04/2017 16:45	12803	1	12.9	3	84.7	0	0
19	42851.69846	26/04/2017 16:45	12932	2	4.9	3	84.7	4	49
20	42851.69852	26/04/2017 16:45	12981	1	6.7	3	84.7	0	0
21	42851.6986	26/04/2017 16:45	13048	2	0.9	3	84.7	2	133
22	42851.69861	26/04/2017 16:46	13057	1	8.1	3	84.7	0	0
23	42851.6987	26/04/2017 16:46	13138	2	7.6	3	84.7	10	79
24	42851.69879	26/04/2017 16:46	13214	1	0.9	3	84.7	0	0
25	42851.6988	26/04/2017 16:46	13223	0	413.7	0	0	0	0
26	42851.70359	26/04/2017 16:53	17360	1	0.8	4	79.5	0	0
27	42851.7036	26/04/2017 16:53	17368	2	42.3	4	79.5	64	91
28	42851.70409	26/04/2017 16:53	17791	1	21.1	4	79.5	0	0
29	42851.70433	26/04/2017 16:54	18002	2	13.1	4	79.5	18	82
30	42851.70448	26/04/2017 16:54	18133	1	2.2	4	79.5	0	0

Figure 4.1. Screenshot of activPAL stepping output .csv file open in Excel. Columns of data utilised for deriving metrics are highlighted in yellow.

Although the stepping bout output includes upright bout number and upright bout duration columns, these were ignored, and upright events were calculated manually. We opted to do this as we were exploring different minimum durations of upright event for inclusion in various analyses, discussed later. Upright events were defined as the time between two consecutive sedentary events. The cadence column was also ignored, and our step-weighted cadence metric was calculated using step count and durations. This was because cadence values in the stepping output were rounded to the nearest integer, and we opted to calculate the most accurate cadence possible with the data available.

Individual stepping outputs were appended in Stata (v17.0, StataCorp LLC: TX, USA).

Data were cleaned, per participant, using the date to remove the first partial day and any data after the 8th day (the 7th full day of data). Any periods of non-wear (classified by the activPAL software) were removed. The total, continuous, wear duration was calculated and checked, removing the final bout that crossed midnight. The Stata syntax for processing the data and deriving metrics is included in Appendix 8.9.

4.4.1 Minimum number of valid days

The minimum number of valid days was chosen to be six. This is higher than typical in both physical function research and physical activity research more broadly but was decided based on the following reasons. In both BCS70 and DMS, the device was attached by a member of the cohort team (nurse or research assistant). Instructions were to wear the device continuously and not attempt to reapply if the device was removed or became detached. We allowed for one day of data loss at the end of the measurement period, due to early removal, but otherwise considered six or seven continuous days to be adherence to the protocols.

4.4.2 Waking wear time

When selecting waking wear algorithms to employ, we considered the available options, which included the activPAL's proprietary CREA classification and an open source sleep algorithm.[319] Differences between algorithms designed to detect sleep and waking wear, have been shown not to be comparable,

including previously validated ActiGraph, activPAL, and the CREA classification methods.[320] We opted to employ our own simple method for classifying waking wear for two reasons. 1) The current methods are available for aggregate/summary outputs, i.e. they process the summary outputs using their waking wear algorithms, whereas we required the stepping outputs. These summary outputs provide the average step count, posture durations, etc. per measurement period or per day of measurement period, respectively. 2) We wanted a simple method that could be employed across any device. Or if we wanted to derive these metrics in additional samples, we wanted to remain consistent. Therefore, we chose not to use an activPAL specific algorithm.

Our simple method to isolate valid waking wear time from sleep worked as follows. Waking wear time was estimated using the first upright event (≥10 seconds) after 03:00h until the event preceding the one that crossed the following midnight. This estimation method was based on the average midsleep point reported in a large UK cohort study,[321] and assumed that the next upright event ≥10 seconds after this midsleep point represented the arise time. Sensitivity analyses on this threshold is performed in Chapter 5. A minimum of 10 hours of waking wear and >3 upright events (≥10 seconds) was required for a day to be valid.

Applying these rules did not remove many valid days, but it did remove days that were classified as ‘wear’ (i.e. not non-wear) by the activPAL but may have been from participants who were bed ridden on these days or were just extremely sedentary. Removal of these days was justified due to our interest in a general ambulatory population and stepping behaviour. The limitations of this method are

discussed within each paper, and more generally in the limitations section of Chapter 8, the general discussion.

4.5 Derivation of metrics

A suite of metrics was derived that intended to explore the composition of upright and stepping events, and the temporal distribution of upright and sedentary events. These metrics were derived for the waking wear time of each 24-hour period.

4.5.1 Frequency, duration, composition, and cadence metrics

All metrics are described in Table 4.1 and Table 4.2. The mean daily value of all metrics were derived per person. The step count (steps/day), frequency of upright events (n/day), and stepping events (n/day) were derived from counting these events within waking wear periods. The mean duration of stepping event (min) and number of steps per stepping event (steps/event) were derived for individual stepping events.

The mean step-weighted cadence (steps/min) weighted the cadence of every stepping event (≥10 steps) to the step count within the event. A minimum of ten steps was employed during cadence calculation, as it has been determined that 6 to 10 consecutive steps are necessary to precisely capture stepping cadence.[322]

The characteristics of each individual upright event were defined by its duration (mins), the percentage of time spent stepping (%), the count of stepping events (n/event), and the step count (steps/event). The mean daily values of

these four within event composition metrics, across the measurement period, were calculated per person.

The distributions (by sex) of all derived metrics are visualised via histograms in Figure 4.2. The correlations between metrics are displayed in a correlation matrix in Figure 4.3. Most correlations are significantly correlated; however, the only metric strongly correlated ($r > 0.5$) with step count is the number of stepping events.

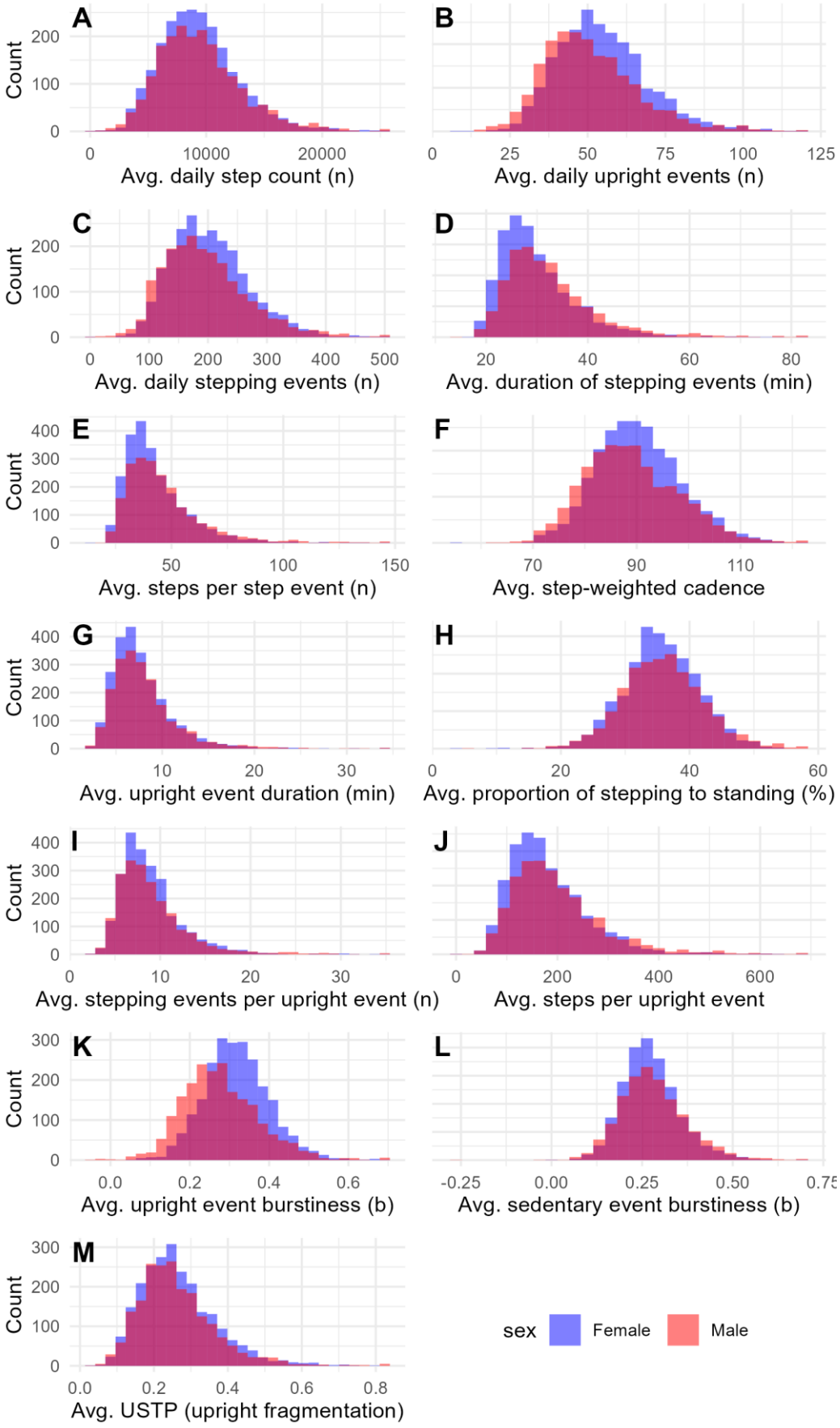


Figure 4.2. Histograms of each physical activity metric, by sex. Letters correspond with the metrics listed in tables. Letters denote the metric outlined in Tables 4.1 and 4.2.

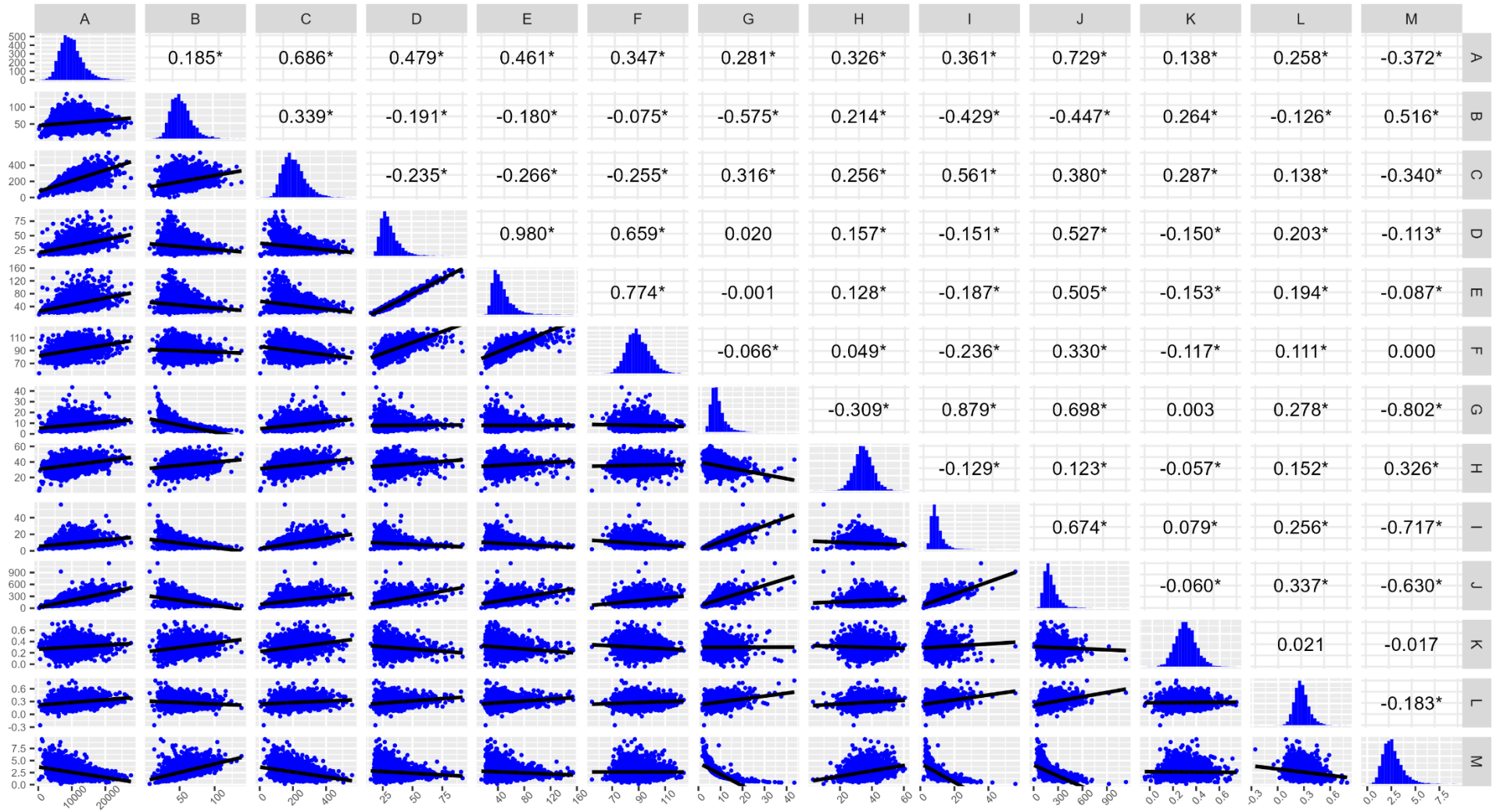


Figure 4.3. Correlation matrix of all derived physical activity metrics. Letters denote the metric, which can be looked up in Tables 4.1 and 4.2. Values represent Pearson's correlation coefficient. Letters denote physical activity metrics as follows: A. Daily step count; B. Daily upright events; C. Daily stepping events; D. Duration of stepping events; E. Steps per stepping event; F. Step-weighted cadence; G. Upright event duration; H. Proportion of stepping to standing time; I. Stepping events per upright event; J. Steps per upright event; K. Upright event burstiness; L. Sedentary event burstiness; M. Upright to sedentary transition probability (USTP).

Table 4.1. Summary of composition and temporal duration metrics of upright and stepping events.

Composition of upright and stepping events	Description	Units
A. Daily step count	Average number of steps per day across the measurement period. Indicator of volume of physical activity	steps/day
B. Daily upright events	Average number of upright events per day across the measurement period. Equivalent to the number of sit-to-stand transitions	n/day
C. Daily stepping events	Average number of stepping events per day across the measurement period. Indicator of how fragmented stepping behaviour is across the day	n/day
D. Duration of stepping events	Average duration of all stepping events.	min/event
E. Steps per stepping event	Average number of steps per stepping event.	steps/event
F. Step-weighted cadence	Average step-weighted cadence per day across the measurement period. Calculated as the mean daily step-weighted cadence (weighted by steps per event) of all stepping events. Indicator of step-rate (a proxy for intensity) that takes into account all steps	steps/min
G. Upright event duration	Average duration of upright event.	min
H. Proportion of stepping to standing time	Average proportion of time spent stepping when upright	%
I. Stepping events per upright event	Average number of stepping events per upright event. Indicator of how fragmented stepping is within upright events on average	n/event
J. Steps per upright event	Average number of steps per upright event. Indicator of the average stepping volume per upright event	steps/event

4.5.2 Temporal distribution and fragmentation metrics

The fragmentation metric chosen for this study is based on ASTP, which has been widely used in the literature to assess the breakdown of physical activity into active and inactive periods throughout the day.[104] ASTP is characterised as the probability of transitioning from an active to a sedentary state and is computed as the reciprocal of the average active bout duration. In the context of this study, the reciprocal of the average upright event duration is applied, serving as an indicator of the likelihood of transitioning from an upright posture to a sedentary posture. To avoid confusion, we refer this to metric as the Upright-to-Sedentary Transition Probability (USTP). USTP was calculated per day and averaged across valid days per participant.

Fragmentation is particularly relevant for this study due to its mechanistic link to physical function. For example, frequent transitions between activity and rest may reflect reduced endurance capacity, which can lead to altered activity behaviour, such as shorter or more frequent bouts of activity. These patterns not only reflect physical capacity but may also be influenced by a person's confidence in sustaining activity without excessive fatigue or concerns about the risk of falling.

ASTP has been employed across various studies examining outcomes such as physical function, mortality, and chronic disease management, reviewed in detail in Chapter 3. The widespread use and clinical validity make ASTP highly translatable to different populations, including those at risk for functional decline. However, it is important to acknowledge that previous use of ASTP, which typically relies on minute-epoch analysis, has potential for misclassifying the start and end of activity events. Employing an event-based approach, using the

precise start and end times of postural transitions, overcomes this limitation and may therefore improve the precision in associations between the measure and measures of physical function. An additional limitation of the method used to compute ASTP is the reliance on a single threshold of acceleration within each 1-minute epoch to categorise the epoch as active or inactive. This is likely to lead to misclassification of some epochs as the value of acceleration that discriminates between activity and rest will value between individuals. In this thesis, the ASTP is based on transitions between upright and sedentary postures using a validated device designed to accurately capture postural changes, that avoids the problem of selecting an acceleration threshold to segment the data. The combination of an event based method and the use of a valid device for accurately capturing posture changes will improve the precision of associations between behavioural measures and physical function.

As previously discussed, ASTP does not capture the temporal distribution of events, potentially overlooking important patterns. To address this, we employed burstiness measures, which quantify the clustering of activity and rest periods throughout the day. This measure complements the fragmentation metric by providing insights into the distribution of activity, which may implications for understanding physical function and health such as the timing between sequences of upright events. This is potentially important as a cluster of sit to stand transitions would lead to a level of fatigue that would be higher than the same number of transitions more evenly spread over a period of time. The review in Chapter 2 did not identify any suitable measures for capturing this aspect of physical activity accumulation. Therefore, I sought advice from university colleagues with expertise in the analysis of time series data (personal communication). I was guided towards the ‘burstiness’ measure, a measure of

the extent to which time series of events occur in bursts followed by long breaks or are more uniformly across time.

Burstiness complements the fragmentation metric by providing insights into the distribution of activity, whereas the fragmentation metric mainly describes the frequency and duration of events. It is possible for two people to have a similar fragmentation value but different values of burstiness. For example, they may both have the same number of active events and the same total time being active, but the extent to which the number of events are clustered together could vary. As discussed in the previous chapter, burstiness has been employed in two studies of human physical behaviour with interesting findings,[323] suggesting further investigation is warranted.

The 'burstiness' parameter was used to describe the temporal distribution of upright events and sedentary events, based on variation of inter-event times.[263] Burstiness quantifies the degree to which the events of interest (upright or sedentary) occur in short, frequent clusters followed by longer gaps between events. On a scale of -1 to +1, the burstiness coefficient expresses a uniform time-series with -1, a Poissonian or random time-series with 0, and 'extreme' standard deviation of inter-event times with +1.[324] Burstiness was computed per day during waking hours, then averaged per person, utilising the following equation to adjust for number of events:[323]

$$B_n = \frac{\sqrt{n+1}\ \left(\frac{\sigma}{\langle\tau\rangle}\right) - \sqrt{\mathrm{n}-1}}{\left(\sqrt{n+1}-2\right)\ \left(\frac{\sigma}{\langle\tau\rangle}\right) + \sqrt{\mathrm{n}-1}}$$

Here, *n*, σ, and ⟨τ⟩ represent the number of events, standard deviation of inter-event time, and mean of inter-event time, respectively. This formula was

similarly applied to assess the inter-event time distribution (burstiness) of sedentary events (where inter-event time refers to the duration of upright events). A lower B_n indicates a smaller standard deviation of inter-event times compared to the mean, implying lower burstiness. Conversely, a higher B_n suggests a larger standard deviation compared to the mean, indicating 'burstier' behaviour.[324]

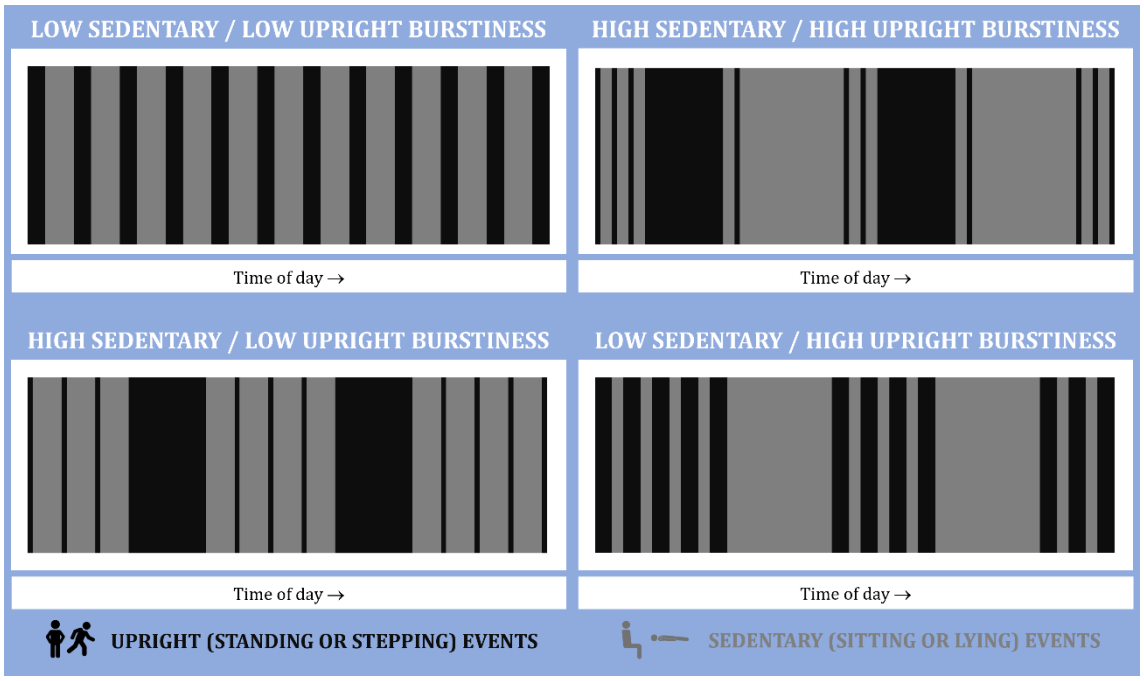


Figure 4.4. Schematic diagram depicting examples of burstiness for sedentary and upright events. The examples are matched for daily event count, waking wear time, and duration of upright events to ensure a fair comparison. Low burstiness is represented by a coefficient of -1, while high burstiness is indicated by a coefficient of +0.5. (From Culverhouse et al., 2024; reproduced under CC BY licence.)

The illustration in Figure 4.4 showcases both high and low burstiness for sedentary and upright events. The low sedentary / low upright example displays an even distribution of both event types throughout the day. The high sedentary / low upright example exhibits consistent sedentary event durations but features two longer upright events amid several shorter ones, achieving high burstiness in sedentary events through a mix of durations. Conversely, high burstiness in upright events (low sedentary / high burstiness) is characterised by clusters of short gaps between upright events, followed by more extended sedentary

periods. The high sedentary / high upright example demonstrates a combination of both scenarios. These examples visually elucidate burstiness, although real-world movement data presents a more intricate and diverse picture.

Table 4.2. Summary of temporal duration metrics of upright events.

Temporal distribution of upright and stepping events	Description	Units
K. Upright event burstiness	Average daily upright event burstiness (inter-event time distribution) across the measurement period. Indicator of the degree to which upright events are clustered together with longer sedentary events between clusters, versus a more uniform distribution of upright events through the day	B_n
L. Sedentary event burstiness	Average daily sedentary event burstiness (inter-event time distribution) across the measurement period. Indicator of the degree to which sedentary events are clustered together with longer upright events between clusters, versus a more uniform distribution of sedentary events through the day	B_n
M. Upright to sedentary transition probability (USTP)	Average daily USTP across the measurement period. USTP was defined as the probability of transitioning from an upright state to a sedentary state, and calculated as the reciprocal of the average upright event duration.[104] A higher USTP is an indicator of more fragmented pattern of upright behaviour.	USTP

4.6 Physical function measures

The protocols for collecting physical function measures are detailed below for each cohort study. We carefully selected BCS70 and DMS based on their population characteristics, accelerometer measures, and available physical function outcomes. While these cohorts met most of our criteria, we did not obtain a measure of gait speed. Therefore, the physical function outcomes included in this thesis are as follows:

4.6.1 Grip strength

In BCS70, grip strength was assessed using a Smedley spring-gauge hand-held dynamometer.[168] Participants were instructed to hold the device in the specified hand and exert maximum force by squeezing its handle for two seconds. The research nurse recorded the achieved value in kilograms (kg) before resetting the device. Participants were given the option to stand without arm support during the test, although they were permitted to conduct the assessment with arm support while seated if necessary. The assessment was repeated up to six times, with three trials performed on each hand, alternating between hands. The average of three attempts with the dominant hand was used for analysis within this thesis.

In DMS, grip strength was measured using the Jamar handheld dynamometer (SEHAN Corp., Korea-Biometrics Europe BV, Almere).[159] Participants were instructed to stand straight against a wall, with the upper arm positioned along the trunk and the elbow flexed at a 90° angle. They were then directed to squeeze the dynamometer with maximal force for a duration of 3 to 5 seconds, while receiving standardised encouragement. The measurement was

conducted three times on each hand, with participants alternating between hands. The maximal strength achieved from each trial was recorded, in kg.

4.6.2 Timed chair rise test

In DMS, the timed chair rise stand test (TCST) was conducted using a 46 cm high chair with a straight back and no armrests.[159] Participants began the test in a sitting position with their arms crossed over the chest. They were instructed to rise to a full upright position and return to a seated position as quickly as possible without utilising their arms or hands for support. The time taken (in seconds) to complete 10 repetitions was measured to the nearest decimal. (Note: the TCST is the only physical function outcome included where a lower value indicates better performance).

4.6.3 Six-minute walt test (6MWT)

In DMS, the six-minute walk test (6MWT) was conducted in a designated hallway, with two cones positioned 20 meters apart around which participants navigated turns.[159] They were instructed to walk as many laps as possible in 6 minutes at a brisk pace without running. Standardised encouragement was provided every minute during the test. Upon completion of 6 minutes or when the participant was unwilling or unable to continue, the distance covered was measured, in meters.

4.6.4 Single leg stance test (balance)

In BCS70, balance was assessed using a single leg stance test.[168] Participants were allowed to support themselves on a chair, table, or wall while

assuming the test position. They were permitted to use their arms, bend their knee, or make body movements to maintain balance during the test but were instructed not to move their standing foot. Timing commenced as soon as the participant raised one leg off the ground and concluded when balance was lost, indicated by the raised foot touching the floor or the foot on the floor shifting out of position, or after 30 seconds had elapsed. Participants who achieved a balance time of 30 seconds with eyes open were then asked to repeat the test with their eyes closed. Any participant who felt unsafe or reported health-related reasons for being unable to complete the tests had this recorded by the nurse.

4.6.5 SF-36 physical functioning

Self-reported physical functioning was evaluated using the physical function score derived from the 36-Item Short Form Health Survey (SF-36).[283] This questionnaire, widely used for assessing health-related quality of life, comprises eight domain scores, including 'physical functioning' (SF-36pf).[284] The physical functioning domain consists of 10 items assessing various activities such as walking specified distances, carrying groceries, and bathing or dressing. Each item is scored based on perceived limitations, with scores summed to obtain a total score scaled relative to its range. The SF-36pf scale has demonstrated good internal consistency and reliability among community-dwelling older adults.[284,315]

4.7 Summary

Chapter 4 (with the support of Chapter 3) has addressed the second objective of this thesis: 2) Derive a suite of physical activity pattern metrics from thigh worn accelerometer postural and stepping data. In Chapter 3, we outlined

the limitations of current research and justified our focus on physical activity patterns alongside volume in relation to physical function. Chapter 4 has provided an overview of the general methods used across Chapters 5, 6, and 7, based on the methodological challenges highlighted in Chapter 3.

We described the activPAL device, our data processing, and how we derived the metrics employed in the following chapters. Two cohort studies and their protocols for collecting the physical function outcomes are detailed. These studies provide baseline activPAL measures and physical function assessments essential for our analyses. This chapter has laid the groundwork for the subsequent research chapters, outlining our approach to studying physical activity patterns and their impact on physical function across different populations.

Chapter 5
Descriptive Epidemiology of Physical Activity Accumulation

5.1 Overview

Chapter 5 aims to address the third thesis objective by exploring the variation in the pattern metrics, derived in the previous chapter, across sociodemographic factors. We identify variations in the accumulation, temporal distribution, and composition of upright and stepping events. Potential phenotypes of postural and stepping behaviour emerged, which could potentially be differentially associated with health outcomes. This chapter was published as a peer reviewed paper: *Unravelling upright events: a descriptive epidemiology of the behavioural composition and temporal distribution of upright events in participants from the 1970 British Cohort Study.*[325] The published version is available digitally using the following DOI: https://doi.org/10.1186/s12889-024-17976-2.

5.2 Introduction

As discussed in Chapter 1, and highlighted in Chapter 2, most physical activity research using accelerometers is still restricted to a small number of aggregate metrics, such as the number of minutes of at least moderate intensity activity, or time spent sedentary. However, there is growing research interest in utilising time stamped data to move beyond these simple metrics.[326] For example, frequency of postural (sit-to-stand) transitions has been associated with metabolic health;[272,327] the timing of physical activity is undertaken has been

associated with cardiovascular disease risk and mortality;[328,329] and how fragmented (transient) or sustained physical activity events are has been associated with a range of age related health outcomes.[101,102,105,106]

When in an upright posture people can be either standing or ambulating, with evidence that stepping confers greater metabolic health benefits than standing-only upright events.[272] Therefore, the next step beyond counting the frequency of upright events is to characterise their durations, temporal distribution, and their composition (the mix of standing and stepping). Standing and stepping events within each upright event can further be characterised by their frequency, duration, and stepping rate (cadence).[330]

A recent cross-sectional study examined the associations between sitting interruptions (upright events), demographic factors, diabetes status, and BMI.[273] The frequency of all interruptions, active interruptions (≥5-minutes duration and/or ≥2-minutes stepping) and ambulatory interruptions (≥2-minutes stepping) were extracted from 7-days of thigh worn activPAL data. Fewer interruptions of any type and fewer steps per day were associated with higher BMI and diabetes status. However, the study did not take account of the stepping vs standing composition of upright events, the temporal distribution of events, the number and composition of stepping events, and did not control for all steps accumulated.

This is important as the proportions and total duration of standing and stepping, the number and distribution of stepping and standing events, and the stepping volume and cadence can all vary even when the total number and duration of upright events is the same. Moreover, the temporal distribution of upright events can vary while the frequency, duration and composition of events

is the same. These features of activity accumulation all have the potential to be associated with health outcomes and warrant further investigation.

Given emerging evidence regarding the importance of the patterns in which physical activity is accumulated,[99] a deeper understanding of the composition, and temporal distribution, of upright events, may provide new insights into their relationship with health outcomes and how they differ between people. Such, insights may be masked when behaviours such as sitting, standing, and stepping are confined to measures of frequency, average duration, average time between events, or the volume of time in each event over different observation periods. To our knowledge, no study to date has fully described the composition and temporal distribution of upright events recorded in a free-living setting. Therefore, in this chapter we address this need by providing a comprehensive description of the composition and temporal distribution of free-living uprights events and how they vary by demographic and health factors, in a cohort of midlife UK adults.

5.3 Methods

For detailed descriptions of the study design, physical activity measurement, and data processing methods, derived metrics, and physical function measures refer to the general methods in Chapter 4.

5.3.1 Demographic and health-related characteristics

Participants provided information on a range of socio-demographic, lifestyle, and health factors. Body Mass Index (BMI in kg/m^2) was calculated for nurse measured height (portable Leicester stadiometer) and weight (Tanita BF - 522W scales), and categorised as under-weight (<18.5), normal-weight (18.5–

24.9), overweight (25.0–25.9), obese (30.0–34.9), or morbidly obese (≥35.0). Educational qualification was reported and classified into the following: none, GSCE, A-level, degree. Socio-economic status was reported using the five-class National Statistics Socio-economic Classification (NS-SEC),[331] which categorises occupations hierarchically ranging from high-level managerial/professional roles to routine jobs. The European Union Statistics on Income and Living Conditions (EU-SILC)[332] provided disability categorisation ranging from: none, some extent, severely hampered. Occupational activity was classified into the following: sitting, standing, physical work, and heavy manual work. Self-reported smoking status was grouped into four categories: never, past smoker, occasional smoker, daily smoker. Self-rated health was categorised as poor, fair, good, very good, or excellent, and was used here as a simple measure of general health.

5.3.2 Statistical analyses

Participants with six or more valid days of activPAL wear (≥10 waking wear hours) and complete demographic and health-related data were included in the analyses. Generalised linear regression models were employed to describe and compare upright event metrics across sex, socio-economic status, education level, disability status, BMI classification, smoking status, and self-rated health; additionally adjusted for waking wear time and mean daily step count. Multi-collinearity was checked using the variance inflation factor (VIF).

5.3.2.1 Sensitivity analyses

To assess the robustness of our results, analyses were repeated to assess the impact of EU-SILC disability classification in the analytical sample. These

included rerunning analyses excluding participants classified as severely hampered, and again excluding the ‘some extent’ and severely hampered classifications.

5.4 Results

5.4.1 Participant characteristics

A total of 4526 participants (78% of the 5795 activPAL files available) had six or more valid days (≥10 $h \cdot d^{-1}$ waking wear and >3 upright events) of activPAL data. This resulted in 30,992 valid days with an average waking wear time of 16.2±0.9 $h \cdot d^{-1}$ (mean ± SD), and a total of 1,638,009 upright events. Participants had an average of 52.9±15.3 upright events per day, and 198.4±69.6 stepping events per day. Upright duration averaged 6.4±1.9 $h \cdot d^{-1}$, with stepping duration 2.0±0.7 $h \cdot d^{-1}$, and the mean daily step count for was 9389±3586 $steps \cdot d^{-1}$. A total of 3965 participants had valid accelerometer wear and complete covariates data, this sample was included in regression analyses. Table 5.1 provides a descriptive summary of upright events by sex for this sample and presents the samples demographics. For all regression models, VIF was <2 for each independent variable.

5.4.2 Characterisation, composition, and temporal distribution of upright events

All analyses were adjusted for average number of steps per day, therefore, the reported variances across demographics for these metrics were present when adjusting for a proxy measure of volume.

Table 5.1. Descritpives of participant demographics (n (%)), and device-derived metrics (mean(SD)).

Demographics	**Men (n=1897)**	**Women (n=2068)**
Highest qualification		
None	523 (56.3%)	406 (43.7%)
GCSE	571 (46.4%)	660 (53.6%)
FE	252 (40.1%)	377 (59.9%)
HE	551 (46.9%)	625 (53.1%)
Disability		
None	1701 (49.0%)	1771 (51.0%)
Some extent	151 (38.9%)	237 (61.1%)
Severely hampered	44 (42.7%)	59 (57.3%)
Self-rated health		
Excellent	353 (43.4%)	461 (56.6%)
Very good	743 (47.6%)	817 (52.4%)
Good	557 (50.6%)	543 (49.4%)
Fair	211 (51.2%)	201 (48.8%)
Poor	33 (41.8%)	46 (58.2%)
NS-SEC group		
Professional	1049 (52.6%)	947 (47.4%)
Intermediate	564 (46.7%)	643 (53.3%)
Routine	235 (43.5%)	305 (56.5%)
BMI		
Normal (18.5<25)	428 (34.8%)	801 (65.2%)
Overweight (25<35)	862 (56.8%)	656 (43.2%)
Obese (30<35)	540 (52.3%)	493 (47.7%)
Morbidly obese (≥35)	27 (25.2%)	80 (74.8%)
Underweight (<18.5)	40 (51.3%)	38 (48.7%)
Occupational activity		
Sitting	1029 (47.0%)	1159 (53.0%)
Standing	190 (30.3%)	437 (69.7%)
Physical work	510 (52.8%)	455 (47.2%)
Heavy manual	168 (90.8%)	17 (9.2%)
Smoking habits		
Never	954 (58.6%)	1082 (41.4%)
Past smoker	612 (47.6%)	673 (52.4%)
Occasional smoker	93 (51.4%)	88 (48.6%)
Daily smoker	238 (51.4%)	225 (48.6%)
Device-derived metrics	**Men (n=2077)**	**Women (n=2387)**
Summary metrics		
Upright events (n)	50.8 (15.5)	54.7 (14.8)
Stepping events (n)	194.7 (72.6)	201.7 (66.8)
Upright duration (h)	6.3 (1.9)	6.6 (1.9)
Standing duration (h)	4.3 (1.5)	4.6 (1.5)
Stepping duration (h)	2.0 (0.7)	2.0 (0.7)
Pattern metrics		
Upright event burstiness (B_n)	0.28 (0.10)	0.31 (0.08)
Sedentary event burstiness (B_n)	0.28 (0.09)	0.27 (0.08)
Stepping metrics		
Step count (steps)	9451 (3670)	9334 (3483)
Step-weighted cadence (steps/min)	88.8 (9.2)	90.1 (8.4)
Stepping event duration (s)	32.5 (9.2)	29.7 (7.5)
Step count per stepping event (steps)	46.1 (17.8)	42.4 (14.4)
Composition metrics		
Upright event duration (min)	8.0 (3.7)	7.7 (3.8)
Stepping proportion (%)	35.8 (6.4)	35.5 (5.9)
Stepping events per upright event (n)	9.1 (4.1)	8.9 (3.6)
Step count per upright event (n)	198.8 (97.5)	179.6 (79.4)

n = number/count. h = hour. min = minute. s = seconds

Females moved to an upright posture more frequently than males (4.39 [3.41,5.38] n), spent more time upright and standing, and the upright events were more bursty than males (more clustered together with longer between event times (0.05 [0.04,0.05] B_n)) (Table 5.2). Although there was no difference in the total number of steps taken between the sexes, females recorded a higher daily frequency of stepping events (13.39 [10.24,16.53] n), with shorter durations; with fewer steps per stepping and upright event, but steps taken were at a higher average cadence (0.89 [0.39,1.40] steps·min^{-1}) (Table 5.3, Table 5.4).

There was very little difference in upright events and total steps per day according to educational attainment. However, participants with the highest qualification recorded fewer stepping events per day (-8.07 [-12.56,-3.59] n), but each event was longer (1.42 [0.75,2.10] s) and contained more steps (2.13 [0.83,3.43] steps) than people without educational qualifications (Table 5.3). The main difference between people with different levels of disability was in the total number of steps taken per day. The most disabled people took an average of 1271 steps less per day than more abled people (Table 5.3). Similarly, there were only weak associations between characteristics of upright events and self-rated health. By contrast, the worse a person's self-rated health, the fewer total steps they recorded each day; they recorded more stepping events overall, but they tended to be shorter and at a lower cadence, compared to people reporting better health (Table 5.3). In other words, people in poorer health undertook fewer sustained periods of stepping.

People with a higher BMI stood up less often than people with a healthy BMI, and their upright events were longer in duration on average, had more steps, and were less bursty (overweight -0.02 [-0.02,-0.01] B_n; obese -0.03 [-0.04,-0.02]

B_n) (Table 5.2, Table 5.4). When they were stood up, they had a higher stepping proportion (overweight 0.62 [0.17,1.07] %; obese 0.81 [0.31,1.32] %) (Table 5.4). However, a higher BMI was associated with considerably fewer total steps per day compared with a healthy BMI (overweight -419.58 [-675.23,-163.93] steps; obese -1232.63 [-1518.66,-946.59] steps), accumulated at a lower cadence for those who were obese (-0.69 [-1.34,-0.03] steps·min^{-1}).

There were no differences in the frequency of upright events by occupational activity, but people in more active occupations were upright for longer each day, because the duration of each of their upright events was longer compared with sedentary occupations (Table 5.2, Table 5.4). Their pattern of being upright was more bursty than sedentary workers (standing 0.04 [0.03,0.05] B_n; physical work 0.05 [0.04,0.05] B_n; heavy manual 0.06 [0.04,0.07] B_n), as was their patten of sedentary events (standing 0.02 [0.01,0.02] B_n; physical work 0.02 [0.01,0.03] B_n; heavy manual 0.03 [0.01,0.04] B_n). Active workers recorded more stepping events per day and per upright event, leading to a higher daily step count. Although each upright event contained more stepping events than sedentary workers, the events were longer, and step-rate was lower compared to the stepping rate of sedentary workers.

Daily smokers were upright more than non-smokers, and a greater proportion of upright time was standing compared to stepping, resulting in a lower daily step count. The individual upright and stepping event durations, step count, step events, stepping proportion, and step-weighted cadence distributions are shown in histograms (Appendix 8.1).

Table 5.2. Daily summaries metrics by socioeconomic and health-related factors in adults aged-46 (BCS70).

		Upright events (n)		Upright duration (min)		Standing duration (min)		Stepping duration (min)		Upright event burstiness (B_n)		Sedentary event burstiness (B_n)	
	N	B	[95% CI]	B	[95% CI]	B	[95% CI]	B	[95% CI]	B	[95% CI]	B	[95% CI]
Sex (Ref: Male)	1897	Ref.		Ref.		Ref.		Ref.		Ref.		Ref.	
Female	2068	4.39***	[3.41,5.38]	22.68***	[17.20,28.16]	22.86***	[17.69,28.03]	-0.18	[-0.91,0.54]	0.05***	[0.04,0.05]	0.00	[-0.01,0.00]
Highest qualification (Ref: None)	929	Ref.		Ref.		Ref.		Ref.		Ref.		Ref.	
GCSE	1231	0.22	[-1.03,1.46]	0.85	[-6.11,7.81]	0.59	[-5.97,7.15]	0.26	[-0.66,1.18]	0.00	[-0.00,0.01]	-0.01	[-0.01,0.00]
FE	629	0.10	[-1.41,1.60]	0.97	[-7.45,9.38]	0.53	[-7.41,8.46]	0.44	[-0.67,1.55]	0.00	[-0.00,0.01]	-0.01*	[-0.02,-0.00]
HE	1176	-0.95	[-2.35,0.45]	-6.87	[-14.62,0.87]	-6.45	[-13.76,0.85]	-0.42	[-1.45,0.60]	0.00	[-0.01,0.01]	-0.02***	[-0.03,-0.01]
Disability (Ref: None)	3472	Ref.		Ref.		Ref.		Ref.		Ref.		Ref.	
Some extent	388	-0.48	[-2.12,1.15]	3.57	[-5.43,12.56]	3.29	[-5.19,11.78]	0.27	[-0.92,1.46]	0.00	[-0.01,0.01]	0.00	[-0.01,0.01]
Severely hampered	103	-2.72	[-6.00,0.56]	-17.26	[-34.89,0.37]	-17.69*	[-34.32,-1.07]	0.44	[-1.90,2.77]	0.01	[-0.01,0.03]	-0.02	[-0.04,0.00]
Self-rated health (Ref: Excellent)	814	Ref.		Ref.		Ref.		Ref.		Ref.		Ref.	
Very good	1560	0.83	[-0.42,2.08]	9.76**	[2.83,16.69]	7.69*	[1.16,14.23]	2.07***	[1.15,2.98]	0.01*	[0.00,0.01]	0.00	[-0.00,0.01]
Good	1100	0.94	[-0.45,2.32]	8.50*	[0.78,16.23]	6.61	[-0.67,13.89]	1.89***	[0.87,2.91]	0.01*	[0.00,0.02]	0.00	[-0.00,0.01]
Fair	412	0.53	[-1.37,2.42]	11.46*	[0.98,21.94]	8.83	[-1.05,18.72]	2.63***	[1.24,4.01]	0.01	[-0.00,0.02]	0.00	[-0.01,0.01]
Poor	79	-1.29	[-5.07,2.49]	-4.75	[-25.53,16.04]	-5.73	[-25.33,13.87]	0.98	[-1.77,3.73]	-0.01	[-0.04,0.01]	-0.01	[-0.04,0.01]
NS-SEC group (Ref: Professional)	1996	Ref.		Ref.		Ref.		Ref.		Ref.		Ref.	
Intermediate	1207	1.81**	[0.68,2.94]	13.16***	[6.75,19.57]	10.78***	[4.73,16.82]	2.38***	[1.54,3.23]	0.01	[-0.00,0.01]	0.01	[-0.00,0.01]
Routine	540	-0.54	[-2.09,1.02]	6.86	[-1.96,15.67]	4.57	[-3.74,12.87]	2.29***	[1.12,3.46]	0.00	[-0.01,0.01]	0.01*	[0.00,0.02]
Body mass index (Ref: 18.5<25)	1229	Ref.		Ref.		Ref.		Ref.		Ref.		Ref.	
Overweight (25<35)	1518	-3.18***	[-4.30,-2.06]	-6.84*	[-13.09,-0.60]	-6.38*	[-12.27,-0.49]	-0.47	[-1.29,0.36]	-0.02***	[-0.02,-0.01]	0.00	[-0.01,0.01]
Obese (30<35)	1033	-6.38***	[-7.65,-5.12]	-7.09*	[-14.13,-0.06]	-6.40	[-13.03,0.24]	-0.69	[-1.63,0.24]	-0.03***	[-0.04,-0.02]	0.00	[-0.01,0.01]
Morbidly obese (≥35)	107	-12.97***	[-15.87,-10.06]	-3.88	[-20.22,12.47]	-2.43	[-17.84,12.98]	-1.44	[-3.61,0.72]	-0.04***	[-0.06,-0.02]	0.01	[-0.01,0.03]
Underweight (<18.5)	78	-8.15***	[-11.52,-4.78]	-8.04	[-26.67,10.58]	-7.59	[-25.15,9.97]	-0.45	[-2.92,2.01]	-0.01	[-0.03,0.01]	0.01	[-0.01,0.03]
Occupational activity (Ref: Sitting)	2188	Ref.		Ref.		Ref.		Ref.		Ref.		Ref.	
Standing	627	-0.39	[-1.73,0.96]	69.24***	[61.84,76.65]	63.28***	[56.30,70.27]	5.96***	[4.98,6.94]	0.04***	[0.03,0.05]	0.02***	[0.01,0.02]
Physical work	965	-0.2	[-1.45,1.05]	62.74***	[55.80,69.68]	54.16***	[47.61,60.70]	8.58***	[7.66,9.50]	0.05***	[0.04,0.05]	0.02***	[0.01,0.03]
Heavy manual	185	-0.27	[-2.60,2.06]	75.74***	[62.53,88.94]	61.31***	[48.85,73.76]	14.43***	[12.69,16.18]	0.06***	[0.04,0.07]	0.03***	[0.01,0.04]
Smoking habits (Ref: Never)	2036	Ref.		Ref.		Ref.		Ref.		Ref.		Ref.	
Past smoker	1285	1.52**	[0.50,2.54]	-5.65	[-11.33,0.02]	-6.27*	[-11.63,-0.92]	0.62	[-0.13,1.37]	0.00	[-0.01,0.00]	0.00	[-0.01,0.00]
Occasional smoker	181	2.64*	[0.44,4.85]	15.42*	[3.12,27.73]	15.23*	[3.63,26.83]	0.19	[-1.43,1.82]	0.00	[-0.01,0.01]	0.00	[-0.02,0.01]
Daily smoker	463	2.79***	[1.28,4.30]	11.82**	[3.37,20.27]	10.66**	[2.69,18.62]	1.16*	[0.04,2.28]	-0.01*	[-0.02,-0.00]	-0.01*	[-0.02,-0.00]

Multivariate linear regressions of upright event metrics. Presented as the unstandardised regression coefficient (B) and 95% confidence intervals [95% CI]. Mutually adjusted for all socioeconomic, lifestyle and health factors, and daily wear time. Additionally adjusted for daily step count. N = sub-group sample size. * p < 0.05, ** p < 0.01, *** p < 0.001

Table 5.3. Stepping metrics by socioeconomic and health-related factors in adults aged-46 (BCS70).

		Daily steps (steps)		Step-weighted cadence (steps·min^{-1})		Stepping events (n)		Duration of stepping events (s)		Steps per stepping event (n)	
	N	B	[95% CI]	B	[95% CI]	B	[95% CI]	B	[95% CI]	B	[95% CI]
Sex (Ref: Male)	1897	Ref.		Ref.		Ref.		Ref.		Ref.	
Female	2068	-26.89	[-251.00,197.21]	0.89***	[0.39,1.40]	13.39***	[10.24,16.53]	-3.16***	[-3.63,-2.69]	-4.46***	[-5.37,-3.54]
Highest qualification (Ref: None)	929	Ref.		Ref.		Ref.		Ref.		Ref.	
GCSE	1231	-216.65	[-501.06,67.77]	-0.05	[-0.70,0.60]	0.78	[-3.21,4.77]	-0.05	[-0.65,0.55]	-0.25	[-1.40,0.91]
FE	629	-137.28	[-480.97,206.41]	-0.09	[-0.87,0.69]	-1.58	[-6.40,3.24]	0.35	[-0.37,1.07]	0.29	[-1.11,1.68]
HE	1176	343.72*	[24.32,663.11]	0.41	[-0.31,1.14]	-8.07***	[-12.56,-3.59]	1.42***	[0.75,2.10]	2.13**	[0.83,3.43]
Disability (Ref: None)	3472	Ref.		Ref.		Ref.		Ref.		Ref.	
Some extent	388	-170.99	[-543.27,201.29]	-0.03	[-0.87,0.82]	-2.95	[-8.17,2.27]	0.26	[-0.52,1.05]	0.42	[-1.09,1.94]
Severely hampered	103	-1270.69***	[-2018.05,-523.33]	-1.46	[-3.16,0.23]	-2.47	[-12.97,8.02]	0.49	[-1.08,2.06]	0.43	[-2.62,3.48]
Self-rated health (Ref: Excellent)	814	Ref.		Ref.		Ref.		Ref.		Ref.	
Very good	1560	-713.36***	[-996.76,-429.95]	-1.26***	[-1.91,-0.62]	9.38***	[5.39,13.37]	-1.44***	[-2.04,-0.84]	-2.85***	[-4.00,-1.69]
Good	1100	-1077.61***	[-1391.10,-764.12]	-1.58***	[-2.30,-0.86]	11.09***	[6.67,15.52]	-1.63***	[-2.30,-0.97]	-3.25***	[-4.53,-1.96]
Fair	412	-1376.50***	[-1807.03,-945.96]	-2.14***	[-3.12,-1.15]	14.20***	[8.13,20.27]	-1.79***	[-2.70,-0.88]	-3.61***	[-5.38,-1.85]
Poor	79	-1930.99***	[-2791.33,-1070.65]	-2.77**	[-4.72,-0.81]	10.21	[-1.89,22.30]	-1.66	[-3.47,0.16]	-3.35	[-6.86,0.16]
NS-SEC group (Ref: Professional)	1996	Ref.		Ref.		Ref.		Ref.		Ref.	
Intermediate	1207	86.3	[-171.06,343.67]	-1.22***	[-1.80,-0.64]	6.48***	[2.87,10.09]	-0.92***	[-1.47,-0.38]	-2.06***	[-3.11,-1.01]
Routine	540	522.07**	[168.06,876.09]	-1.20**	[-2.00,-0.40]	3.24	[-1.73,8.21]	-0.26	[-1.00,0.49]	-1.02	[-2.46,0.42]
Body mass index (Ref: 18.5<25)	1229	Ref.		Ref.		Ref.		Ref.		Ref.	
Overweight (25<35)	1518	-419.58**	[-675.23,-163.93]	-0.20	[-0.78,0.38]	-0.70	[-4.29,2.89]	0.18	[-0.36,0.72]	0.22	[-0.82,1.27]
Obese (30<35)	1033	-1232.63***	[-1518.66,-946.59]	-0.69*	[-1.34,-0.03]	-2.46	[-6.51,1.59]	0.42	[-0.18,1.03]	0.49	[-0.68,1.67]
Morbidly obese (≥35)	107	-2546.18***	[-3203.49,-1888.87]	-1.75*	[-3.25,-0.25]	-8.28	[-17.57,1.01]	1.33	[-0.06,2.73]	1.54	[-1.15,4.24]
Underweight (<18.5)	78	-1533.72***	[-2300.48,-766.96]	-1.28	[-3.03,0.46]	-2.38	[-13.16,8.39]	0.62	[-1.00,2.24]	0.61	[-2.52,3.73]
Occupational activity (Ref: Sitting)	2188	Ref.		Ref.		Ref.		Ref.		Ref.	
Standing	627	1315.56***	[1010.91,1620.20]	-3.53***	[-4.23,-2.84]	28.57***	[24.25,32.88]	-3.92***	[-4.57,-3.27]	-7.72***	[-8.98,-6.47]
Physical work	965	1701.66***	[1421.66,1981.65]	-5.83***	[-6.47,-5.18]	35.58***	[31.58,39.58]	-4.69***	[-5.29,-4.09]	-9.87***	[-11.03,-8.71]
Heavy manual	185	2146.26***	[1618.79,2673.73]	-8.41***	[-9.61,-7.20]	52.40***	[44.94,59.86]	-6.34***	[-7.45,-5.22]	-13.71***	[-15.87,-11.54]
Smoking habits (Ref: Never)	2036	Ref.		Ref.		Ref.		Ref.		Ref.	
Past smoker	1285	123.34	[-109.80,356.48]	-0.28	[-0.81,0.24]	0.00	[-3.27,3.28]	-0.05	[-0.54,0.44]	-0.25	[-1.20,0.70]
Occasional smoker	181	-384.68	[-888.11,118.74]	-0.02	[-1.16,1.12]	4.27	[-2.80,11.33]	-0.78	[-1.84,0.28]	-1.11	[-3.16,0.94]
Daily smoker	463	-908.34***	[-1251.84,-564.84]	-1.12**	[-1.90,-0.34]	9.14***	[4.30,13.97]	-1.15**	[-1.87,-0.42]	-2.04**	[-3.44,-0.64]

Multivariate linear regressions of upright event metrics. Presented as the unstandardised regression coefficient (B) and 95% confidence intervals [95% CI]. Mutually adjusted for all socioeconomic, lifestyle and health factors, and daily wear time. Additionally adjusted for daily step count (except daily steps). N = sub-group sample size. * p < 0.05, ** p < 0.01, *** p < 0.001

Table 5.4. Upright event composition metrics by socioeconomic and health-related factors in adults aged-46 (BCS70).

		Duration (min)		Stepping proportion (%)		Steps (n)		Stepping events (n)	
	N	B	[95% CI]	B	[95% CI]	B	[95% CI]	B	[95% CI]
Sex (Ref: Male)	1897	Ref.		Ref.		Ref.		Ref.	
Female	2068	-0.24	[-0.49,0.01]	-0.12	[-0.51,0.27]	-17.90***	[-22.04,-13.76]	-0.03	[-0.27,0.21]
Highest qualification (Ref: None)	929	Ref.		Ref.		Ref.		Ref.	
GCSE	1231	-0.13	[-0.45,0.18]	-0.01	[-0.50,0.49]	-3.40	[-8.66,1.85]	-0.07	[-0.37,0.23]
FE	629	-0.14	[-0.52,0.24]	-0.36	[-0.96,0.24]	-3.05	[-9.40,3.30]	-0.19	[-0.55,0.18]
HE	1176	-0.15	[-0.50,0.20]	0.03	[-0.53,0.59]	0.37	[-5.53,6.28]	-0.29	[-0.63,0.04]
Disability (Ref: None)	3472	Ref.		Ref.		Ref.		Ref.	
Some extent	388	0.30	[-0.11,0.71]	-0.65	[-1.29,0.00]	4.11	[-2.77,10.99]	0.20	[-0.20,0.59]
Severely hampered	103	-0.07	[-0.89,0.76]	0.26	[-1.05,1.56]	7.74	[-6.09,21.57]	0.16	[-0.63,0.95]
Self-rated health (Ref: Excellent)	814	Ref.		Ref.		Ref.		Ref.	
Very good	1560	0.06	[-0.25,0.37]	0.21	[-0.29,0.70]	-2.84	[-8.09,2.41]	0.28	[-0.02,0.58]
Good	1100	0.02	[-0.33,0.36]	0.34	[-0.21,0.89]	-2.13	[-7.96,3.69]	0.28	[-0.05,0.61]
Fair	412	0.38	[-0.10,0.85]	-0.03	[-0.78,0.72]	-1.05	[-9.05,6.94]	0.54*	[0.09,1.00]
Poor	79	-0.19	[-1.15,0.76]	0.93	[-0.57,2.43]	-1.38	[-17.32,14.56]	0.13	[-0.78,1.05]
NS-SEC group (Ref: Professional)	1996	Ref.		Ref.		Ref.		Ref.	
Intermediate	1207	0.16	[-0.12,0.44]	-0.15	[-0.60,0.30]	-3.75	[-8.50,1.01]	0.37**	[0.10,0.64]
Routine	540	0.41*	[0.02,0.80]	0.14	[-0.48,0.76]	2.82	[-3.72,9.37]	0.54**	[0.16,0.91]
Body mass index (Ref: 18.5<25)	1229	Ref.		Ref.		Ref.		Ref.	
Overweight (25<35)	1518	0.31*	[0.03,0.59]	0.62**	[0.17,1.07]	9.56***	[4.83,14.29]	0.25	[-0.02,0.52]
Obese (30<35)	1033	0.94***	[0.62,1.26]	0.81**	[0.31,1.32]	25.06***	[19.73,30.40]	0.80***	[0.50,1.11]
Morbidly obese (≥35)	107	2.37***	[1.64,3.10]	1.05	[-0.10,2.20]	48.64***	[36.40,60.88]	1.80***	[1.10,2.50]
Underweight (<18.5)	78	1.29**	[0.44,2.14]	0.67	[-0.67,2.01]	29.23***	[15.03,43.43]	1.16**	[0.34,1.97]
Occupational activity (Ref: Sitting)	2188	Ref.		Ref.		Ref.		Ref.	
Standing	627	1.73***	[1.39,2.07]	-1.58***	[-2.11,-1.04]	1.31	[-4.37,7.00]	1.90***	[1.58,2.23]
Physical work	956	1.42***	[1.10,1.73]	-1.38***	[-1.87,-0.88]	2.06	[-3.21,7.33]	2.17***	[1.87,2.47]
Heavy manual	185	1.83***	[1.24,2.42]	-1.09*	[-2.01,-0.16]	6.34	[-3.49,16.17]	3.13***	[2.56,3.69]
Smoking habits (Ref: Never)	2036	Ref.		Ref.		Ref.		Ref.	
Past smoker	1285	-0.29*	[-0.55,-0.04]	0.29	[-0.12,0.69]	-4.30	[-8.61,0.01]	-0.13	[-0.38,0.11]
Occasional smoker	181	-0.05	[-0.60,0.51]	-0.88*	[-1.76,-0.01]	-7.95	[-17.26,1.35]	-0.09	[-0.62,0.44]
Daily smoker	463	0.21	[-0.17,0.59]	-0.57	[-1.17,0.03]	-5.05	[-11.42,1.32]	0.21	[-0.16,0.57]

Multivariate linear regressions of upright event metrics. Presented as the unstandardised regression coefficient (B) and 95% confidence intervals [95% CI]. Mutually adjusted for all socioeconomic, lifestyle and health factors, and daily wear time. Additionally adjusted for daily step count. N = sub-group sample size. * p < 0.05, ** p < 0.01, *** p < 0.001

5.4.2.1 Sensitivity analyses

When conducting sensitivity analyses by excluding participants with an EU-SILC disability classification of 'severely hampered' (n = 103) and subsequently excluding both 'some extent' and 'severely hampered' (n = 491), it was observed that the overall interpretation of the results remained largely consistent. Although certain values within a categorical variable changed, the fundamental conclusions drawn from the analyses remained unaffected (Appendix 8.11).

5.5 Discussion

This chapter aimed to describe accumulation patterns of upright and stepping events in midlife adults according to sociodemographic and health related factors. On average participants stood up 52.9±15.3 times a day and were upright for an average 6.4±1.9 $h \cdot d^{-1}$. The majority of upright events comprised more standing than stepping (35.6±6.1% stepping) and were characterised by intermittent rather than continuous standing or stepping. Upright events were not uniformly distributed across the day but tended to occur in bursts. The duration of the events also varied with the typical event duration lasting just 8.0±3.7 minutes.

Overall, participants accumulated 9389±3586 $steps \cdot d^{-1}$ with an average 198±70 stepping events per day, an average of 44.1±16.2 steps per event, and a step-weight average cadence 89.5±8.8 $steps \cdot min^{-1}$. Previous studies employing thigh worn accelerometers in midlife populations have reported similar frequencies of upright events (either as sit-to-stand transitions, sedentary breaks, or sitting interruptions);[151,273,333] whereas devices located at the hip or waist have

tended to report higher frequencies.[334–336] Though, wrist worn devices have recently demonstrated good agreement with the activPAL algorithm.[337] Average duration of upright events were similar to those that have previously been reported.[273,334]

People with the same number and total time spent in upright postures can vary considerably in the composition of standing and stepping. Likewise, people recording the same total daily step count can accumulate the steps in many different ways; differences which are likely to moderate the relationship between total daily steps and health outcomes. In agreement with Blankenship et al.,[273] upright events cannot all be treated the same for the purposes of studying the relationship between interruptions in sitting postures and health outcomes. However, in addition to Blankenship, this study also shows that it is insufficient to only report the average duration of upright events, the duration of stepping time within the event, and the average time between events. The temporal distribution of the upright events, and how sustained or intermittent stepping is, can also vary when people have the same average duration of upright events, mean duration of stepping time, and average time between events. Furthermore, this study showed that these associations persist even when adjusting for total daily step count.

This chapter highlights that the time spent upright is made up of varying combinations of stepping and standing and that the time spent stepping, within an upright event, can be comprised of a single sustained stepping event or multiple short stepping events interspersed with periods of standing. This also means that the same average cadence of the steps within an upright event could be based on a single stepping event done at the same step-rate or multiple

stepping events each with its own cadence ranging from high to low. Current cadence-based metrics typically report time or number of steps above set step-rates;[237] and associations with health outcomes do not always remain after adjusting for total volume.[238,239] Weighting cadence by steps per stepping event, is a simple way of accounting for all steps when examining associations between step-rate and health outcomes.

The burstiness of upright events in this study revealed that events are often clustered together followed by longer periods of sedentary time. In addition, sedentary event burstiness (the variation in the duration of the upright events) suggests that some people have more uniform upright durations, while others have more variation. It is highly unlikely that people will only have long sustained upright events, so the most uniform patterns of duration are likely to reflect people who are only upright for short periods – a more transient pattern of being upright.

The fragmentation of upright events has been shown to be associated with health outcomes regardless of volume of activity.[101,104] Therefore, these new metrics which characterise the number and temporal distribution of events, in addition to the variance of event durations, and the composition of standing and stepping, provide new knowledge about how people accumulate daily values of standing and stepping through different patterns.

This chapter further highlights that key demographic and health factors are characterised by distinct postural and stepping phenotypes that may be differentially associated with health outcomes. These differences in the pattern of upright events and accumulation of steps would be expected to moderate any observed relationships between total daily steps and health outcomes.[102,104–106,238] For example, patterns of posture and stepping varied considerably by

occupational physical activity. More active occupations were characterised by more time being upright, accumulated in both higher upright and sedentary event bursts compared to sedentary occupations. The upright time was composed of a higher proportion of standing than sedentary occupations, but a greater number of shorter and slower stepping events.

This type of work pattern may partly explain why studies comparing the association of occupational activity and leisure time activity on health outcomes, find that for the same volume of activity, occupational activity is less healthy.[338] If people in sedentary occupations get more of their activity from less frequent, but longer, more intense and sustained periods of physical activity during their non-work time, then they would be expected to have better health outcomes even if they have the same volume of activity. This supports the suggestion of others that occupational activity may be insufficiently intense[338], but also highlights that observed differences may be due to different patterns of accumulation.

Patterns of activity that are characterised by frequent transient/fragmented durations have consistently been associated with a range of health outcomes including fatigue, heart failure, physical function, cognitive impairment, and mortality, independent of the total volume of physical activity.[101,102,105,254,339] This chapter adds to these findings by describing a new dimension to the way in which postural activity is accumulated – the burstiness of upright events.[263,323,324] Whilst the burstiness metric has not been studied in aetiological studies of physical activity and health, a phenotype of both bursty and fragmented upright postures accompanied by intermittent, rather than sustained periods of stepping is likely to be associated with a loss of capacity and less confidence about undertaking sustained periods of activity.

The findings of this chapter have important implications for research, as much of the variation in the accumulation of activity events described here, is masked by analytical approaches which aggregate posture, stepping and standing over time or simply sum upright events.[272,273] The novel phenotypes identified will help to advance research into physical activity and health, and healthy ageing. The findings highlight why simple aggregate measures of posture and stepping can mask important variations in behaviour and why future studies cannot afford to ignore patterns of accumulation.

5.5.1 Strengths and limitations

This chapter is not without limitations. Accelerometers are not direct measures of behaviour but rather a proxy. Many, including the activPAL, rely on proprietary algorithms to translate the accelerometer signal into behavioural information, which is then further processed to derive outcome metrics of interest.[340,341] In addition, algorithm versions may change over time; it is important to note we used the activPAL VANE algorithm, which may not be comparable with the CREA algorithm, particularly with regards to transitions between sedentary and upright postures.[342]

Detection of valid wake and sleep times using accelerometers is challenging, with disagreement between currently available algorithms.[320] We employed a simple and pragmatic method to identify and characterise waking wear time but, like other wake/sleep time algorithms, it is challenging to assess criterion validity against a true gold-standard, and as such there may have been some misclassification.[320,343]

The particular accelerometer used in this study may underestimate step count at slower paced walking steps, potentially leading to an overestimate of stepping cadence.[344] The resolution used to categorise postures (activPAL software recommended minimum 10 seconds) may also be shorter than they actually take place, leading to misclassification of the time spent in different postures.

Whilst not necessarily a limitation, the age of the sample (all participants were 46 years old) has likely led to an underestimate of the true level of variation in the measures reported in this study. A wider age range, that included older people, might be expected to show greater variation. BCS70 is a rich dataset, and access to the raw accelerometer files allowed us to look beyond the aggregate measures of standing and stepping from previous studies using BCS70 summary data,[168,345] was a strength of this study. However, the cross-sectional design of this study means we cannot determine causality.

As previously described, participants who declined to wear an accelerometer were more likely to be male, smokers, report poorer health, and have a higher BMI, limiting the generalisability of our findings.[225] Finally, Chapter 2 noted the lack of adjustment for total volume of physical activity in most physical function studies;[99] this chapter demonstrated that associations persisted after adjustment for daily step count.

5.6 Summary

This chapter has revealed novel phenotypes of standing, sitting and stepping that go beyond simply describing average amounts and durations of these behaviours. Findings indicate that a given volume of physical activity is

accumulated in different patterns by different population subgroups defined by sociodemographic, and general health characteristics. These different patterns may have important relations with functional and health outcomes. The findings may provide potential explanations for why particular population sub-groups appear to have different health outcomes even when the volume of physical activity is similar. The chapter lays the groundwork for the following chapters to investigate how different patterns of physical activity accumulation can add to our understanding of the relationship between physical activity and physical function.

Chapter 6
Physical Activity Accumulation and Physical Function: Insights from The Maastricht Study

6.1 Overview

Chapter 6 aims to address the fourth thesis objective by investigating the associations between the pattern metrics, derived in Chapter 4, and physical function outcomes from DMS. This chapter was published as a peer reviewed paper: *Cross-sectional associations between patterns and composition of upright and stepping events with physical function: insights from The Maastricht Study*.[346] The published version is available digitally using the following DOI: https://doi.org/10.1186/s11556-024-00343-w.

6.2 Introduction

As described in earlier chapters, physical activity characterised by short, transient events, often labelled as fragmented activity, has been associated with various health outcomes. These include physical function outcomes, even after adjustment for total volume of physical activity.[100–102,347] One limitation of much of this evidence, and the wider physical activity field arises from its reliance on epoch-based activity measures, where active events are defined as contiguous minutes registering a specified acceleration or count threshold.[100]

An alternative approach which offers more detail and precision involves 'event-based' analysis that segments the data into a contiguous time-series of

postures (sit/lying, standing, ambulating).[179] A time-series of different postures allows upright and stepping events to be quantified by their composition, and temporal distribution.[273,325] Very limited evidence exists on the association between event-based physical activity metrics and health outcomes. Palmberg et al.[101] examined the fragmentation of minute-by-minute posture classifications (upright or sit\lying postures) and reported that more fragmented upright time was positively associated with mental fatigue.

To our best knowledge, no studies have explored the associations between physical function and composition of upright events and stepping events, or their temporal distribution (burstiness). If patterns of accumulation of physical activity are associated with physical function, independent of volume of physical activity, then there is the potential to broaden the current physical activity guidelines that primarily focus on increasing volume. This chapter aims to investigate the association between event-based metrics that capture the composition and temporal distribution of upright and stepping events with measures of physical function, including grip strength, the six-minute walk test, chair-rise test, and SF-36 physical functioning score.

6.3 Methods

For detailed descriptions of the study design, physical activity measurement, and data processing methods, derived metrics, and physical function measures refer to the general methods in Chapter 4.

6.3.1 Covariates

Covariates were selected a priori based on the commonly selected covariates in the literature that are known to influence physical activity, as well as covariates shown to be associated with the upright and stepping metrics within this study.[325] These included age (in years) and sex. Body mass index (BMI) was calculated using the standard formulae (kg)/height $(m)^2$, using values from measurements taken during the examination. BMI was kept continuous in analyses but reported in the descriptives table using standardised categories of; healthy weight (15 to 24.9 kg/m²), overweight (25 to 29.9 kg/m²), obese (30 to 39.9 kg/m²), and severely obese (≥40 kg/m²).

Education level was divided into low ((un)completed primary education, or lower vocational education), middle (intermediate vocational education or higher secondary education), and high (higher vocational education or university education). Smoking status was categorised into non-smoker, former smoker, and current smoker. Presence of T2DM was defined according to the fasting glucose state and directly after an oral glucose tolerance test and the use of glucose lowering medication,[214] and was included in the main model as a binary variable. Dutch Healthy Diet index (DHD) score, (which includes assessment of alcohol consumption), was used as measure of diet quality.[348]

6.3.2 Statistical analyses

Participant characteristics were described by sex and presented as mean ± SD for continuous variables and number (%) for categorical variables. Multivariable linear regressions were used to assess the variation in upright event metrics across participant characteristics. Further multivariable linear regression

models were used to assess the associations of each upright/stepping event metric with each physical function outcome. Associations were expressed as a one standard deviation increase in the upright/stepping event metric equating to an absolute change in the physical function outcome. The associations in model 1 were adjusted for age, sex, and waking wear time. Model 2 was further adjusted for education level, BMI, smoking status, and T2DM (to account for oversampling in the study). Model 3 was additionally adjusted for daily step count (step volume), to test if the associations persisted over and above a traditional metric of activity volume. Given the established sex-related differences in physical activity[349] and physical function,[350,351] we tested and reported sex interaction effects. Subsequently, for consistency, all analyses were stratified by sex. The interaction with diabetes (yes/no) was also tested and reported. We assessed the assumptions of linear regression, including linearity, homoscedasticity, and multicollinearity, to ensure the validity of our models. All analyses were run on the sample with complete data for all accelerometer metrics, covariates, and physical function outcomes.

6.3.2.1 Sensitivity analysis

To assess the robustness of our results, analyses were repeated to assess the impact of slight variations in the analytical sample due to the availability of data for different covariates. These included rerunning analyses involving participants with any combination of the physical function outcomes (rather than just on those with data on all outcomes). In addition, to further assess the potential impact of oversampling of diabetes, we repeated analyses and substituted the binary classification of T2DM status (yes/no) for a 3-level classification which included a class for pre-diabetes. Finally, we additionally

included DHD as an additional predictor to evaluate the potential influence of self-reported diet quality on the association between physical activity and physical function.

6.4 Results

A total of 6085 participants, (50.5% female), with a mean (SD) age of 59.6 ± 8.7 years, had 6 (18.8%) or 7 (88.2%) valid days of accelerometer data (with an average waking wear time of 16.4 ± 1.0 hours), covariates data, and all physical function outcomes (Figure 6.1). Excluded participants were more likely to be overweight, current smokers, have lower education, and poorer performance in physical function tests, except for grip strength. Men had higher grip strength, 6MWT distance, and SF-36pf (all p-values <0.05), but there was no difference between chair rise test time (p = 0.56). Participant characteristics are presented in Table 6.1.

When mutually adjusted for all covariates, there were clear differences in upright event metrics by age, sex, diabetes, education, BMI, smoking status (Appendix 8.12). Total step volume was associated with better performance in all three performance-based physical function outcomes (except for grip strength in males), and a higher SF-36pf score for both males and females. The associations in the fully adjusted model are summarised for each physical function outcome below.

6.4.1 Grip strength

A higher number of stepping events per day was associated with lower grip strength in both males and females. Duration of stepping event was

positively associated with grip strength, and number of steps per stepping event was positively associated in females (Table 6.2, Figure 6.2).

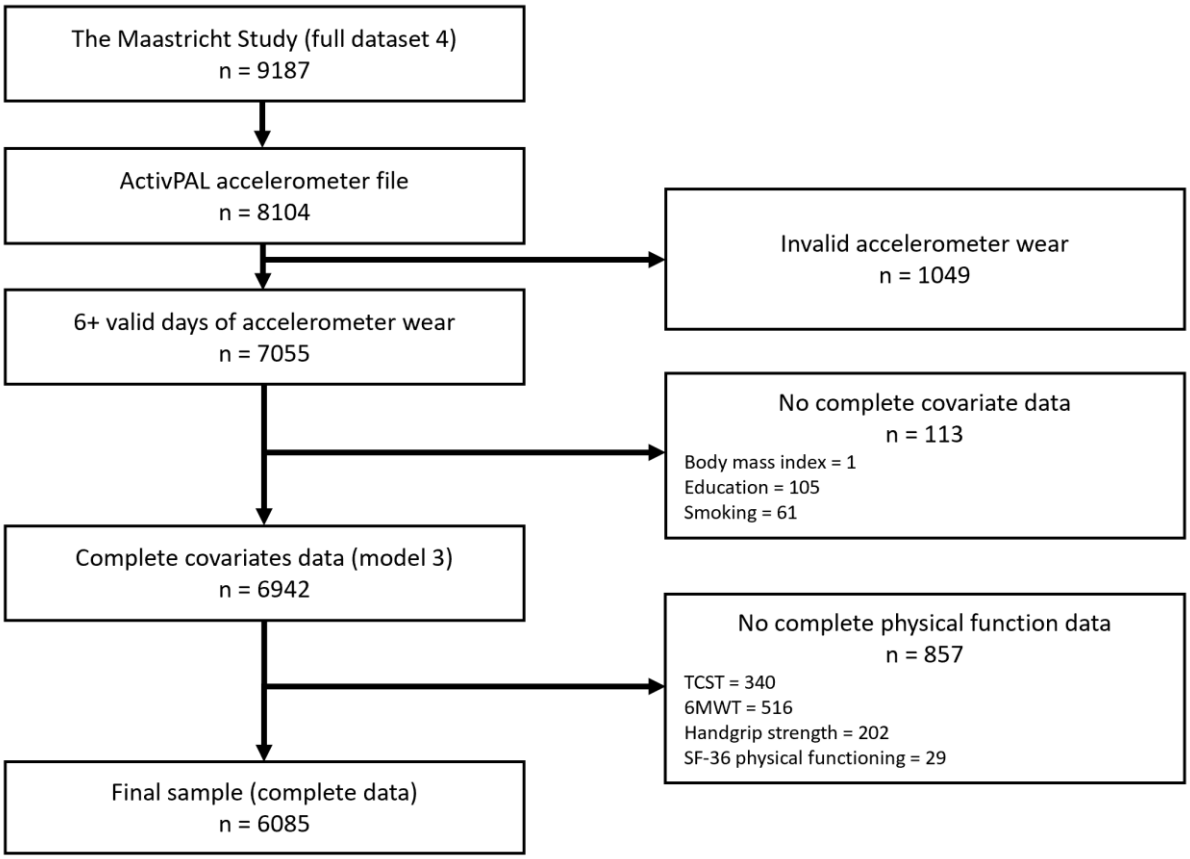


Figure 6.1. Flow chart of The Maastricht Study participants through our study.

6.4.2 Timed chair stand test

Upright event metric associations with TCST performance were differentially associated with sex. For males, duration of stepping event and number of steps per stepping event were associated with poorer TCST performance, as was step count within upright events. For females, number of upright events per day and step-weighted average cadence was associated with better TCST performance, as was a higher sedentary burstiness (Table 6.3, Figure 6.3).

Table 6.1. Summary of participant characteristics, upright and stepping event metrics, and physical function outcomes.

Participant characteristics	Male (n = 3013)	Female (n = 3072)	Total (n = 6085)
Age	60.7 ± 8.6	58.6 ± 8.7	59.6 ± 8.7
Type 2 diabetes, *n* (%)[a]	812 (27%)	367 (12%)	1179 (24%)
BMI category, *n* (%)			
Healthy (18.5 to 24.9 kg/m^2)	915 (30%)	1470 (48%)	2,385
Overweight (25 to 29.9 kg/m^2)	1485 (49%)	1096 (36%)	2,581
Obese (30 to 39.9 kg/m^2)	588 (20%)	477 (16%)	1,065
Morbidly Obese (≥40 kg/m^2)	25 (1%)	29 (1%)	54
Education level, *n* (%)			
High	1345 (45%)	1109 (36%)	2,454
Medium	805 (27%)	884 (29%)	1,689
Low	863 (29%)	1079 (35%)	1,942
Smoking status, *n* (%)			
Never	1091 (36%)	1325 (43%)	2,416
Former	1527 (51%)	1426 (46%)	2,953
Current	395 (13%)	321 (10%)	716
Upright and stepping event metrics			
Daily step count (steps/day)	9457 ± 3759	9747 ± 3395	9604 ± 3582
Daily number of upright events (n/day)	52.2 ± 13.3	52.9 ± 13.0	52.6 ± 13.1
Daily number of stepping events (n/day)	186.7 ± 58.9	209.0 ± 57.1	198.0 ± 59.1
Mean duration of all step events (min/event)	33.3 ± 9.7	30.0 ± 7.6	31.6 ± 8.8
Mean number of steps per all stepping events (n/event)	48.1 ± 18.6	43.2 ± 14.2	45.6 ± 16.7
Step-weighted mean cadence (steps/min)	90.4 ± 9.4	90.7 ± 7.8	90.6 ± 8.6
Duration of all upright events (min)	7.0 ± 2.6	8.0 ± 3.0	7.5 ± 2.9
Proportion of stepping to standing time (%)	35.7 ± 5.8	34.9 ± 5.2	35.3 ± 5.6
Number of steps per upright event (n/event)	189.2 ± 85.4	192.9 ± 79.0	191.1 ± 82.2
Number of stepping events per upright event (n/event)	7.9 ± 2.8	9.2 ± 3.1	8.5 ± 3.0
Upright event burstiness (B_n)	0.28 ± 0.09	0.33 ± 0.08	0.31 ± 0.09
Sedentary event burstiness (B_n)	0.32 ± 0.09	0.32 ± 0.07	0.32 ± 0.08
Physical function metrics			
Grip strength (kg)	41.8 ± 8.2	26.0 ± 5.6	33.8 ± 10.6
Six-min walk test (meters)	604.7 ± 82.8	579.4 ± 73.3	591.9 ± 79.2
10x chair stand test (s)	24.7 ± 5.5	24.8 ± 5.7	24.7 ± 5.6
SF-36 Physical functioning score	88.8 ± 14.8	86.5 ± 16.2	87.7 ± 15.6

Mean ± SD or *n* (%)

[a] Row percentage

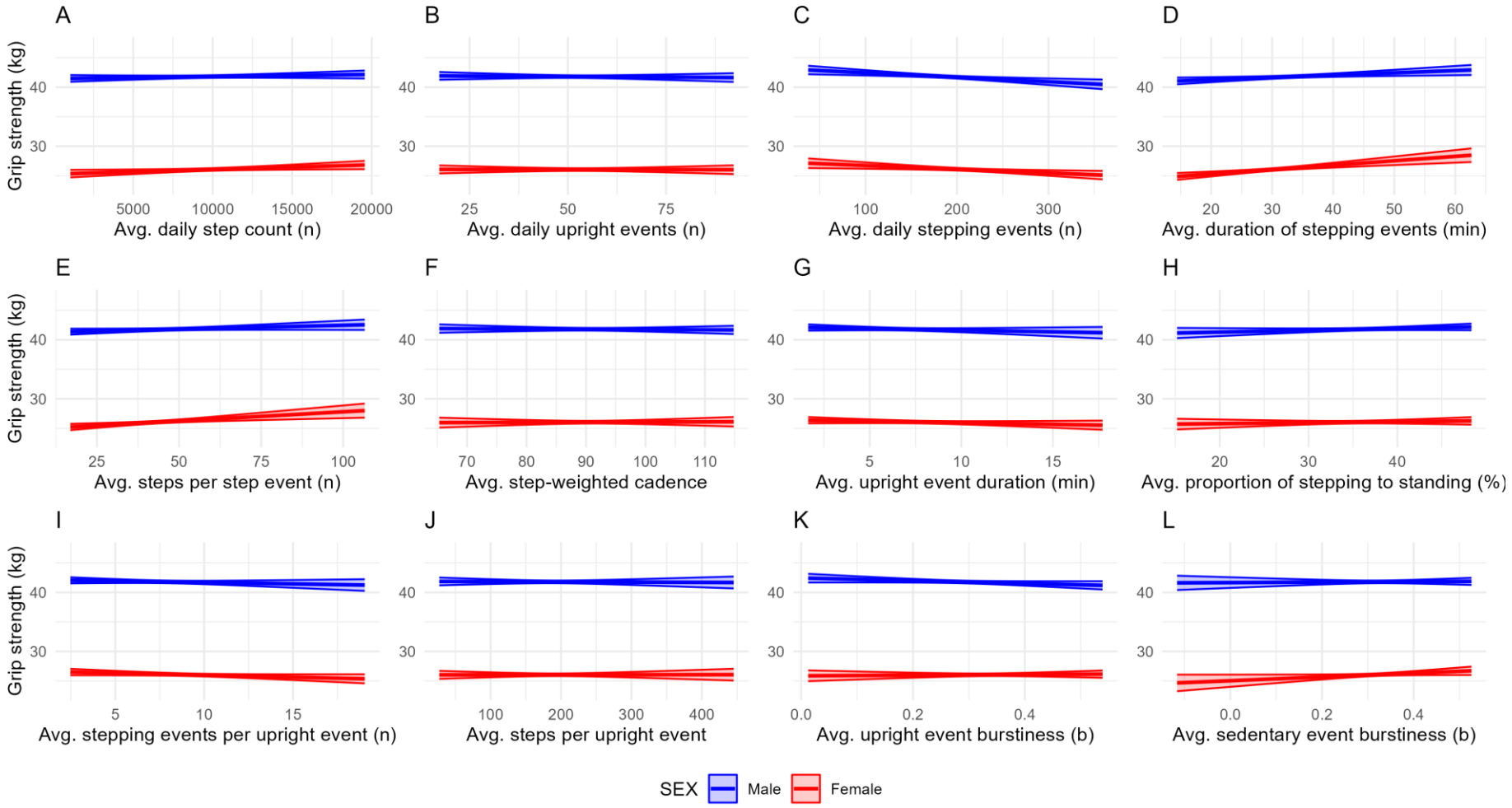


Figure 6.2. Regression plots for each activity metric with grip strength, by sex. Adjusted for age, type 2 diabetes, education level, body mass index, smoking status, waking wear time, and average daily step count

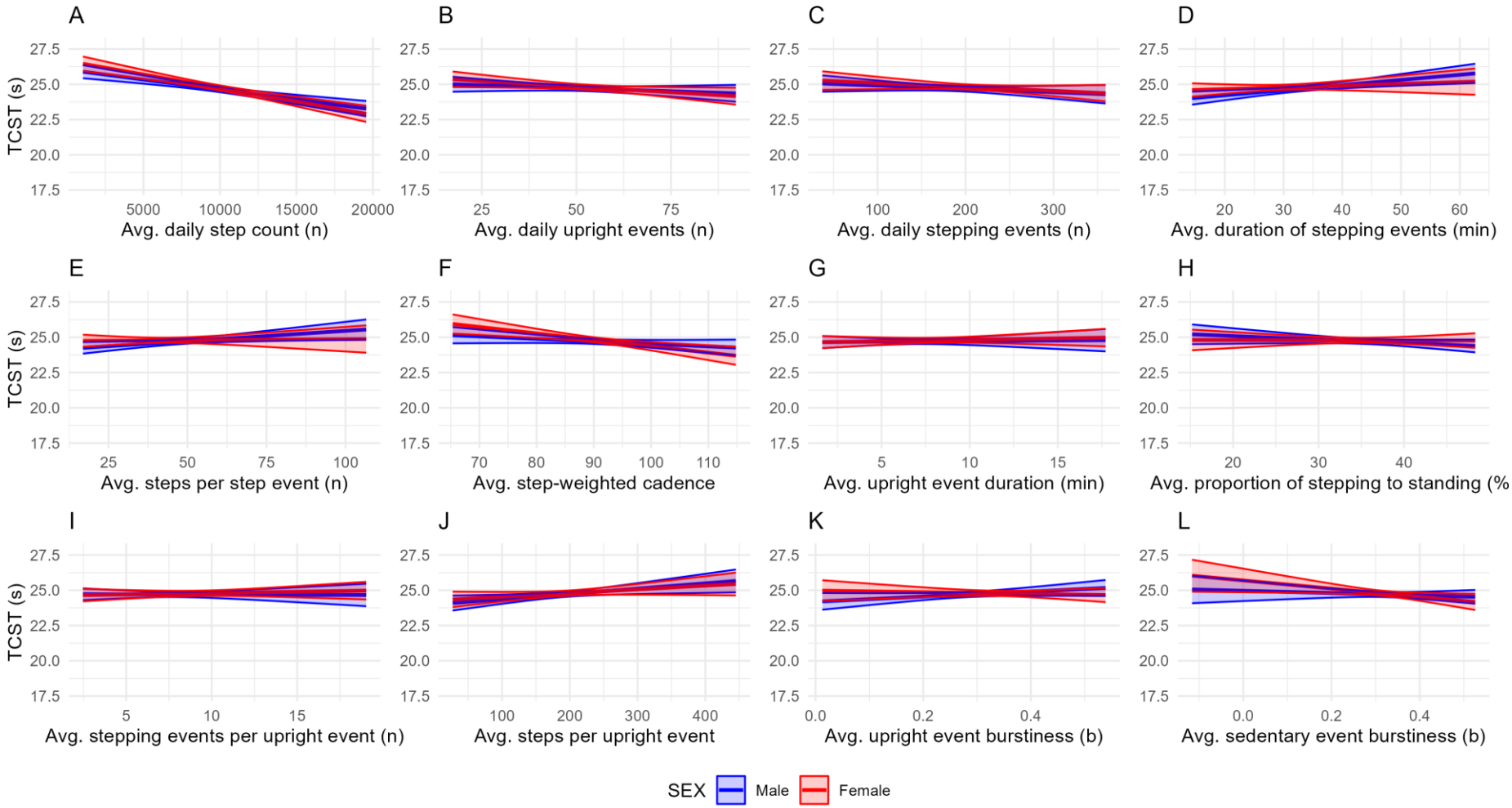


Figure 6.3. Regression plots for each activity metric with the timed chair stand test, by sex. Adjusted for age, type 2 diabetes, education level, body mass index, smoking status, waking wear time, and average daily step count.

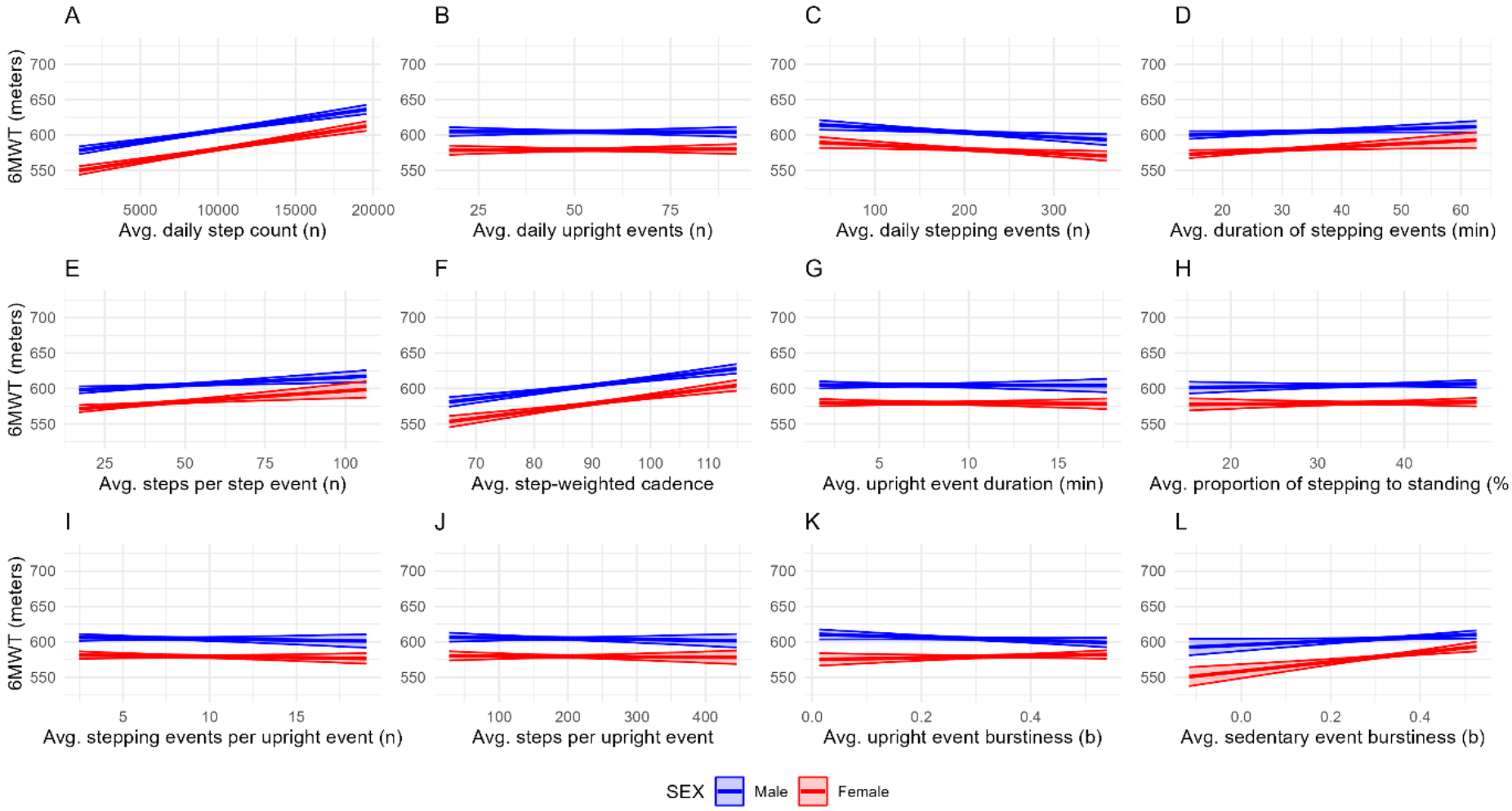


Figure 6.4. Regression plots for each activity metric with the six-minute walk test (6MWT), by sex. Adjusted for age, type 2 diabetes, education level, body mass index, smoking status, waking wear time, and average daily step count.

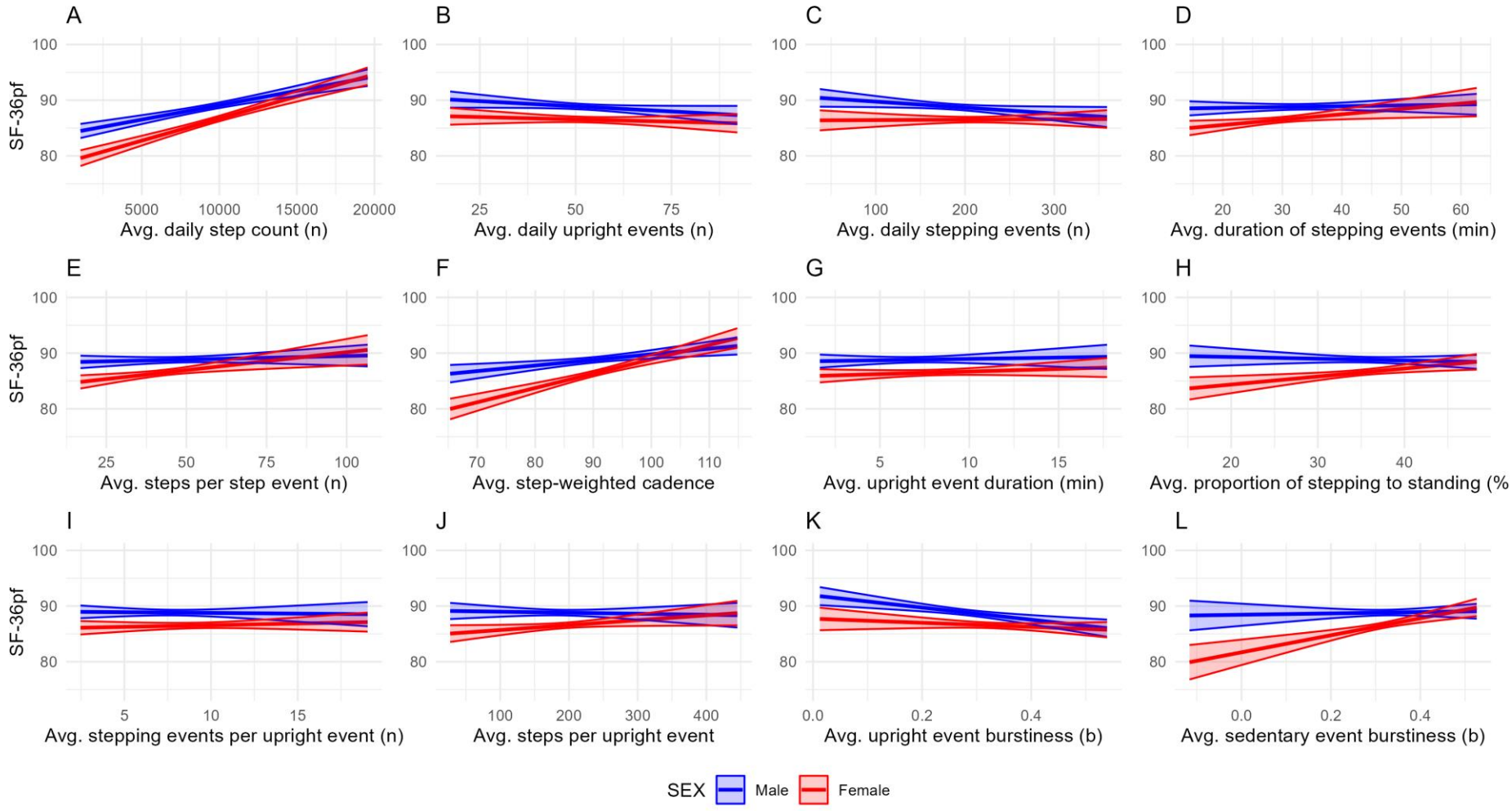


Figure 6.5. Regression plots for each activity metric with the Short From-36 physical functioning sub-scale (SF-36pf), by sex. Adjusted for age, type 2 diabetes, education level, body mass index, smoking status, waking wear time, and average daily step count.

6.4.3 Six-minute walk test

Sedentary burstiness was associated with better 6MWT test performance in both males and females. Number of steps per stepping event, and step-weighted average cadence were also both associated with better 6MWT in both males and females. Duration of stepping events was positively associated with 6MWT in females only. For both sexes, a higher number of stepping events was associated with poorer performance the 6MWT (Table 6.4, Figure 6.4).

6.4.4 SF-36 physical function

A higher upright event burstiness score was associated with a poorer SF-36pf score in males. A higher sedentary burstiness was associated with a better SF-36pf score in females. For both males and females, step-weighted average cadence was positively associated with SF-36pf, but to a greater degree in females. Females also had a positive association with duration and number of steps per stepping event and SF-36pf, as was within upright event stepping proportion and step count (Table 6.5, Figure 6.5).

6.4.5 Sensitivity analyses

When running analyses on participants without all physical function outcomes, sample sizes increased for all outcomes; handgrip strength (n = 6740), TCST (n = 6602), 6MWT (n = 6426), and SF-36pf (n = 6913). With the larger sample sizes, nine of the 88 associations across all upright metrics and physical function outcomes in males and females changed significance. The four of these which became non-significant were sedentary burstiness with 6MWT for males,

number of step events with SF-36pf for males, and duration of step events and within upright event step count with SF-36pf for females (Appendix 8.13).

When substituting the binary diabetes classification for the WHO classification, which includes pre-diabetes, none of the associations changed significance. These associations are highlighted in Appendix 8.13. Inclusion of DHD score as an additional predictor yielded negligible changes to the observed study findings. Further, the reduction in sample size (n = 5668) due to availability of DHD score precludes definitive conclusions about whether these small changes can be attributed to confounding effects of diet quality per se, or to differences in the analytical sample.

6.5 Discussion

This chapter aimed to investigate the associations between features of upright and stepping events, including the composition and the temporal distribution, with objective measures of physical function in a large population-based cohort. We observed that greater sedentary burstiness, duration of stepping events, volume of steps per stepping event, and step-weighted cadence were associated with better physical function in one or more of the 6MWT, TCST, SF-36f, and grip strength outcomes, independent of total volume of steps.

Number of stepping events was negatively associated with physical function. Upright event composition metrics (within event; duration, proportion of stepping, step count, and number of stepping events) were not associated with physical function outcomes after adjustment for volume. Secondary to our initial focus, it was interesting that there were clear differences in associations between males and females, though the explanation for this is not immediately obvious.

Table 6.2. Associations of upright and stepping event metrics with handgrip strength.

	Model 1		Model 2		Model 3	
	Males	***Females***	***Males***	***Females***	***Males***	***Females***
	B [95% CI] (*p*-value)	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**
Daily step count [b] *(per + 3582 steps)*	0.15 [-0.08,0.38] (0.19)	0.21 [-0.04,0.46] (0.094)	0.12 [-0.11,0.36] (0.294)	**0.27 [0.02,0.52]** (0.037)	- -	- -
Upright events *(per + 13.1 n)*	-0.11 [-0.35,0.13] (0.36)	-0.15 [-0.39,0.09] (0.222)	-0.02 [-0.25,0.22] (0.89)	0.01 [-0.23,0.25] (0.934)	-0.04 [-0.28,0.20] (0.729)	0.00 [-0.25,0.24] (0.971)
Stepping events [b] *(per + 59.1 n)*	-0.17 [-0.41,0.08] (0.18)	-0.19 [-0.43,0.06] (0.141)	-0.17 [-0.42,0.07] (0.156)	-0.12 [-0.36,0.13] (0.346)	**-0.45 [-0.73,-0.17]** (0.001)	**-0.38 [-0.66,-0.10]** (0.007)
Duration of stepping events *(per + 8.8 sec)*	**0.31 [0.09,0.53]** (0.005)	**0.60 [0.33,0.88]** (<0.001)	**0.29 [0.07,0.50]** (0.01)	**0.60 [0.32,0.88]** (<0.001)	**0.35 [0.09,0.61]** (0.007)	**0.67 [0.35,0.99]** (<0.001)
Steps per stepping event *(per + 16.7 steps)*	**0.24 [0.02,0.45]** (0.029)	**0.51 [0.23,0.79]** (<0.001)	0.21 [-0.01,0.42] (0.057)	**0.51 [0.22,0.79]** (<0.001)	0.22 [-0.03,0.48] (0.081)	**0.52 [0.20,0.84]** (0.001)
Step-weighted cadence *(per + 8.6 steps/min)*	0.12 [-0.10,0.34] (0.267)	0.11 [-0.15,0.37] (0.404)	0.05 [-0.17,0.27] (0.655)	0.11 [-0.15,0.38] (0.405)	-0.04 [-0.28,0.20] (0.722)	0.02 [-0.27,0.30] (0.913)
Duration of upright events *(per + 2.9 min)*	-0.01 [-0.27,0.24] (0.911)	-0.04 [-0.26,0.19] (0.746)	-0.07 [-0.33,0.18] (0.577)	-0.10 [-0.32,0.13] (0.398)	-0.16 [-0.43,0.10] (0.233)	-0.16 [-0.38,0.07] (0.176)
Stepping proportion of upright events *(per + 5.6 %)*	**0.30 [0.07,0.53]** (0.011)	0.20 [-0.06,0.45] (0.126)	**0.23 [0.00,0.46]** (0.047)	0.13 [-0.12,0.38] (0.308)	0.18 [-0.05,0.42] (0.126)	0.09 [-0.17,0.34] (0.496)
Step count of upright events *(per + 82.3 steps)*	0.20 [-0.03,0.43] (0.086)	0.20 [-0.04,0.45] (0.106)	0.13 [-0.10,0.35] (0.281)	0.15 [-0.09,0.40] (0.22)	-0.03 [-0.36,0.29] (0.834)	0.00 [-0.33,0.33] (0.997)
Stepping events within upright events *(per + 3.0 n)*	-0.03 [-0.28,0.23] (0.845)	-0.11 [-0.34,0.11] (0.322)	-0.06 [-0.31,0.20] (0.671)	-0.14 [-0.37,0.08] (0.217)	-0.15 [-0.42,0.12] (0.266)	-0.22 [-0.45,0.01] (0.065)
Upright event burstiness *(per + 0.09)*	-0.24 [-0.48,-0.00] (0.05)	-0.02 [-0.28,0.24] (0.882)	-0.20 [-0.44,0.04] (0.1)	0.05 [-0.21,0.31] (0.697)	-0.22 [-0.46,0.02] (0.075)	0.04 [-0.22,0.30] (0.75)
Sedentary event burstiness *(per + 0.08)*	0.07 [-0.15,0.29] (0.545)	0.24 [-0.02,0.50] (0.074)	0.08 [-0.14,0.29] (0.486)	**0.29 [0.03,0.55]** (0.029)	0.03 [-0.20,0.25] (0.816)	0.26 [-0.01,0.52] (0.058)

Results are presented as regression coefficient (B) with 95% confidence interval [95% CI] and p-value, where the predictor is standardised and the outcome is unstandardised (a one standard deviation increase in the predictor equates to an absolute change in the physical function outcome. Associations were adjusted for the following covariates; Model 1: age, sex, and waking wear time. Model 2: model 1 + type 2 diabetes, education level, body mass index, and smoking status. Model 3: model 2 + average daily step count. [a] denotes significant sex interaction ($p < 0.05$) for Model 1. [b] denotes significant type 2 diabetes interaction ($p < 0.05$) for Model 2. Bold indicates statistical significance ($p < 0.05$)

Table 6.3. Associations of upright and stepping event metrics with timed chair stand test.

	Model 1		Model 2		Model 3	
	Males	***Females***	***Males***	***Females***	***Males***	***Females***
	B [95% CI] (*p*-value)	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**
Daily step count *(per + 3582 steps)*	**-0.78 [-0.97,-0.60]** (<0.001)	**-1.03 [-1.23,-0.82]** (<0.001)	**-0.51 [-0.70,-0.33]** (<0.001)	**-0.68 [-0.89,-0.48]** (<0.001)	- -	- -
Upright events *(per + 13.1 n)*	**-0.33 [-0.52,-0.13]** (0.001)	**-0.43 [-0.62,-0.23]** (<0.001)	**-0.20 [-0.40,-0.01]** (0.038)	**-0.26 [-0.46,-0.07]** (0.009)	-0.13 [-0.32,0.06] (0.191)	**-0.22 [-0.42,-0.02]** (0.029)
Stepping events *(per + 59.1 n)*	**-0.55 [-0.75,-0.35]** (<0.001)	**-0.52 [-0.73,-0.32]** (<0.001)	**-0.46 [-0.65,-0.26]** (<0.001)	**-0.46 [-0.66,-0.26]** (<0.001)	-0.16 [-0.38,0.07] (0.174)	-0.17 [-0.39,0.05] (0.138)
Duration of stepping events [a] *(per + 8.8 sec)*	**-0.38 [-0.56,-0.21]** (<0.001)	**-0.83 [-1.06,-0.60]** (<0.001)	-0.11 [-0.28,0.07] (0.244)	**-0.37 [-0.60,-0.14]** (0.001)	**0.33 [0.13,0.54]** (0.001)	0.13 [-0.13,0.38] (0.337)
Steps per stepping event [a] *(per + 16.7 steps)*	**-0.42 [-0.60,-0.25]** (<0.001)	**-0.89 [-1.12,-0.67]** (<0.001)	-0.15 [-0.33,0.02] (0.089)	**-0.43 [-0.66,-0.21]** (<0.001)	**0.25 [0.05,0.45]** (0.016)	0.03 [-0.22,0.29] (0.791)
Step-weighted cadence [a] [b] *(per + 8.6 steps/min)*	**-0.66 [-0.84,-0.48]** (<0.001)	**-1.02 [-1.24,-0.81]** (<0.001)	**-0.38 [-0.56,-0.20]** (<0.001)	**-0.62 [-0.83,-0.40]** (<0.001)	-0.16 [-0.35,0.04] (0.113)	**-0.39 [-0.62,-0.16]** (0.001)
Duration of upright events *(per + 2.9 min)*	**-0.22 [-0.43,-0.00]** (0.046)	-0.03 [-0.22,0.15] (0.727)	-0.2 [-0.41,0.01] (0.065)	-0.09 [-0.27,0.09] (0.314)	0.02 [-0.19,0.24] (0.826)	0.06 [-0.12,0.24] (0.526)
Stepping proportion of upright events *(per + 5.6 %)*	**-0.38 [-0.57,-0.20]** (<0.001)	**-0.24 [-0.45,-0.03]** (0.025)	**-0.33 [-0.52,-0.15]** (<0.001)	-0.16 [-0.36,0.04] (0.116)	-0.15 [-0.34,0.04] (0.123)	0.00 [-0.21,0.21] (0.999)
Step count of upright events *(per + 82.3 steps)*	**-0.51 [-0.70,-0.33]** (<0.001)	**-0.58 [-0.78,-0.38]** (<0.001)	**-0.32 [-0.51,-0.14]** (0.001)	**-0.38 [-0.58,-0.18]** (<0.001)	**0.31 [0.05,0.57]** (0.018)	0.23 [-0.04,0.49] (0.090)
Stepping events within upright events *(per + 3.0 n)*	-0.20 [-0.41,0.02] (0.072)	-0.01 [-0.20,0.18] (0.906)	**-0.23 [-0.44,-0.02]** (0.030)	-0.12 [-0.30,0.07] (0.213)	-0.01 [-0.22,0.21] (0.946)	0.06 [-0.12,0.25] (0.506)
Upright event burstiness *(per + 0.09)*	-0.01 [-0.21,0.19] (0.902)	-0.20 [-0.42,0.01] (0.062)	0.12 [-0.07,0.31] (0.22)	-0.07 [-0.28,0.14] (0.489)	0.17 [-0.02,0.36] (0.084)	-0.05 [-0.25,0.16] (0.666)
Sedentary event burstiness *(per + 0.08)*	**-0.31 [-0.49,-0.13]** (0.001)	**-0.41 [-0.62,-0.19]** (<0.001)	**-0.24 [-0.41,-0.06]** (0.009)	**-0.35 [-0.56,-0.14]** (0.001)	-0.06 [-0.24,0.12] (0.510)	**-0.23 [-0.44,-0.02]** (0.035)

Results are presented as regression coefficient (B) with 95% confidence interval [95% CI] and p-value, where the predictor is standardised and the outcome is unstandardised (a one standard deviation increase in the predictor equates to an absolute change in the physical function outcome. Associations were adjusted for the following covariates; Model 1: age, sex, and waking wear time. Model 2: model 1 + type 2 diabetes, education level, body mass index, and smoking status. Model 3: model 2 + average daily step count. [a] denotes significant sex interaction ($p < 0.05$) for Model 1. [b] denotes significant type 2 diabetes interaction ($p < 0.05$) for Model 2. Bold indicates statistical significance ($p < 0.05$)

Table 6.4. Associations of upright and stepping event metrics with six-minute walk test.

	Model 1		Model 2		Model 3	
	Males	***Females***	***Males***	***Females***	***Males***	***Females***
	B [95% CI] (*p*-value)	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**
Daily step count *(per + 3582 steps)*	**19.98 [17.57,22.39]** (<0.001)	**22.33 [19.69,24.98]** (<0.001)	**11.25 [9.04,13.47]** (<0.001)	**12.02 [9.60,14.44]** (<0.001)	- -	- -
Upright events *(per + 13.1 n)*	**6.06 [3.46,8.67]** (<0.001)	**6.66 [4.00,9.31]** (<0.001)	1.65 [-0.64,3.95] (0.158)	1.33 [-1.02,3.69] (0.268)	0.13 [-2.14,2.41] (0.909)	0.45 [-1.88,2.78] (0.704)
Stepping events [b] *(per + 59.1 n)*	**8.54 [5.89,11.20]** (<0.001)	**7.26 [4.56,9.97]** (<0.001)	**4.88 [2.55,7.22]** (<0.001)	**4.65 [2.27,7.02]** (<0.001)	**-3.69 [-6.34,-1.04]** (0.006)	**-3.49 [-6.14,-0.83]** (0.01)
Duration of stepping events [a] *(per + 8.8 sec)*	**15.77 [13.45,18.10]** (<0.001)	**22.23 [19.27,25.18]** (<0.001)	**7.98 [5.88,10.09]** (<0.001)	**10.1 [7.40,12.79]** (<0.001)	2.10 [-0.34,4.54] (0.092)	**3.44 [0.40,6.47]** (0.027)
Steps per stepping event [a] *(per + 16.7 steps)*	**16.46 [14.17,18.74]** (<0.001)	**23.20 [20.24,26.15]** (<0.001)	**8.85 [6.78,10.92]** (<0.001)	**11.00 [8.30,13.70]** (<0.001)	**3.61 [1.21,6.02]** (0.003)	**4.89 [1.83,7.94]** (0.002)
Step-weighted cadence [a] *(per + 8.6 steps/min)*	**19.90 [17.58,22.22]** (<0.001)	**23.61 [20.83,26.38]** (<0.001)	**11.83 [9.72,13.94]** (<0.001)	**12.54 [10.00,15.07]** (<0.001)	**8.32 [6.03,10.61]** (<0.001)	**8.92 [6.23,11.61]** (<0.001)
Duration of upright events [a] *(per + 2.9 min)*	**5.08 [2.23,7.94]** (<0.001)	1.21 [-1.24,3.67] (0.333)	**4.18 [1.69,6.66]** (0.001)	**2.59 [0.45,4.73]** (0.018)	-0.10 [-2.64,2.44] (0.940)	-0.34 [-2.51,1.82] (0.756)
Stepping proportion of upright events *(per + 5.6 %)*	**6.25 [3.72,8.77]** (<0.001)	**5.1 [2.33,7.87]** (<0.001)	**4.77 [2.57,6.97]** (<0.001)	**3.71 [1.30,6.12]** (0.003)	1.06 [-1.19,3.31] (0.357)	0.43 [-2.01,2.87] (0.730)
Step count of upright events *(per + 82.3 steps)*	**14.32 [11.85,16.79]** (<0.001)	**14.14 [11.49,16.78]** (<0.001)	**8.57 [6.37,10.76]** (<0.001)	**8.52 [6.18,10.86]** (<0.001)	-1.02 [-4.09,2.06] (0.517)	-0.61 [-3.72,2.50] (0.699)
Stepping events within upright events *(per + 3.0 n)*	**3.15 [0.30,6.00]** (0.030)	0.20 [-2.29,2.70] (0.873)	**3.52 [1.03,6.01]** (0.006)	**2.60 [0.42,4.78]** (0.019)	-0.94 [-3.48,1.60] (0.470)	-0.98 [-3.20,1.24] (0.387)
Upright event burstiness *(per + 0.09)*	**3.30 [0.66,5.94]** (0.014)	**5.82 [2.95,8.68]** (<0.001)	-1.11 [-3.43,1.20] (0.346)	1.60 [-0.90,4.11] (0.209)	-2.07 [-4.35,0.21] (0.075)	1.05 [-1.42,3.52] (0.404)
Sedentary event burstiness *(per + 0.08)*	**8.16 [5.77,10.54]** (<0.001)	**9.54 [6.65,12.44]** (<0.001)	**5.54 [3.45,7.64]** (<0.001)	**7.57 [5.05,10.10]** (<0.001)	**2.19 [0.04,4.33]** (0.045)	**5.24 [2.72,7.77]** (<0.001)

Results are presented as regression coefficient (B) with 95% confidence interval [95% CI] and p-value, where the predictor is standardised and the outcome is unstandardised (a one standard deviation increase in the predictor equates to an absolute change in the physical function outcome. Associations were adjusted for the following covariates; Model 1: age, sex, and waking wear time. Model 2: model 1 + type 2 diabetes, education level, body mass index, and smoking status. Model 3: model 2 + average daily step count. [a] denotes significant sex interaction ($p < 0.05$) for Model 1. [b] denotes significant type 2 diabetes interaction ($p < 0.05$) for Model 2. Bold indicates statistical significance ($p < 0.05$)

Table 6.5. Associations of upright and stepping event metrics with SF-36 physical functioning subscale.

	Model 1		Model 2		Model 3	
	Males	***Females***	***Males***	***Females***	***Males***	***Females***
	B [95% CI] (*p*-value)	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**
Daily step count [a b] *(per + 3582 steps)*	**3.14 [2.62,3.67]** (<0.001)	**4.44 [3.87,5.01]** (<0.001)	**1.88 [1.37,2.40]** (<0.001)	**2.87 [2.31,3.43]** (<0.001)	- -	- -
Upright events *(per + 13.1 n)*	0.55 [-0.01,1.11] (0.056)	**0.87 [0.30,1.44]** (0.003)	-0.16 [-0.69,0.37] (0.556)	-0.04 [-0.58,0.50] (0.888)	-0.47 [-1.00,0.06] (0.080)	-0.22 [-0.76,0.32] (0.423)
Stepping events *(per + 59.1 n)*	**1.45 [0.88,2.02]** (<0.001)	**1.94 [1.36,2.52]** (<0.001)	**0.94 [0.40,1.48]** (0.001)	**1.52 [0.98,2.07]** (<0.001)	**-0.63 [-1.24,-0.01]** (0.046)	0.04 [-0.57,0.65] (0.899)
Duration of stepping events [a b] *(per + 8.8 sec)*	**2.52 [2.01,3.02]** (<0.001)	**4.08 [3.44,4.72]** (<0.001)	**1.36 [0.87,1.84]** (<0.001)	**2.23 [1.61,2.86]** (<0.001)	0.14 [-0.43,0.70] (0.628)	**0.85 [0.15,1.56]** (0.017)
Steps per stepping event [a b] *(per + 16.7 steps)*	**2.51 [2.01,3.00]** (<0.001)	**4.29 [3.65,4.93]** (<0.001)	**1.37 [0.89,1.85]** (<0.001)	**2.42 [1.80,3.05]** (<0.001)	0.23 [-0.33,0.78] (0.424)	**1.09 [0.38,1.79]** (0.003)
Step-weighted cadence [a b] *(per + 8.6 steps/min)*	**2.86 [2.35,3.36]** (<0.001)	**4.75 [4.14,5.35]** (<0.001)	**1.66 [1.17,2.15]** (<0.001)	**3.05 [2.46,3.64]** (<0.001)	**0.90 [0.37,1.43]** (0.001)	**2.26 [1.64,2.88]** (<0.001)
Duration of upright events *(per + 2.9 min)*	**1.08 [0.46,1.69]** (0.001)	**0.59 [0.06,1.11]** (0.029)	**0.97 [0.40,1.55]** (0.001)	**0.84 [0.35,1.34]** (0.001)	0.14 [-0.44,0.73] (0.630)	0.27 [-0.23,0.77] (0.285)
Stepping proportion of upright events [a] *(per + 5.6 %)*	**0.77 [0.23,1.31]** (0.005)	**1.67 [1.07,2.26]** (<0.001)	**0.58 [0.07,1.08]** (0.026)	**1.46 [0.91,2.02]** (<0.001)	-0.16 [-0.68,0.36] (0.547)	**0.81 [0.25,1.38]** (0.005)
Step count of upright events [a b] *(per + 82.3 steps)*	**2.33 [1.80,2.86]** (<0.001)	**3.14 [2.57,3.71]** (<0.001)	**1.51 [1.00,2.01]** (<0.001)	**2.30 [1.76,2.84]** (<0.001)	-0.15 [-0.86,0.57] (0.687)	**0.73 [0.01,1.45]** (0.047)
Stepping events within upright events *(per + 3.0 n)*	**0.68 [0.06,1.29]** (0.030)	0.46 [-0.07,0.99] (0.091)	**0.78 [0.20,1.35]** (0.008)	**0.87 [0.37,1.37]** (0.001)	-0.09 [-0.67,0.50] (0.773)	0.18 [-0.34,0.69] (0.498)
Upright event burstiness *(per + 0.09)*	-0.14 [-0.71,0.42] (0.624)	0.42 [-0.19,1.04] (0.177)	**-0.82 [-1.36,-0.29]** (0.002)	-0.25 [-0.83,0.33] (0.399)	**-1.02 [-1.55,-0.49]** (<0.001)	-0.36 [-0.93,0.21] (0.215)
Sedentary event burstiness [a] *(per + 0.08)*	**1.16 [0.65,1.67]** (<0.001)	**2.01 [1.39,2.64]** (<0.001)	**0.77 [0.29,1.26]** (0.002)	**1.72 [1.14,2.31]** (<0.001)	0.08 [-0.41,0.58] (0.745)	**1.24 [0.66,1.83]** (<0.001)

Results are presented as regression coefficient (B) with 95% confidence interval [95% CI] and (p-value), where the predictor is standardised and the outcome is unstandardised (a one standard deviation increase in the predictor equates to an absolute change in the physical function outcome. Associations were adjusted for the following covariates; Model 1: age, sex, and waking wear time. Model 2: model 1 + type 2 diabetes, education level, body mass index, and smoking status. Model 3: model 2 + average daily step count. [a] denotes significant sex interaction ($p < 0.05$) for Model 1. [b] denotes significant type 2 diabetes interaction ($p < 0.05$) for Model 2. Bold indicates statistical significance ($p < 0.05$)

Collectively, these findings suggest that some specific dimensions of the pattern in which physical activity is accumulated, are related to physical function, over and above the volume of activity.

These findings contribute to the growing body of research examining the relationship between physical activity patterns and physical function.[99] Our results align with previous studies that have established associations between a higher frequency of short or transient stepping event durations and poorer physical function performance.[102,105] The mechanism behind these associations is assumed to relate to the capacity of an individual. Higher capacity would likely show a less fragmented physical activity profile, due to the capacity to perform longer bouts of sustained stepping.

Our additional examination of the temporal distribution and the composition of upright events provides further insight into how different patterns of physical activity accumulation are related to physical function. Higher sedentary burstiness was associated with better 6MWT performance in both men and women, and better TCST and SF-36pf results particularly in females. Again, we assume these associations relate to capacity, with higher sedentary burstiness meaning greater variation in upright event duration. Conversely, lower sedentary burstiness would be characterised by more uniform upright event durations, which would be shorter due to the finite period of a day, when adjusted for volume. Observed sex differences in many of the associations was interesting, and not an immediately understood finding. However, significant sex differences in the upright and stepping metrics were observed here, and in previous research in a midlife population.[325]

A potential explanation for positive associations between sedentary burstiness and physical function is that those who undertake a mix of both short and long upright event durations (higher sedentary burstiness) have a higher endurance capacity, compared to females who record mainly short duration upright events. In addition, as the direction of causality is not known due to the cross-sectional design, the associations could also be due to declining physical function decreasing sedentary burstiness. Despite associations with demographic and lifestyle factors,[325] the upright event burstiness was not associated with the three performance-based physical function outcomes, and only the SF-36pf in males.

Higher step volume is associated with a range of health outcomes,[352] though evidence on the independent effect of step-rate is equivocal.[238] Step-rate has been shown to be associated with a range of health outcomes,[353,354] including the 400-m walk test in older adults;[355] though, conversely, step-rate has not always been shown to be associated with mortality when adjusted for volume.[180,239] Our results also show that higher step-weighted cadence is associated with better 6MWT performance and SF36-pf score in both males and females, and TCST performance in females, even after adjustment for volume (total daily step count).

This could be attributed to our approach to cadence quantification. Unlike previous studies, which primarily relied on step counts above predefined thresholds (e.g., 100 steps/min) and peak cadence metrics (e.g., the 30 highest cadence values per day),[180,239,353] or simply the average (unweighted) step-rate over the measurement period,[354] our method involves calculating a step-weighted average of all steps. This approach considers the cadence of every step,

potentially mitigating the bias associated with fixed thresholds, such as the possibility of someone consistently maintaining a cadence of 90 steps/min without registering any higher-paced stepping, as opposed to individuals who briefly exceed 100 steps/min but predominantly perform lower-paced steps.

6.5.1 Strengths and limitations

This chapter has several strengths, including a large and diverse sample from a population-based cohort and a comprehensive range of physical function outcomes. Previous work has demonstrated the causal relationship between physical activity and physical function,[98,356] however, the cross-sectional nature of this chapter prevents us from establishing causality. The possibility of reverse causation is present due to the study design. A degree of bidirectional causation is assumed due to the outcome of choice, poor physical function would be expected to impact physical activity behaviour. Nevertheless, the presence of these associations, irrespective of direction, remains an important finding. Understanding that patterns of physical activity differ for those with poor physical function offers valuable insights for further exploration in this area.

Some limitations of the device-based accelerometer data processing are acknowledged. We have discussed these in previous chapters and will further discuss these limitations in detail in Chapter 8. We used the previously employed, simple, pragmatic method to identify waking wear time, which may have impacted the accuracy of temporal distribution of sedentary and upright burstiness metrics. In addition, accelerometers are not direct measures of physical activity behaviour but rather a proxy, which may result in a level of misclassification.

Our study revealed magnitudes of effects that do not reach the clinically meaningful differences established for conventional measures of physical function.[357–359] However, given the novelty of these physical activity metrics (particularly burstiness) and the absence of well-defined standards, we made the deliberate choice to standardise them for analysis. This approach equates a one-standard-deviation change in the predictor to an absolute change in the physical function outcome. Our findings suggest that upright and stepping event measures of physical activity are associated with health outcomes that are not wholly explained by the volume of physical activity undertaken. Accumulation of patterns is different across population sub-groups,[325] and having demonstrated these are associated with health outcomes, independent of volume, future work should not ignore how steps are accumulated.

6.6 Summary

This chapter addressed the fourth thesis objective by determining patterns of upright and stepping event accumulation, independent of stepping volume, are an important consideration in research into physical function. Future research into physical activity and health should examine both physical activity volume and patterns of accumulation to add to our understanding of the benefits of physical activity. Longitudinal studies with repeated measures are now needed to examine how physical activity patterns change with age, and their prospective association with physical function and other health outcomes. In addition, future research should aim to understand these associations at earlier life stages, beyond the focus in later life only.

Chapter 7
Physical Activity Accumulation and Physical Function: Insights from The 1970 British Cohort Study

7.1 Overview

Chapter 7 aims to address the fifth thesis objective by investigating the associations between the physical activity pattern metrics and physical function outcomes in an early midlife population. This chapter builds on the previous by applying the same analysis to an early midlife population with the addition of balance as an unexplored function outcome. This chapter was published as a peer reviewed paper: *Cross-sectional associations between temporal patterns and composition of upright and stepping events with physical function in mid-life: Insights from the 1970 British Cohort Study*. The published version is available digitally using the following DOI:[360] https://doi.org/10.1111/sms.14645.

7.2 Introduction

In previous chapters we have described the significant variation in the frequency, duration, composition, and distribution of upright events and stepping events across sociodemographic and health-related characteristics, with potential phenotypes emerging.[325]

We further examined associations between these upright and stepping metrics and performance-based physical function.[346] After adjusting for total stepping volume, we observed associations with higher sedentary burstiness (the clustering of sedentary events), higher duration of stepping events, and higher

step-weighted cadence (mean cadence of all stepping events, weighted by number of steps per events) with better physical function performance. A higher number of stepping events, when adjusted for stepping volume, i.e. more fragmented stepping, was associated with poorer physical function performance.

The mechanistic explanation behind these associations was thought to be related to endurance capacity. Higher endurance capacity would be expected to be associated with less fragmented physical activity, due to the capacity to perform longer bouts of sustained stepping without experiencing fatigue. Given the cross-sectional nature of the study, causation was not implied; however, these findings emphasise the importance of further investigating the influence of how physical activity is accumulated on health outcomes.

This previous evidence was derived from The Maastricht Study, a large cohort study (n = 6085).[214] Though the age range was 40 to 79 years, (mean age was 59.6 ± 8.7 years), no analysis was performed on age differences in these associations. However, as function is strongly associated with age,[361] and endurance capacity reduces with age,[362] it is possible that the strength of associations between patterns of physical activity accumulation and function would differ between younger and older adults.

Midlife presents a potential window of opportunity for intervention for preserving physical function, in this study we aimed to explore whether associations observed in The Maastricht Study remained in a cohort of adults all at the same age (46 years) in early midlife. Although, declines in function do occur from midlife, it is unclear whether any changes are associated with changes in physical activity volume or patterns of accumulation. In addition, we introduce the upright-to-sedentary transition probability (USTP), a variation of ASTP, and we

would like to know if previous associations extend to measures of balance, a previously unexplored physical function outcome.

If specific patterns of physical activity accumulation are associated with physical function in early midlife, independently of volume, then it raises the possibility that changes in pattern of accumulation could help people to preserve physical function without the need to increase volume. However, longitudinal and intervention studies would be required before such conclusions could be made. Finally, replication of research results is important and unexplained sex differences seen in the previous study need further examination.

Therefore, the aim of this study was to examine whether a range of measures of patterns of physical activity accumulation were associated with physical function in a cohort of adults all in midlife. Based on previous findings, we hypothesise that:

a) More fragmented upright and stepping activity will be associated with poorer function.
b) Higher burstiness of upright events will be associated with poorer function.
c) Longer durations of stepping events and higher step-weighted cadence will be associated with better function.

7.3 Methods

For detailed descriptions of the study design, physical activity measurement, and data processing methods, derived metrics, and physical function measures refer to the general methods in Chapter 4. For a detailed description of covariates, see the methods section of Chapter 5.

7.3.1 Statistical analyses

Linear and multinomial logistic regression models were used to assess the associations of all upright and stepping event metrics with grip strength, balance, and the SF-36pf. Given the established sex-related differences in physical activity and functional capacity,[325] each association was formally tested for a sex interaction. For clarity, and due to the number of regressions, all analyses were stratified by sex whether interactions were significant or not. Sex interaction p-values were reported.

Model 1 was adjusted for waking wear time. Model 2 was additionally adjusted for other covariates listed above. Model 3 was further adjusted for total stepping volume (daily step count), to test if the associations persisted for a given value of a traditional metric of activity volume. We assessed the assumptions of linear and multinomial logistic regressions, including linearity, homoscedasticity, and multicollinearity, to ensure the validity of our models. Chi squared analyses were used to determine differences between the included sample, versus all eligible participants at the age 46 follow-up of BCS70 measures. All analyses were run on the final sample with complete data for all accelerometer metrics, covariates, and physical function outcomes.

7.3.1.1 Sensitivity analyses

To assess the robustness of our results, analyses were repeated to assess the impact of the waking wear time method. Our original method may be subject to misclassification of arise/bed-time. For example, an upright event at 04:00h (the individual's first upright event after 03:00h) might be to visit the toilet and return to bed for several hours, thus misclassifying arise time and registering an extended sedentary event, therefore skewing daily pattern metrics. We re-

processed the data using a per-day window with fixed times from 06:00h to 22:00h, though this method is similarly prone to bias if an individual arose before or after 06:00h.

7.4 Results

A total of 4378 participants (53.4% female) had 6+ valid days of accelerometer data, covariates data, and all physical function outcomes. Figure 7.1 shows the flow of participants through the study. Compared to the invited sample at the age 46 measurement phase (n = 8581), the included sample in this study were more likely to; be female, have a healthier BMI, have a higher level of education, have higher self-reported health, and be less likely to smoke.

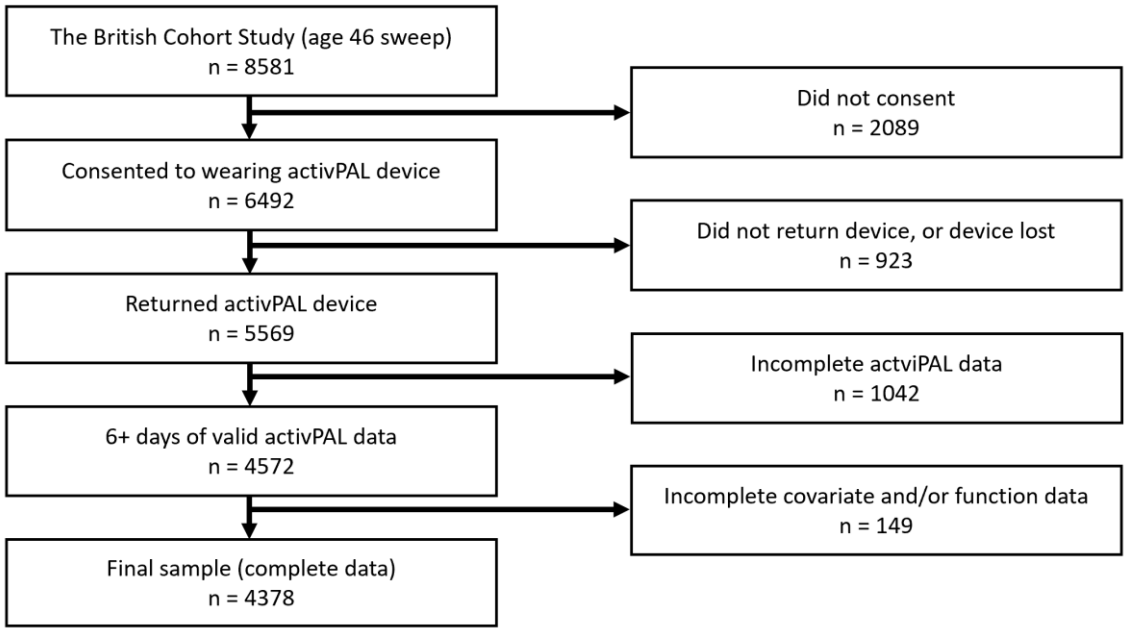


Figure 7.1. Flow chart of included participants through the study that had 6+ valid days of activPAL data, and all covariate and physical function outcome data.

Participant characteristics are presented in Table 7.1. Males tended to have a higher BMI and were more likely to be smokers. They also had a higher grip strength, higher SF-36pf scores, and better balance performance. The variation

in upright and stepping event metrics across the included covariates is described in Chapter 5.[325] Briefly, females had more upright events than males, spent more time upright, and patterns of upright events were more likely to be clustered together in bursts. Higher BMI was associated with fewer upright events and a lower daily step count, but the temporal distribution of upright events was less bursty. Also, on average, each upright event had a higher step count. People in active occupations were upright for longer, and displayed burstier patterns of upright events, with a greater variance in durations. Compared to people in sedentary occupations stepping events were shorter and slower paced. Assumptions of statistical tests stated in the methods were met for each analysis.

7.4.1 Grip strength

A higher total step volume was associated was only associated with higher grip strength in females. A higher number of stepping events per day was associated with higher grip strength in both males and females, as was a higher upright event burstiness. A higher USTP was negatively associated with grip strength in both males and females.

A higher number of upright events was associated with higher grip strength in males but not females. Duration of stepping events, number of steps per stepping event, and step-weighted cadence were all negatively associated with grip strength in males. In males, within upright event step count was negatively associated, and number of stepping events was positively associated with grip strength (Table 7.2, Figure 7.2).

Table 7.1. Summary of participant characteristics, upright event metrics, and physical function outcomes (n = 4378, The 1970 British Cohort Study).

Participant characteristics	Male	Female	Total
Sex	2040 (46.6%)	2338 (53.4%)	4378
BMI category, *n* (%)			
Healthy (18.5 to 24.9 kg/m^2)	479 (23.5%)	900 (38.5%)	1379
Overweight (25 to 29.9 kg/m^2)	919 (45.0%)	753 (32.2%)	1672
Obese (30 to 39.9 kg/m^2)	572 (28.0%)	548 (23.4%)	1120
Morbidly Obese (≥40 kg/m^2)	28 (1.4%)	90 (3.8%)	118
Underweight (<18.5 kg/m^2)	42 (2.1%)	47 (2.0%)	89
Highest qualification, *n* (%)			
None	588 (28.8%)	504 (21.6%)	1092
GCSE	612 (30.0%)	744 (31.8%)	1356
A Level	268 (13.1%)	395 (16.9%)	663
Degree and higher	572 (28.0%)	695 (29.7%)	1267
Socioeconomic group (NS-SEC), *n* (%) [a]			
Managerial, administrative, and professional	1063 (55.0%)	970 (48.9%)	2033
Intermediate occupations	587 (30.4%)	662 (33.4%)	1249
Routine and manual occupations	249 (12.9%)	330 (16.6%)	579
Never worked and long-term unemployed	34 (1.8%)	22 (1.1%)	56
Smoking status, *n* (%)			
Never	989 (48.5%)	1212 (51.8%)	2201
Did, but not at all now	664 (32.5%)	754 (32.2%)	1418
Occasionally	108 (5.3%)	102 (4.4%)	210
Daily	279 (13.7%)	270 (11.5%)	549
Upright event metrics			
Daily number of steps (n)	9514 ± 3672	9422 ± 3430	9465 ± 3545
Daily number of upright events (n)	50.9 ± 15.6	54.8 ± 14.7	53.0 ±15.2
Upright event burstiness	0.28 ± 0.10	0.32 ± 0.08	0.29 ± 0.09
Sedentary burstiness	0.28 ± 0.09	0.27 ± 0.08	0.28 ± 0.09
USTP (%)	2.6 ± 1.1	2.6 ± 1.0	2.6 ± 1.0
Daily number of stepping events (n)	195.5 ± 72.5	203.0 ± 65.9	199.5 ± 69.1
Mean duration of all step events (s)	32.6 ± 9.2	29.8 ± 7.5	31.1 ± 8.5
Mean number of steps per all stepping events (n)	46.3 ± 17.8	42.7 ± 14.4	44.3 ± 16.2
Step-weighted mean cadence (steps/min)	88.9 ± 9.1	90.4 ± 8.2	89.7 ± 8.6
Duration of all upright events (minutes)	8.0 ± 3.7	7.8 ± 3.8	7.9 ± 3.8
Daily proportion of stepping to standing time (%)	35.9 ± 6.4	35.6 ± 5.8	35.7 ± 6.1
Mean number stepping events per upright event (n)	9.1 ± 4.2	8.9 ± 3.6	9.0 ± 3.9
Mean number of steps per upright event (n)	199.6 ± 97.4	181.1 ± 79.0	189.7 ± 88.5
Physical function metrics			
Grip strength (kg)	45.6 ± 8.6	28.0 ± 5.6	36.2 ± 11.3
Single-leg stance balance, *n* (%)			
<30s open	217 (10.6%)	293 (12.5%)	510
0-<15s closed	1206 (59.1%)	1453 (62.1%)	2659
15-30s closed	617 (30.2%)	592 (25.3%)	1209
SF-36 Physical functioning score	90.6 ± 18.7	89.1 ± 18.9	89.8 ± 18.9

Mean ± SD or *n* (%)

[a] *n* = 3917

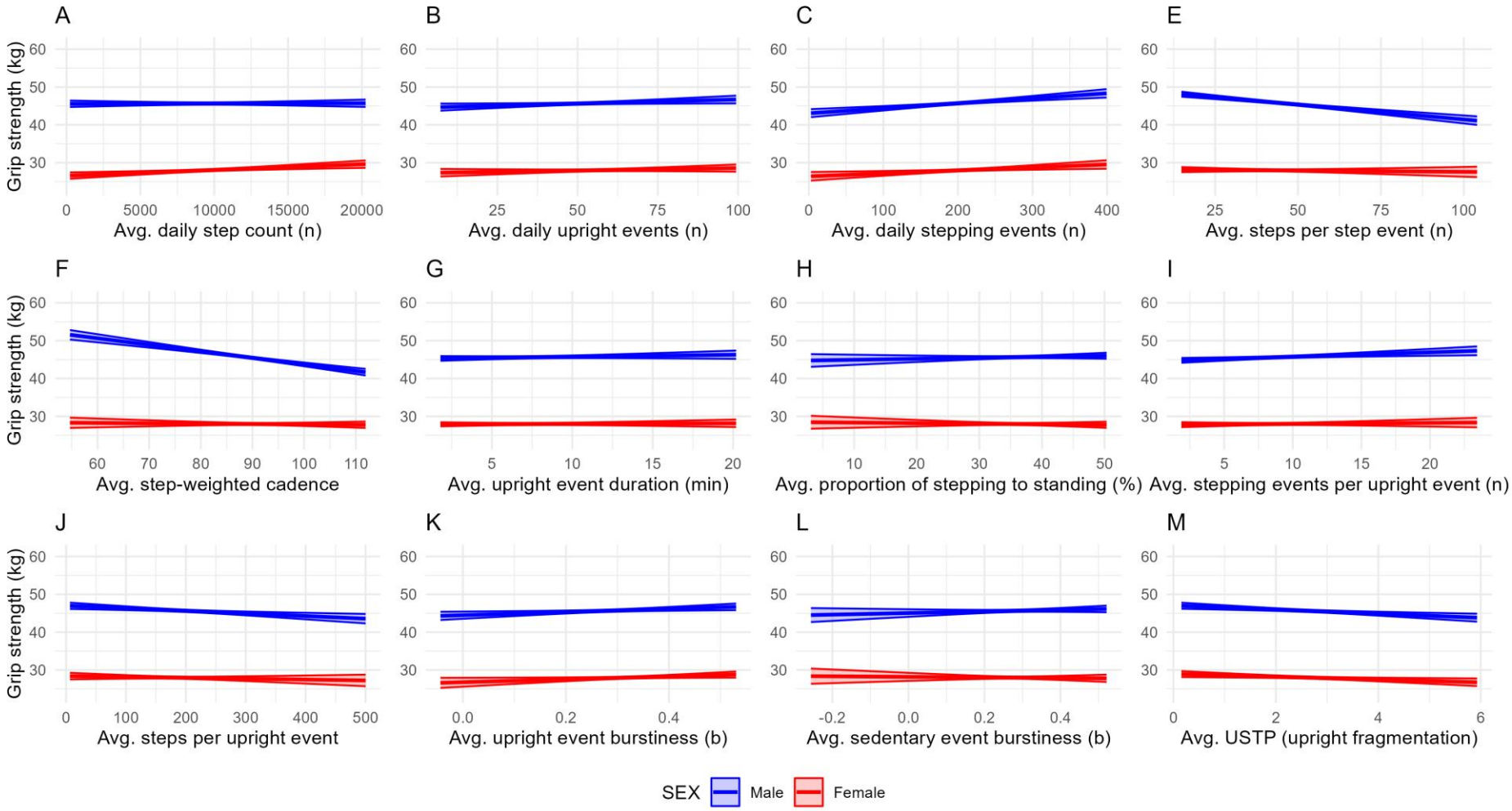


Figure 7.2. Regression plots for each activity metric with grip strength, by sex. Adjusted for sex, waking wear time, education level, socioeconomic status, body mass index, smoking status, and average daily step count.

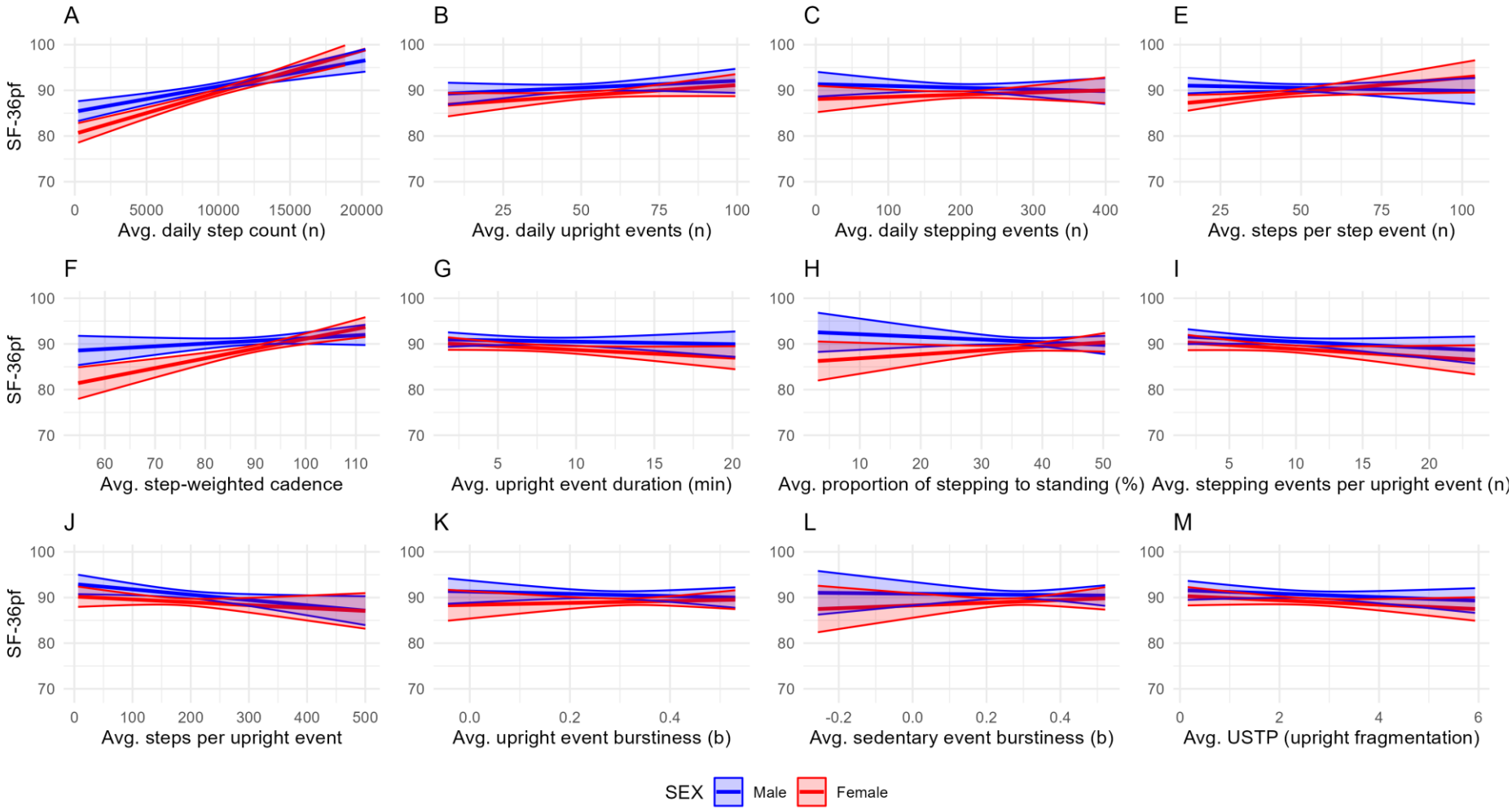


Figure 7.3. Regression plots for each activity metric with grip strength, by sex. Adjusted for sex, waking wear time, education level, socioeconomic status, body mass index, smoking status, and average daily step count

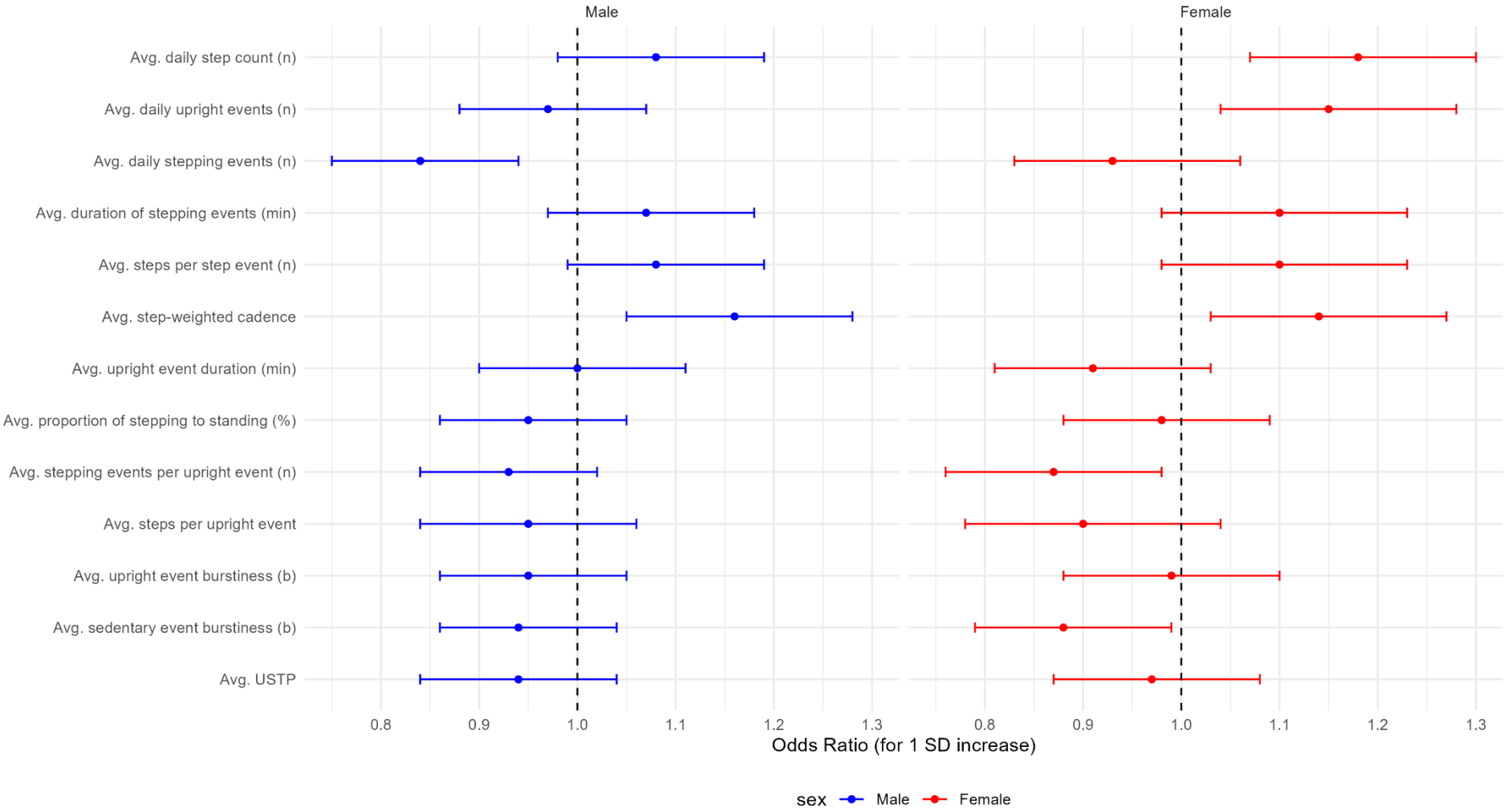


Figure 7.4. Coefficient plots of odds ratios for each activity metric with balance, by sex. Odds ratios [95% CI] of achieving a better single-leg stance balance performance, based on <30s eyes open as the reference category, followed by 0-<15s eyes closed, and >15s eyes closed. Adjusted for sex, waking wear time, education level, socioeconomic status, body mass index, smoking status, and average daily step count.

7.4.2 SF-36 physical functioning

Both a higher total step volume and a higher step-weighted cadence was associated with a better SF-36pf score in both males and females. In females, number of upright events, duration of stepping events, and steps per stepping event were associated a better SF-36pf score, as was within upright event stepping proportion. USTP was negatively associated with SF-36pf score in females. In males, within upright event step count was negatively associated with SF-36pf score (Table 7.3, Figure 7.3).

7.4.3 Balance

A higher total step volume was associated with better balance performance in females. A higher step-weighted cadence was associated with better balance performance in both males and females. In males, number of upright events was positively associated with balance, and number of stepping events was negatively associated. In females, sedentary event burstiness and within upright event number of stepping events was negatively associated with balance performance (Table 7.4, Figure 7.4).

7.4.4 Sensitivity analyses

When rerunning analyses using the alternative waking wear time classification of 06:00h to 22:00h, the results remained largely consistent (Appendix 8.14).

Table 7.2. Associations of upright and stepping event metrics with handgrip strength (n = 4378).

	Model 1		Model 2		Model 3	
	Males	***Females***	***Males***	***Females***	***Males***	***Females***
	B [95% CI] (*p*-value)	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**
Daily step count *(per + 3545 steps)*	0.07 [-0.24,0.37] (0.673)	**0.41 [0.11,0.72]** (0.008)	0.10 [-0.21,0.40] (0.540)	**0.58 [0.28,0.89]** (<0.001)	- -	- -
Upright events *(per + 15.2 n)*	0.29 [-0.02,0.60] (0.0670)	0.10 [-0.20,0.41] (0.513)	**0.37 [0.06,0.68]** (0.020)	0.30 [-0.01,0.61] (0.061)	**0.32 [0.01,0.63]** (0.041)	0.26 [-0.06,0.57] (0.107)
Stepping events [a] *(per + 69.1 n)*	**0.82 [0.52,1.12]** (<0.001)	**0.32 [0.01,0.64]** (0.042)	**0.79 [0.48,1.10]** (<0.001)	**0.45 [0.14,0.77]** (0.005)	**0.90 [0.53,1.28]** (<0.001)	**0.57 [0.19,0.95]** (0.004)
Duration of stepping events [a] *(per + 8.5 sec)*	**-0.82 [-1.10,-0.53]** (<0.001)	0.25 [-0.08,0.58] (0.143)	**-0.74 [-1.03,-0.45]** (<0.001)	0.29 [-0.04,0.62] (0.089)	**-1.03 [-1.34,-0.71]** (<0.001)	-0.06 [-0.42,0.30] (0.754)
Steps per stepping event [a] *(per + 16.2 steps)*	**-0.95 [-1.23,-0.66]** (<0.001)	0.21 [-0.12,0.53] (0.219)	**-0.88 [-1.17,-0.59]** (<0.001)	0.24 [-0.09,0.57] (0.154)	**-1.17 [-1.48,-0.86]** (<0.001)	-0.11 [-0.47,0.24] (0.535)
Step-weighted cadence [a] *(per + 8.6 steps/min)*	**-1.14 [-1.44,-0.84]** (<0.001)	0.15 [-0.16,0.46] (0.331)	**-1.11 [-1.41,-0.80]** (<0.001)	0.20 [-0.11,0.51] (0.212)	**-1.30 [-1.62,-0.98]** (<0.001)	-0.02 [-0.35,0.30] (0.884)
Duration of upright events *(per + 3.8 min)*	**0.41 [0.09,0.73]** (0.013)	0.18 [-0.10,0.47] (0.210)	0.32 [-0.00,0.64] (0.052)	0.10 [-0.19,0.39] (0.478)	0.22 [-0.11,0.55] (0.189)	0.04 [-0.26,0.33] (0.796)
Stepping proportion of upright events *(per + 6.1 %)*	**0.36 [0.06,0.66]** (0.019)	0.07 [-0.24,0.38] (0.674)	0.29 [-0.01,0.59] (0.062)	0.03 [-0.28,0.33] (0.862)	0.18 [-0.13,0.49] (0.256)	-0.07 [-0.38,0.25] (0.670)
Step count of upright events *(per + 88.5 steps)*	-0.11 [-0.40,0.17] (0.438)	0.28 [-0.04,0.61] (0.090)	-0.15 [-0.44,0.13] (0.295)	0.29 [-0.04,0.62] (0.084)	**-0.59 [-0.95,-0.23]** (0.001)	-0.23 [-0.65,0.19] (0.275)
Stepping events within upright events *(per + 3.9 n)*	**0.61 [0.32,0.90]** (<0.001)	0.22 [-0.09,0.54] (0.168)	**0.51 [0.22,0.81]** (0.001)	0.19 [-0.13,0.50] (0.253)	**0.43 [0.12,0.74]** (0.006)	0.09 [-0.24,0.42] (0.579)
Upright event burstiness *(per + 0.09)*	0.23 [-0.07,0.53] (0.141)	0.29 [-0.04,0.62] (0.085)	**0.34 [0.03,0.64]** (0.030)	**0.47 [0.14,0.80]** (0.006)	**0.31 [0.01,0.62]** (0.042)	**0.43 [0.10,0.76]** (0.011)
Sedentary event burstiness *(per + 0.09)*	**0.40 [0.11,0.69]** (0.007)	0.01 [-0.32,0.33] (0.968)	**0.38 [0.09,0.67]** (0.010)	-0.07 [-0.39,0.25] (0.676)	0.29 [-0.00,0.59] (0.050)	-0.13 [-0.46,0.19] (0.429)
USTP *(per + 1.0)*	**-0.86 [-1.18,-0.55]** (<0.001)	**-0.49 [-0.79,-0.19]** (0.001)	**-0.73 [-1.05,-0.42]** (<0.001)	**-0.47 [-0.77,-0.17]** (0.002)	**-0.69 [-1.01,-0.36]** (<0.001)	**-0.42 [-0.74,-0.11]** (0.008)

Results are presented as regression coefficient (B) with 95% confidence interval [95% CI] and p-value, where the predictor is standardised and the outcome is unstandardised (a one standard deviation increase in the predictor equates to an absolute change in the physical function outcome. Associations were adjusted for the following covariates; ; Model 3: sex, waking wear time, education level, socioeconomic status, body mass index, smoking status, and average daily step count

Table 7.3. Associations of upright and stepping event metrics with the SF-36 physical functioning subscale (n = 4378).

	Model 1		Model 2		Model 3	
	Males	***Females***	***Males***	***Females***	***Males***	***Females***
	B [95% CI] (*p*-value)	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**
Daily step count [a] *(per + 3545 steps)*	**3.42 [2.57,4.26]** (<0.001)	**5.29 [4.46,6.12]** (<0.001)	**2.51 [1.70,3.32]** (<0.001)	**4.20 [3.39,5.01]** (<0.001)	- -	- -
Upright events *(per + 15.2 n)*	**1.54 [0.67,2.41]** (0.001)	**2.27 [1.41,3.12]** (<0.001)	**0.94 [0.11,1.77]** (0.026)	**1.44 [0.62,2.27]** (0.001)	0.49 [-0.33,1.32] (0.240)	**0.95 [0.13,1.77]** (0.023)
Stepping events *(per + 69.1 n)*	**1.54 [0.69,2.39]** (<0.001)	**3.18 [2.32,4.04]** (<0.001)	**1.67 [0.85,2.49]** (<0.001)	**3.09 [2.26,3.91]** (<0.001)	-0.57 [-1.56,0.41] (0.253)	0.76 [-0.25,1.76] (0.139)
Duration of stepping events [a] *(per + 8.5 sec)*	**2.37 [1.58,3.17]** (<0.001)	**4.42 [3.50,5.34]** (<0.001)	**1.29 [0.52,2.06]** (0.001)	**2.81 [1.92,3.70]** (<0.001)	-0.14 [-0.97,0.68] (0.736)	**1.04 [0.08,2.00]** (0.034)
Steps per stepping event [a] *(per + 16.2 steps)*	**2.52 [1.74,3.31]** (<0.001)	**4.73 [3.82,5.65]** (<0.001)	**1.41 [0.64,2.17]** (<0.001)	**3.02 [2.13,3.91]** (<0.001)	0.10 [-0.71,0.91] (0.806)	**1.39 [0.44,2.34]** (0.004)
Step-weighted cadence [a] *(per + 8.6 steps/min)*	**3.48 [2.66,4.30]** (<0.001)	**5.68 [4.85,6.52]** (<0.001)	**2.17 [1.36,2.97]** (<0.001)	**3.90 [3.08,4.72]** (<0.001)	**1.30 [0.47,2.13]** (0.002)	**2.89 [2.04,3.74]** (<0.001)
Duration of upright events *(per + 3.8 min)*	0.53 [-0.38,1.44] (0.251)	-0.24 [-1.04,0.57] (0.564)	**0.91 [0.05,1.77]** (0.038)	0.41 [-0.36,1.17] (0.301)	-0.23 [-1.10,0.65] (0.612)	-0.34 [-1.11,0.43] (0.386)
Stepping proportion of upright events *(per + 6.1 %)*	**1.01 [0.16,1.86]** (0.019)	**2.81 [1.96,3.66]** (<0.001)	0.63 [-0.18,1.43] (0.126)	**2.05 [1.24,2.85]** (<0.001)	-0.46 [-1.28,0.36] (0.275)	**1.06 [0.25,1.88]** (0.010)
Step count of upright events *(per + 88.5 steps)*	**1.81 [1.01,2.61]** (<0.001)	**3.41 [2.49,4.33]** (<0.001)	**1.46 [0.71,2.21]** (<0.001)	**2.94 [2.07,3.82]** (<0.001)	**-1.09 [-2.04,-0.14]** (0.024)	-0.10 [-1.22,1.01] (0.855)
Stepping events within upright events *(per + 3.9 n)*	-0.14 [-0.97,0.69] (0.743)	0.26 [-0.63,1.14] (0.568)	0.47 [-0.32,1.27] (0.240)	**1.09 [0.24,1.94]** (0.012)	-0.78 [-1.59,0.04] (0.061)	-0.29 [-1.16,0.59] (0.521)
Upright event burstiness *(per + 0.09)*	-0.13 [-0.97,0.72] (0.770)	0.74 [-0.19,1.68] (0.119)	0.02 [-0.79,0.83] (0.961)	0.85 [-0.04,1.73] (0.060)	-0.19 [-0.99,0.61] (0.640)	0.40 [-0.47,1.28] (0.365)
Sedentary event burstiness *(per + 0.09)*	**1.04 [0.21,1.86]** (0.014)	**1.33 [0.43,2.23]** (0.004)	**1.11 [0.33,1.89]** (0.005)	**1.02 [0.16,1.87]** (0.020)	0.21 [-0.58,1.00] (0.608)	0.33 [-0.53,1.18] (0.452)
USTP *(per + 1.0)*	**-2.26 [-3.15,-1.37]** (<0.001)	**-2.75 [-3.56,-1.94]** (<0.001)	**-1.87 [-2.71,-1.03]** (<0.001)	**-2.56 [-3.33,-1.78]** (<0.001)	-0.76 [-1.62,0.11] (0.088)	**-1.57 [-2.36,-0.77]** (<0.001)

Results are presented as regression coefficient (B) with 95% confidence interval [95% CI] and p-value, where the predictor is standardised and the outcome is unstandardised (a one standard deviation increase in the predictor equates to an absolute change in the physical function outcome. Associations were adjusted for the following covariates; Model 1: sex, and waking wear time. Model 2: model 1 + education level, socioeconomic status, body mass index, and smoking status. Model 3: model 2 + average daily step count.

[a] denotes significant sex interaction ($p < 0.05$) for Model 1

Bold indicates statistical significance ($p < 0.05$)

Table 7.4. Associations of upright and stepping event metrics with single-leg stance balance test (n = 4378). Odds ratios [95% CI] of achieving a better single-leg stance balance performance, based on <30s eyes open as the reference category, followed by 0-<15s eyes closed, and >15s eyes closed.

	Model 1		Model 2		Model 3	
	Males	***Females***	***Males***	***Females***	***Males***	***Females***
	OR [95% CI] (*p*-value)	**OR [95% CI] (*p*-value)**	**OR [95% CI] (*p*-value)**	**OR [95% CI] (*p*-value)**	**OR [95% CI] (*p*-value)**	**OR [95% CI] (*p*-value)**
Daily step count *(per + 3545 steps)*	**1.13 [1.03,1.24]** (0.007)	**1.28 [1.17,1.41]** (<0.001)	1.08 [0.98,1.19] (0.123)	**1.18 [1.07,1.30]** (0.001)		
Upright events [a] *(per + 15.2 n)*	1.03 [0.94,1.13] (0.480)	**1.25 [1.14,1.38]** (<0.001)	0.99 [0.90,1.09] (0.834)	**1.17 [1.06,1.29]** (0.002)	0.97 [0.88,1.07] (0.600)	**1.15 [1.04,1.28]** (0.006)
Stepping events *(per + 69.1 n)*	0.94 [0.86,1.03] (0.179)	1.08 [0.98,1.19] (0.119)	0.96 [0.87,1.06] (0.435)	1.07 [0.97,1.19] (0.174)	**0.84 [0.75,0.94]** (0.004)	0.93 [0.83,1.06] (0.276)
Duration of stepping events *(per + 8.5 sec)*	**1.20 [1.10,1.30]** (<0.001)	**1.28 [1.16,1.41]** (<0.001)	**1.11 [1.01,1.21]** (0.022)	**1.15 [1.03,1.27]** (0.011)	1.07 [0.97,1.18] (0.163)	1.10 [0.98,1.23] (0.103)
Steps per stepping event *(per + 16.2 steps)*	**1.22 [1.12,1.32]** (<0.001)	**1.28 [1.16,1.42]** (<0.001)	**1.12 [1.03,1.22]** (0.010)	**1.14 [1.03,1.27]** (0.011)	1.08 [0.99,1.19] (0.086)	1.10 [0.98,1.23] (0.091)
Step-weighted cadence *(per + 8.6 steps/min)*	**1.31 [1.20,1.44]** (<0.001)	**1.33 [1.21,1.47]** (<0.001)	**1.18 [1.08,1.30]** (<0.001)	**1.18 [1.06,1.30]** (0.002)	**1.16 [1.05,1.28]** (0.004)	**1.14 [1.03,1.27]** (0.013)
Duration of upright events *(per + 3.8 min)*	0.99 [0.90,1.09] (0.903)	**0.88 [0.79,0.99]** (0.027)	1.04 [0.94,1.15] (0.426)	0.95 [0.85,1.07] (0.435)	1.00 [0.90,1.11] (0.985)	0.91 [0.81,1.03] (0.150)
Stepping proportion of upright events *(per + 6.1 %)*	1.01 [0.92,1.10] (0.847)	1.06 [0.96,1.17] (0.221)	0.99 [0.90,1.09] (0.884)	1.02 [0.92,1.13] (0.689)	0.95 [0.86,1.05] (0.296)	0.98 [0.88,1.09] (0.701)
Step count of upright events *(per + 88.5 steps)*	1.08 [0.99,1.17] (0.087)	1.07 [0.96,1.18] (0.222)	1.07 [0.98,1.16] (0.155)	1.04 [0.94,1.16] (0.434)	0.95 [0.84,1.06] (0.358)	0.90 [0.78,1.04] (0.161)
Stepping events within upright events *(per + 3.9 n)*	0.92 [0.84,1.01] (0.085)	**0.86 [0.78,0.96]** (0.009)	0.98 [0.89,1.08] (0.665)	0.93 [0.83,1.05] (0.223)	0.93 [0.84,1.02] (0.137)	**0.87 [0.76,0.98]** (0.023)
Upright event burstiness *(per + 0.09)*	0.96 [0.88,1.06] (0.432)	1.03 [0.93,1.15] (0.536)	0.96 [0.87,1.06] (0.423)	1.00 [0.90,1.12] (0.938)	0.95 [0.86,1.05] (0.324)	0.99 [0.88,1.10] (0.831)
Sedentary event burstiness *(per + 0.09)*	0.96 [0.88,1.05] (0.374)	0.91 [0.82,1.01] (0.080)	0.98 [0.89,1.07] (0.662)	0.91 [0.82,1.02] (0.101)	0.94 [0.86,1.04] (0.212)	**0.88 [0.79,0.99]** (0.031)
USTP *(per + 1.0)*	**0.91 [0.82,1.00]** (0.049)	0.95 [0.87,1.05] (0.322)	**0.90 [0.81,1.00]** (0.046)	0.93 [0.84,1.04] (0.200)	0.94 [0.84,1.04] (0.225)	0.97 [0.87,1.08] (0.576)

Results are presented as odds ratios (OR) with 95% confidence interval [95% CI] and p-value, where the predictor is standardised. Associations were adjusted for the following covariates; Model 1: sex, and waking wear time. Model 2: model 1 + education level, socioeconomic status, body mass index, and smoking status. Model 3: model 2 + average daily step count.

[a] denotes significant sex interaction ($p < 0.05$) for Model 1

Bold indicates statistical significance ($p < 0.05$)

7.5 Discussion

This study evaluated the relationships between the temporal distribution and composition of upright and stepping events, with physical function outcomes in a large and representative sample of UK adults all aged 46 years. A number of measures describing differences in patterns of upright and stepping accumulation were associated with a range of physical function measures, even after adjusting for the overall volume of stepping. However, the associations were not consistent and often not in the expected direction.

For grip strength, a higher number of stepping events and more bursty (clustered) upright events were associated with higher grip strength, whereas the more transient the upright events were the lower the grip strength. Relationships with measures of the composition of stepping and upright events were not consistently associated with grip strength and were often in the wrong direction.

For SF-36pf, total steps per day, and a higher step-weighted cadence were associated with higher scores. More transient sedentary events (less prolonged) were also associated with higher SF-36pf scores and more transient upright events lower scores. These results were in the expected direction but were mostly attenuated to the null when adjusted for average daily step count, except for step-weighted cadence. This suggests people perceive better function when they do more daily stepping independent of how the steps were accumulated. As with grip strength, measures of the composition of upright events were inconsistently associated with SF-36pf and varied between males and females. Only stepping at a higher cadence was associated with better balance in both males and females.

It might be expected that in both sexes, recording a higher number of longer duration and higher cadence stepping events would be indicative of better capacity, and therefore function, compared to shorter, lower cadence stepping. However, this was not consistently supported by the findings. It might also be expected that bursts of transient sit-to-stand transitions might also be associated with better function due to the strength and power required to get up and down frequently. Although this was associated with grip strength it was not associated with perceptions of function or balance.

Further, the majority of results varied considerably between sexes. Though sex differences were observed in Chapter 6, in a population with a wider age range and older average age, the contradictory findings here were unexpected and an explanation is not immediately obvious. Three possible explanations for the inconsistent and sometimes contradictory findings of this study are proposed. Firstly, exercise training outcomes are very exercise-type specific.[363] Daily stepping events and postural transitions may not be sufficiently specific to alter hand grip strength or balance, especially in a population of adults aged 46 years who would not be expected to have experienced major losses in function. It may be that the expected associations would be more consistent in cardiovascular or metabolic outcomes rather than musculoskeletal outcomes.

Secondly, the most inconsistent results of this study were in the measures of the composition of upright results – number of stepping events, durations, and the mix of standing and stepping. Compared to estimating postural transitions, measures of standing and stepping are more subject to misclassification. For example, detecting slower paced steps appears to be a problem for accelerometers and the activPAL used in this study does not accurately detect

steps recording at lower cadences.[213] Therefore, within each upright event the duration of standing could be overestimated and stepping underestimated. Also, the true step cadence may be overestimated due to the absence of lower cadence steps. The resulting misclassification would attenuate associations toward the null. Finally, it is possible that the null findings may be due to insufficient, between person variation in stepping activity and minimal changes in function at age 46 years to demonstrate a consistent association with measures of muscle strength.

Despite the inconsistency of the findings in this study, they still contribute to the growing body of research examining the relationship between patterns of physical activity accumulation and physical function.[99] Higher step volume is associated with a range of health outcomes,[352] and stepping cadence has been linked to various health outcomes.[353,354] However, its association with mortality is inconsistent when adjusted for volume.[180,239] Unlike prior research, which has predominantly relied on fixed thresholds or peak cadence metrics, our approach calculates a step-weighted average, considering the cadence of all stepping. This method addresses potential biases associated with classifying stepping using fixed thresholds, where epochs may be misclassified based on very brief changes in cadence. The respective negative and null associations in males and females observed between step-weighted cadence and grip strength was contrary to the other physical function outcomes, an unexpected finding.

Our findings align with a number of previous studies that have established associations between a higher frequency of short or transient step event durations and poorer physical function performance in older adults.[104,105] These studies employed the ASTP index of fragmentation using the epoch method,

where activity (or posture) is classified over a fixed period of time. We employed an event-based approach for a similar index of upright events.[179] In addition, previous studies have focused on older adults whereas we have demonstrated associations of physical activity metrics with better physical function outcomes in an early midlife population where losses in function would be expected to be much lower. No association was seen between USTP and balance. The burstiness of upright events was positively associated with grip strength in both sexes, but inconsistently so with SF-36pf.

The inconsistent sex differences in the reported associations are not immediately intuitive. We note that a previous study also reported sex differences in associations of step volume and grip strength in midlife, and the authors again were unable to offer an explanation beyond potential residual confouding.[157] This represents an interesting avenue for further exploration. It is possible that the study population may contribute to some of the counterintuitive findings. Relative to Chapter 6, which included a wide age range, the homogeneity in both physical function and physical activity metrics in BCS70 may explain some of the deviation from expected associations. For example, the degree of decline in physical function and/or physical activity in midlife may not be large enough to detect associations seen in the older population of our previous study. We also only have a limited number of measures of function that may not be as closely associated with postural changes and stepping activity compared to measures such as timed sit-to-stand and gait speed.

We also note that our analyses were adjusted for BMI due to the known association between higher BMI and higher grip strength,[364] though the potential of residual confounding by body composition remains, which may potentially

impact the observed direction and magnitude of associations. We are wary of overinterpreting our findings. The small magnitude of the associations and multiple associations tested raises the possibility that some of these results could be attributed to artifacts.

7.5.1 Strengths and Limitations

To our knowledge this chapter is the first study to examine associations between physical activity patterns and physical function in early midlife. Further strengths of our study include the large and diverse sample from a population-based cohort, with multiple physical function outcomes. Moreover, the choice of device, which provided high resolution, time-stamped postural data, allowed for an event-based analysis.[365] The data processing techniques further allowed for extraction of specific metrics of interest. However, the cross-sectional design prevents the establishment of causality. In addition, selection bias was introduced resulting from non-response to acceleration data collection.

The included sample was generally healthier than those who declined to participate or were excluded due to insufficient data. Again, this may have limited the ability to detect associations between patterns of physical activity accumulation and physical function. Acknowledging limitations in accelerometer data processing, we employed a previously utilised, practical method for identifying waking wear time.[325] Criterion validity assessment of wake/sleep algorithms is challenging, potentially leading to misclassification, affecting the accuracy of sedentary and upright burstiness metrics. For example, misclassifying the arise time of an individual, could add an extended sedentary event (which is actually sleep) to the contiguous posture events and inflate the

burstiness of upright event metrics. However, sensitivity analyses showed no changes in results when employing an alternative method of fixed hours of waking wear (06:00h to 22:00h).

As discussed in previous chapters, accelerometers are proxy measures of physical activity, which may introduce misclassification. In addition, the activPAL underestimates slower-paced stepping,[344] highlighting the need for more precise measures of slower paced stepping in physical activity research.[337] Nevertheless, the methods used here are a considerable advance in what could be achieved previously with self-report-measures.

The measures of postural transitions allowed us to examine the effects of these on physical function separate from the composition of the events, similar to the research that has investigated sedentary breaks.[273] In addition, we have then investigated the distribution and composition of upright events (the breaks in sedentary events). The variation in the composition of uprights events highlights that all sedentary breaks are not the same, even when matched for duration. Simply counting sedentary events (or postural transitions) may lead to misleading conclusions about associations with health outcomes.

In this preliminary investigation of physical activity patterns, we made the pragmatic choice to average pattern metrics across valid measured days, as previous ASTP studies have done.[104] This ignores potentially important between day differences in physical activity accumulation , an area that warrants further investigation.

It is possible that changes in patterns of physical activity accumulation occur before changes in physical function, or even before declines in volume of activity. Being able to detect changes in activity accumulation (prior to declines in

volume), could be important at a time in the life course when sufficient function remains to participate successfully in interventions. There is evidence that trajectories of stepping volume and cadence are associated with trajectories in physical function, at least in older adults.[337] Increasing the number of faster paced steps as a proportion of total steps was associated with an improvement in physical function over 2-years. Consequently, there is a need for more prospective studies with multiple measures of patterns of physical activity accumulation starting in midlife.

7.6 Summary

This chapter has addressed the fifth and final objective of the thesis and demonstrated that the pattern in which upright and stepping events are accumulated, is associated with levels of physical function, in early midlife. The associations remained even after controlling for the volume of physical activity, suggesting that patterns of accumulation are likely to be at least as important as the total volume of activity in understanding associations with health outcomes. While our findings offer valuable insights into the associations between these metrics and physical function, the inconsistency in results indicate that much remains to be explored. However, if the findings were repeated in longitudinal studies with repeat measures, then future guidance on physical activity for health should reflect this evidence and guide people not only on how much physical activity to do but also on different patterns of accumulation. A better understanding of how patterns of accumulation are related to health could in the future lead to the refining of public health recommendations, affording individuals greater flexibility in achieving guideline adherence.

Chapter 8
General discussion

8.1 Primary aims

The primary aim of this thesis is to improve our understanding of patterns of physical activity accumulation and their association with physical function. Firstly, we conducted a systematic review to examine the current evidence for the association between physical activity and physical function across different populations. Then, we developed a suite of novel metrics to describe the patterns of upright and stepping events including measures of upright fragmentation (USTP), and the temporal distribution of upright and sedentary events (burstiness).

We utilised these measures to examine whether patterns of physical activity accumulation were associated with sociodemographic factors and physical function outcomes in both late and early midlife, independent of total volume of physical activity. These findings provide valuable insights into the relationship between physical activity patterns and physical function, laying the groundwork for future research that could impact the development of physical activity guidelines and screening strategies for early declines in physical function.

8.2 Synthesis of existing evidence

In Chapter 2, we systematically reviewed the literature to understand the association between physical activity and physical function, establishing that higher levels of physical activity are generally associated with better physical function across a range of performance-based measures of physical function.

This review highlighted a significant gap: most studies focused on older populations and relied on aggregate measures of physical activity, which fail to capture the nuances of how activity is accumulated. Addressing this gap became a central objective of the subsequent chapters.

8.3 Derived pattern metrics

In response to the limitations identified in the existing literature, Chapter 3 delved into the methodological challenges of processing accelerometer data to create meaningful physical activity measures. We emphasised the importance of examining physical function during midlife—a critical period often overlooked in research. Chapter 4 then focused on deriving a suite of pattern metrics from thigh-worn accelerometer data, emphasising an event-based approach to capture upright and stepping behaviours more accurately. These metrics included measures of fragmentation, temporal distribution, and the composition of upright events, providing new and nuanced views of physical activity patterns.

8.4 Population sub-groups associations

We examined the variation in patterns of physical activity accumulation by a range of sociodemographic factors in a midlife population. We identified that upright and stepping behaviour is accumulated in different ways across different populations, even for a given volume of activity. These differences in accumulation patterns could have significant implications for understanding associations with health outcomes. For example, individuals in more active occupations may have more fragmented activity patterns, which could in-part explain why associations between occupational physical activity are often far

smaller than this observed for leisure time PA, or null. Similarly, the variations in physical activity patterns observed across different BMI categories, smoking statuses, and self-rated health statuses highlight the need for tailored interventions that consider these factors. Understanding these differences is crucial for developing targeted strategies to improve physical function and overall health in diverse populations.

The observed differences between the BCS70 and DMS cohorts provide further insight into how physical activity patterns might vary by age and other sociodemographic factors. The BCS70 cohort, being uniformly younger (aged 46), likely represents a population that has not yet experienced the age-related changes in physical activity patterns that are more evident in the older DMS cohort. This age difference could account for the variations in stepping cadence, frequency of stepping and upright events, and the burstiness of these events. The younger BCS70 cohort may maintain more consistent activity patterns due to fewer age-related declines in physical function and overall health, leading to fewer changes in their daily routines and activity levels.

In contrast, the wider age range of the DMS cohort (40 to 75 years) may capture a broader spectrum of physical activity patterns influenced by the natural aging process. As people age, there are typically decreases in physical function, increases in chronic health conditions, and changes in lifestyle that are reflected in more fragmented and less intense physical activity patterns. This broader age range and the inclusion of older adults in DMS likely contribute to the observed negative associations between age and daily step count, cadence, and frequency of stepping and upright events, with function.

8.5 Associations with physical function

In Chapters 6 and 7 we conducted two cross-sectional studies to explore the associations between upright and stepping metrics and physical function outcomes in DMS and BCS70. Some consistent associations emerged, as did some unexpected and contradictory findings. The studies within this thesis collectively highlight the complex relationship between physical activity patterns and physical function. A consistent theme is the mechanistic link between activity fragmentation, burstiness, and physical function, where frequent transitions between activity and inactivity (high fragmentation) often signal reduced endurance and capacity, particularly in older adults. For example, a higher number of stepping event for the same given volume of steps (more fragmented) was associated with poorer 6MWT performance, balance, and self-reported SF-36pf. Higher USTP (fragmented uprigtht events) was even associated with lower upper body strength (grip), in addition to poorer scoring on the SF-36pf.

The findings suggest that higher fragmentation, reflected in frequent, brief bouts of activity, may indicate underlying issues such as early onset fatigue or lower cardiovascular endurance. This mechanistic pathway is particularly relevant in older adults, where maintaining sustained activity becomes increasingly difficult. The associations observed between higher cadence and better physical function outcomes, like the 6MWT, further support the idea that sustained, higher intensity activity is crucial for maintaining physical function. However, the nuanced nature of these relationships was evident in the observed sex differences, with some metrics showing positive associations with function in one sex but not the other.

Sex differences were particularly notable in the associations with physical function. These differences likely stem from both physiological factors, such as

variations in muscle mass and cardiovascular response, and behavioural factors, like differences in the types of physical activity typically performed by men and women. Further, the sometimes contradictory associations in the mid-life population might be partly explained by the specificity of exercise training outcomes and different functional measures.[363] Daily stepping events and postural transitions may not be sufficiently specific to alter the musculoskeletal performance, especially in a population of adults aged 46 years who would not be expected to have experienced major losses in function.

The most inconsistent results were in the measures of the composition of upright events. Compared to estimating postural transitions, measures of standing and stepping are more subject to misclassification. For example, detecting slower paced steps appears to be a problem for accelerometers, including the activPAL used in this study.[213]

The introduction of the burstiness metrics provided deeper insights into how physical activity is distributed throughout the day. While high USTP (indicating fragmented upright activity) was generally associated with poorer function, burstiness, characterising the clustering of activity, revealed more complex relationships. For example, higher burstiness of sedentary events was associated with better 6MWT performance, suggesting that the ability to cluster activity, especially postural transitions that require power in the lower extremity, may reflect greater functional capacity. However, these associations were not always consistent, highlighting the complexity of physical activity patterns and their impact on function.

These findings contribute to the growing body of research examining the relationship between physical activity patterns and physical function.[99] We have added new knowledge to the literature by exploring measures of the temporal

distribution of upright and sedentary events and their association with function. By adopting an event-based approach rather than an epoch approach, we have improved the accuracy of the metrics employed. Overall, these findings underscore the complexity of the relationship between physical activity patterns and physical function outcomes, highlighting the need for further research to elucidate these associations, both in mid- and later-life.

8.6 Strengths and limitations

The choice of performance-based measures in this study, including grip strength, gait speed, chair rise tests, walk tests, and balance tests, was driven by the need for objective, reliable, and precise measures of physical function. These measures offer significant advantages over self-report tools, particularly in their ability to detect early decline that may occur before they would be reported. In addition, objective measures have been consistently associated with future health outcomes. However, performance-based measures lack self-report measures' ability to capture an individual's perception of their physical function, which is a distinct and important aspect of physical function.[20] The SF-36 physical functioning sub-scale was included to capture subjective perceptions of physical function. This dual approach ensured a comprehensive understanding of physical function, acknowledging the value of both objective performance and subjective experience in assessing overall health.

The choice of pattern metrics were based on previous research, reviewed in Chapter 3. This includes the growing body of literature around fragmentation as a measure of physical behaviour, and it's associations with health outcomes. We built on this evidence by emplying a more precise, and particularly

appropriate, event-based approach to address certain limitations of previous studies. In addition, we chose to include burstiness as a novel measure for classifying habitual physical activity behaviour. Further metrics include simple counts and durations, in addition to a novel step-weighted method of classifying step-rate. Alternative pattern metrics were reviewed and described in Chapter 3, these measures could also have provided interesting evidence, and should be explored. However, we justified our choice of measures, which included the appropriateness of these measures for the event-based approach taken with data processing, and the growing interest with fragmentation of physical activity, which includes physical function. The inclusion of further metrics was not feasible within the scope of this thesis.

The device employed in this thesis is a significant strength. The issues related to self-report measures and those related the epoch-based approaches prevalent in physical activity research have been outline in previous chapters. The thigh worn activPAL provided high resolution time-stamped event data. This allowed for an event-based approach, and the derivation of a suite of novel metrics that quantified the composition and temporal distribution of upright and stepping events.

The range of metrics derived allowed us to answer questions about how physical activity was accumulated, a previously under-explored area of the research. These metrics, and the subsequent analysis, provide evidence for the inclusion of pattern metrics in physical activity research, and move on from the reliance on summary volume measures alone.

The two cohort studies utilised in this thesis were a further strength. Both had large sample sizes, and one included only adults in midlife, allowing us to

examine the relationship between physical activity and physical function in an age-group expected to be functioning reasonably well, but at a time when things are likely to be changing. The wide range of performance-based physical function measures available in both cohorts allowed for a comprehensive analysis of associations with physical activity. This allowed us to identify differences in associations for specific measures of function including perceived and objectively measured function. In addition, the range of covariates allowed for adjustment of potential confounding factors known to be associated with both physical activity and physical function.

The thesis is not without limitation. The original research Chapters (5, 6, and 7) describe cross-sectional analyses, making it impossible to establish causation. BCS70 was scheduled to collect self-report measures of health and the SF-36pf in 2020. However, due to the pandemic, this was postponed, and data collection was only completed in January 2024, with data expected to be available for research in autumn 2024. DMS data was collected in the early 2010s, with the follow-up data collection currently underway. Unfortunately, this meant that prospective analysis using these cohorts was not feasible during this PhD.

Linked with the cross-sectional designs is the challenge posed by the bi-directional nature of the physical activity – physical function relationship. Previous studies have demonstrated the causal relationship between physical activity and physical function.[98,356] However, the possibility of reverse causation exists and is to some extent assumed. The level of a person's physical function is likely to impact their physical activity behaviour in terms of both volume and pattern. Nonetheless, the presence of these associations, regardless of direction, remains

a significant finding. Understanding that patterns of physical activity differ for those with poor physical function offers valuable insights for further exploration in this area.

Despite selecting the most appropriate device to address the thesis objectives, the activPAL does have limitations. Like other devices, it underestimates slower-paced stepping, as the minimum cadence registered is 20 steps/min and evidence suggesting underestimate occurs from cadences below 69 steps/min, potentially leading to an underestimation of total steps and overestimate of stepping cadence.[317,344] In addition, accelerometers are not direct measures of physical activity behaviour but rather proxies, and proprietary algorithms apply rules to the activPAL. Minimum resolution of event durations (10 s here) may result in a level of misclassification, potentially underestimating the number of upright events, and therefore the related metrics. There is also a minimum signal threshold required to change the classification of an event, but the exact rules are not disclosed due to the proprietary nature of the activPAL algorithm. This could lead to misclassification of shorter events and inflation of the preceding or subsequent event, depending on these rules. While the exact impact is unknown, it is assumed that this affects stepping behaviour more significantly due to the error at lower cadences, likely underestimating all stepping metrics and thereby attenuating associations.

Some limitations of the accelerometer data processing are acknowledged. We employed a simple, pragmatic method to identify waking wear time. Like other wake/sleep time algorithms, assessing criterion validity is challenging, and as such, there may have been some misclassification. This would have had the most significant impact on the accuracy of the temporal distribution of sedentary and

upright burstiness metrics (e.g., if an upright event was registered before the person's true arise time). We also made the pragmatic choice to average pattern metrics across valid measured days. This ignores potentially important between-day differences in physical activity accumulation, an area that warrants further investigation.

The studies within the thesis required a high number of valid days of activPAL wear and all covariate and function outcomes, allowing for analysis of habitual activity and robust adjustment. However, this reduced our sample size and introduced the potential for selection bias, as the final samples included in each study were considerably smaller than the cohort study sizes. In both cases, the final sample included in the studies generally had a healthier BMI, a higher level of education or socioeconomic class, and were less likely to be smokers. Consequently, the findings might not be fully representative of the broader population. This selection bias could lead to an overestimation of the associations between physical activity patterns and physical function, as the healthier, more active individuals included in the sample may naturally exhibit stronger relationships between these variables. Conversely, the exclusion of less healthy individuals might underestimate the variability and range of physical activity patterns and their impacts on physical function in the general population.

8.7 Implications and future directions

While the preliminary nature of the research in this thesis means that it is too early to draw any clinical or policy recommendations, the findings offer practical implications for future physical activity and physical function research. Broadly speaking, physical activity is related to physical function as evidenced by

the systematic review in Chapter 2. However, researchers should consider the complex interplay between patterns of physical activity accumulation and physical function when developing exposure measures in future prospective studies.

These findings of this thesis align with align closely with the WHO's ICF framework, which emphasises a holistic view of health that integrates physical, environmental, and personal factors. The ICF framework supports thethat recognises the importance of early intervention and prevention in maintaining physical function and delaying the onset of disability and frailty, a key theme throughout this thesis. By focusing on the patterns of physical activity accumulation and their relationship to physical function, this research contributes to a nuanced understanding of how health outcomes can be optimised within the ICF's broader conceptual model. Future research should continue to explore these patterns within the ICF framework, with longitudinal analyses, potentially informing public health strategies that prioritise both the prevention of functional decline and the promotion of healthy aging, especially in mid-life.

Analyses of physical activity volume alone masks important between-person differences in how the volume was accumulated in ways that can affect outcomes. Confirmation of these findings by future studies, employing prospective or repeated measures designs, could present several new opportunities. For example, the integration of technology-based approaches in healthcare holds promise for utilising movement sensors to gain insights into individuals' functioning, potentially enabling remote screening.

Longitudinal studies, ideally with repeat measures, may highlight that changes in patterns of physical activity are a precursor to changes in physical

function and could therefore be used to identify people at the early stages of decline prior to engagement in the healthcare system. Moreover, incorporating pattern metrics to evaluate intervention success ensures that effective interventions are appropriately assessed. For example, even if people didn't increase the volume of physical activity as a result of intervention but increased the proportion of their volume undertaken in more sustained events, that could have important functional benefits and improved quality of life.

8.7.1 Incorporating pattern metrics into research

To advance beyond the scope of this thesis, prospective studies, with repeated measures are imperative to establish causality and elucidate the impact of physical activity pattern metrics on subsequent physical function. Additionally, examining the trajectories of physical activity patterns across the lifespan can provide valuable insights into how activity accumulation changes over time. Integrating pattern metrics of physical activity accumulation into study designs can enhance our comprehension of their role in shaping health outcomes.

Efforts to refine and standardise metrics for defining patterns of physical activity accumulation are crucial to improve comparability across studies and enhance the accuracy of associations with health outcomes. The diverse range of potential physical activity metrics, coupled with the use of different measurement devices, poses a challenge to achieving comparability and building a robust evidence base.

8.7.2 Additional pattern metrics

As introduced in the earlier chapters, the concept of "pattern" in relation to physical activity behaviours lacks a standard definition. While we explored various pattern metrics in this research, there remains scope for further investigation into additional metrics that could shed light on the complex relationship between physical activity behaviours and physical function.

Exploring metrics related to temporal distribution, similar to burstiness, or entirely different patterns, could uncover novel insights into the dynamics of physical activity and its impact on physical function. Limited research has examined the variability or stability of physical activity behaviours, particularly in relation to within and between day variability.

8.7.3 Additional health outcomes of interest

Given the bi-directional nature of the physical activity – physical function relationship, and the specificity of exercise in relation to different types of physical function, alternative health outcomes warrant exploration. Cardiovascular or metabolic outcomes, that are more influenced by the acute effects of the last bout performed, may be more likely to exhibit stronger associations with how fragmented physical activity is and how bursty it is. For example, recent evidence in DMS used 24-h time-use compositions to show that shorter sitting times (along with other posture and activity metrics) are associated with preferable cardiometabolic health.[366]

In addition to mortality and morbidity risk, examining the progression from declining physical function to frailty and subsequent disability would be informative for public health prevention strategies. Determining associations

between physical activity patterning and the progression through these states, could identify key times in the life course when interventions to preserve function as we age could be optimised.

8.8 Conclusion

This thesis comprehensively reviewed the current literature and identified limitations in our understanding of the association between physical activity and physical function.

We have highlighted how people accumulate their physical activity in different ways, even when they are doing similar amounts. Specific populations sub-groups accumulate their physical activity in ways that may not be optimal for health and function. We have demonstrated that independent of the amount of physical activity, patterns of accumulation are associated with various measures of function. The replication of these findings in a midlife population further emphasises the importance of considering activity patterns in understanding physical function earlier in the life course than is typically done. However, the findings leave further questions for future research to investigate.

By moving beyond traditional summary measures of physical activity and exploring how physical activity is accumulated we have shown that future public health guidance should avoid one size fits all messaging. These findings also raise the potential for screening of people with or at risk of poor health, using remote accelerometer devices, potentially detecting early changes in activity patterns in midlife that indicate a trajectory towards declining function. In addition, future physical activity intervention trials should look beyond aggregate measures of physical activity as the primary outcomes.

References

1. United Nations (UN). World Population Prospects 2022 [Internet]. United Nation. 2022. 1–52 p. Available from: www.un.org/development/ desa/pd/.

2. Rudnicka E, Napierała P, Podfigurna A, Męczekalski B, Smolarczyk R, Grymowicz M. The World Health Organization (WHO) approach to healthy ageing. Maturitas [Internet]. 2020 Sep;139(January):6–11. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0378512220302826

3. Marmot M. Health equity in England: The Marmot review 10 years on. BMJ [Internet]. 2020;368(February):1–4. Available from: http://dx.doi.org/doi:10.1136/bmj.m693

4. Robine JM, Ritchie K. Healthy life expectancy: Evaluation of global indicator of change in population health. Br Med J. 1991;302(6774):457–60.

5. Office for National Statistics. Health state life expectancies, UK 2018 to 2020 [Internet]. 2022. Available from: https://www.ons.gov.uk/peoplepopulationandcommunity/healthandsocialcare/healthandlifeexpectancies/bulletins/healthstatelifeexpectanciesuk/2018to2020

6. Topinková E. Aging, disability and frailty. Ann Nutr Metab. 2008;52(SUPPL. 1):6–11.

7. World Health Organization. World Health Organization, Geneva. World Rep Child Inj Prev [Internet]. 2001; Available from: https://www.who.int/classifications/icf/en/

8. Fried LP, Ferrucci L, Darer J, Williamson JD, Anderson G. Untangling the Concepts of Disability, Frailty, and Comorbidity: Implications for Improved Targeting and Care. Journals Gerontol - Ser A Biol Sci Med Sci. 2004;59(3):255–63.

9. Gill TM, Kurland B. The burden and patterns of disability in activities of daily living among community-living older persons. Journals Gerontol - Ser A Biol Sci Med Sci. 2003;58(1):70–5.

10. Kopp P. Fit for practice. Nurs Times. 2001;97(4):41–4.

11. Fried LP, Tangen CM, Walston J, Newman AB, Hirsch C, Gottdiener J, et al. Frailty in Older Adults: Evidence for a Phenotype. Journals Gerontol Ser A Biol Sci Med Sci [Internet]. 2001 Mar 1;56(3):M146–57. Available from: https://academic.oup.com/biomedgerontology/article-lookup/doi/10.1093/gerona/56.3.M146

12. Fried LP. Interventions for human frailty: Physical activity as a model. Cold Spring Harb Perspect Med. 2016;6(6):1–14.

13. Forman-Hoffman VL, Ault KL, Anderson WL, Weiner JM, Stevens A, Campbell VA, et al. Disability Status, Mortality, and Leading Causes of Death in the United States Community Population. Med Care [Internet]. 2015 Apr;53(4):346–54. Available from: https://journals.lww.com/00005650-201504000-00009

14. Alkhodary A. A., Syed Mohamed Aljunid, Ismail A, Nur A. M., Shahar S. THE ECONOMIC BURDEN OF FRAILTY AMONG ELDERLY PEOPLE: A REVIEW OF THE CURRENT LITERATURE. Malaysian J Public Heal Med [Internet]. 2020 Oct 1;20(2):224–32. Available from:

http://mjphm.org/index.php/mjphm/article/view/304

15. O'Donovan MR, Sezgin D, Liew A, O'Caoimh R. Burden of disease, disability-adjusted life years and frailty prevalence. QJM An Int J Med . 2019;112(4):261–7.

16. Xue QL. The Frailty Syndrome: Definition and Natural History. Clin Geriatr Med. 2011;27(1):1–15.

17. Asim M, Aftab M, Bhatti SH, Ahmad T, Ali Shah SM, Akram M. Identifying factors causing decline in physical functionality of geriatric population. Eur J Inflamm. 2021;19.

18. Bravell ME, Zarit SH, Johansson B. Self-reported activities of daily living and performance-based functional ability: A study of congruence among the oldest old. Eur J Ageing. 2011;8(3):199–209.

19. Painter P, Marcus RL. Assessing physical function and physical activity in patients with CKD. Clin J Am Soc Nephrol. 2013;8(5):861–72.

20. Wittink H, Rogers W, Sukiennik A, Carr DB. Physical functioning: Self-report and performance measures are related but distinct. Spine (Phila Pa 1976). 2003;28(20):2407–13.

21. Tomey KM, Sowers MFR. Assessment of physical functioning: A conceptual model encompassing environmental factors and individual compensation strategies. Phys Ther. 2009;89(7):705–14.

22. Patrizio E, Calvani R, Marzetti E, Cesari M. Physical Functional Assessment in Older Adults. J Frailty Aging. 2021;10(2):141–9.

23. Freiberger E, De vreede P, Schoene D, Rydwik E, Mueller V, Frändin K,

et al. Performance-based physical function in older community-dwelling persons: A systematic review of instruments. Age Ageing. 2012;41(6):712–21.

24. Lee L, Patel T, Costa A, Bryce E, Hillier LM, Slonim K, et al. Screening for frailty in primary care: Accuracy of gait speed and hand-grip strength. Can Fam Physician [Internet]. 2017 Jan;63(1):e51–7. Available from: http://www.ncbi.nlm.nih.gov/pubmed/28115460

25. Meier NF, Lee D chul. Physical activity and sarcopenia in older adults. Aging Clin Exp Res [Internet]. 2020;32(9):1675–87. Available from: https://doi.org/10.1007/s40520-019-01371-8

26. Studenski S, Perera S, Patel K, Rosano C, Faulkner K, Inzitari M, et al. Gait speed and survival in older adults. Jama. 2011;305(1):50–8.

27. Bohannon RW. Muscle strength: Clinical and prognostic value of hand-grip dynamometry. Curr Opin Clin Nutr Metab Care. 2015;18(5):465–70.

28. Cooper R, Kuh D, Cooper C, Gale CR, Lawlor DA, Matthews F, et al. Objective measures of physical capability and subsequent health: A systematic review. Age Ageing. 2011;40(1):14–23.

29. Piotrowicz K, Kujawska-Danecka H, Jagiełło K, Hajduk A, Skalska A, Mossakowska M, et al. The national burden of frailty and disproportionate distribution of its components—the predominance of slow gait speed: a 2018–19 face-to-face epidemiologic assessment representative of population of older Poles. Aging Clin Exp Res [Internet]. 2023;35(3):571–9. Available from: https://doi.org/10.1007/s40520-022-02331-5

30. Stover E, Andrew S, Batesole J, Berntson M, Carling C, Fitzsimmons S,

et al. Prevalence and Trends of Slow Gait Speed in the United States. 2023;1–12.

31. Dodds RM, Syddall HE, Cooper R, Benzeval M, Deary IJ, Dennison EM, et al. Grip strength across the life course: Normative data from twelve British studies. PLoS One. 2014;9(12):1–15.

32. Xie YJ, Liu EY, Anson ER, Agrawal Y. Age-Related Imbalance Is Associated With Slower Walking Speed: An Analysis From the National Health and Nutrition Examination Survey. J Geriatr Phys Ther [Internet]. 2017 Oct;40(4):183–9. Available from: https://journals.lww.com/00139143-201710000-00002

33. Robinson SM, Jameson KA, Syddall HE, Dennison EM, Cooper C, Aihie Sayer A. Clustering of lifestyle risk factors and poor physical function in older adults: The hertfordshire cohort study. J Am Geriatr Soc. 2013;61(10):1684–91.

34. Mayhew AJ, Griffith LE, Gilsing A, Beauchamp MK, Kuspinar A, Raina P. The association between self-reported and performance-based physical function with activities of daily living disability in the canadian longitudinal study on aging. Journals Gerontol - Ser A Biol Sci Med Sci. 2020;75(1):147–54.

35. Manning KM, Hall KS, Sloane R, Magistro D, Rabaglietti E, Lee CC, et al. Longitudinal analysis of physical function in older adults: The effects of physical inactivity and exercise training. Aging Cell [Internet]. 2024 Jan 8;23(1). Available from: https://onlinelibrary.wiley.com/doi/10.1111/acel.13987

36. Angulo J, El Assar M, Álvarez-Bustos A, Rodríguez-Mañas L. Physical activity and exercise: Strategies to manage frailty. Redox Biol [Internet]. 2020 Aug;35:101513. Available from: https://linkinghub.elsevier.com/retrieve/pii/S2213231720301178

37. Dent E, Morley JE, Cruz-Jentoft AJ, Woodhouse L, Rodríguez-Mañas L, Fried LP, et al. Physical Frailty: ICFSR International Clinical Practice Guidelines for Identification and Management. J Nutr Heal aging [Internet]. 2019 Nov;23(9):771–87. Available from: https://linkinghub.elsevier.com/retrieve/pii/S1279770723011491

38. Sayer AA, Robinson SM, Patel HP, Shavlakadze T, Cooper C, Grounds MD. New horizons in the pathogenesis, diagnosis and management of sarcopenia. Age Ageing [Internet]. 2013 Mar 1;42(2):145–50. Available from: https://academic.oup.com/ageing/article-lookup/doi/10.1093/ageing/afs191

39. Cruz-Jentoft AJ, Bahat G, Bauer J, Boirie Y, Bruyère O, Cederholm T, et al. Sarcopenia: Revised European consensus on definition and diagnosis. Age Ageing. 2019;48(1):16–31.

40. Zhao Y, Duan Y, Feng H, Nan J, Li X, Zhang H, et al. Trajectories of physical functioning and its predictors in older adults: A 16-year longitudinal study in China. Front Public Heal [Internet]. 2022 Aug 25;10. Available from: https://www.frontiersin.org/articles/10.3389/fpubh.2022.923767/full

41. Xia Q, Zhou P, Li X, Li X, Zhang L, Fan X, et al. Factors associated with balance impairments in the community-dwelling elderly in urban China. BMC Geriatr [Internet]. 2023 Sep 7;23(1):545. Available from:

https://bmcgeriatr.biomedcentral.com/articles/10.1186/s12877-023-04219-z

42. Osoba MY, Rao AK, Agrawal SK, Lalwani AK. Balance and gait in the elderly: A contemporary review. Laryngoscope Investig Otolaryngol [Internet]. 2019 Feb 4;4(1):143–53. Available from: https://onlinelibrary.wiley.com/doi/10.1002/lio2.252

43. Schoene D, Heller C, Aung YN, Sieber CC, Kemmler W, Freiberger E. A systematic review on the influence of fear of falling on quality of life in older people: is there a role for falls? Clin Interv Aging [Internet]. 2019 Apr;Volume 14:701–19. Available from: https://www.dovepress.com/a-systematic-review-on-the-influence-of-fear-of-falling-on-quality-of--peer-reviewed-article-CIA

44. James SL, Lucchesi LR, Bisignano C, Castle CD, Dingels Z V, Fox JT, et al. The global burden of falls: global, regional and national estimates of morbidity and mortality from the Global Burden of Disease Study 2017. Inj Prev [Internet]. 2020 Oct;26(Suppl 2):i3–11. Available from: https://injuryprevention.bmj.com/lookup/doi/10.1136/injuryprev-2019-043286

45. Vaishya R, Vaish A. Falls in Older Adults are Serious. Indian J Orthop [Internet]. 2020 Feb 24;54(1):69–74. Available from: https://link.springer.com/10.1007/s43465-019-00037-x

46. Hunter SK, Pereira HM, Keenan KG. The aging neuromuscular system and motor performance. J Appl Physiol [Internet]. 2016 Oct 1;121(4):982–95. Available from: https://www.physiology.org/doi/10.1152/japplphysiol.00475.2016

47. Seidler RD, Bernard JA, Burutolu TB, Fling BW, Gordon MT, Gwin JT, et al. Motor control and aging: Links to age-related brain structural, functional, and biochemical effects. Neurosci Biobehav Rev [Internet]. 2010 Apr;34(5):721–33. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0149763409001596

48. Walston J, Buta B, Xue QL. Frailty Screening and Interventions. Clin Geriatr Med [Internet]. 2018 Feb;34(1):25–38. Available from: https://www.ncbi.nlm.nih.gov/pmc/articles/PMC5726589/

49. Daskalopoulou C, Stubbs B, Kralj C, Koukounari A, Prince M, Prina AM. Physical activity and healthy ageing: A systematic review and meta-analysis of longitudinal cohort studies. Ageing Res Rev [Internet]. 2017;38:6–17. Available from: http://dx.doi.org/10.1016/j.arr.2017.06.003

50. Cooper R, Kuh D, Hardy R. Objectively measured physical capability levels and mortality: Systematic review and meta-analysis. BMJ. 2010;341(7774):639.

51. Murray ET, Hardy R, Strand BH, Cooper R, Guralnik JM, Kuh D. Gender and life course occupational social class differences in trajectories of functional limitations in midlife: Findings from the 1946 british birth cohort. Journals Gerontol - Ser A Biol Sci Med Sci. 2011;66 A(12):1350–9.

52. KarvKarvonen-Gutierrez, C. A., & Strotmeyer, E. S. (2020). The urgent need for disability studies among midlife adults. Women's Midlife Health, 6(1), 4–8. https://doi.org/10.1186/s40695-020-00057-wonen-Gutierrez CA, Strotmeyer ES. The urgent need for disability studies among midlife adults. Women's Midlife Heal. 2020;6(1):4–8.

53. Freedman VA, Spillman BC, Andreski PM, Cornman JC, Crimmins EM, Kramarow E, et al. Trends in Late-Life Activity Limitations in the United States: An Update From Five National Surveys. Demography. 2013;50(2):661–71.

54. Tseng LA, El Khoudary SR, Young EA, Farhat GN, Sowers M, Sutton-Tyrrell K, et al. The association of menopause status with physical function: The Study of Women's Health Across the Nation. Menopause. 2012;19(11):1186–92.

55. Sowers M, Pope S, Welch G, Sternfeld B, Albrecht G. The association of menopause and physical functioning in women at midlife. J Am Geriatr Soc. 2001;49(11):1485–92.

56. Ylitalo KR, Karvonen-Gutierrez CA, Fitzgerald N, Zheng H, Sternfeld B, El Khoudary SR, et al. Relationship of race-ethnicity, body mass index, and economic strain with longitudinal self-report of physical functioning: The Study of Women's Health Across the Nation. Ann Epidemiol [Internet]. 2013;23(7):401–8. Available from: http://dx.doi.org/10.1016/j.annepidem.2013.04.008

57. Hanlon P, Nicholl BI, Jani BD, Lee D, McQueenie R, Mair FS. Frailty and pre-frailty in middle-aged and older adults and its association with multimorbidity and mortality: a prospective analysis of 493 737 UK Biobank participants. Lancet Public Heal [Internet]. 2018;3(7):e323–32. Available from: http://dx.doi.org/10.1016/S2468-2667(18)30091-4

58. Kojima G, Taniguchi Y, Iliffe S, Jivraj S, Walters K. Transitions between frailty states among community-dwelling older people: A systematic review and meta-analysis. Ageing Res Rev. 2019;50(November

2018):81–8.

59. Bowling A, Dieppe P. What is successful ageing and who should define it? Br Med J. 2005;331(7531):1548–51.

60. Brown RT, Covinsky KE. Moving prevention of functional impairment upstream: is middle age an ideal time for intervention? Women's Midlife Heal. 2020;6(1):1–9.

61. Geirsdottir OG, Chang M, Briem K, Jonsson P V., Thorsdottir I, Ramel A. Determinants of physical function in community dwelling old people. J Gerontol Geriatr. 2022;70(1):9–16.

62. Caspersen C, Powell K, Gregory C. Physical activity, exercise, and physical fitness: definitions and distinctions for health-related research. Public Health Rep. 1985;Mar-Apr100(2):126-31. US Natl Libr Med [Internet]. 1985;100 (2)(2):126–31. Available from: /pmc/articles/PMC1424733/?report=abstract%0Ahttps://www.ncbi.nlm.nih.gov/pmc/articles/PMC1424733/%0A/pmc/articles/PMC1424733/?report=abstract%0Ahttps://www.ncbi.nlm.nih.gov/pmc/articles/PMC1424733/%0A/pmc/articles/PMC1424733/?report=abstract%0Ahttps://www

63. Warburton DER, Bredin SSD. Health benefits of physical activity: A systematic review of current systematic reviews. Curr Opin Cardiol. 2017;32(5):541–56.

64. Nystoriak MA, Bhatnagar A. Cardiovascular Effects and Benefits of Exercise. Front Cardiovasc Med. 2018;5(September):1–11.

65. Gallanagh S, Quinn TJ, Alexander J, Walters MR. Physical Activity in the Prevention and Treatment of Stroke. ISRN Neurol. 2011;2011:1–10.

66. Colberg SR, Sigal RJ, Fernhall B, Regensteiner JG, Blissmer BJ, Rubin RR, et al. Exercise and type 2 diabetes: The American College of Sports Medicine and the American Diabetes Association: Joint position statement. Diabetes Care. 2010;33(12).

67. Mctiernan A, Friedenreich CM, Katzmarzyk PT, Powell KE, Macko R, Buchner D, et al. Physical Activity in Cancer Prevention and Survival: A Systematic Review. Med Sci Sports Exerc. 2019;51(6):1252–61.

68. Anderson E, Durstine JL. Physical activity, exercise, and chronic diseases: A brief review. Sport Med Heal Sci [Internet]. 2019;1(1):3–10. Available from: https://doi.org/10.1016/j.smhs.2019.08.006

69. Nocon M, Hiemann T, Müller-Riemenschneider F, Thalau F, Roll S, Willich SN. Association of physical activity with all-cause and cardiovascular mortality: A systematic review and meta-analysis. Eur J Prev Cardiol. 2008;15(3):239–46.

70. Mandolesi L, Polverino A, Montuori S, Foti F, Ferraioli G, Sorrentino P, et al. Effects of physical exercise on cognitive functioning and wellbeing: Biological and psychological benefits. Front Psychol. 2018;9(APR):1–11.

71. Thivel D, Tremblay A, Genin PM, Panahi S, Rivière D, Duclos M. Physical Activity, Inactivity, and Sedentary Behaviors: Definitions and Implications in Occupational Health. Front Public Heal. 2018;6(October):1–5.

72. World Health Organization. Global status report on physical activity 2022 [Internet]. WHO Press, World Health Organization. 2022. 1–112 p. Available from: https://www.who.int/teams/health-promotion/physical-activity/global-status-report-on-physical-activity-2022

73. Nikitara K, Odani S, Demenagas N, Rachiotis G, Symvoulakis E, Vardavas C. Prevalence and correlates of physical inactivity in adults across 28 European countries. Eur J Public Health. 2021;31(4):840–5.

74. Kari JT, Nerg I, Huikari S, Leinonen AM, Nurkkala M, Farrahi V, et al. The Individual-Level Productivity Costs of Physical Inactivity. Med Sci Sports Exerc. 2023;55(2):255–63.

75. Pate RR, Pratt M, Blair SN, Haskell WL, Macera CA, Bouchard C, et al. Public Health and Prevention and the American College of Sports Medicine. J Am Med Assoc. 1995;273(5):402–7.

76. Haskell WL, Lee IM, Pate RR, Powell KE, Blair SN, Franklin BA, et al. Physical activity and public health: Updated recommendation for adults from the American College of Sports Medicine and the American Heart Association. Med Sci Sports Exerc. 2007;39(8):1423–34.

77. Davies DSC, Atherton F, McBride M, Calderwood C. UK Chief Medical Officers' Physical Activity Guidelines. Dep Heal Soc Care [Internet]. 2019;(September):1–65. Available from: https://www.gov.uk/government/publications/physical-activity-guidelines-uk-chief-medical-officers-report

78. Murphy MH, Lahart I, Carlin A, Murtagh E. The Effects of Continuous Compared to Accumulated Exercise on Health: A Meta-Analytic Review. Sport Med [Internet]. 2019;49(10):1585–607. Available from: https://doi.org/10.1007/s40279-019-01145-2

79. Bull FC, Al-Ansari SS, Biddle S, Borodulin K, Buman MP, Cardon G, et al. World Health Organization 2020 guidelines on physical activity and

sedentary behaviour. Br J Sports Med. 2020;54(24):1451–62.

80. Heath GW, Parra DC, Sarmiento OL, Andersen LB, Owen N, Goenka S, et al. Evidence-based intervention in physical activity: lessons from around the world. Lancet [Internet]. 2012 Jul;380(9838):272–81. Available from: https://doi.org/10.1093/ajcn/79.5.913S

81. Patterson R, McNamara E, Tainio M, de Sá TH, Smith AD, Sharp SJ, et al. Sedentary behaviour and risk of all-cause, cardiovascular and cancer mortality, and incident type 2 diabetes: a systematic review and dose response meta-analysis. Eur J Epidemiol. 2018;33(9):811–29.

82. Momma H, Kawakami R, Honda T, Sawada SS. Muscle-strengthening activities are associated with lower risk and mortality in major non-communicable diseases: a systematic review and meta-analysis of cohort studies. Br J Sports Med. 2022;56(13):755–63.

83. Sherrington C, Fairhall N, Kwok W, Wallbank G, Tiedemann A, Michaleff ZA, et al. Evidence on physical activity and falls prevention for people aged 65+ years: systematic review to inform the WHO guidelines on physical activity and sedentary behaviour. Int J Behav Nutr Phys Act [Internet]. 2020 Dec 26;17(1):144. Available from: https://ijbnpa.biomedcentral.com/articles/10.1186/s12966-020-01041-3

84. Du Y, Liu B, Sun Y, Snetselaar LG, Wallace RB, Bao W. Trends in Adherence to the Physical Activity Guidelines for Americans for Aerobic Activity and Time Spent on Sedentary Behavior among US Adults, 2007 to 2016. JAMA Netw Open. 2019;2(7):1–11.

85. Jefferis BJ, Sartini C, Lee IM, Choi M, Amuzu A, Gutierrez C, et al.

Adherence to physical activity guidelines in older adults, using objectively measured physical activity in a population-based study. BMC Public Health [Internet]. 2014;14(1):382. Available from: https://ovidsp.ovid.com/ovidweb.cgi?T=JS&CSC=Y&NEWS=N&PAGE=fulltext&D=med11&AN=24745369: https://uoelibrary.idm.oclc.org/login?url=http://resolver.ebscohost.com/openurl?sid=OVID:medline&id=pmid:24745369&id=doi:10.1186%2F1471-2458-14-382&issn=1471-2458&isb

86. Jørgensen LB, Bricca A, Bernhardt A, Juhl CB, Tang LH, Mortensen SR, et al. Objectively measured physical activity levels and adherence to physical activity guidelines in people with multimorbidity—A systematic review and meta-analysis. PLoS One. 2022;17(10 October):1–22.

87. Bennie JA, Shakespear-Druery J, De Cocker K. Muscle-strengthening Exercise Epidemiology: a New Frontier in Chronic Disease Prevention. Sport Med - Open. 2020;6(1).

88. Taylor J, Walsh S, Kwok W, Pinheiro MB, de Oliveira JS, Hassett L, et al. A scoping review of physical activity interventions for older adults. Int J Behav Nutr Phys Act. 2021;18(1):1–14.

89. Kettle VE, Madigan CD, Coombe A, Graham H, Thomas JJC, Chalkley AE, et al. Effectiveness of physical activity interventions delivered or prompted by health professionals in primary care settings: systematic review and meta-analysis of randomised controlled trials. BMJ. 2022;376:1–13.

90. Wahlich C, Chaudhry UAR, Fortescue R, Cook DG, Hirani S, Knightly R, et al. Effectiveness of adult community-based physical activity

interventions with objective physical activity measurements and long-term follow-up: A systematic review and meta-analysis. BMJ Open. 2020;10(5).

91. Howlett N, Trivedi D, Troop NA, Chater AM. Are physical activity interventions for healthy inactive adults effective in promoting behavior change and maintenance, and which behavior change techniques are effective? A systematic review and meta-analysis. Transl Behav Med. 2019;9(1):147–57.

92. Adams SA, Matthews CE, Ebbeling CB, Moore CG, Cunningham JE, Fulton J, et al. The effect of social desirability and social approval on self-reports of physical activity. Am J Epidemiol [Internet]. 2005 Feb 15;161(4):389–98. Available from: https://academic.oup.com/aje/article-lookup/doi/10.1093/aje/kwi054

93. Chase JAD, Phillips LJ, Brown M. Physical activity intervention effects on physical function among community-dwelling older adults: A systematic review and meta-analysis. J Aging Phys Act. 2017;25(1):149–70.

94. Paterson DH, Warburton DER. Physical activity and functional limitations in older adults: A systematic review related to Canada's Physical Activity Guidelines. Int J Behav Nutr Phys Act. 2010;7.

95. Dipietro L, Campbell WW, Buchner DM, Erickson KI, Powell KE, Bloodgood B, et al. Physical Activity, Injurious Falls, and Physical Function in Aging: An Umbrella Review. Med Sci Sports Exerc. 2019;51(6):1303–13.

96. Fried LP, Cohen AA, Xue QL, Walston J, Bandeen-Roche K, Varadhan R. The physical frailty syndrome as a transition from homeostatic symphony

to cacophony. Nat Aging [Internet]. 2021;1(1):36–46. Available from: http://dx.doi.org/10.1038/s43587-020-00017-z

97. Henderson RM, Miller ME, Fielding RA, Gill TM, Glynn NW, Guralnik JM, et al. Maintenance of Physical Function 1 Year after Exercise Intervention in At-Risk Older Adults: Follow-up from the LIFE Study. Journals Gerontol - Ser A Biol Sci Med Sci. 2018;73(5):688–94.

98. Ward-Ritacco CL, Greaney ML, Clark PG, Riebe D. The Longitudinal Association Between Physical Activity and Physical Function in Older Women. Front Sport Act Living. 2022;4(July):1–9.

99. Brady R, Brown WJ, Hillsdon M, Mielke GI. Patterns of Accelerometer-Measured Physical Activity and Health Outcomes in Adults: A Systematic Review. Med Sci Sports Exerc. 2022;54(7):1155–66.

100. Wanigatunga AA, Liu F, Wang H, Urbanek JK, An Y, Spira AP, et al. Daily Physical Activity Patterns as a Window on Cognitive Diagnosis in the Baltimore Longitudinal Study of Aging (BLSA). J Alzheimer's Dis. 2022;88(2):459–69.

101. Palmberg L, Rantalainen T, Rantakokko M, Karavirta L, Siltanen S, Skantz H, et al. The Associations of Activity Fragmentation with Physical and Mental Fatigability among Community-Dwelling 75-, 80-, and 85-Year-Old People. Journals Gerontol - Ser A Biol Sci Med Sci. 2020;75(9):e103–10.

102. Wanigatunga AA, Di J, Zipunnikov V, Urbanek JK, Kuo PL, Simonsick EM, et al. Association of Total Daily Physical Activity and Fragmented Physical Activity With Mortality in Older Adults. JAMA Netw Open

[Internet]. 2019 Oct 2;2(10):e1912352. Available from: https://ovidsp.ovid.com/ovidweb.cgi?T=JS&CSC=Y&NEWS=N&PAGE=fulltext&D=med16&AN=31577355: https://uoelibrary.idm.oclc.org/login?url=http://resolver.ebscohost.com/openurl?sid=OVID:medline&id=pmid:31577355&id=doi:10.1001%2Fjamanetworkopen.2019.12352&issn=257

103. Del Pozo-Cruz J, Del Pozo Cruz B, Perez-Sousa M, Alfonso-Rosa RM. High Fragmented Physical Activity as an Early Risk Indicator of Frailty and Mortality in Adults Aged 50 Years and Over. Gerontology. 2023;69(3):370–8.

104. Schrack JA, Kuo PL, Wanigatunga AA, Di J, Simonsick EM, Spira AP, et al. Active-to-Sedentary Behavior Transitions, Fatigability, and Physical Functioning in Older Adults. Journals Gerontol - Ser A Biol Sci Med Sci. 2019;74(4):560–7.

105. Wilson JJ, McMullan I, Blackburn NE, Klempel N, Jerez-Roig J, Oviedo GR, et al. The Association of Physical Activity Fragmentation with Physical Function in Older Adults: Analysis from the SITLESS Study. J Ageing Longev. 2022;2(1):63–73.

106. Wanigatunga AA, Ferrucci L, Schrack JA. Physical activity fragmentation as a potential phenotype of accelerated aging. Oncotarget. 2019;10(8):807–9.

107. Hillsdon MM, Brunner EJ, Guralnik JM, Marmot MG. Prospective study of physical activity and physical function in early old age. Am J Prev Med. 2005;28(3):245–50.

108. Pettee Gabriel K, Sternfeld B, Colvin A, Stewart A, Strotmeyer ES, Cauley JA, et al. Physical activity trajectories during midlife and subsequent risk of physical functioning decline in late mid-life: The Study of Women's Health Across the Nation (SWAN). Prev Med (Baltim) [Internet]. 2017 Dec;105:287–94. Available from: https://linkinghub.elsevier.com/retrieve/pii/S0091743517303559

109. Culverhouse J, Hillsdon M, Metcalf B, Nunns M, Lear R, Brailey G, et al. Associations between device-measured physical activity and performance-based physical function outcomes in adults: a systematic review and meta-analysis. BMJ Public Heal [Internet]. 2023 Oct 30;1(1):e100000. Available from: https://bmjpublichealth.bmj.com/lookup/doi/10.1136/bmjph-2023-100000

110. Verbrugge LM, Jette AM. The disablement process. Soc Sci Med. 1994;38(1):1–14.

111. Nagi SZ. a Study in the Evaluation of Disability and Rehabilitation Potential: Concepts, Methods, and Procedures. Am J Public Health Nations Health. 1964;54(9):1568–79.

112. Cöster ME, Karlsson M, Ohlsson C, Mellström D, Lorentzon M, Ribom E, et al. Physical function tests predict incident falls: A prospective study of 2969 men in the Swedish Osteoporotic Fractures in Men study. Scand J Public Health. 2020;48(4):436–41.

113. Cesari M, Kritchevsky SB, Newman AB, Simonsick EM, Harris TB, Penninx BW, et al. Added value of physical performance measures in predicting adverse health-related events: Results from the health, aging and body composition study. J Am Geriatr Soc. 2009;57(2):251–9.

114. Guralnik JM, Ferrucci L, Simonsick EM, Salive ME, Wallace RB. Lower-Extremity Function in Persons over the Age of 70 Years as a Predictor of Subsequent Disability. N Engl J Med. 1995;332(9):556–62.

115. Keevil VL, Cooper AJM, Wijndaele K, Luben R, Wareham NJ, Brage S, et al. Objective Sedentary Time, Moderate-to-Vigorous Physical Activity, and Physical Capability in a British Cohort. Med Sci Sports Exerc. 2016;48(3):421–9.

116. Gill TM, Gahbauer EA, Allore HG, Han L. Transitions between frailty states among community-living older persons. Arch Intern Med. 2006;166(4):418–23.

117. Majumder S, Mondal T, Deen MJ. Wearable sensors for remote health monitoring. Sensors (Switzerland). 2017;17(1).

118. Dias D, Cunha JPS. Wearable health devices—vital sign monitoring, systems and technologies. Sensors (Switzerland). 2018;18(8).

119. Karas M, Glynn NW, Harris T. Accelerometry data in health research: challenges and opportunities. 2020;11(2):210–37.

120. Ramsey KA, Rojer AGM, Andrea LD, Heymans MW, Trappenburg MC, Verlaan S, et al. The association of objectively measured physical activity and sedentary behavior with skeletal muscle strength and muscle power in older adults : A systematic review and meta-analysis. 2021;67(January).

121. Dekkers OM, Vandenbroucke JP, Cevallos M, Renehan AG, Altman DG, Egger M. COSMOS-E: Guidance on conducting systematic reviews and meta-analyses of observational studies of etiology. PLOS Med [Internet].

2019 Feb 21;16(2):e1002742. Available from: https://dx.plos.org/10.1371/journal.pmed.1002742

122. Higgins J, Green S. Chapter 22: Overview of reviews. Cochrane handbook for systematic reviews of interventions. Cochrane Database Syst Rev [Internet]. 2008;187–235. Available from: http://onlinelibrary.wiley.com/doi/10.1002/9780470712184.fmatter/summary

123. Page MJ, McKenzie JE, Bossuyt PM, Boutron I, Hoffmann TC, Mulrow CD, et al. The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. BMJ. 2021;372.

124. Beaudart C, Rolland Y, Cruz-Jentoft AJ, Bauer JM, Sieber C, Cooper C, et al. Assessment of Muscle Function and Physical Performance in Daily Clinical Practice: A position paper endorsed by the European Society for Clinical and Economic Aspects of Osteoporosis, Osteoarthritis and Musculoskeletal Diseases (ESCEO). Calcif Tissue Int [Internet]. 2019;105(1):1–14. Available from: https://doi.org/10.1007/s00223-019-00545-w

125. Guralnik JM, Simonsick EM, Ferrucci L, Glynn RJ, Berkman LF, Blazer DG, et al. A short physical performance battery assessing lower extremity function: Association with self-reported disability and prediction of mortality and nursing home admission. Journals Gerontol. 1994;49(2):85–94.

126. Peterson RA, Brown SP. On the use of beta coefficients in meta-analysis. J Appl Psychol. 2005;90(1):175–81.

127. Nieminen P, Lehtiniemi H, Vähäkangas K, Huusko A, Rautio A. Standardised regression coefficient as an effect size index in summarising findings in epidemiological studies. Epidemiol Biostat Public Heal. 2013;10(4).

128. Nieminen P. Application of Standardized Regression Coefficient in Meta-Analysis. BioMedInformatics. 2022;2(3):434–58.

129. Riley RD, Moons KGM, Snell KIE, Ensor J, Hooft L, Altman DG, et al. A guide to systematic review and meta-analysis of prognostic factor studies. BMJ. 2019;364.

130. Egger M, Smith GD, Schneider M, Minder C. Bias in meta-analysis detected by a simple, graphical test. Br Med J. 1997;315(7109):629–34.

131. Hsueh MC, Rutherford R, Chou CC, Park JH, Park HT, Liao Y. Objectively assessed physical activity patterns and physical function in community-dwelling older adults: A cross-sectional study in Taiwan. BMJ Open. 2020;10(8):1–9.

132. Hsueh MC, Lin CY, Lai TF, Yu YC, Chang SH, Bae JY, et al. Is achieving 7,000 steps/day cross-sectionally and prospectively associated with older adults' lower-extremity performance? BMC Geriatr. 2021;21(1):1–7.

133. Gobbo LA, Júdice PB, Hetherington-Rauth M, Sardinha LB, Dos Santos VR. Sedentary patterns are associated with bone mineral density and physical function in older adults: Cross-sectional and prospective data. Int J Environ Res Public Health. 2020;17(21):1–13.

134. Mizumoto H.: Makino, K.: Saitoh, S.: Ohnishi, H.: Furuna, T. A. I. Physical Activity during Winter in Old-Old Women Associated with

Physical Performance after One Year: A Prospective Study. Curr Gerontol Geriatr Res [Internet]. 2015;2015:253451. Available from: https://ovidsp.ovid.com/ovidweb.cgi?T=JS&CSC=Y&NEWS=N&PAGE=fulltext&D=pmnm3&AN=26185495: https://uoelibrary.idm.oclc.org/login?url=http://resolver.ebscohost.com/openurl?sid=OVID:medline&id=pmid:26185495&id=doi:10.1155%2F2015%2F253451&issn=1687-7063&isbn=&

135. Yerrakalva D, Hajna S, Wijndaele K, Dempsey PC, Westgate K, Wareham N, et al. Bidirectional associations of accelerometer-assessed physical activity and sedentary time with physical function among older English adults: the EPIC-Norfolk cohort study. Eur J Ageing [Internet]. 2022;(0123456789). Available from: https://doi.org/10.1007/s10433-022-00733-y

136. Hall KS, Cohen HJ, Pieper CF, Fillenbaum GG, Kraus WE, Huffman KM, et al. Physical performance across the adult life Span: Correlates with age and physical activity. Journals Gerontol - Ser A Biol Sci Med Sci. 2017;72(4):572–8.

137. Izawa KP, Shibata A, Ishii K, Miyawaki R, Oka K. Associations of low-intensity light physical activity with physical performance in community-dwelling elderly Japanese: A cross-sectional study. PLoS One [Internet]. 2017;12(6):1–9. Available from: http://dx.doi.org/10.1371/journal.pone.0178654

138. Jantunen H, Wasenius N, Salonen MK, Perälä MM, Osmond C, Kautiainen H, et al. Objectively measured physical activity and physical performance in old age. Age Ageing. 2017;46(2):232–7.

139. Johansson J, Morseth B, Scott D, Strand BH, Hopstock LA, Grimsgaard S. Moderate-to-vigorous physical activity modifies the relationship between sedentary time and sarcopenia: the Tromsø Study 2015–2016. J Cachexia Sarcopenia Muscle. 2021;12(4):955–63.

140. Kim M, Yoshida H, Sasai H, Kojima N, Kim H. Association between objectively measured sleep quality and physical function among community-dwelling oldest old Japanese: A cross-sectional study. Geriatr Gerontol Int. 2015;15(8):1040–8.

141. Kruger HS, Havemann-Nel L, Ravyse C, Moss SJ, Tieland M. Physical activity energy expenditure and sarcopenia in black South African urban women. J Phys Act Heal. 2016;13(3):296–302.

142. Lai TF, Liao Y, Lin CY, Huang WC, Hsueh MC, Chan DC. Moderate-to-vigorous physical activity duration is more important than timing for physical function in older adults. Sci Rep [Internet]. 2020;10(1):1–6. Available from: https://doi.org/10.1038/s41598-020-78072-0

143. Lerma NL, Cho CC, Swartz AM, Miller NE, Keenan KG, Strath SJ. Isotemporal Substitution of Sedentary Behavior and Physical Activity on Function. Med Sci Sports Exerc. 2018;50(4):792–800.

144. Lohne-Seiler H, Kolle E, Anderssen SA, Hansen BH. Musculoskeletal fitness and balance in older individuals (65-85 years) and its association with steps per day: A cross sectional study Physical functioning, physical health and activity. BMC Geriatr [Internet]. 2016;16(1):1–11. Available from: http://dx.doi.org/10.1186/s12877-016-0188-3

145. Manãs A, Del Pozo-Cruz B, Rodríguez-Gómez I, Leal-Martín J, Losa-

Reyna J, Rodríguez-Manãs L, et al. Dose-response association between physical activity and sedentary time categories on ageing biomarkers. BMC Geriatr. 2019;19(1):1–9.

146. Mendham J. H.: Micklesfield, L. K.: Brooks, N. E.: Faber, M.: Christensen, D. L.: Gallagher, I. J.: Lundin-Olsson, L.: Myburgh, K. H.: Odunitan-Wayas, F. A.: Lambert, E. V.: Kalula, S.: Hunter, A. M. AE. G. Understanding factors associated with sarcopenic obesity in older African women from a low-income setting: a cross-sectional analysis. BMC Geriatr [Internet]. 2021;21(1):247. Available from: https://ovidsp.ovid.com/ovidweb.cgi?T=JS&CSC=Y&NEWS=N&PAGE=fulltext&D=medl&AN=33853546: https://uoelibrary.idm.oclc.org/login?url=http://resolver.ebscohost.com/openurl?sid=OVID:medline&id=pmid:33853546&id=doi:10.1186%2Fs12877-021-02132-x&issn=1471-2318&is

147. Nagai K, Tamaki K, Kusunoki H, Wada Y, Tsuji S, Ito M, et al. Isotemporal substitution of sedentary time with physical activity and its associations with frailty status. Clin Interv Aging. 2018;13:1831–6.

148. Oguma Y.: Takayama, M.: Abe, Y.: Tanaka, S.: Lee, I. M.: Arai, Y. Y. O, Oguma. Validation of Questionnaire-Assessed Physical Activity in Comparison with Objective Measures Using Accelerometers and Physical Performance Measures Among Community-Dwelling Adults Aged ≥85 Years in Tokyo, Japan. J Ohysical Act Heal [Internet]. 2017;14(4):245–52. Available from: https://journals.humankinetics.com/view/journals/jpah/14/4/article-p245.xml

149. Osuka Y, Yabushita N, Kim M, Seino S, Nemoto M, Jung S, et al. Association between habitual light-intensity physical activity and lower-extremity performance: A cross-sectional study of community-dwelling older Japanese adults. Geriatr Gerontol Int. 2015;15(3):268–75.

150. Pina A. E.: Tomaz, S. A.: Goedecke, J. H.: Micklesfield, L. K.: Brooks, N. E.: Gallagher, I. J.: Crockett, R.: Dudchenko, P.: Hunter, A. M. I. M. Intensity Matters for Musculoskeletal Health: A Cross-Sectional Study on Movement Behaviors of Older Adults from High-Income Scottish and Low-Income South African Communities. Int J Environ Res Public Heal [Electronic Resour [Internet]. 2021;18(8):19. Available from: https://ovidsp.ovid.com/ovidweb.cgi?T=JS&CSC=Y&NEWS=N&PAGE=fulltext&D=medl&AN=33921644: https://uoelibrary.idm.oclc.org/login?url=http://resolver.ebscohost.com/openurl?sid=OVID:medline&id=pmid:33921644&id=doi:10.3390%2Fijerph18084310&issn=1660-4601&isbn=&

151. Reid N, Daly RM, Winkler EAH, Gardiner PA, Eakin EG, Owen N, et al. Associations of monitor-assessed activity with performance-based physical function. PLoS One [Internet]. 2016;11(4):1–14. Available from: http://dx.doi.org/10.1371/journal.pone.0153398

152. Ribeiro AGSV, Verlengia R, de Oliveira MRM, Oliveira MVA, Pellegrinotti IL, Crisp AH. Compliance of the Physical Activity Guidelines Accumulated in Bouts ≥10 Min and Nonbouts and Its Association With Body Composition and Physical Function: A Cross-Sectional Study in Brazilian Older Adults. J Aging Phys Act [Internet]. 2021 Apr 1;29(2):319–26. Available from:

https://journals.humankinetics.com/view/journals/japa/29/2/article-p319.xml

153. Sánchez-Sánchez JL, Mañas A, García-García FJ, Ara I, Carnicero JA, Walter S, et al. Sedentary behaviour, physical activity, and sarcopenia among older adults in the TSHA: isotemporal substitution model. J Cachexia Sarcopenia Muscle. 2019;10(1):188–98.

154. Santos DA, Silva AM, Baptista F, Santos R, Vale S, Mota J, et al. Sedentary behavior and physical activity are independently related to functional fitness in older adults. Exp Gerontol [Internet]. 2012;47(12):908–12. Available from: http://dx.doi.org/10.1016/j.exger.2012.07.011

155. Savikangas T, Tirkkonen A, Alen M, Rantanen T, Fielding RA, Rantalainen T, et al. Associations of physical activity in detailed intensity ranges with body composition and physical function. a cross-sectional study among sedentary older adults. Eur Rev Aging Phys Act. 2020;17(1):1–11.

156. Adachi T, Kono Y, Iwatsu K, Shimizu Y, Yamada S. Duration of moderate to vigorous daily activity is negatively associated with slow walking speed independently from step counts in elderly women aged 75 years or over: A cross-sectional study. Arch Gerontol Geriatr [Internet]. 2018;74(October 2017):94–9. Available from: https://doi.org/10.1016/j.archger.2017.10.003

157. Spartano A.: Larson, M. G.: Tran, T.: Andersson, C.: Blease, S. J.: Esliger, D. W.: Vasan, R. S.: Murabito, J. M. NL. L. Objective physical activity and physical performance in middle-aged and older adults. Exp Gerontol [Internet]. 2019;119:203–11. Available from:

https://ovidsp.ovid.com/ovidweb.cgi?T=JS&CSC=Y&NEWS=N&PAGE=fulltext&D=med16&AN=30771463: https://uoelibrary.idm.oclc.org/login?url=http://resolver.ebscohost.com/openurl?sid=OVID:medline&id=pmid:30771463&id=doi:10.1016%2Fj.exger.2019.02.003&issn=0531-5565&

158. Thiebaud RS, Abe T, Ogawa M, Loenneke JP, Mitsukawa N. Accelerometer-Determined Intensity and Duration of Habitual Physical Activity and Walking Performance in Well-Functioning Middle-Aged and Older Women: A Cross-Sectional Study. J Frailty Aging. 2020;9(3):139–43.

159. van der Velde JHPMPM, Savelberg HHCMCM, van der Berg JD, Sep SJSS, van der Kallen CJHH, Dagnelie PC, et al. Sedentary Behavior Is Only Marginally Associated with Physical Function in Adults Aged 40–75 Years—the Maastricht Study. Front Physiol [Internet]. 2017 Apr 25;8(APR):1–9. Available from: http://journal.frontiersin.org/article/10.3389/fphys.2017.00242/full

160. Ward-Ritacco A. L.: Johnson, M. A.: Rogers, L. Q.: Evans, E. M. CL. A. Adiposity, physical activity, and muscle quality are independently related to physical function performance in middle-aged postmenopausal women. Menopause [Internet]. 2014;21(10):1114–21. Available from: https://ovidsp.ovid.com/ovidweb.cgi?T=JS&CSC=Y&NEWS=N&PAGE=fulltext&D=med11&AN=24618768: https://uoelibrary.idm.oclc.org/login?url=http://resolver.ebscohost.com/openurl?sid=OVID:medline&id=pmid:24618768&id=doi:10.1097%2FGME.0000000000000225&issn=1072-3714

161. Ward-Ritacco CL, Meyer A, Walker G, Riebe D, Sabik NJ. Percent body fat, but not lean mass, is associated with objectively measured physical function in middle-aged women. Maturitas. 2020;142(September 2019):11–6.

162. Westbury LD, Dodds RM, Syddall HE, Baczynska AM, Shaw SC, Dennison EM, et al. Associations Between Objectively Measured Physical Activity, Body Composition and Sarcopenia: Findings from the Hertfordshire Sarcopenia Study (HSS). Calcif Tissue Int [Internet]. 2018;103(3):237–45. Available from: http://dx.doi.org/10.1007/s00223-018-0413-5

163. Yamada H.: Nagai, K.: Uemura, K.: Mori, S.: Aoyama, T. M. A. Differential determinants of physical daily activities in frail and nonfrail community-dwelling older adults. J Clin Gerontol Geriatr [Internet]. 2011;2(2):42–6. Available from: http://www.elsevier.com/wps/find/journaldescription.cws_home/724909/description#description: https://ovidsp.ovid.com/ovidweb.cgi?T=JS&CSC=Y&NEWS=N&PAGE=fulltext&D=emed12&AN=362075359: https://uoelibrary.idm.oclc.org/login?url=http://resolver.ebscohost.com

164. Yasunaga A, Shibata A, Ishii K, Koohsari MJ, Inoue S, Sugiyama T, et al. Associations of sedentary behavior and physical activity with older adults' physical function: an isotemporal substitution approach. BMC Geriatr. 2017;17(1):280.

165. Aggio DA, Sartini C, Papacosta O, Lennon LT, Ash S, Whincup PH, et al. Cross-sectional associations of objectively measured physical activity and

sedentary time with sarcopenia and sarcopenic obesity in older men. Prev Med (Baltim) [Internet]. 2016;91:264–72. Available from: http://dx.doi.org/10.1016/j.ypmed.2016.08.040

166. Aoyagi Y, Park H, Watanabe E, Park S, Shephard RJ. Habitual physical activity and physical fitness in older Japanese adults: The nakanojo study. Gerontology. 2009;55(5):523–31.

167. Cooper AJM, Simmons RK, Kuh D, Brage S, Cooper R, Hardy R, et al. Physical activity, sedentary time and physical capability in early old age: British birth cohort study. PLoS One [Internet]. 2015;10(5):1–14. Available from: http://dx.doi.org/10.1371/journal.pone.0126465

168. Cooper R, Stamatakis E, Hamer M. Associations of sitting and physical activity with grip strength and balance in mid-life: 1970 British Cohort Study. Scand J Med Sci Sport. 2020;30(12):2371–81.

169. Davis MG, Fox KR, Stathi A, Trayers T, Thompson JL, Cooper AR. Objectively measured sedentary time and its association with physical function in older adults. J Aging Phys Act. 2014;22(4):474–81.

170. Duck M. W.: Robinson, J. C. AA. S. Physical activity and postural balance in rural community dwelling older adults. Appl Nurs Res [Internet]. 2019;48:1–7. Available from: https://ovidsp.ovid.com/ovidweb.cgi?T=JS&CSC=Y&NEWS=N&PAGE=fulltext&D=med16&AN=31266601: https://uoelibrary.idm.oclc.org/login?url=http://resolver.ebscohost.com/openurl?sid=OVID:medline&id=pmid:31266601&id=doi:10.1016%2Fj.apnr.2019.05.012&issn=0897-1897&i

171. Troiano RP, Berrigan D, Dodd KW, Mâsse LC, Tilert T, Mcdowell M. Physical activity in the United States measured by accelerometer. Med Sci Sports Exerc. 2008;40(1):181–8.

172. Freedson PS, Melanson E, Sirard J. Calibration of the Computer Science and Applications, Inc. accelerometer. Med Sci Sports Exerc [Internet]. 1998 May;30(5):777—781. Available from: https://doi.org/10.1097/00005768-199805000-00021

173. Rojer AGM, Reijnierse EM, Trappenburg MC, van Lummel RC, Niessen M, van Schooten KS, et al. Instrumented Assessment of Physical Activity Is Associated With Muscle Function but Not With Muscle Mass in a General Population. J Aging Health. 2018;30(9):1462–81.

174. Spartano NL, Lyass A, Larson MG, Tran T, Andersson C, Blease SJ, et al. Objective physical activity and physical performance in middle-aged and older adults. Exp Gerontol. 2019;119(December 2018):203–11.

175. Borenstein, M., Hedges, L., Higgins, J., & Rothstein H. Regression in Meta-Analysis. C Meta-Regression Man. 2015;1–357.

176. Sylvia LG, Bernstein EE, Hubbard JL, Keating L, Anderson EJ. Practical guide to measuring physical activity. J Acad Nutr Diet. 2014;114(2):199–208.

177. Cleland CL, Ferguson S, McCrorie P, Schipperijn J, Ellis G, Hunter RF. Considerations in processing accelerometry data to explore physical activity and sedentary time in older adults. J Aging Phys Act. 2020;28(4):623–33.

178. Lee IM, Shiroma EJ. Using accelerometers to measure physical activity in

large-scale epidemiological studies: Issues and challenges. Br J Sports Med. 2014;48(3):197–201.

179. Granat MH. Event-based analysis of free-living behaviour. Physiol Meas. 2012;33(11):1785–800.

180. Shiroma EJ, Lee IM, Schepps MA, Kamada M, Harris TB. Physical Activity Patterns and Mortality: The Weekend Warrior and Activity Bouts. Med Sci Sports Exerc. 2019;51(1):35–40.

181. Dall PM, Skelton DA, Dontje ML, Coulter EH, Stewart S, Cox SR, et al. Characteristics of a Protocol to Collect Objective Physical Activity/Sedentary Behavior Data in a Large Study: Seniors USP (Understanding Sedentary Patterns). J Meas Phys Behav. 2018;1(1):26–31.

182. Atrsaei A, Dadashi F, Hansen C, Warmerdam E, Mariani B, Maetzler W, et al. Postural transitions detection and characterization in healthy and patient populations using a single waist sensor. J Neuroeng Rehabil. 2020;17(1):1–14.

183. de Carvalho IA, Epping-Jordan J, Beard JR. Integrated Care for Older People. 2019. 185–195 p.

184. Westerterp KR. Doubly labelled water assessment of energy expenditure: principle, practice, and promise. Eur J Appl Physiol. 2017;117(7):1277–85.

185. Sattler MC, Ainsworth BE, Andersen LB, Foster C, Hagströmer M, Jaunig J, et al. Physical activity self-reports: Past or future? Br J Sports Med. 2021;55(16):889–90.

186. Warren JM, Ekelund U, Besson H, Mezzani A, Geladas N, Vanhees L. Assessment of physical activity - A review of methodologies with reference to epidemiological research: A report of the exercise physiology section of the European Association of Cardiovascular Prevention and Rehabilitation. Eur J Cardiovasc Prev Rehabil. 2010;17(2):127–39.

187. Prince SA, Adamo KB, Hamel ME, Hardt J, Connor Gorber S, Tremblay M. A comparison of direct versus self-report measures for assessing physical activity in adults: A systematic review. Int J Behav Nutr Phys Act. 2008;5.

188. Shephard RJ, Vuillemin A. Limits to the measurement of habitual physical activity by questionnaires * Commentary. Br J Sports Med [Internet]. 2003 Jun 1;37(>3):206. Available from: https://bjsm.bmj.com/lookup/doi/10.1136/bjsm.37.3.197

189. Brenner PS, DeLamater JD. Social Desirability Bias in Self-reports of Physical Activity: Is an Exercise Identity the Culprit? Soc Indic Res [Internet]. 2014 Jun 1;117(2):489–504. Available from: http://link.springer.com/10.1007/s11205-013-0359-y

190. Rush EC, Valencia ME, Plank LD. Validation of a 7-day physical activity diary against doubly-labelled water. Ann Hum Biol. 2008;35(4):416–21.

191. WELK GJ, KIM Y, STANFILL B, OSTHUS DA, CALABRO MA, NUSSER SM, et al. Validity of 24-h Physical Activity Recall. Med Sci Sport Exerc [Internet]. 2014 Oct;46(10):2014–24. Available from: https://journals.lww.com/00005768-201410000-00018

192. Silfee VJ, Haughton CF, Jake-Schoffman DE, Lopez-Cepero A, May CN,

Sreedhara M, et al. Objective measurement of physical activity outcomes in lifestyle interventions among adults: A systematic review. Prev Med Reports. 2018;11(May):74–80.

193. Bauman A, Pedišić Ž, Bragg K. Objective Measurement in Physical Activity Surveillance: Present Role and Future Potential. In 2016. p. 347–67. Available from: http://link.springer.com/10.1007/978-3-319-29577-0_13

194. Saunders JB dec. M, Inman VT, Eberhart HD. THE MAJOR DETERMINANTS IN NORMAL AND PATHOLOGICAL GAIT. JBJS [Internet]. 1953;35(3). Available from: https://journals.lww.com/jbjsjournal/fulltext/1953/35030/the_major_determinants_in_normal_and_pathological.3.aspx

195. Morris JRW. Accelerometry-A technique for the measurement of human body movements. J Biomech. 1973;6(6):729–36.

196. Troiano RP, McClain JJ, Brychta RJ, Chen KY. Evolution of accelerometer methods for physical activity research. Br J Sports Med. 2014;48(13):1019–23.

197. Troiano RP. Evolution of Public Health Physical Activity Applications of Accelerometers: A Personal Perspective. J Meas Phys Behav. 2023;6(1):13–8.

198. Montoye AHK, Moore RW, Bowles HR, Korycinski R, Pfeiffer KA. Reporting accelerometer methods in physical activity intervention studies: A systematic review and recommendations for authors. Br J Sports Med. 2018;52(23):1507–16.

199. Pulsford RM, Brocklebank L, Fenton SAM, Bakker E, Mielke GI, Tsai LT, et al. The impact of selected methodological factors on data collection outcomes in observational studies of device-measured physical behaviour in adults: A systematic review. Int J Behav Nutr Phys Act [Internet]. 2023;20(1):1–14. Available from: https://doi.org/10.1186/s12966-022-01388-9

200. Trost SG, Mciver KL, Pate RR. Conducting accelerometer-based activity assessments in field-based research. Med Sci Sports Exerc. 2005;37(11 SUPPL.):531–43.

201. Ward DS, Evenson KR, Vaughn A, Rodgers AB, Troiano RP. Accelerometer use in physical activity: Best practices and research recommendations. Med Sci Sports Exerc. 2005;37(11 SUPPL.).

202. Matthews CE, Hagströmer M, Pober DM, Bowles HR. Best Practices for Using Physical Activity Monitors. Med Sci Sport Exerc. 2012;44(1):1–17.

203. Ullrich A, Baumann S, Voigt L, John U, Ulbricht S. Measurement Reactivity of Accelerometer-Based Sedentary Behavior and Physical Activity in 2 Assessment Periods. J Phys Act Heal. 2021;18(2):185–91.

204. Bassett DR, Toth LP, LaMunion SR, Crouter SE. Step Counting: A Review of Measurement Considerations and Health-Related Applications. Sport Med. 2017;47(7):1303–15.

205. BASSETT DR, AINSWORTH BE, LEGGETT SR, MATHIEN CA, MAIN JA, HUNTER DC, et al. Accuracy of five electronic pedometers for measuring distance walked. Med &amp Sci Sport &amp Exerc [Internet]. 1996 Aug;28(8):1071–7. Available from:

http://journals.lww.com/00005768-199608000-00019

206. Evenson KR, Scherer E, Peter KM, Cuthbertson CC, Eckman S. Historical development of accelerometry measures and methods for physical activity and sedentary behavior research worldwide: A scoping review of observational studies of adults. PLoS One [Internet]. 2022;17(11 November):1–27. Available from: http://dx.doi.org/10.1371/journal.pone.0276890

207. KERR J, MARINAC CR, ELLIS K, GODBOLE S, HIPP A, GLANZ K, et al. Comparison of Accelerometry Methods for Estimating Physical Activity. Med Sci Sport Exerc [Internet]. 2017 Mar;49(3):617–24. Available from: https://journals.lww.com/00005768-201703000-00028

208. Migueles JH, Cadenas-Sanchez C, Ekelund U, Delisle Nyström C, Mora-Gonzalez J, Löf M, et al. Accelerometer Data Collection and Processing Criteria to Assess Physical Activity and Other Outcomes: A Systematic Review and Practical Considerations. Sport Med. 2017;47(9):1821–45.

209. Staudenmayer J, He S, Hickey A, Sasaki J, Freedson P. Methods to estimate aspects of physical activity and sedentary behavior from high-frequency wrist accelerometer measurements. J Appl Physiol. 2015;119(4):396–403.

210. TUDOR-LOCKE C, BARREIRA T V., SCHUNA JM. Comparison of Step Outputs for Waist and Wrist Accelerometer Attachment Sites. Med Sci Sport Exerc [Internet]. 2015 Apr;47(4):839–42. Available from: https://journals.lww.com/00005768-201504000-00021

211. Liu F, Wanigatunga AA, Schrack JA. Assessment of Physical Activity in

Adults Using Wrist Accelerometers. Epidemiol Rev. 2021;43(1):65–93.

212. O'Brien MW, Wu Y, Petterson JL, Bray NW, Kimmerly DS. Validity of the ActivPAL monitor to distinguish postures: A systematic review. Gait Posture [Internet]. 2022;94(February):107–13. Available from: https://doi.org/10.1016/j.gaitpost.2022.03.002

213. Wu Y, Petterson JL, Bray NW, Kimmerly DS, O'Brien MW. Validity of the activPAL monitor to measure stepping activity and activity intensity: A systematic review. Gait Posture [Internet]. 2022;97(April):165–73. Available from: https://doi.org/10.1016/j.gaitpost.2022.08.002

214. Schram MT, Sep SJS, Van Der Kallen CJ, Dagnelie PC, Koster A, Schaper N, et al. The Maastricht Study: An extensive phenotyping study on determinants of type 2 diabetes, its complications and its comorbidities. Eur J Epidemiol. 2014;29(6):439–51.

215. Asvold BO, Langhammer A, Rehn TA, Kjelvik G, Grontvedt TV, Sorgjerd EP, et al. Cohort Profile Update: The HUNT Study, Norway. Int J Epidemiol. 2023;52(1):E80–91.

216. Sullivan A, Brown M, Hamer M, Ploubidis GB. Cohort Profile Update: The 1970 British Cohort Study (BCS70). Int J Epidemiol. 2023;52(3):E179–86.

217. Clevenger KA, Brønd JC, Mackintosh KA, Pfeiffer KA, Montoye AHK, McNarry MA. Impact of ActiGraph sampling rate on free-living physical activity measurement in youth. Physiol Meas. 2022;43(10):287–97.

218. McGrath R, Vella CA, Scruggs PW, Peterson MD, Williams CJ, Paul DR. The impact of low accelerometer wear time on the estimates and application of sedentary behavior and physical activity data in adults. J

Phys Act Heal. 2017;14(12):919–24.

219. Airlie J, Forster A, Birch KM. An investigation into the optimal wear time criteria necessary to reliably estimate physical activity and sedentary behaviour from ActiGraph wGT3X+ accelerometer data in older care home residents. BMC Geriatr [Internet]. 2022;22(1):1–14. Available from: https://doi.org/10.1186/s12877-021-02725-6

220. Rich C, Geraci M, Griffiths L, Sera F, Dezateux C, Cortina-Borja M. Quality Control Methods in Accelerometer Data Processing: Defining Minimum Wear Time. PLoS One. 2013;8(6):1–8.

221. Herrmann SD, Barreira T V., Kang M, Ainsworth BE. How Many Hours Are Enough? Accelerometer Wear Time May Provide Bias in Daily Activity Estimates. J Phys Act Heal [Internet]. 2013 Jul;10(5):742–9. Available from: https://journals.humankinetics.com/view/journals/jpah/10/5/article-p742.xml

222. Ricardo LIC, Wendt A, Galliano LM, De Andrade Muller W, Cruz GIN, Wehrmeister F, et al. Number of days required to estimate physical activity constructs objectively measured in different age groups: Findings from three Brazilian (Pelotas) population-based birth cohorts. PLoS One. 2020;15(1):1–13.

223. Dillon CB, Fitzgerald AP, Kearney PM, Perry IJ, Rennie KL, Kozarski R, et al. Number of days required to estimate habitual activity using wrist-worn geneActiv accelerometer: A cross-sectional study. PLoS One. 2016;11(5):1–11.

224. Lee PH, Macfarlane DJ, Lam TH. Factors associated with participant compliance in studies using accelerometers. Gait Posture [Internet]. 2013;38(4):912–7. Available from: http://dx.doi.org/10.1016/j.gaitpost.2013.04.018

225. Hamer M, Stamatakis E, Chastin S, Pearson N, Brown M, Gilbert E, et al. Feasibility of measuring sedentary time using data from a thigh-worn accelerometer. Am J Epidemiol. 2020;189(9):963–71.

226. Nettlefold L, Naylor PJ, Warburton DER, Bredin SSD, Race D, McKay HA. The Influence of Epoch Length on Physical Activity Patterns Varies by Child's Activity Level. Res Q Exerc Sport. 2016;87(1):110–23.

227. Altenburg TM, Wang X, Van Ekris E, Andersen LB, Møller NC, Wedderkopp N, et al. The consequences of using different epoch lengths on the classification of accelerometer based sedentary behaviour and physical activity. PLoS One. 2021;16(7 July 2021):1–14.

228. Ayabe M, Kumahara H, Morimura K, Tanaka H. Epoch length and the physical activity bout analysis: an accelerometry research issue. BMC Res Notes [Internet]. 2013;6(1):20. Available from: BMC Research Notes

229. Dall PM, McCrorie PRW, Granat MH, Stansfield BW. Step accumulation per minute epoch is not the same as cadence for free-living adults. Med Sci Sports Exerc. 2013;45(10):1995–2001.

230. Orme M, Wijndaele K, Sharp SJ, Westgate K, Ekelund U, Brage S. Combined influence of epoch length, cut-point and bout duration on accelerometry-derived physical activity. Int J Behav Nutr Phys Act. 2014;11(1):1–8.

231. Pulsford RM, Cortina-Borja M, Rich C, Kinnafick FE, Dezateux C, Griffiths LJ. Actigraph Accelerometer-Defined boundaries for sedentary behaviour and physical activity intensities in 7 year old children. PLoS One. 2011;6(8).

232. Trost SG, Brookes DSK, Ahmadi MN. Evaluation of Wrist Accelerometer Cut-Points for Classifying Physical Activity Intensity in Youth. Front Digit Heal. 2022;4(May):1–11.

233. Migueles JH, Cadenas-Sanchez C, Alcantara JMA, Leal-Martín J, Mañas A, Ara I, et al. Calibration and cross-validation of accelerometer cut-points to classify sedentary time and physical activity from hip and non-dominant and dominant wrists in older adults. Sensors. 2021;21(10):1–14.

234. Bianchim MS, McNarry MA, Larun L, Mackintosh KA. Calibration and validation of accelerometry to measure physical activity in adult clinical groups: A systematic review. Prev Med Reports [Internet]. 2019;16(February):101001. Available from: https://doi.org/10.1016/j.pmedr.2019.101001

235. Troiano RP, Stamatakis E, Bull FC. How can global physical activity surveillance adapt to evolving physical activity guidelines? Needs, challenges and future directions. Br J Sports Med. 2020;54(24):1468–73.

236. Gil-Rey E, Maldonado-Martín S, Gorostiaga EM. Individualized Accelerometer Activity Cut-Points for the Measurement of Relative Physical Activity Intensity Levels. Res Q Exerc Sport [Internet]. 2019;90(3):327–35. Available from: https://doi.org/10.1080/02701367.2019.1599801

237. Tudor-Locke C, Han H, Aguiar EJ, Barreira T V., Schuna JM, Kang M, et al. How fast is fast enough? Walking cadence (steps/min) as a practical estimate of intensity in adults: A narrative review. Br J Sports Med. 2018;52(12):776–88.

238. Paluch AE, Bajpai S, Bassett DR, Carnethon MR, Ekelund U, Evenson KR, et al. Daily steps and all-cause mortality: a meta-analysis of 15 international cohorts. Lancet Public Heal. 2022;7(3):e219–28.

239. Saint-Maurice PF, Troiano RP, Bassett DR, Graubard BI, Carlson SA, Shiroma EJ, et al. Association of Daily Step Count and Step Intensity with Mortality among US Adults. JAMA - J Am Med Assoc. 2020;323(12):1151–60.

240. Backes A, Gupta T, Schmitz S, Fagherazzi G, van Hees V, Malisoux L. Advanced analytical methods to assess physical activity behavior using accelerometer time series: A scoping review. Scand J Med Sci Sport. 2022;32(1):18–44.

241. Rowlands A V., Edwardson CL, Davies MJ, Khunti K, Harrington DM, Yates T. Beyond Cut Points: Accelerometer Metrics that Capture the Physical Activity Profile. Med Sci Sports Exerc. 2018;50(6):1323–32.

242. Rowlands A V., Dawkins NP, Maylor B, Edwardson CL, Fairclough SJ, Davies MJ, et al. Enhancing the value of accelerometer-assessed physical activity: meaningful visual comparisons of data-driven translational accelerometer metrics. Sport Med - Open. 2019;5(1).

243. To QG, Stanton R, Schoeppe S, Doering T, Vandelanotte C. Differences in physical activity between weekdays and weekend days among U.S.

children and adults: Cross-sectional analysis of NHANES 2011–2014 data. Prev Med Reports [Internet]. 2022;28(March):101892. Available from: https://doi.org/10.1016/j.pmedr.2022.101892

244. Drenowatz C, Gribben N, Wirth MD, Hand GA, Shook RP, Burgess S, et al. The Association of Physical Activity during Weekdays and Weekend with Body Composition in Young Adults. J Obes. 2016;2016.

245. Garriga A, Sempere-Rubio N, Molina-Prados MJ, Faubel R. Impact of seasonality on physical activity: A systematic review. Int J Environ Res Public Health. 2022;19(1).

246. Olds T, Maher C, Dumuid D. Life on holidays: Differences in activity composition between school and holiday periods in Australian children. BMC Public Health. 2019;19(Suppl 2):1–8.

247. MATTHEWS CE, AINSWORTH BE, THOMPSON RW, BASSETT DR. Sources of variance in daily physical activity levels as measured by an accelerometer. Med Sci Sport Exerc [Internet]. 2002 Aug;34(8):1376–81. Available from: http://journals.lww.com/00005768-200208000-00021

248. O'Donovan G, Lee IM, Hamer M, Stamatakis E. Association of "weekend warrior" and other leisure time physical activity patterns with risks for all-cause, cardiovascular disease, and cancer mortality. JAMA Intern Med. 2017;177(3):335–42.

249. Janssen I, Campbell JE, Zahran S, Saunders TJ, Tomasone JR, Chaput JP. Timing of physical activity within the 24-hour day and_its_influence:on_health: _a_systematic_review. Heal Promot Chronic Dis Prev Canada. 2022;42(4):129–38.

250. Chastin SFM, Granat MH. Methods for objective measure, quantification and analysis of sedentary behaviour and inactivity. Gait Posture. 2010;31(1):82–6.

251. Fortune E, Mundell B, Amin S, Kaufman K. A pilot study of physical activity and sedentary behavior distribution patterns in older women. Gait Posture [Internet]. 2017;57(May 2016):74–9. Available from: http://dx.doi.org/10.1016/j.gaitpost.2017.05.014

252. Danilevicz IM, van Hees VT, van der Heide FCT, Jacob L, Landré B, Benadjaoud MA, et al. Measures of fragmentation of rest activity patterns: mathematical properties and interpretability based on accelerometer real life data. BMC Med Res Methodol [Internet]. 2024;24(1):1–15. Available from: https://doi.org/10.1186/s12874-024-02255-w

253. Fanning J, Brooks AK, Robison JT, Irby MB, Ford S, N'Dah K, et al. Associations between patterns of physical activity, pain intensity, and interference among older adults with chronic pain: a secondary analysis of two randomized controlled trials. Front Aging. 2023;4(July):1–9.

254. Gao L, Lim ASP, Wong PM, Gaba A, Cui L, Yu L, et al. Fragmentation of rest/activity patterns in community-based elderly individuals predicts incident heart failure. Nat Sci Sleep. 2020;12:299–307.

255. Hauge ER, Berle JØ, Oedegaard KJ, Holsten F, Fasmer OB. Nonlinear analysis of motor activity shows differences between schizophrenia and depression: A study using fourier analysis and sample entropy. PLoS One. 2011;6(1):1–10.

256. Goldberger AL, Amaral LAN, Hausdorff JM, Ivanov PC, Peng CK, Stanley

HE. Fractal dynamics in physiology: Alterations with disease and aging. Proc Natl Acad Sci U S A. 2002;99(SUPPL. 1):2466–72.

257. Li P, Yu L, Lim ASP, Buchman AS, Scheer FAJL, Shea SA, et al. Fractal regulation and incident Alzheimer's disease in elderly individuals. Alzheimer's Dement [Internet]. 2018;14(9):1114–25. Available from: https://doi.org/10.1016/j.jalz.2018.03.010

258. Hu K, Riemersma-Van Der Lek RF, Patxot M, Li P, Shea SA, Scheer FAJL, et al. Progression of Dementia Assessed by Temporal Correlations of Physical Activity: Results from a 3.5-Year, Longitudinal Randomized Controlled Trial. Sci Rep. 2016;6(December 2015):1–10.

259. Chen HM, Wu YC, Tsai CM, Tzeng JI, Lin CC. Relationships of circadian rhythms and physical activity with objective sleep parameters in Lung cancer patients. Cancer Nurs. 2015;38(3):215–23.

260. Merilahti I. J. K. Association between Continuous Wearable Activity Monitoring and Self-Reported Functioning in Assisted Living Facility and Nursing Home Residents. J Frailty Aging [Internet]. 2016;5(4):225–32. Available from: https://ovidsp.ovid.com/ovidweb.cgi?T=JS&CSC=Y&NEWS=N&PAGE=fulltext&D=med13&AN=27883169: https://uoelibrary.idm.oclc.org/login?url=http://resolver.ebscohost.com/openurl?sid=OVID:medline&id=pmid:27883169&id=doi:10.14283%2Fjfa.2016.102&issn=2260-1341&isbn=&

261. Paraschiv-Ionescu A, Büla CJ, Major K, Lenoble-Hoskovec C, Krief H, El-Moufawad C, et al. Concern about Falling and Complexity of Free-Living Physical Activity Patterns in Well-Functioning Older Adults. Gerontology.

2018;64(6):603–11.

262. Krane-Gartiser K, Henriksen TEG, Morken G, Vaaler A, Fasmer OB. Actigraphic assessment of motor activity in acutely admitted inpatients with bipolar disorder. PLoS One. 2014;9(2).

263. Goh KI, Barabási AL. Burstiness and memory in complex systems. Epl. 2008;81(4).

264. Cencetti G, Battiston F, Lepri B, Karsai M. Temporal properties of higher-order interactions in social networks. Sci Rep [Internet]. 2021;11(1):1–10. Available from: https://doi.org/10.1038/s41598-021-86469-8

265. Zhao X, Omi T, Matsuno N, Shinomoto S. A non-universal aspect in the temporal occurrence of earthquakes. New J Phys. 2010;12.

266. Jeannet PY, Aminian K, Bloetzer C, Najafi B, Paraschiv-Ionescu A. Continuous monitoring and quantification of multiple parameters of daily physical activity in ambulatory Duchenne muscular dystrophy patients. Eur J Paediatr Neurol [Internet]. 2011;15(1):40–7. Available from: http://dx.doi.org/10.1016/j.ejpn.2010.07.002

267. Paraschiv-Ionescu A, Buchser E, Aminian K. Unraveling dynamics of human physical activity patterns in chronic pain conditions. Sci Rep. 2013;3:1–10.

268. Tremblay MS, Aubert S, Barnes JD, Saunders TJ, Carson V, Latimer-Cheung AE, et al. Sedentary Behavior Research Network (SBRN) - Terminology Consensus Project process and outcome. Int J Behav Nutr Phys Act. 2017;14(1):1–17.

269. Saunders TJ, McIsaac T, Douillette K, Gaulton N, Hunter S, Rhodes RE,

et al. Sedentary behaviour and health in adults: an overview of systematic reviews. Appl Physiol Nutr Metab [Internet]. 2020 Oct;45(10 (Suppl. 2)):S197–217. Available from: https://cdnsciencepub.com/doi/10.1139/apnm-2020-0272

270. Piercy KL, Troiano RP, Ballard RM, Carlson SA, Fulton JE, Galuska DA, et al. The physical activity guidelines for Americans. JAMA - J Am Med Assoc [Internet]. 2018;320(19):2020–8. Available from: https://www.ncbi.nlm.nih.gov/pubmed/30418471

271. Soto-Rodríguez FJ, Cabañas EI, Pérez-Mármol JM. Impact of prolonged sitting interruption strategies on shear rate, flow-mediated dilation and blood flow in adults: A systematic review and meta-analysis of randomized cross-over trials. J Sports Sci [Internet]. 2022;40(14):1558–67. Available from: https://doi.org/10.1080/02640414.2022.2091347

272. Buffey AJ, Herring MP, Langley CK, Donnelly AE, Carson BP. The Acute Effects of Interrupting Prolonged Sitting Time in Adults with Standing and Light-Intensity Walking on Biomarkers of Cardiometabolic Health in Adults: A Systematic Review and Meta-analysis. Sport Med [Internet]. 2022 Aug 11;52(8):1765–87. Available from: https://doi.org/10.1007/s40279-022-01649-4

273. Blankenship JM, Winkler EAH, Healy GN, Dempsey PC, Bellettiere J, Owen N, et al. Descriptive Epidemiology of Interruptions to Free-Living Sitting Time in Middle-Age and Older Adults. 2021;2503–11.

274. ROSENBERGER ME, FULTON JE, BUMAN MP, TROIANO RP, GRANDNER MA, BUCHNER DM, et al. The 24-Hour Activity Cycle: A New Paradigm for Physical Activity. Med Sci Sport Exerc [Internet]. 2019

Mar;51(3):454–64. Available from: https://journals.lww.com/00005768-201903000-00009

275. Painter P, Stewart AL, Carey S. Physical functioning: Definitions, measurement, and expectations. Adv Ren Replace Ther [Internet]. 1999;6(2):110–23. Available from: http://dx.doi.org/10.1016/S1073-4449(99)70028-2

276. Solomon DH, Colvin A, Lange-Maia BS, Derby C, Dugan S, Jackson EA, et al. Factors Associated With 10-Year Declines in Physical Health and Function Among Women During Midlife. JAMA Netw Open. 2022;5(1):E2142773.

277. Lachman ME, Teshale S, Agrigoroaei S. Midlife as a pivotal period in the life course: Balancing growth and decline at the crossroads of youth and old age. Int J Behav Dev. 2015;39(1):20–31.

278. Narici M V., Maffulli N. Sarcopenia: characteristics, mechanisms and functional significance. Br Med Bull [Internet]. 2010 Sep 1;95(1):139–59. Available from: https://academic.oup.com/bmb/article-lookup/doi/10.1093/bmb/ldq008

279. Manini TM, Pahor M. Physical activity and maintaining physical function in older adults. Br J Sports Med [Internet]. 2009 Jan;43(1):28–31. Available from: https://bjsm.bmj.com/lookup/doi/10.1136/bjsm.2008.053736

280. Hughes DC, Ellefsen S, Baar K. Adaptations to Endurance and Strength Training. Cold Spring Harb Perspect Med [Internet]. 2018 Jun;8(6):a029769. Available from: http://perspectivesinmedicine.cshlp.org/lookup/doi/10.1101/cshperspect.a

029769

281. Adams M, Gordt-Oesterwind K, Bongartz M, Zimmermann S, Seide S, Braun V, et al. Effects of Physical Activity Interventions on Strength, Balance and Falls in Middle-Aged Adults: A Systematic Review and Meta-Analysis. Sport Med - Open [Internet]. 2023;9(1). Available from: https://doi.org/10.1186/s40798-023-00606-3

282. Edemekong PF, Bomgaars DL, Sukumaran S, Schoo C. Activities of Daily Living [Internet]. StatPearls. 2024. Available from: http://www.ncbi.nlm.nih.gov/pubmed/6418786

283. Ware JE. SF-36 Health Survey update. Spine (Phila Pa 1976). 2000;25(24):3130–9.

284. Syddall HE, Martin HJ, Harwood RH, Cooper C, Aihie Sayer A. The SF-36: A simple, effective measure of mobility-disability for epidemiological studies. J Nutr Heal Aging. 2009;13(1):57–62.

285. Factors E, Strategies C. Assessment of Physical Functioning : Compensation Strategies. Phys Ther. 2009;89(7):705–14.

286. Bohannon RW. Hand-grip dynamometry predicts future outcomes in aging adults. J Geriatr Phys Ther [Internet]. 2008;31(1):3–10. Available from: http://search.ebscohost.com/login.aspx?direct=true&db=cin20&AN=105733289&site=ehost-live

287. Vaishya R, Misra A, Vaish A, Ursino N, D'Ambrosi R. Hand grip strength as a proposed new vital sign of health: a narrative review of evidences. J Heal Popul Nutr [Internet]. 2024;43(1):1–14. Available from:

https://doi.org/10.1186/s41043-024-00500-y

288. Issues S, Test MW, Equipment R, Preparation P. ATS Statement. Am J Respir Crit Care Med [Internet]. 2002 Jul 1;166(1):111–7. Available from: https://www.atsjournals.org/doi/10.1164/ajrccm.166.1.at1102

289. Newman AB, Simonsick EM, Naydeck BL, Boudreau RM, Kritchevsky SB, Nevitt MC, et al. Association of long-distance corridor walk performance with mortality, cardiovascular disease, mobility limitation, and disability. Jama-Journal Am Med Assoc [Internet]. 2006;295(17):2018–26. Available from: https://jamanetwork.com/journals/jama/articlepdf/202790/joc60049.pdf

290. Coulshed A, Coulshed D, Pathan F. Systematic Review of the Use of the 6-Minute Walk Test in Measuring and Improving Prognosis in Patients With Ischemic Heart Disease. CJC Open [Internet]. 2023;5(11):816–25. Available from: https://doi.org/10.1016/j.cjco.2023.08.003

291. Chan WL, Chan HL, Chen KM, Fan HL, Lai WC, Yu SW. Reliability and validity of walk tests for older adults with dementia: A systematic review. Alzheimers Dement. 2021;17:e050371.

292. Du H, Wonggom P, Tongpeth J, Clark RA. Six-Minute Walk Test for Assessing Physical Functional Capacity in Chronic Heart Failure. Curr Heart Fail Rep. 2017;14(3):158–66.

293. Kammin EJ. The 6-Minute Walk Test: Indications and Guidelines for Use in Outpatient Practices. J Nurse Pract [Internet]. 2022;18(6):608–10. Available from: https://doi.org/10.1016/j.nurpra.2022.04.013

294. Shulman MA, Cuthbertson BH, Wijeysundera DN, Pearse RM, Thompson

B, Torres E, et al. Using the 6-minute walk test to predict disability-free survival after major surgery. Br J Anaesth. 2019;122(1):111–9.

295. Henrique DMN, Mourao-Junior CA, Pace F, de Oliveira TMD, Malaguti C, Chebli J. Six-minute walk test predicts future decompensation in patients with compensated liver cirrhosis. Rev Assoc Med Bras. 2022;68(8):991–4.

296. L'Abbe J, Loadman Joyce M, Lau S, Bentley M, Lien D. Predictive value of the 6-minute walk test in lung transplant outcomes. J Hear Lung Transplant [Internet]. 2004 Feb;23(2):S92–3. Available from: https://linkinghub.elsevier.com/retrieve/pii/S1053249803007022

297. Li J, Li X, Deng M, Liang X, Wei H, Wu X. Features and predictive value of 6-min walk test outcomes in interstitial lung disease: An observation study using wearable monitors. BMJ Open. 2022;12(6).

298. Cazzoletti L, Zanolin ME, Dorelli G, Ferrari P, Dalle Carbonare LG, Crisafulli E, et al. Six-minute walk distance in healthy subjects: reference standards from a general population sample. Respir Res [Internet]. 2022;23(1):1–9. Available from: https://doi.org/10.1186/s12931-022-02003-y

299. Herman T, Giladi N, Hausdorff JM. Properties of the "Timed Up and Go" test: More than meets the eye. Gerontology. 2011;57(3):203–10.

300. Christopher A, Kraft E, Olenick H, Kiesling R, Doty A. The reliability and validity of the Timed Up and Go as a clinical tool in individuals with and without disabilities across a lifespan: a systematic review: Psychometric properties of the Timed Up and Go. Disabil Rehabil [Internet].

2021;43(13):1799–813. Available from: https://doi.org/10.1080/09638288.2019.1682066

301. Ansai JH, Farche ACS, Rossi PG, De Andrade LP, Nakagawa TH, Takahashi ACDM. Performance of Different Timed Up and Go Subtasks in Frailty Syndrome. J Geriatr Phys Ther. 2019;42(4):287–93.

302. Albarrati AM, Gale NS, Munnery MM, Reid N, Cockcroft JR, Shale DJ. The Timed Up and Go test predicts frailty in patients with COPD. npj Prim Care Respir Med. 2022;32(1).

303. Eagles D, Perry JJ, Sirois MJ, Lang E, Daoust R, Lee J, et al. Timed Up and Go predicts functional decline in older patients presenting to the emergency department following minor trauma. Age Ageing. 2017;46(2):214–9.

304. Yee XS, Ng YS, Allen JC, Latib A, Tay EL, Abu Bakar HM, et al. Performance on sit-to-stand tests in relation to measures of functional fitness and sarcopenia diagnosis in community-dwelling older adults. Eur Rev Aging Phys Act. 2021;18(1):1–11.

305. Jones CJ, Rikli RE, Beam WC. A 30-s Chair-Stand Test as a Measure of Lower Body Strength in Community-Residing Older Adults. Res Q Exerc Sport [Internet]. 1999 Jun;70(2):113–9. Available from: http://www.tandfonline.com/doi/abs/10.1080/02701367.1999.10608028

306. Bohannon RW. Test-Retest Reliability of the Five-Repetition Sit-to-Stand Test: A Systematic Review of the Literature Involving Adults. J Strength Cond Res [Internet]. 2011 Nov;25(11):3205–7. Available from: https://journals.lww.com/00124278-201111000-00036

307. Muñoz-Bermejo L, Adsuar JC, Mendoza-Muñoz M, Barrios-Fernández S, Garcia-Gordillo MA, Pérez-Gómez J, et al. Test-retest reliability of five times sit to stand test (Ftsst) in adults: A systematic review and meta-analysis. Biology (Basel). 2021;10(6):1–10.

308. Makizako H, Shimada H, Doi T, Tsutsumimoto K, Nakakubo S, Hotta R, et al. Predictive Cutoff Values of the Five-Times Sit-to-Stand Test and the Timed “Up & Go” Test for Disability Incidence in Older People Dwelling in the Community. Phys Ther [Internet]. 2017 Apr 1;97(4):417–24. Available from: https://doi.org/10.2522/ptj.20150665

309. Buatois S, Miljkovic D, Manckoundia P, Gueguen R, Miget P, Vançon G, et al. FIVE TIMES SIT TO STAND TEST IS A PREDICTOR OF RECURRENT FALLS IN HEALTHY COMMUNITY-LIVING SUBJECTS AGED 65 AND OLDER. J Am Geriatr Soc [Internet]. 2008 Aug 2;56(8):1575–7. Available from: https://agsjournals.onlinelibrary.wiley.com/doi/10.1111/j.1532-5415.2008.01777.x

310. Bergquist R, Weber M, Schwenk M, Ulseth S, Helbostad JL, Vereijken B, et al. Performance-based clinical tests of balance and muscle strength used in young seniors: A systematic literature review. BMC Geriatr. 2019;19(1):1–14.

311. Das S, Bagepally BS, Eerike M, Cherian JJ, Dasgupta S, Mathews G, et al. Performance in a Balance Test and Prediction of All-Cause Mortality in Community-Dwelling Elderly Ambulatory Individuals: A Systematic Review and Meta-analysis. Res Aging. 2024;0(0):1–12.

312. Araujo CG, De Souza E Silva CG, Laukkanen JA, Fiatarone Singh M,

Kunutsor SK, Myers J, et al. Successful 10-second one-legged stance performance predicts survival in middle-aged and older individuals. Br J Sports Med. 2022;56(17):975–80.

313. Lins L, Carvalho FM. SF-36 total score as a single measure of health-related quality of life: Scoping review. SAGE Open Med. 2016;4.

314. Nilsson E, Festin K, Lowén M, Kristenson M. SF-36 predicts 13-year CHD incidence in a middle-aged Swedish general population. Qual Life Res [Internet]. 2020;29(4):971–5. Available from: https://doi.org/10.1007/s11136-019-02362-y

315. Bohannon RW, Depasquale L. Physical Functioning Scale of the Short-Form (SF) 36: Internal consistency and validity with older adults. J Geriatr Phys Ther. 2010;33(1):16–8.

316. Bassett DR, John D, Conger SA, Rider BC, Passmore RM, Clark JM. Detection of lying down, sitting, standing, and stepping using two activPAL monitors. Med Sci Sports Exerc. 2014;46(10):2025–9.

317. Stansfield B, Hajarnis M, Sudarshan R. Medical Engineering & Physics Characteristics of very slow stepping in healthy adults and validity of the activPAL3 TM activity monitor in detecting these steps. Med Eng Phys [Internet]. 2015;37(1):42–7. Available from: http://dx.doi.org/10.1016/j.medengphy.2014.10.003

318. John D, Morton A. “ What Is a Step ?” Differences in How a Step Is That Have Impacted Physical Activity Research. 2018;1–15.

319. Winkler EAH, Bodicoat DH, Healy GN, Bakrania K, Yates T, Owen N, et al. Identifying adults’ valid waking wear time by automated estimation in

activPAL data collected with a 24 h wear protocol. Physiol Meas. 2016;37(10):1653–68.

320. Leister KR, Garay J, Barreira T V. Validity of a Novel Algorithm to Detect Bedtime, Wake Time, and Sleep Time in Adults. J Meas Phys Behav. 2022;5(2):76–84.

321. Rowlands A V., Kloecker DE, Chudasama Y, Davies MJ, Dawkins NP, Edwardson CL, et al. Association of Timing and Balance of Physical Activity and Rest/Sleep With Risk of COVID-19: A UK Biobank Study. Mayo Clin Proc. 2021;96(1):156–64.

322. Toth LP, Park S, Pittman WL, Sarisaltik D, Hibbing PR, Morton AL, et al. Effects of Brief Intermittent Walking Bouts on Step Count Accuracy of Wearable Devices. 2019;13–21.

323. Takeuchi M, Sano Y. Burstiness of human physical activities and their characterisation. J Comput Soc Sci [Internet]. 2024 Mar 1;(0123456789). Available from: https://doi.org/10.1007/s42001-024-00247-w

324. Kim EK, Jo HH. Measuring burstiness for finite event sequences. Phys Rev E. 2016;94(3):1–7.

325. Culverhouse J, Hillsdon M, Pulsford R. Unravelling upright events: a descriptive epidemiology of the behavioural composition and temporal distribution of upright events in participants from the 1970 British Cohort Study. BMC Public Health [Internet]. 2024;24(1):1–15. Available from: https://doi.org/10.1186/s12889-024-17976-2

326. Shiroma EJ, Schrack JA, Harris TB. Accelerating Accelerometer Research in Aging. Journals Gerontol - Ser A Biol Sci Med Sci.

2018;73(5):619–21.

327. Homer AR, Taylor FC, Dempsey PC, Wheeler MJ, Sethi P, Townsend MK, et al. Frequency of Interruptions to Sitting Time: Benefits for Postprandial Metabolism in Type 2 Diabetes. Diabetes Care. 2021;44(6):1254–63.

328. Feng H, Yang L, Liang YY, Ai S, Liu Y, Liu Y, et al. Associations of timing of physical activity with all-cause and cause-specific mortality in a prospective cohort study. Nat Commun. 2023;14(1):1–10.

329. Albalak G, Stijntjes M, van Bodegom D, Jukema JW, Atsma DE, van Heemst D, et al. Setting your clock: associations between timing of objective physical activity and cardiovascular disease risk in the general population. Eur J Prev Cardiol [Internet]. 2023;30(3):232–40. Available from: https://doi.org/10.1093/eurjpc/zwac239

330. Granat M, Clarke C, Holdsworth R, Stansfield B, Dall P. Quantifying the cadence of free-living walking using event-based analysis. Gait Posture [Internet]. 2015;42(1):85–90. Available from: http://dx.doi.org/10.1016/j.gaitpost.2015.04.012

331. Chandola T, Jenkinson C. The new UK National Statistics Socio-Economic Classification (NS-SEC); Investigating social class differences in self-reported health status. J Public Health Med. 2000;22(2):182–90.

332. Government Statistical Service. Harmonised Concepts and Questions for Social Data Sources: Primary Standards Long-lasting Health Conditions and Illnesses ; Impairments and Disability. Office for National Statistics. 2015;

333. van der Berg JD, Stehouwer CDA, Bosma H, van der Velde JHPM, Willems PJB, Savelberg HHCM, et al. Associations of total amount and patterns of sedentary behaviour with type 2 diabetes and the metabolic syndrome: The Maastricht Study. Diabetologia. 2016;59(4):709–18.

334. Manns P, Ezeugwu V, Armijo-Olivo S, Vallance J, Healy GN. Accelerometer-derived pattern of sedentary and physical activity time in persons with mobility disability: National Health and Nutrition Examination Survey 2003 to 2006. J Am Geriatr Soc. 2015;63(7):1314–23.

335. Yerrakalva D, Cooper AJ, Westgate K, Khaw KT, Wareham NJ, Brage S, et al. The descriptive epidemiology of the diurnal profile of bouts and breaks in sedentary time in older English adults. Int J Epidemiol. 2017;46(6):1871–81.

336. Jefferis BJ, Sartini C, Shiroma E, Whincup PH, Wannamethee SG, Lee IM. Duration and breaks in sedentary behaviour: Accelerometer data from 1566 community-dwelling older men (British Regional Heart Study). Br J Sports Med. 2015;49(24):1591–4.

337. Schoenfelder A, Metcalf B, Langford J, Stathi A, Western MJ, Hillsdon M. The analytical and clinical validity of the pfSTEP digital biomarker of the susceptibility / risk of declining physical function in community-dwelling older adults. 2023;1–29.

338. Holtermann A, Krause N, Van Der Beek AJ, Straker L. The physical activity paradox: Six reasons why occupational physical activity (OPA) does not confer the cardiovascular health benefits that leisure time physical activity does. Br J Sports Med. 2018;52(3):149–50.

339. Lim ASP, Yu L, Costa MD, Leurgans SE, Buchman AS, Bennett DA, et al. Increased fragmentation of rest-activity patterns is associated with a characteristic pattern of cognitive impairment in older individuals. Sleep. 2012;35(5):633–40.

340. Edwardson CL, Winkler EAH, Bodicoat DH, Yates T, Davies MJ, Dunstan DW, et al. Considerations when using the activPAL monitor in field-based research with adult populations. J Sport Heal Sci [Internet]. 2017;6(2):162–78. Available from: http://dx.doi.org/10.1016/j.jshs.2016.02.002

341. Welk GJ, McClain J, Ainsworth BE. Protocols for evaluating equivalency of accelerometry-based activity monitors. Med Sci Sports Exerc. 2012;44(SUPPL. 1):39–49.

342. Montoye AHK, Vondrasek JD, Neph SE, Basu N, Paul L, Bachmair EM, et al. Comparison of the activPAL CREA and VANE Algorithms for Characterization of Posture and Activity in Free-Living Adults. J Meas Phys Behav. 2022;5(1):49–57.

343. de Almeida Mendes M, da Silva ICM, Ramires V V., Reichert FF, Martins RC, Tomasi E. Calibration of raw accelerometer data to measure physical activity: A systematic review. Gait Posture [Internet]. 2018;61(December 2017):98–110. Available from: https://doi.org/10.1016/j.gaitpost.2017.12.028

344. Taraldsen K, Askim T, Sletvold O, Einarsen EK, Grüner Bjåstad K, Indredavik B, et al. Evaluation of a Body-Worn Sensor System to Measure Physical Activity in Older People With Impaired Function. Phys Ther [Internet]. 2011 Feb 1;91(2):277–85. Available from:

https://academic.oup.com/ptj/article-lookup/doi/10.2522/ptj.20100159

345. Hamer M, Stamatakis E. The descriptive epidemiology of standing activity during free-living in 5412 middle-aged adults: The 1970 British Cohort Study. J Epidemiol Community Health. 2020;74(9):757–60.

346. Culverhouse J, Hillsdon M, Koster A, Bosma H, de Galan BE, Savelberg HHCM, et al. Cross-sectional associations between patterns and composition of upright and stepping events with physical function: insights from The Maastricht Study. Eur Rev Aging Phys Act [Internet]. 2024 May 9;21(1):10. Available from: https://eurapa.biomedcentral.com/articles/10.1186/s11556-024-00343-w

347. Liu F, Wanigatunga AA, Kuo PL, Zipunnikov V, Simonsick EM, Ferrucci L, et al. Association between Walking Energetics and Fragmented Physical Activity in Mid- To Late-Life. Journals Gerontol - Ser A Biol Sci Med Sci. 2021;76(10):E281–9.

348. Looman M, Feskens EJM, De Rijk M, Meijboom S, Biesbroek S, Temme EHM, et al. Development and evaluation of the Dutch Healthy Diet index 2015. Public Health Nutr. 2017;20(13):2289–99.

349. Guthold R, Stevens GA, Riley LM, Bull FC. Worldwide trends in insufficient physical activity from 2001 to 2016: a pooled analysis of 358 population-based surveys with 1·9 million participants. Lancet Glob Heal [Internet]. 2018;6(10):e1077–86. Available from: http://dx.doi.org/10.1016/S2214-109X(18)30357-7

350. Seino S, Shinkai S, Fujiwara Y, Obuchi S, Yoshida H, Hirano H, et al. Reference values and age and sex differences in physical performance

measures for community-dwelling older Japanese: A pooled analysis of six cohort studies. PLoS One. 2014;9(6).

351. Sialino LD, Schaap LA, Van Oostrom SH, Nooyens ACJ, Picavet HSJ, Twisk JWR, et al. Sex differences in physical performance by age, educational level, ethnic groups and birth cohort: The Longitudinal Aging Study Amsterdam. PLoS One [Internet]. 2019;14(12):1–12. Available from: http://dx.doi.org/10.1371/journal.pone.0226342

352. Hall KS, Hyde ET, Bassett DR, Carlson SA, Carnethon MR, Ekelund U, et al. Systematic review of the prospective association of daily step counts with risk of mortality, cardiovascular disease, and dysglycemia. Int J Behav Nutr Phys Act. 2020;17(1).

353. Del Pozo Cruz B, Ahmadi MN, Lee IM, Stamatakis E. Prospective Associations of Daily Step Counts and Intensity with Cancer and Cardiovascular Disease Incidence and Mortality and All-Cause Mortality. JAMA Intern Med. 2022;182(11):1139–48.

354. Mañas A, del Pozo Cruz B, Ekelund U, Losa Reyna J, Rodríguez Gómez I, Carnicero Carreño JA, et al. Association of accelerometer-derived step volume and intensity with hospitalizations and mortality in older adults: A prospective cohort study. J Sport Heal Sci. 2022;11(5):578–85.

355. Gonzales JU, Shephard J, Dubey N. Steps per Day, Daily Peak Stepping Cadence, and Walking Performance in Older Adults. J Aging Phys Act [Internet]. 2015 Jul;23(3):395–400. Available from: https://journals.humankinetics.com/view/journals/japa/23/3/article-p395.xml

356. Inada Y, Tohda C. Causal Relationships between Daily Physical Activity, Physical Function, and Cognitive Function Ultimately Leading to Happiness. Int J Environ Res Public Health. 2023;20(4).

357. Bohannon, Richard W. Minimal clinically important difference for grip strength : a systematic review. J Phys Ther Sci. 2019;31(1):75–8.

358. Wise RA, Brown CD. Minimal clinically important differences in the six-minute walk test and the incremental shuttle walking test. COPD J Chronic Obstr Pulm Dis. 2005;2(1):125–9.

359. Gonzalez-Bautista E, de Souto Barreto P, Salinas-Rodriguez A, Manrique-Espinoza B, Rolland Y, Andrieu S, et al. Clinically meaningful change for the chair stand test: monitoring mobility in integrated care for older people. J Cachexia Sarcopenia Muscle. 2022;13(5):2331–9.

360. Culverhouse J, Hillsdon M, Pulsford R. Cross-sectional associations between temporal patterns and composition of upright and stepping events with physical function in midlife: Insights from the 1970 British Cohort Study. Scand J Med Sci Sports [Internet]. 2024 May 12;34(5):1–16. Available from: https://onlinelibrary.wiley.com/doi/10.1111/sms.14645

361. Melsæter KN, Tangen GG, Skjellegrind HK, Vereijken B, Strand BH, Thingstad P. Physical performance in older age by sex and educational level: the HUNT Study. BMC Geriatr [Internet]. 2022;22(1):1–12. Available from: https://doi.org/10.1186/s12877-022-03528-z

362. Hollenberg M, Yang J, Haight TJ, Tager IB. Longitudinal changes in aerobic capacity: Implications for concepts of aging. Journals Gerontol - Ser A Biol Sci Med Sci. 2006;61(8):851–8.

363. MORRISSEY MC, HARMAN EA, JOHNSON MJ. Resistance training modes: specificity and effectiveness. Med Sci Sport Exerc [Internet]. 1995;27(5). Available from: https://journals.lww.com/acsm-msse/fulltext/1995/05000/resistance_training_modes__specificity_and.6.aspx

364. Sallinen J, Stenholm S, Rantanen T, Heliövaara M, Sainio P, Koskinen S. Hand-grip strength cut points to screen older persons at risk for mobility limitation. J Am Geriatr Soc. 2010;58(9):1721–6.

365. Edwardson CL, Rowlands A V., Bunnewell S, Sanders J, Esliger DW, Gorely T, et al. Accuracy of posture allocation algorithms for thigh- and waist-worn accelerometers. Med Sci Sports Exerc. 2016;48(6):1085–90.

366. Brakenridge CJ, Koster A, de Galan BE, Carver A, Dumuid D, Dzakpasu FQS, et al. Associations of 24 h time-use compositions of sitting, standing, physical activity and sleeping with optimal cardiometabolic risk and glycaemic control: The Maastricht Study. Diabetologia [Internet]. 2024; Available from: https://doi.org/10.1007/s00125-024-06145-0

Appendix

Appendix 8.1. Systematic review search strategy.

Systematic review search strategy:

Associations between physical function and device-based measures of habitual physical activity in mid- and later-life: A systematic review and meta-analysis

Terms:

1. (physical* adj2 (activ* or inactiv* or behavio* or exercis* or fitness)). ti,ab
2. (sedentary adj2 (activ* or behavio*)). ti,ab
3. (habitual* adj2 (activ* or exercise)). ti,ab
4. (sitting adj2 (time or behavio*)). ti,ab
5. energy expend*. ti,ab
6. exercis*. ti,ab

7. acceleromet*. ti,ab
8. (activity adj2 (monitor* or device*)). ti,ab
9. motion sensor*. ti,ab
10. inclinometer*. ti,ab
11. pedometer*. ti,ab
12. Heart rate. ti,ab

13. (physical* adj2 (function* or capacit* or impair* or abilit* or capabilit*)). ti,ab
14. (function* adj2 (capacit* or limitation* or impair* or status or capabilit*)). ti,ab
15. (speed* adj2 (gait or walk*)). ti,ab
16. (mobility* adj2 (capacit* or limitation* or impair* or status or capabilit*)). ti,ab
17. grip strength. ti,ab
18. balance. ti,ab
19. (transition* adj2 (sit* or stand*)). ti,ab
20. (sit* adj2 stand*). ti,ab
21. timed up and go. ti,ab

22. (observational adj2 (stud* or cohort)). ti,ab
23. (cohort ajd2 (stud* or analy*)). ti,ab
24. (follow up adj2 (stud* or analy*)). ti,ab
25. epidemiolog*. ti,ab
26. prospective. ti,ab

27. cross sectional. ti,ab

28. retrospective. ti,ab

29. longitudinal. ti,ab

Example strategy:

1 or 2 or 3 or 4 or 5 or 6

AND

7 or 8 or 9 or 10 or 11 or 12

AND

13 or 14 or 15 or 16 or 17 or 18 or 19 or 20 or 21

AND

22 or 23 or 24 or 25 or 26 or 27 or 28 or 29

Appendix 8.2. Adapted quality assessment tool.

Adapted version of The National Institutes of Health (NIH) quality assessment tool for observational cohort and cross-sectional studies
Website: https://www.nhlbi.nih.gov/health-topics/study-quality-assessment-tools

Major Components	**Response options**		
1. Was the research question or objective in this paper clearly stated?	Yes	No	Not Applicable/ Not Reported
2. Was the study population clearly specified and defined?	Yes	No	Not Applicable/ Not Reported
3. Was the participation rate of eligible persons at least 50%?	Yes	No	Not Applicable/ Not Reported
4. Were all the subjects selected or recruited from the same or similar populations (including the same time period)? Were inclusion and exclusion criteria for being in the study prespecified and applied uniformly to all participants?	Yes	No	Not Applicable/ Not Reported
5. Was a sample size justification, power description, or variance and effect estimates provided?	Yes	No	Not Applicable/ Not Reported
6. For the analyses in this paper, were the exposure(s) of interest measured prior to the outcome(s) being measured?	Yes	No	Not Applicable/ Not Reported
7. Was the timeframe sufficient so that one could reasonably expect to see an association between exposure and outcome if it existed?	Yes	No	Not Applicable/ Not Reported
8. For exposures that can vary in amount or level, did the study examine different levels of the exposure as related to the outcome (e.g., categories of exposure, or exposure measured as continuous variable)?	Yes	No	Not Applicable/ Not Reported
9. Were the exposure measures (independent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	Yes	No	Not Applicable/ Not Reported
10. Was the accelerometer protocol reported up to the standards of the Montoye et al. (2018) guidelines? Reporting of; brand, epoch, placement, days, valid hours/days, non-wear criteria, accelerometer outcomes and interpretation (e.g. MVPA and cut points used)	Yes	No	Not Applicable/ Not Reported
11. Was the exposure(s) assessed more than once over time?	Yes	No	Not Applicable/ Not Reported
12. Were the outcome measures (dependent variables) clearly defined, valid, reliable, and implemented consistently across all study participants?	Yes	No	Not Applicable/ Not Reported
13. Were the outcome assessors blinded to the exposure status of participants?	Yes	No	Not Applicable/ Not Reported
14. Was loss to follow-up after baseline 20% or less?	Yes	No	Not Applicable/ Not Reported
15. Were key potential confounding variables measured and adjusted statistically for their impact on the relationship between exposure(s) and outcome(s) – with age and sex the minimum?	Yes	No	Not Applicable/ Not Reported

Appendix 8.3. Data extraction tables.

Supplementary Table 1-3-1. Ascertainment and measurement characteristics of device-measured physical activity.

Author, Year	Device	Name/Brand	Placement	Wear days (N)	Valid day definition (h/day)	Valid days required	Wear time mean (SD) or *median [IQR]* (h/day)	PA exposure measure/s	Units	Cut-off values/definition	Mean (SD) or *median [IQR]*
Adachi 2018	A/P	Kenz Lifecorder	Waist	7	N/R	N/R	N/R	Step count	Steps/day	Device detected	6523 (2990)
								MVPA	Min/day	Device detected	17.1 (16.6)
Aggio 2016*	A	Actigraph GT3X	Hip	7	≥10	3	*Non-sarcopenia: 854.8 [850.8, 858.8], Sarcopenia: 848.4 [838.3, 858.5], Severe sarcopenia: 839.5 [821.1, 857.9]*	LPA	Min/day	100-1040 CPM	*Non-sarcopenia: 201.9 [198.1, 205.6], Sarcopenia: 196.4 [187.1, 205.7], Severe sarcopenia: 169.2 [152.5, 185.9]*
								MVPA	Min/day	>1040 CPM	*Non-sarcopenia: 42.1 [40.1, 44.0], Sarcopenia: 37.9 [32.8, 43.1], Severe sarcopenia: 19.8 [14.4, 25.1]*
Aoyagi 2009	A/P	Kenz Lifecorder	Waist	1-year	N/R	N/R	N/R	Step count	Steps/day	Device detected	6574 (2715)
								TPA (PA)	Min/day	≥3 METs	17.3 (11.9)
Cooper 2015	HR+A	CamNtech Actiheart	Chest	5	N/R	≥2	N/R	TPA (PAEE)	Min/day	Device detected	*M:* 38.1 (15.7), *F:* 34.2 (13.3)
								MVPA	kJ/kg/day	≥3 METs	*M:* 90.5 (64.9), *F:* 79.9 (54.9)
Cooper 2020	A	activPAL3 micro	Thigh	7	≥10	1	*M:* 16 (1.3), *F:* 15.7 (1.3)	TPA	Hour/day	Device detected	*M:* 2.0 (0.7), *F:* 2.0 (0.7)
								MVPA	Hour/day	≥100 step cadence threshold	*M:* 0.8 (0.4), *F:* 0.8 (0.4)
Davis 2014	A	ActiGraph GT1M	Waist	7	≥10	5	14.4 (1.4)	MVPA	Min/registered hour	>1951 CPM	0.9 (1.3)
Duck 2019	A	ActiGraph GT3X	Waist/Hip	7	≥10	4	N/R	LPA	Min/day	100-1951 CPM	114.17 (55.91)
								MPA	Min/day	1952-5724 CPM	10.88 (11.91)
								VPA	Min/day	N/R	0.52 (2.80)
								MVPA	Min/day	≥1952 CPM	11.40 (13.11)
Gobbo 2020	A	ActiGraph GT3X	Waist	5	≥10	3 (inc. 1 w/e day)	N/R	MVPA	Min/day	≥2020 CPM	21.1 (22.5)
Hall 2017	A	ActiGraph GT3X and GT3X+	Waist	7	≥10	4	14 (N/R)	Step count	Sum of steps	Device detected	N/R

Supplementary Table 1-3-1. Ascertainment and measurement characteristics of device-measured physical activity.

Author, Year	Device	Name/Brand	Placement	Wear days (N)	Valid day definition (h/day)	Valid days required	Wear time mean (SD) or *median [IQR]* (h/day)	PA exposure measure/s	Units	Cut-off values/definition	Mean (SD) or *median [IQR]*
								LPA	% of total wear time in LPA	Device detected	N/R
								MVPA	%of total wear time in MVPA	Device detected	N/R
Hsueh 2020	A	ActiGraph GT3X	Waist	7	≥10	4 (inc. 1 w/e day)	*M*: 905.7 (109.5), *F:* 925.3 (73.2) min/day	Step count	Steps/day	Device detected	*M:* 8408 (4051.7), *F:* 7079.0 (3034.2)
								TPA	Min/day	≥100 CPM	*M:* 292.0 (90.3), *F:* 326.4 (79.6)
								MVPA	Min/day	≥2020 CPM	*M:* 36.7 (27.8), *F:* 19.5 (19.1)
Izawa 2017	A	Omron HJA-750C	N/R	7	≥10	4 (inc. 1 w/e day)	N/R	MVPA (MPA)	Min/day	≥3 METs	*M:* 50.9 (37.6), *F:* 48.1 (27.3)
Jantunen 2017		Sense-Wear Pro 3 Armband	Upper Arm	10	N/R	5 (inc. 1 w/e day)	1436.8 (6.0) min/day	TPA	MET min/day	>1.5 METs	1779.6 (298.5)
								LPA	MET min/day	>1.5 to <3.0 METs	496.7 (181.6)
								MVPA	MET min/day	>3.0 METs	295.6 (230.0)
Johansson 2021	A	ActiGraph wGT3X-BT	Hip	8	≥10	4	*M:* 116.9 (17.1), *F:* 116.6 (15.6) total hours	LPA	Min/day	150-2698 CPM	*M:* 380.8(87.9), *F:* 415.6(87.3)
								MVPA	Min/day	≥2690 CPM	*M:* 41.1(32.5), *F:* 34.8(26.6)
Kim 2015	A	ActiGraph GT3X+	Wrist	8	N/R	5	N/R	TPA (PA)	counts/min/day	Mean count per minute of vector magnitude (daily total counts divided by valid wear-time)	1771.8 (520.6)
Kruger 2016	HR+A	CamNtech ActiHeart	N/R	7	N/R	4	6.97 day/week	TPA (PAEE)	kJ	Device detected	4893 (3763)
Lai 2020	A	ActiGraph GT3X+	Waist	7	≥10	4	15.4 (1.4)	MVPA	Min/day	≥2020 CPM	25.0 (26.2)
Lerma 2018	A	ActiGraph GT3X+	Hip	7	N/R	N/R	13.99 (0.13)	LPA	Min/day	100-1951 CPM	283.1 (73.3)
								MVPA	Min/day	≥1952 CPM	25.0 (20.9)
Lohne-Seiler 2016	A	ActiGraph GT1M	Hip	7	≥10	1	14.0 (1.2) h/day	Step count	Steps/day	N/R	*M:* 7356, *F:* 7551

Supplementary Table 1-3-1. Ascertainment and measurement characteristics of device-measured physical activity.

Author, Year	Device	Name/Brand	Placement	Wear days (N)	Valid day definition (h/day)	Valid days required	Wear time mean (SD) or *median [IQR]* (h/day)	PA exposure measure/s	Units	Cut-off values/definition	Mean (SD) or *median [IQR]*
Manas 2019*	A	ActiGraph GT3X and ActiTrainer	Hip	7	≥8	4	786.0 (82.6) min/day	LPA	Min/day	100-1951 CPM	226.8 (86.2)
								MVPA	Min/day	≥1952 CPM	19.4 (23.8)
Meier 2020	P	Omron HJ-321	Waist	7	N/R	N/R	94.4% had complete data	Step count	Steps/day	Device detected	4943(2632)
Mendham 2021	A	Actigraph GTX3+ and ActivPAL	Waist + Thigh	7	≥10	4	N/R	TPA	Min/day	≥100 CPM	N/R
								LPA	Min/day	100-2019 CPM	326.2 (91.0)
								MVPA	Min/day	≥2020 CPM	*9.1 [2.3, 15.9]*
Mizumoto 2015*	A/P	Kenz Lifecorder GS	Buttock	1-week	N/R	N/R	N/R	Step count	Steps/day	N/R	*Baseline:* 4244.0 (2683.3), *Follow up:* 4809.8 (3116.3)
								MVPA	Mins/day	N/R	*Baseline:* 8.7 (12.1), *Follow up:* 8.2 (9.6)
Nagai 2018*	A	TDK ActiBand	Wrist	14	≥10	4	1015 (74) min/day	LPA	Min/day	≥1.5 to <3 METs	463 (150)
								MVPA	Min/day	≥3 METs	42 (34)
Oguma 2017*	A	Kenz Lifecorder EX	Waist	7	≥10	4	N/R	Step count	Steps/day	Device detected	*2691 [1607-4423]*
								TPA (PA Index)	METh/week	Equation reported in paper	*2.6 [0.6-69]*
Osuka 2015	A	Kenz Lifecorder	Hip	7	≥10	5	875.3 (92.4) min/day	LPA	Min/day	Device detected 1.8-2.9 METs	57.1 (22.7)
								MVPA	Min/day	Device detected ≥3.6 METs	17.6 (15.3)
Pina 2021	A	Actigraph GT3X+	Hip	7	≥10	4	*Scot:* 913 (46), *SA:* 878 (80) min/day	TPA	Min/day	≥100 CPM	*Scot:* 324 (64), *SA:* 334 (96)
								LPA	Min/day	100-2019 CPM	*Scot: 287* (55), *SA:* 318 (92)
								MVPA	Min/day	≥2020 CPM	*Scot: 27 [15-44], SA: 11 [3-21]*
Reid 2016*	A	ActivPAL3	Thigh	7	≥10 + ≥80% of waking hours	N/R	15.7 (1.1)	Step count (all stepping)	Hour/day	Device detected	2.0 (0.6)
								LPA (stepping)	Hour/day	Device detected	1.0 (0.4)

Supplementary Table 1-3-1. Ascertainment and measurement characteristics of device-measured physical activity.

Author, Year	Device	Name/Brand	Placement	Wear days (N)	Valid day definition (h/day)	Valid days required	Wear time mean (SD) or *median [IQR]* (h/day)	PA exposure measure/s	Units	Cut-off values/definition	Mean (SD) or *median [IQR]*
								MVPA (stepping)	Hour/day	Device detected	1.0 (0.4)
								Sit-to-stand transitions	Transitions/day	Device detected	53.3 (14.8)
Ribeiro 2020	A	ActiGraph GT3X+	Hip	7	≥10	7	*1058.6 [1000.1-1125.7]* min/day	MVPA	Min/day min/day	Freedson	*16.1 [6.7-25.1]*
Rojer 2018	A	DynaPort MoveMonitor	Lower back	7	≥18	4	6.9 days	TPA	Min/day	N/R	271.6 (64.5)
								Step count	Steps/day	Device detected	8608.1 (2961.8)
Sanchez-Sanchez 2019	A	ActiGraph ActiTrainer	Hip	7	≥8	4	84.39 (16.03) total hours	TPA	Counts/day	≥1.5 METs	409365.6 (180677.0)
								LPA	Hour/day	1.5-2.99 METs	5.01 (1.5)
								MVPA	Hour/day	≥3 METs	1.02 (0.78)
Santos 2012	A	Actigraph GT1M	Hip	4	≥10	3 (inc 1 w/e day)	819.6 (87.5) min/day	TPA	Min/day	≥100 CPM	239.7 (100.5)
								LPA	Min/day	100-2019 CPM	213.8 (88.7)
								MVPA	Min/day	≥2020 CPM	26.0 (24.1)
Savikangas 2020	A	UKK RM42	Waist	7	≥10	3	14.1 (1.3)	LPA	Min/day	≥0.0167 to <0.091g	210.3 (66.3)
								MVPA	Min/day	≥0.091g	32.5 (20.1)
Schrack 2019	A	CamNtech Actiheart	Chest	7	95% of data	3	N/R	TPA	Total log activity counts	Device detected	*Low ASTP:* 53009.04 (25578.54), *Mid ASTP:* 35114.73 (13698.46), *High ASTP:* 21675.93 (11309.85)
Spartano 2019	A	Actical (model no. 198-0200-00)	Hip	8	≥10	4	749 (71) mins/d	Step count	Steps/day	Device detected	6927 (3678)
								MVPA	Min/day	>1486 CPM	19 (22)
Thiebaud 2020*	A	Lifecorder EX	Hip	30	>12	N/R	N/R	LPA	Min/day	<3 METs	60.1 (18.9)
								MPA	Min/day	3-6 METs	21.2 (14.0)
								VPA	Min/day	>6 METs	1.9 (2.0)
van der Velde 2017	A	ActivPAL3	Thigh	8	≥10	1	15.7 (0.9)	TPA	Hour/day	Device detected	2.0 (0.7)
								High intensity PA	Min/day	Device detected (≥110 step/min)	*19.2 [9.6-32.0]*

Supplementary Table 1-3-1. Ascertainment and measurement characteristics of device-measured physical activity.

Author, Year	Device	Name/Brand	Placement	Wear days (N)	Valid day definition (h/day)	Valid days required	Wear time mean (SD) or *median [IQR]* (h/day)	PA exposure measure/s	Units	Cut-off values/definition	Mean (SD) or *median [IQR]*
Ward-Ritacco 2014	A	New Lifestyles-1000	Hip	7 to 10	≥10	4	N/R	Step count	Steps/day	Device detected	9076.2 (3822)
								MVPA	Min/day	≥3.6 METs	30.0 (20.8)
Ward-Ritacco 2020	A	ActiGraph GT9X	Hip	7 to 10	≥10	4	N/R	Step count	Steps/day	Device detected	7711 (2838)
Westbury 2018	A	GENEActiv	Wrist	7	N/R	7	N/R	TPA	Min/day	≥40mg	*M: 137.8 [81.7, 217.2], F: 186.0 [122.1, 240.4]*
								MVPA	Min/day	≥100mg	*M: 14.3 [1.8, 30.2], F: 9.5 [2.1, 18.6]*
Yamada 2011*	P	Yamax PowerWalker EX-510	Pocket	14	N/R	N/R	N/R	Step count	Steps/day	TPA ≥40	4414.4 (2726.3)
Yasunaga 2017	A	Omron HJA-350IT	Waist	7	≥10	4 (inc. 1 w/e day)	901.1 (87.5) min/day	LPA	Min/day	>1.5 to <3.0METs	328.7 (101.4)
								MVPA	Min/day	≥3METs	50.2 (33.5)
Yerrakalva 2022	A	*Baseline:* ActiGraph GT1M *Follow-up:* GT3X	Hip	7	≥10	4	N/R	TPA	Min/day	≥100cpm	251 (117)
								LPA	Min/day	100-808cpm	224.9 (56.5)
								MVPA	Min/day	≥809cpm	77.4 (46.3)

*Asterisk denotes not included in meta-analyses, N/A = not applicable, N/R = not reported, A = accelerometer, P = pedometer, HR= heart rate, PA = physical activity LPA = light intensity physical activity, MVPA = moderate-to-vigorous physical activity, Steps = average or total step count, TPA = total physical activity, MET = metabolic equivalent of task, PAEE = physical activity energy expenditure, kJ = kilojoule, CPM = counts per minute

Supplementary Table 1-3-2. Ascertainment and measurement characteristics of performance-based physical function outcomes.

Author, Year	Measure	Device	Definition and protocol	Units	Mean (SD)
Adachi 2018	Gait	N/A	Usual gait over 10-m; faster of 2 attempts. Slow Gait <1.0m/s	n	*N*=41 (13.3%)
Aggio 2016*	Gait	N/A	Gait over 3-m	Meters/s	*Non-sarcopenia:* 0.95 (0.2), *Sarcopenia:* 0.82 (0.2), *Severe sarcopenia:* 0.62 (0.1)
	HGS	Jamar hydraulic dynamometer	3 attempts with each hand, max used	kg	*Non-sarcopenia:*32.3 (9.9), *Sarcopenia:*28.7 (10.1), *Severe sarcopenia:* 22.2 (6.1)
Aoyagi 2009	Gait	GaitScan8000 Pressure sensors	Usual gait over 5-m	Meters/s	1.43 (0.22)
	HGS	Smedley dynamometer	2 attempts with dominant hand, max used	Newtons	262 (83)
	Balance	Force platform (G-5500)	Stand eyes-open 30s, then closed 30s. Total movement of CoG in horizontal axis was measured over 30s (body sway)	Meters	*Eyes open:* .45 (.17), *Eyes closed:* .94 (.39)
Cooper 2015	HGS	Nottingham electronic dynamometer	3 attempts with each hand, max used	kg	*M:* 46.4 (11.5), *F:* 27.0 (7.5)
	Chair rise	N/A	Time to complete 10 chair rises.	Stands/min	*M:* 26.2 (7.3), *F:* 24.9 (7.3)
	TUG	N/A	Time taken to rise from a chair, walk 3-m, return, and sit back down	Meters/s	*M:* 0.7 (0.2), *F:* 0.7 (0.1)
	Balance	N/A	Time (up to max of 30s) participant could maintain one-legged stand eyes closed	ln/s	*M:* 1.6 (0.6), *F:* 1.6 (0.5)
Cooper 2020	HGS	Smedley dynamometer	Up to 3 attempts with each hand, max used	kg	*M:* 48.2 (8.8), *F:* 29.9 (5.6)
Davis 2014	Gait	N/A	Usual gait over 3 or 4 -m	Score (0-4)	3.5 (0.8)
	Chair rise	N/A	Time to complete 5 chair rises	Score (0-4)	2.7 (1.3)
	Balance	N/A	Ability to maintain tandem, semi, and side-by-side stance for 10s	Score (0-4)	3.6 (0.8)
Duck 2019	TUG	N/A	Time taken to rise from a chair, walk 10-m, return, and sit back down	Score	9.11 (2.93)
	Balance	Berg Balance Scale	14-item instrument, with each item rated 0 (poor balance) to 4 (better balance)	Seconds	50.35 (6.05)
Gobbo 2020	Gait	N/A	2 attempts at gait over 4-m, max used	Meters/s	1.0 (0.2)
	HGS	Camry digital dynamometer model EH101	2 attempts with dominant hand, max used	kg	26.2 (8.2)
	TUG	N/A	Time taken to rise from a chair, walk 3-m, return, and sit back down	Seconds	9.6 (2.4)
Hall 2017	Gait	N/A	2 attempts at gait over 4-m, max used	Meters/s	†
	Chair rise	N/A	No. of chair rises completed in 30-s	n	†
	Walk	N/A	*6MWT:* Distance covered in 6-min walking	Yards	†
	Balance	N/A	Duration of single-leg stance, eyes-open (up to 60s)	Seconds	†
Hsueh 2020	Gait	N/A	Gait over 11-m (central 5-m used)	Seconds	*M:* 2.89 (1.08) *F:* 3.11 (0.71)

Supplementary Table 1-3-2. Ascertainment and measurement characteristics of performance-based physical function outcomes.

Author, Year	Measure	Device	Definition and protocol	Units	Mean (SD)
	HGS	Jamar Plus+ digital dynamometer	2 attempts with both hands, max used	kg	*M:* 33.3 (6.5) *F:* 21.4 (3.5)
	Chair rise	N/A	Time taken to complete 5 chair rises	Seconds	*M:* 7.54 (2.16) *F:* 7.45 (2.70)
	TUG	N/A	Time taken to rise from a chair, walk 3-m, return, and sit back down	Seconds	*M:* 7.13 (2.90) *F:* 7.20 (1.82)
	Balance	N/A	Duration of single leg stance (up to 60s), eyes open, 2 attempts	Seconds	*M:* 39.6 (23.8) *F:* 34.8 (23.0)
Izawa 2017	Gait	N/A	2 attempts at gait over 5-m, max used	Meters/s	*M:*1.8 (0.3), *F:* 1.7 (0.3)
	TUG	N/A	Time taken to rise from a chair, walk 3-m, return, and sit back down	Seconds	*M:* 6.1 (1.2), *F:* 6.5 (1.4)
	Balance	N/A	Duration of single leg stance (up to 60s), eyes open, 2 attempts	Seconds	*M:* 41.8 (21.6), *F:* 44.2 (22.1)
Jantunen 2017	Chair rise	N/A	No. of chair rises completed in 30-s	n	11.5 (2.3)
	Walk	N/A	*6MWT:* Distance covered in 6-min walking	Meters	584.8 (103.6)
	SFT	N/A	Senior Fitness test battery, composite score of 5 tests	Score	46.4 (17.5)
Johansson 2021	HGS	Jamar Plus+ Digital hand Dynamometer	3 attempts with each hand, max used	kg	N/R
	Chair rise	N/A	Time taken to complete 5 chair rises, two attempts, max used	Seconds	N/R
Kim 2015	Gait	N/A	Gait over 11-m (central 5-m used)	Meters/s	1.20 (0.25)
	HGS	Smedley dynamometer	3 attempts, max used	kg	23.4 (7.5)
Kruger 2016	Gait	N/A	Gait over 6-m	Meters/s	1.36 (0.33)
	HGS	Jamar dynamometer	3 attempts with dominant hand, max used	kg	20.4 (6.7)
Lai 2020	Gait	N/A	Gait over 11-m (central 5-m used)	Seconds	N/R
	HGS	Jamar Plus+ dynamometer	3 attempts with both hands, max used	kg	N/R
	Chair rise	N/A	Time taken to complete 5 chair rises, two attempts, max used, two attempts, fastest used	Seconds	N/R
	TUG	N/A	Time taken to rise from a chair, walk 3-m, return, and sit back down, 2 attempts, max used	Seconds	N/R
Lerma 2018	Gait	N/A	2 attempts at gait, faster used	Meters/s	1.1 (0.3)
	Chair rise	N/A	Time taken to complete 5 chair rises, two attempts, max used, two attempts, fastest used	Seconds	15.2 (4.8)
	Walk	N/A	*400mWT:* Time taken to walk 400-m	Meters/s	1.4 (0.3)
	SPPB	N/A	SPPB	Score	9.8 (1.6)

Supplementary Table 1-3-2. Ascertainment and measurement characteristics of performance-based physical function outcomes.

Author, Year	Measure	Device	Definition and protocol	Units	Mean (SD)
Lohne-Seiler 2016	HGS	Chattanooga dynamometer	3 attempts with dominant hand, max used	kg	*Mean {95%CIs}:* 33.5 {32.3, 34.8}
	Balance	N/A	Duration of single leg stance, eyes open	Seconds	*Mean {95%CIs}:* 19.5 {16.7, 22.2}
Manas 2019*	SPPB	N/A	SPPB	Score	8.4 (3.2)
Meier 2020	Gait	N/A	Gait over 4-m	Meters/s	1.1(0.2)
	HGS	Jamar Plus+ dynamometer	3 attempts with each hand, max used	kg	29.9(10.3)
Mendham 2021	Gait	N/A	Gait over 12-m (central 10-m used)	Meters/s	1.5 (0.3)
	HGS	T.K.K. 5401, Grip-D, Takei	3 attempts with non-dominant hand, max used	kg	19.6 (4.5)
	Walk	N/A	*6MWT:* Distance covered in 6-min walking	Meters	*450 [395, 490]*
	TUG	N/A	Time taken to rise from a chair, walk 3-m, return, and sit back down	Seconds	*6.9 [6.2, 8.1]*
Mizumoto 2015*	Gait	Walk Way MW-1000 pressure sensor	Gait over 2.4-m (central 2-m used) on a pressure sensor, mean of 5 attempts	Dichotomous	N/R
	HGS	Smedley-type dynamometer	2 attempts with dominant hand, max used	Dichotomous	N/R
Nagai 2018*	Gait	N/A	Gait over 12-m (first 10-m used)	Meters/s	1.4 (0.3)
	HGS	Smedley dynamometer	N/R	kg	26.7 (7.6)
Oguma 2017*	HGS	Tanita 6103 dynamometer	2 attempts with dominant hand, max used	kg	19.0 (4.9)
	Chair rise	N/A	N/R	Stands/30s	*11 [9-13]*
	TUG	N/A	N/R	Seconds	*12.1 [9.9-15.9]*
	Balance	N/A	One leg standing test, eyes open	Seconds	*4.0 [2.5-6.5]*
Osuka 2015	Chair rise	N/A	Average of 2 attempts, time taken to complete 5 chair rises	Seconds	*6.8*
	TUG	N/A	Average of 2 attempts, time taken to rise from a chair, walk 3-m, return, and sit back down	Seconds	*6.3*
	Balance	N/A	Average of 2 attempts, single leg stance, eyes open, up to 60s	Seconds	*38.9*
Pina 2021	Gait	N/A	Gait over 10-m (central 6-m used)	Meters/s	*Scot: 1.5 [1.4, 1.7], SA: 1.6 [1.4, 1.7]*
	HGS	*Scot:* T.K.K.5001, Grip-A, Takei. *SA:* T.K.K. 5401, Grip-D	3 attempts with non-dominant hand, max used	kg	*Scot: 23.0 [19.5, 27.5], SA: 20.1 [17.0, 23.8]*
Reid 2016*	TUG	N/A	Time taken to rise from a chair, walk 8-ft, return, and sit back down	Seconds	*5.6 [4.9, 6.5]*
Ribeiro 2020	PF composite score	TKK dynamometer	Composite score between 0-16 was derived from the following tests: 5x Chair rise, HGS, 6MWT, sit-and-reach	Score	*10.0 [8.0-12.0]*
Rojer 2018	Gait	N/A	Gait over 4-m, faster of two attempts used	Meters/s	1.43 (0.21)
	HGS	Jamar dynamometer	3 attempts with each hand, max used	kg	35.1 (11.0)
Sanchez-Sanchez 2019	Gait	N/A	2 attempts, gait over 3-m, fastest used	Meters/s	0.73 (0.26)
	HGS	Jamar dynamometer	3 attempts with dominant hand, max used	kg	22.26 (8.21)
Santos 2012	Chair rise	N/A	No. of chair rises completed in 30-s	n	13.7 (4.7)
	Walk	N/A	*6MWT:* Distance covered in 6-min walking	Meters	450.2 (148.4)
	TUG	N/A	Time taken to rise from a chair, walk 8-ft, return, and sit back down	Seconds	8.5 (5.7)

Supplementary Table 1-3-2. Ascertainment and measurement characteristics of performance-based physical function outcomes.

Author, Year	Measure	Device	Definition and protocol	Units	Mean (SD)
Savikangas 2020	Gait	N/A	Gait over 10-m	Meters/s	1.98 (0.38)
	Walk	N/A	*6MWT:* Distance covered in 6-min walking	Meters	477.55 (82.56)
	SPPB	N/A	SPPB	Score	10.19 (1.54)
Schrack 2019	Gait	N/A	Gait over 6-m	Meters/s	*Mid ASTP:* 1.21 (0.22)
	Walk	N/A	*400mWT:* Time taken to walk 400-m at a fast pace	Seconds	*Mid ASTP:* 264.84 (51.51
	ExSPPB	N/A	ExSPPB	Score	*Mid ASTP:* 2.99 (0.53)
Spartano 2019	Gait	N/A	Gait: faster of two trials over 4m course	Meters/s	1.17 (0.19)
	HGS	Jamar dynamometer	3 attempts with each hand, max used	kg	*M:* 39.1 (8.7), *F:* 23.3 (5.7)
	Chair rise	N/A	Time taken to complete 5 chair rises	Seconds	9.9 (2.6)
Thiebaud 2020*	Gait	N/A	Gait over 24-m (central 20-m used)	Seconds	1.56 (0.18)
van der Velde 2017	HGS	Jamar dynamometer	3 attempts with each hand, max used	kg	35.7 (10.6)
	Chair rise	N/A	Time taken to complete 10 chair rises	Seconds	23.8 (5.5)
	Walk	N/A	*6MWT:* Distance covered in 6-min walking	Meters	585.1 (80.5)
Ward-Ritacco 2014	Chair rise	N/A	No. of chair rises completed in 30-s	n	21.8 (6.9)
	Walk	N/A	*6MWT:* Distance covered in 6-min walking	Meters	651.5 (104.2)
	TUG	N/A	Time taken to rise from a chair, walk 8-ft, return, and sit back down	Seconds	4.5 (0.8)
Ward-Ritacco 2020	Chair rise	N/A	No. of chair rises completed in 30-s	n	20.00 (5.00)
	Walk	N/A	*6MWT:* Distance covered in 6-min walking	Meters	565.8 (68.5)
	TUG	N/A	Time taken to rise from a chair, walk 8-ft, return, and sit back down	Seconds	5.35 (0.86)
Westbury 2018	Gait	N/A	Gait over 3-m	Meter/s	1.0 (0.2)
	HGS	Jamar dynamometer	3 attempts with each hand, max used	kg	24.1 (8.4)
Yamada 2011*	Gait	N/A	Gait over 10-m	Seconds	9.9 (2.2)
	Chair rise	N/A	Time taken to complete 5 chair rises	Seconds	8.9 (3.6)
	TUG	N/A	N/R	Seconds	8.8 (2.1)
	Balance	N/A	Time participant could maintain one-legged stand (hands on waist)	Seconds	13.3 (12.1)
Yasunaga 2017	Gait	N/A	Gait over 11-m (central 5-m used), fastest of 2 attempts	Meters/s	1.3 (0.2)
	HGS	Smedley-type dynamometer	1 attempt with dominant hand	kg	27.4 (8.3)
	TUG	N/A	Time taken to rise from a chair, walk 3-m, return, and sit back down, fastest of 2 attempts	Seconds	6.2 (1.2)
	Balance	N/A	Time (up to max of 60s) participant could maintain one-legged stand eyes open, best of 2 attempts	Seconds	42.9 (21.7)
Yerrakalva 2022	Gait	N/A	Gait over 5-m (first 4-m used)	cm/s	111.4 (25.0)
	HGS	Smedley dynamometer	2 attempts with both hands, max used	kg	28.9 (10.3)
	Chair rise	N/A	Time take to complete 5 chair rises	Stands/min	27.7 (7.7)

*Asterisk denotes not included in meta-analyses, N/A = not applicable, N/R = not reported, HGS = handgrip strength, Gait = gait speed, TUG = timed up-and-go test, 6MWT = 6-minute walk test, 400mWT = 400-meter walk test, kg = kilograms, SPPB = short physical performance battery, M = male, F = female, PF = physical function.
† = reported across six age bands

Supplementary Table 1-3-3. Associations between device-measured physical activity metrics with performance-based physical function outcomes.

Author, Year	PA exposure measure/s	PF outcome measure/s	Adjustment	Effect size (95%CI) or [SE]	p-value
Adachi et al 2018	Step count	Gait	Age + additional	OR = 0.94 (0.73,1.21)	0.695
	MVPA	Gait	Age + additional	OR = 0.94 (0.73,0.99)	**0.031**
Aggio 2016*	LPA	Gait	Age + additional	B = 0.02 (0.02, 0.03)	**<0.001**
	LPA	HGS	Age + additional	B = 0.21 (-0.06, 0.48)	0.125
	MVPA	Gait	Age + additional	B = 0.03 (0.02, 0.03)	**<0.001**
	MVPA	HGS	Age + additional	B = 0.58 (0.34, 0.82)	**<0.001**
Aoyagi 2009	Step count	Gait	Age and/or sex	R = 0.31	**<0.05**
	Step count,	HGS	Age and/or sex	R = 0.12	>0.05
	Step count,	Balance	Age and/or sex	R = -0.14, -0.15	>0.05
	TPA (PA >3METs)	Gait	Age and/or sex	R = 0.34	**<0.05**
	TPA (PA >3METs)	HGS	Age and/or sex	R = 0.12	>0.05
	TPA (PA >3METs)	Balance	Age and/or sex	R = -0.13, -0.13	>0.05
Cooper 2015	TPA (PAEE)	HGS	Sex	β‡ = 0.632 (0.158, 1.105)	**<0.05**
	TPA (PAEE)	Chair rise	Sex	β‡ = 0.943 (0.594, 1.292)	**<0.05**
	TPA (PAEE)	TUG	Sex	β‡ = 0.029 (0.021, 0.036)	**<0.05**
	TPA (PAEE)	Balance	Sex	β‡ = 0.073 (0.047, 0.099)	**<0.05**
	MVPA	HGS	Sex	β‡ = 0.638 (0.166, 1.110)	**<0.05**
	MVPA	Chair rise	Sex	β‡ = 0.670 (0.321, 1.018)	**<0.05**
	MVPA	TUG	Sex	β‡ = 0.023 (0.016, 0.031)	**<0.05**
	MVPA	Balance	Sex	β‡ = 0.036 (0.010, 0.062)	**<0.05**
Cooper 2020	TPA	HGS	Sex + additional	B = 0.60 (0.30, 0.90)	N/R
	MVPA	HGS	Additional	*M:* B = −1.17 (−2.01, −0.33), *F:* B = 0.73 (0.19, 1.27)	N/R, N/R
Davis 2014	MVPA	Gait	Age, sex + additional	B = 0.659 (0.398, 0.920)	**<0.001**
	MVPA	Chair rise	Age, sex + additional	B = 0.851 (0.429, 1.272)	**<0.001**
	MVPA	Balance	Age, sex + additional	B = 0.269 (0.005, 0.532)	**0.046**
Duck 2019	LPA	TUG	Unadjusted	R = −0.404	**<0.01**
	LPA	Balance	Age, sex + additional	B = 0.013 (0.011), β = 0.146	Non-sig.
	MPA	TUG	Unadjusted	R = -0.363	**<0.01**
	MPA	Balance	Age, sex + additional	B = -0.006 (0.049), β = -0.013	Non-sig.
	VPA	TUG	Unadjusted	R = −0.105	**<0.01**
	VPA	Balance	Unadjusted	R = 0.091	Non-sig.
	MVPA	TUG	Unadjusted	R = -0.337	N/R
	MVPA	Balance	Unadjusted	R = 0.270	N/R
Gobbo 2020	MVPA	Gait	Age + additional	*M:* B = 0.01 (-0.00, 0.02), *F:* B = 0.00 (-0.00, 0.00)	>0.05, >0.05
		HGS	Age + additional	*M:* B = -0.08 (-0.21, 0.04), *F:* B = -0.05 (-0.14, 0.03)	>0.05, >0.05
		TUG	Age + additional	*M:* B = -0.02 (-0.14, 0.09), *F:* B = 0.02 (-0.09, 0.14)	>0.05, >0.05
Hall 2017	Step count	Gait	Unadjusted	R†	N/A
	Step count	Chair rise	Unadjusted	R†	N/A
	Step count	Walk	Unadjusted	R†	N/A
	Step count	Balance	Unadjusted	R†	N/A

Supplementary Table 1-3-3. Associations between device-measured physical activity metrics with performance-based physical function outcomes.

Author, Year	PA exposure measure/s	PF outcome measure/s	Adjustment	Effect size (95%CI) or [SE]	p-value
	LPA	Gait	Unadjusted	R†	N/A
	LPA	Chair rise	Unadjusted	R†	N/A
	LPA	Walk	Unadjusted	R†	N/A
	LPA	Balance	Unadjusted	R†	N/A
	MVPA	Gait	Unadjusted	R†	N/A
	MVPA	Chair rise	Unadjusted	R†	N/A
	MVPA	Walk	Unadjusted	R†	N/A
	MVPA	Balance	Unadjusted	R†	N/A
Hsueh 2020	Step count	Gait	Age + additional	*M:* β = −0.19 (−0.60, 0.22), *F:* β = −0.31 (−0.57, −0.001)	0.35, **0.049**
	Step count	HGS	Age + additional	*M:* β = 0.04 (−0.44, 0.51), *F:* β = 0.46 (0.12, 0.78)	0.87, **0.009**
	Step count	Chair rise	Age + additional	*M:* β = 0.30 (−0.36, 0.96), *F:* β = −0.35 (−0.70, 0.01)	0.36, 0.05
	Step count	TUG	Age + additional	*M:* β = −0.09 (−0.50, 0.32), *F:* β = −0.20 (−0.50, 0.12)	0.66, 0.22
	Step count	Balance	Age + additional	*M:* β = 0.16 (−0.32, 0.63), *F:* β = 0.26 (−0.04, 0.55)	0.50, 0.09
	TPA	Gait	Age + additional	*M:* β = −0.24 (−0.64, 0.17), *F:* β = −0.11 (−0.36, 0.16)	0.23, 0.44
	TPA	HGS	Age + additional	*M:* β = 0.07 (−0.39, 0.53), *F:* β = 0.21 (−0.10, 0.52)	0.75, 0.19
	TPA	Chair rise	Age + additional	*M:* β = −0.13 (−0.78, 0.52), *F:* β = −0.23(−0.54, 0.10)	0.69, 0.17
	TPA	TUG	Age + additional	*M:* β = −0.30 (−0.69, 0.10), *F:* β = −0.15 (−0.42, 0.13)	0.14, 0.31
	TPA	Balance	Age + additional	*M:* β = 0.23 (−0.23, 0.68), *F:* β = 0.06 (−0.21, 0.33)	0.31, 0.67
	MVPA	Gait	Age + additional	*M:* β = −0.24 (−0.57, 0.08), *F:* β = −0.12 (−0.36, 0.11)	0.13, 0.29
	MVPA	HGS	Age + additional	*M:* β = 0.07 (−0.31, 0.45), *F:* β = 0.39 (0.12, 0.64)	0.70, **0.004**
	MVPA	Chair rise	Age + additional	*M:* β = 0.05 (−0.50, 0.60), *F:* β = −0.22 (−0.49, 0.05)	0.85, 0.11
	MVPA	TUG	Age + additional	*M:* β = −0.19 (−0.51, 0.14), *F:* β = −0.13 (−0.37, 0.12)	0.24, 0.32
	MVPA	Balance	Age + additional	*M:* β = 0.23 (−0.15, 0.59), *F:* β = 0.25 (0.02, 0.49)	0.23, **0.036**
Izawa 2017	MVPA (MPA)	Gait	Age + additional	*M:* β = 0.310 (0.001, 0.004), *F:* β = 0.396, (0.002, 0.006)	**0.001**, **0.001**
	MVPA (MPA)	TUG	Age + additional	*M:* β = -0.321 (-0.015, -0.006), *F:* β = -0.473 (-0.031, -0.014)	**0.001, 0.001**
	MVPA (MPA)	Balance	Age + additional	*M:* β = 0.217 (0.042, 0.208), *F:* β = 0.252 (0.048, 0.355)	**0.003**, **0.011**
Jantunen 2017	TPA	Chair rise	Age, sex	β = 0.06 (0.05, 0.07)	**<0.001**
	TPA	Walk	Age, sex	β = 0.09 (0.08, 0.10)	**<0.001**
	TPA	SFT	Age, sex	β = 0.08 (0.07, 0.10)	**<0.001**
	LPA	SFT	Age, sex	β = 0.09 (0.07, 0.12)	**<0.001**
	MVPA	SFT	Age, sex	β = 0.10 (0.08, 0.11)	**<0.001**
Johansson 2021	LPA	HGS	Age	N/R	N/R
	LPA	Chair rise	Age	N/R	N/R
	MVPA	HGS	Age	*M:* β = -0.09, *F:* β = 0.08	**<0.001, 0.001**
	MVPA	Chair rise	Age	*M:* β = 0.31, *F:* β = -0.26	**<0.001, <0.001**
Kim 2015	TPA (PA)	Gait	Age, sex	R_s = 0.231	**0.001**
	TPA (PA)	HGS	Age, sex	R_s = 0.081	0.251
Kruger 2016	TPA (PAEE)	Gait	Age + additional	β = 0.15	**0.04**
	TPA (PAEE)	HGS	Age + additional	β = 0.07	0.45
Lai 2020	MVPA	Gait	Age, sex + additional	B = −0.061 (−0.091, −0.031)	**<0.001**
	MVPA	HGS	Age, sex + additional	B = 0.045 (0.017, 0.072)	**0.002**

Supplementary Table 1-3-3. Associations between device-measured physical activity metrics with performance-based physical function outcomes.

Author, Year	PA exposure measure/s	PF outcome measure/s	Adjustment	Effect size (95%CI) or [SE]	p-value
	MVPA	Chair rise	Age, sex + additional	B = −0.037 (−0.081, 0.006)	0.094
	MVPA	TUG	Age, sex + additional	B = −0.045 (−0.079, −0.011)	**0.009**
Lerma 2018	LPA	Gait	Age, sex + additional	B = 0.026 (-0.014, 0.066)	>0.05
	LPA	Chair rise	Age, sex + additional	B = −0.622 (-1.349, 0.104)	>0.05
	LPA	Walk	Age, sex + additional	B = 0.064 (0.013, 0.116)	**<0.05**
	LPA	SPPB	Age, sex + additional	B = 0.430 (-0.015, 0.876)	>0.05
	MVPA	Gait	Age, sex + additional	B = 0.295 (0.146, 0.444)	**<0.05**
	MVPA	Chair rise	Age, sex + additional	B = -4.433 (−7.217, −1.650)	**<0.05**
	MVPA	Walk	Age, sex + additional	B = 0.407 (0.219, 0.595)	**<0.05**
	MVPA	SPPB	Age, sex + additional	B = 3.233 (1.045, 5.422)	**<0.05**
Lohne-Seiler 2016	Step count	HGS	Age, sex + additional	B = -0.133^^^ (-0.61, 0.34)	>0.05
	Step count	Balance	Age, sex + additional	B = 1.88 (0.85, 2.90)	**<0.05**
Manas 2019*	LPA (SB ratio)	SPPB	Age, sex + additional	B = 0.96 (0.09, 1.82)	**0.03**
	MVPA (SB ratio)	SPPB	Age, sex + additional	B = 0.03 (0.02, 0.04)	**< 0.001**
Meier 2020	Step count	Gait	Age, sex + additional	β = 0.01 [0.004]	0.05
	Step count	HGS	Age, sex + additional	β = 0.01 [0.16]	0.53
Mendham 2021	TPA	Gait	Age	N/R	N/R
	TPA	HGS	Age	N/R	N/R
	TPA	Walk	Age	N/R	N/R
	TPA	TUG	Age	N/R	N/R
	LPA	Gait	Age	N/R	N/R
	LPA	HGS	Age	N/R	N/R
	LPA	Walk	Age	N/R	N/R
	LPA	TUG	Age	N/R	N/R
	MVPA	Gait	Age	N/R	N/R
	MVPA	HGS	Age	N/R	N/R
	MVPA	Walk	Age	N/R	N/R
	MVPA	TUG	Age	N/R	N/R
Mizumoto 2015*	Step count	Gait	Age, sex + additional	OR = 1.72 (0.77, 3.86)	>0.05
	Step count	HGS	Age, sex + additional	OR = 2.89 (1.10, 7.58)	**<0.05**
	MVPA	Gait	Age, sex + additional	OR = 0.74 (0.33, 1.64)	>0.05
	MVPA	HGS	Age, sex + additional	OR = 1.86 (0.71, 4.89)	>0.05
Nagai 2018*	LPA	Gait	Unadjusted	R_{pb} = -0.30	**<0.01**
	LPA	HGS	Unadjusted	R_{pb} = -0.16	**<0.01**
	MVPA	Gait	Unadjusted	R_{pb} = -0.17	**<0.01**
	MVPA	HGS	Unadjusted	R_{pb} = -0.12	**<0.01**
Oguma 2017*	Step count	HGS	Unadjusted	R_s = 0.24	**0.003**
	Step count	Chair rise	Unadjusted	R_s = 0.35	**<0.001**
	Step count	TUG	Unadjusted	R_s = -0.51	**<0.001**
	Step count	Balance	Unadjusted	R_s = 0.32	**<0.001**
	TPA (PA Index)	HGS	Unadjusted	R_s = 0.28	**<0.001**
	TPA (PA Index)	Chair rise	Unadjusted	R_s = 0.39	**<0.001**
	TPA (PA Index)	TUG	Unadjusted	R_s = -0.56	**<0.001**

Supplementary Table 1-3-3. Associations between device-measured physical activity metrics with performance-based physical function outcomes.

Author, Year	PA exposure measure/s	PF outcome measure/s	Adjustment	Effect size (95%CI) or [SE]	p-value
	TPA (PA Index)	Balance	Unadjusted	$R_s = 0.34$	**<0.001**
Osuka 2015	LPA	Chair rise	Age, sex + additional	β = -0.07	**0.047**
	LPA	TUG	Age, sex + additional	β = -0.08	**0.013**
	LPA	Balance	Unadjusted	$R_s = 0.23$	**<0.001**
Pina 2021	LPA	Gait	Age, sex + additional	γ = −0.012	0.876
	LPA	HGS	Age, sex + additional	γ = −0.045	0.644
	MVPA	Gait	Age, sex + additional	γ = 0.007	0.773
	MVPA	HGS	Age, sex + additional	γ = 0.097	**0.001**
Reid 2016*	Step count (All stepping)	TUG	Age, sex + additional	RR = 0.98 (0.95, 1.02)	0.341
	LPA (Light stepping)	TUG	Age, sex + additional	RR = 0.98 (0.93, 1.03)	0.378
	MVPA (MVPA stepping)	TUG	Age, sex + additional	RR = 0.97 (0.92, 1.03)	0.383
	Sit-to-stand transitions	TUG	Age, sex + additional	RR = 1.00 (1.00, 1.00)	0.961
Ribeiro 2020	Active/Inactive	PF composite score	Age, sex + additional	OR = 1.81 (0.95, 3.46)	0.074
Rojer 2018	TPA	HGS	Age, sex	*Y:* B = 0.001 [0.001] *O:* B = 0.002 [0.001]	>0.05, >0.05
	TPA	Gait	Age, sex	*Y:* B = 0.001 [0.001] *O:* B = 0.005 [0.002]	>0.05, **<0.05**
	Step count	HGS	Age, sex	*Y:* B = 0.051 [0.024] *O:* B = 0.052 [0.038]	**<0.05**, >0.05
	Step count	Gait	Age, sex	*Y:* B = 0.026 [0.027] *O:* B = 0.182 [0.041]	>0.05, **<0.05**
Sanchez-Sanchez 2019	TPA	Gait	Age, sex + additional	B = 0.041 (0.019, 0.063)	**<0.001**
	TPA	HGS	Age, sex + additional	B = 0.857 (0.312, 1.402)	**<0.01**
	LPA	Gait	Age, sex + additional	B = -0.006 (-0.021, 0.009)	>0.05
	LPA	HGS	Age, sex + additional	B = 0.428 (0.051, 0.805)	**<0.05**
	MVPA	Gait	Age, sex + additional	B = 0.070 (0.043, 0.097)	**<0.001**
	MVPA	HGS	Age, sex + additional	B = 0.933 (0.246, 1.620)	**<0.01**
Santos 2012	MVPA	Chair rise	Age, sex + additional	B = 0.035 (0.014, 0.055)	N/R
		Walk	Age, sex + additional	B = 1.770 (1.178, 2.632)	N/R
		TUG	Age, sex + additional	B = -0.023 (-0.049, 0.003)	N/R
Savikangas 2020	LPA	Gait	Age, sex	R = 0.203	**<0.01**
	LPA	Walk	Age, sex	R = 0.279	**<0.001**
	LPA	SPPB	Age, sex	R = 0.145	**<0.01**
	MVPA	Gait	Age, sex	R = 0.315	**<0.001**
	MVPA	Walk	Age, sex	R = 0.465	**<0.001**
	MVPA	SPPB	Age, sex	R = 0.220	**<0.001**
Schrack 2019	TPA (Log activity counts)	Gait	Age, sex + additional	0.11 [0.04]	**0.004**
		Walk	Age, sex + additional	-0.16 [0.03]	**<0.001**
		ExSPPB	Age, sex + additional	0.13 [0.04]	**<0.001**
Spartano 2019	Step count	Gait	Age, sex + additional	B = 0.006 [0.001]	**0.0001**
	Step count	HGS	Age, sex + additional	*M:* B = -0.16 [0.09], *F:* B = 0.09 [0.06]	0.077, 0.125
	Step count	Chair rise	Age, sex + additional	B = -0.010 [0.002]	**<0.0001**
	MVPA	Gait	Age, sex + additional	B = 0.048 [0.005]	**<0.0001**
	MVPA	HGS	Age, sex + additional	*M:* B = 0.58 [0.34], *F:* B = 0.64 [0.19]	0.090, **0.0008**
	MVPA	Chair rise	Age, sex + additional	B = -0.057 [0.006]	**<0.0001**
Thiebaud 2020*	LPA	Gait	Age + additional	β = -0.250	**0.016**
	MPA	Gait	Age + additional	β = -0.112	0.337

Supplementary Table 1-3-3. Associations between device-measured physical activity metrics with performance-based physical function outcomes.

Author, Year	PA exposure measure/s	PF outcome measure/s	Adjustment	Effect size (95%CI) or [SE]	p-value
	VPA	Gait	Age + additional	β = 0.357	**0.003**
van der Velde 2017	TPA, High intensity PA	HGS	Age, sex + additional	B = 0.02 (0.01; 0.03)	**<0.05**
	TPA	Chair rise	Age, sex + additional	B = −0.88 (−1.24; −0.52)	**<0.05**
	TPA	Walk	Age, sex + additional	B = 24.45 (19.74, 29.15)	**<0.05**
	High intensity PA	HGS	Age, sex + additional	B = 0.04 (0.03; 0.06)	**<0.05**
	High intensity PA	Chair rise	Age, sex + additional	B = −2.82 (−3.62; −2.03)	**<0.05**
	High intensity PA	Walk	Age, sex + additional	B = 61.25 (50.73, 71.77)	**<0.05**
Ward-Ritacco 2014	Step count	Chair rise	Age + additional	β = 0.23 (0.000, 0.001)	>0.05
	Step count	Walk	Age + additional	β = 0.31 (0.002, 0.01)	**<0.01**
	Step count	TUG	Age + additional	β = -0.16 (0.000, 0.000)	>0.05
	MVPA	Chair rise	Age + additional	R = 0.38	**<0.01**
	MVPA	Walk	Age + additional	R = 0.50	**<0.01**
	MVPA	TUG	Age + additional	R = -0.32	**<0.05**
Ward-Ritacco 2020	Step count	Chair rise	Age + additional	B = 0.67 (0.28, 1.05)	**0.001**
		Walk	Age + additional	B = 4.09 (-0.85, 9.03)	0.103
		TUG	Age + additional	B = −0.04 (-0.11, 0.02)	0.200
Westbury 2018	TPA	Gait	Sex	B = 0.29 (0.12, 0.47)	**<0.001**
	TPA	HGS	Sex	B = 0.15 (-.02, 0.33)	0.08
	MVPA	Gait	Sex	B = 0.19 (0.01, 0.37)	**0.04**
	MVPA	HGS	Sex	B = 0.10 (-0.08, 0.27)	0.29
Yamada 2011*	Step count	Gait	Unadjusted	R = -0.475	**<0.01**
		Chair rise	Unadjusted	R = -0.297	**<0.01**
		TUG	Unadjusted	R = -0.412	**<0.01**
		Balance	Unadjusted	R = 0.440	**<0.01**
Yasunaga 2017	LPA	Gait	Age, sex + additional	B = 0.001 (-0.001, 0.004)	>0.05
	LPA	HGS	Age, sex + additional	B = 0.058 (-0.024, 0.141)	>0.05
	LPA	TUG	Age, sex + additional	B = -0.011 (-0.025, 0.004)	>0.05
	LPA	Balance	Age, sex + additional	B = 0.139 (-0.131, 0.409)	>0.05
	MVPA	Gait	Age, sex + additional	B = 0.019 (0.011, 0.026)	**<0.001**
	MVPA	HGS	Age, sex + additional	B = 0.092 (-0.135, 0.318)	>0.05
	MVPA	TUG	Age, sex + additional	B = -0.155 (-0.153, -0.077)	**<0.001**
	MVPA	Balance	Age, sex + additional	B = 1.187 (0.462, 1.913)	**<0.01**
Yerrakalva 2022	TPA	HGS	Age, sex + additional	B = 0.1 (-0.2, 0.4)	>0.05
	TPA	Gait	Age, sex + additional	B = 4.4 (2.0, 6.7)	**<0.05**
	TPA	Chair rise	Age, sex + additional	B = 1.1 (0.7, 1.4)	**<0.05**
	LPA	HGS	Age, sex + additional	B = -0.04 (-0.5, 0.4)	>0.05
	LPA	Gait	Age, sex + additional	B = 3.0 (1.8, 4.2)	**<0.05**
	LPA	Chair rise	Age, sex + additional	B = 0.6 (0.4, 0.8)	**<0.05**
	MVPA	HGS	Age, sex + additional	B = 0.2 (-0.2, 0.6)	>0.05
	MVPA	Gait	Age, sex + additional	B = 5.4 (4.2, 6.0)	**<0.05**
	MVPA	Chair rise	Age, sex + additional	B = 1.2 (0.6, 1.8)	**<0.05**

*Asterisk denotes not included in meta-analyses, N/A = not applicable, N/R = not reported, B = unstandardised regression coefficient, β = standardised regression coefficient, R = correlation coefficient, R_{pb} = point biserial correlation, γ = compositional linear regression coefficient, † = reported across six age bands, ‡ = standardised by physical activity exposure only, LPA = light

Supplementary Table 1-3-3. Associations between device-measured physical activity metrics with performance-based physical function outcomes.

Author, Year	PA exposure measure/s	PF outcome measure/s	Adjustment	Effect size (95%CI) or [SE]	p-value

intensity physical activity, MVPA = moderate-to-vigorous physical activity, Steps = average or total step count, TPA = total physical activity, HGS = handgrip strength, Gait = gait speed, TUG = timed up-and-go test.

Appendix 8.4. Quality assessment of the methodological quality of included studies

Author	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Total
Adachi (2018)	y	y	nr	y	n	na	na	y	y	n	n	y	nr	y	y	8
Aggio (2016)	y	y	y	y	n	na	na	y	y	y	n	y	nr	y	y	10
Aoyagi (2009)	y	y	nr	y	n	na	na	n	y	n	n	y	nr	nr	y	6
Cooper (2015)	y	y	y	y	n	na	na	y	y	y	n	y	nr	n	y	9
Cooper (2020)	y	y	y	y	n	na	na	y	y	y	n	y	nr	n	y	9
Davis (2014)	y	y	nr	y	n	na	na	n	y	y	n	y	nr	y	y	8
Duck (2019)	y	y	nr	y	n	na	na	n	y	y	n	y	nr	y	y	8
Gobbo (2020)	y	y	n	y	y	y	y	n	y	y	n	y	nr	n	y	10
Hall (2017)	y	y	nr	y	n	na	na	y	y	y	n	y	nr	n	n	7
Hsueh (2020)	y	y	nr	y	n	na	na	y	y	y	n	y	nr	n	y	8
Izawa (2017)	y	y	n	y	n	na	na	y	y	n	n	y	nr	y	y	8
Jantunen (2017)	y	y	y	y	n	na	na	y	y	n	n	y	nr	n	y	8
Johansson (2021)	y	y	y	y	n	na	na	y	y	y	n	y	nr	n	y	9
Kim (2015)	y	y	y	y	n	na	na	n	y	n	n	y	nr	n	y	7
Kruger (2016)	y	y	nr	y	y	na	na	n	y	n	n	y	nr	nr	y	7
Lai (2020)	y	y	nr	y	n	na	na	y	y	y	n	y	nr	y	y	9
Lerma (2018)	y	y	nr	y	n	na	na	y	y	n	n	y	nr	y	y	8
Lohne-Seiler (2016)	y	y	n	y	n	na	na	n	y	n	n	y	nr	y	y	7
Manas (2019)	y	y	nr	y	n	na	na	y	y	y	n	y	nr	y	y	9
Meier (2020)	y	y	nr	y	n	na	na	n	y	n	n	y	nr	nr	y	6
Mendham (2021)	y	y	nr	y	y	na	na	y	y	n	n	y	nr	nr	y	8
Mizumoto (2015)	y	y	n	y	n	n	n	y	y	n	y	y	nr	n	y	8
Nagai (2018)	y	y	nr	y	n	na	na	y	y	y	n	y	nr	y	n	8
Oguma (2017)	y	y	y	y	n	na	na	n	y	y	n	y	nr	y	n	8
Osuka (2015)	y	y	y	y	n	na	na	y	y	y	n	y	nr	n	y	9
Pina (2021)	y	y	nr	n	n	na	na	y	y	y	n	y	nr	y	y	8
Reid (2016)*	y	y	n	y	y	na	na	y	y	y	n	y	nr	nr	y	9
Ribeiro (2020)	y	y	y	y	y	na	na	n	y	y	n	y	nr	n	y	9
Rojer (2018)	Y	Y	nr	Y	n	na	na	y	y	y	n	y	nr	y	y	9

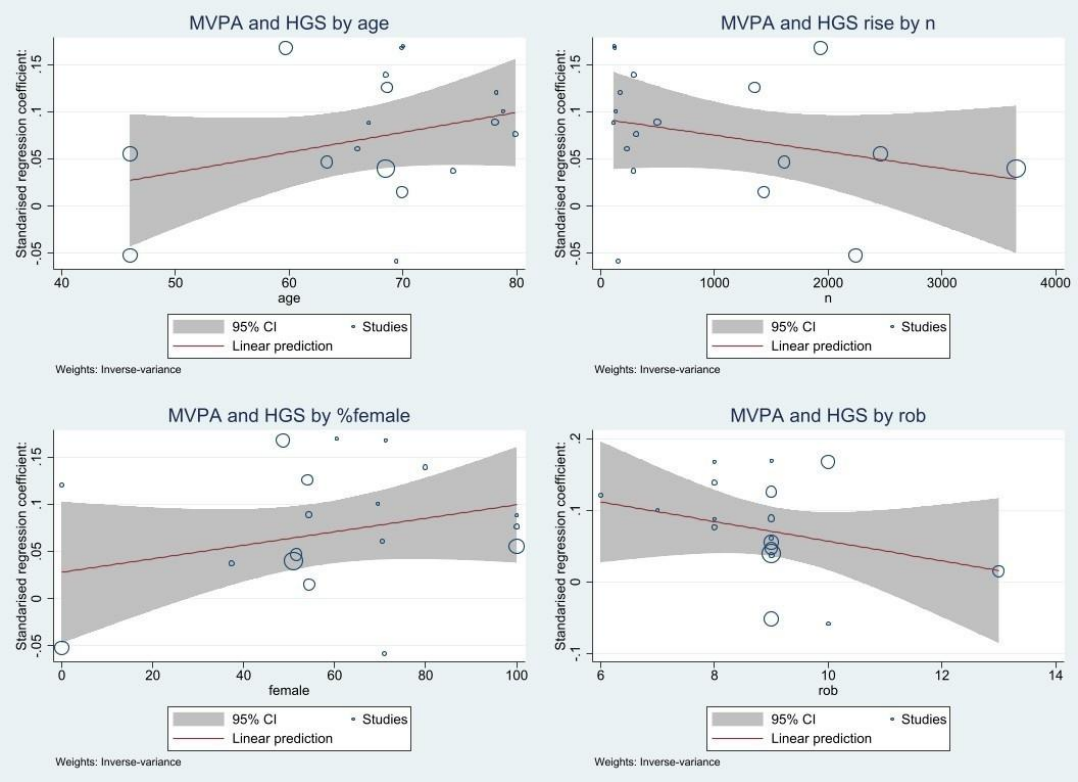
Author	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Q11	Q12	Q13	Q14	Q15	Total
Sanchez-Sanchez (2019)	y	y	nr	y	n	na	na	y	y	y	n	y	nr	y	y	9
Santos (2012)	y	y	nr	y	n	na	na	n	y	y	n	n	nr	nr	y	6
Savikangas (2020)	y	y	n	y	n	na	na	y	y	y	n	y	nr	n	y	8
Schrack (2019)	y	y	nr	y	n	na	na	n	y	y	n	y	nr	nr	y	7
Spartano (2019)	y	y	y	y	n	na	na	y	y	y	n	y	nr	nr	y	9
Thiebaud (2020)*	y	n	nr	n	n	na	na	y	y	y	n	y	nr	nr	y	6
van der Velde (2017)	y	y	y	y	n	na	na	y	y	y	n	y	nr	y	y	10
Ward-Ritacco (2014)	y	y	nr	y	n	na	na	y	y	y	n	y	nr	nr	y	8
Ward-Ritacco (2020)	y	y	nr	y	y	na	na	n	y	y	n	y	nr	nr	y	8
Westbury (2018)	y	y	n	y	n	na	na	y	y	n	n	y	nr	y	n	7
Yamada (2011)	y	y	nr	n	n	na	na	n	y	n	n	n	nr	nr	n	3
Yasunaga (2017)	y	y	n	y	n	na	na	y	y	y	n	y	nr	y	y	9
Yerrakalva (2022)	y	y	y	y	n	y	y	y	y	y	y	y	nr	y	y	13

y; yes. n; no. na; not applicable. nr; not reported.

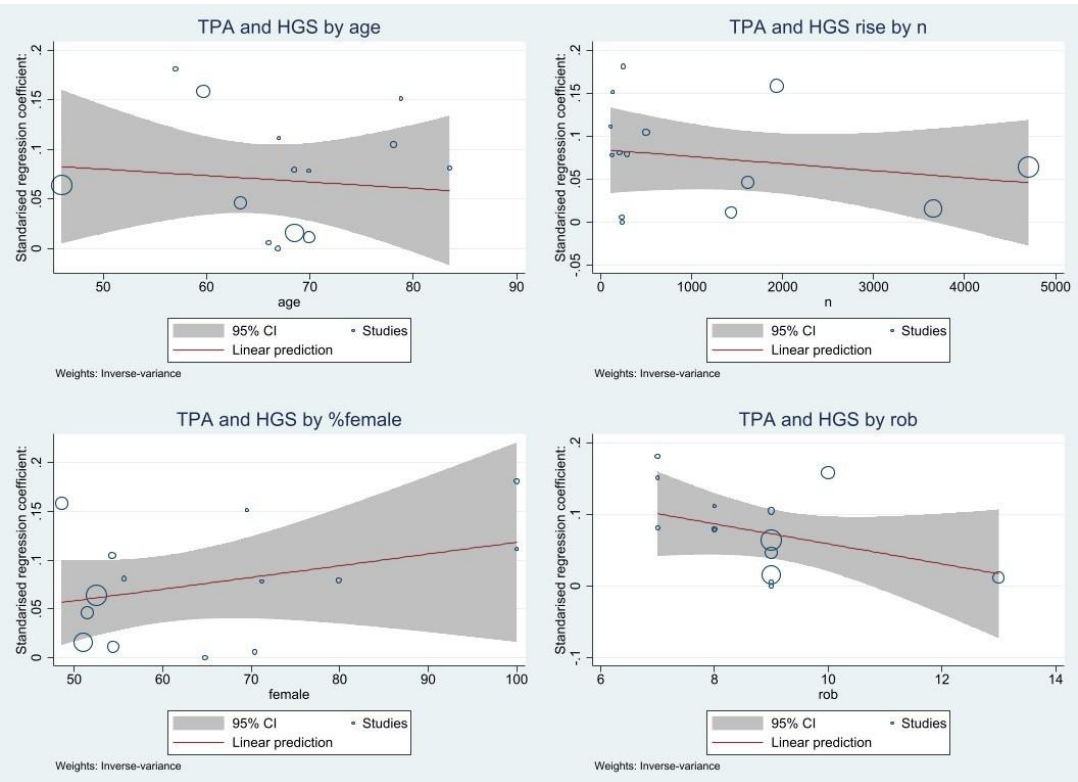
Q1 - Was the research question or objective in this paper clearly stated? Q2 - Was the study population clearly specified and defined? Q3 - Was the participation rate of eligible participants >50%? Q4 - Were all the subjects selected or recruited from the same or similar populations (including the same time period)? Were inclusion and exclusion criteria for being in the study prespecified and applied uniformly to all participants? Q5 - Was a sample size justification, power description, or variance and effect estimates provided? Q6 - For the analyses in this paper, were the exposure(s) of interest measured prior to the outcome(s) being measured? Q7 - Was the timeframe sufficient so that one could reasonably expect to see an association between exposure and outcome if it existed? Q8 - For exposures that can vary in amount or level, did the study examine different levels of the exposure as related to the outcome (e.g., categories of exposure, or exposure measured as continuous variable)? Q9 - Were the exposure measures (independent variables) clearly defined, valid, reliable, and implemented consistently across all study participants? Q10 - Was the accelerometer protocol reported up to the standards of the Montoye et al. (2018) guidelines? Reporting of; brand, epoch, placement, days, valid hours/days, non-wear criteria, accelerometer outcomes and interpretation (e.g. MVPA and cut points used) Q11 - Was the exposure(s) assessed more than once over time? Q12 - Were the outcome measures (dependent variables) clearly defined, valid, reliable, and implemented consistently across all study participants? Q13 - Were the outcome assessors blinded to the exposure status of participants? Q14 - Was loss to follow-up after baseline 20% or less? Q15 - Were key potential confounding variables measured and adjusted statistically for their impact on the relationship between exposure(s) and outcome(s) – with age + sex the minimum?

	QA score Mean (SD)	QA score Range
All reports (n = 42)	8.1 (1.5)	3, 13
Reports included in meta-analyses (k = 34)	8.2 (1.3)	6, 13

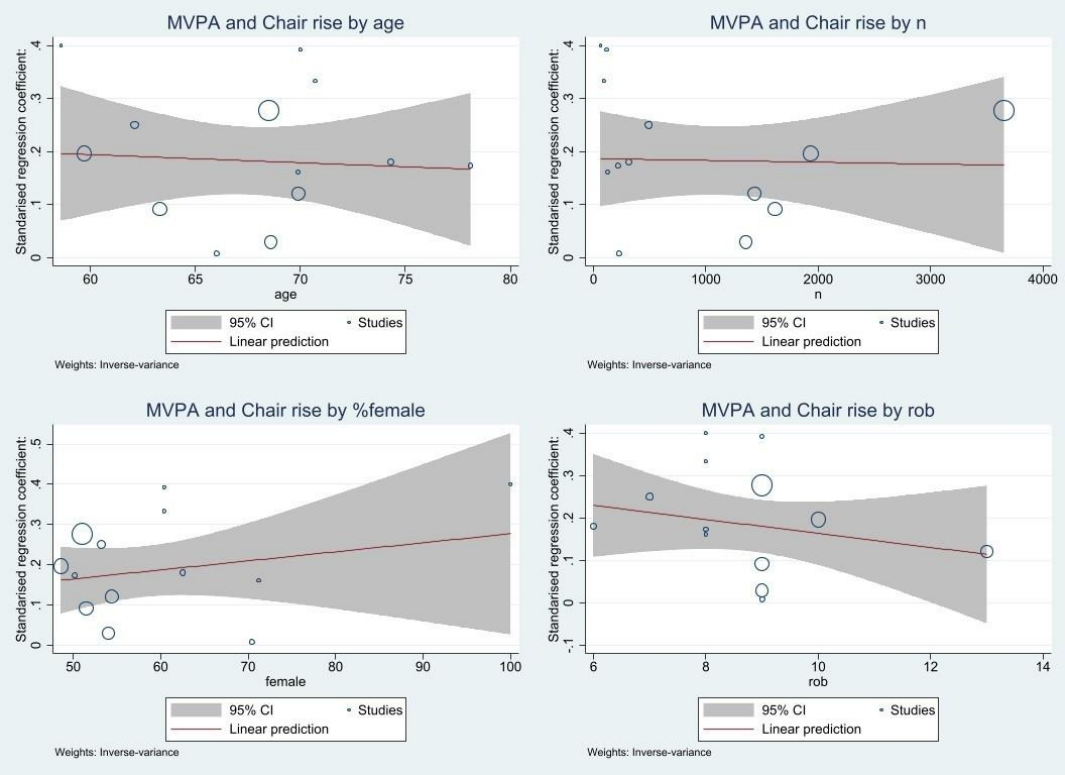
Appendix 8.5. Meta regressions and bubble plots.



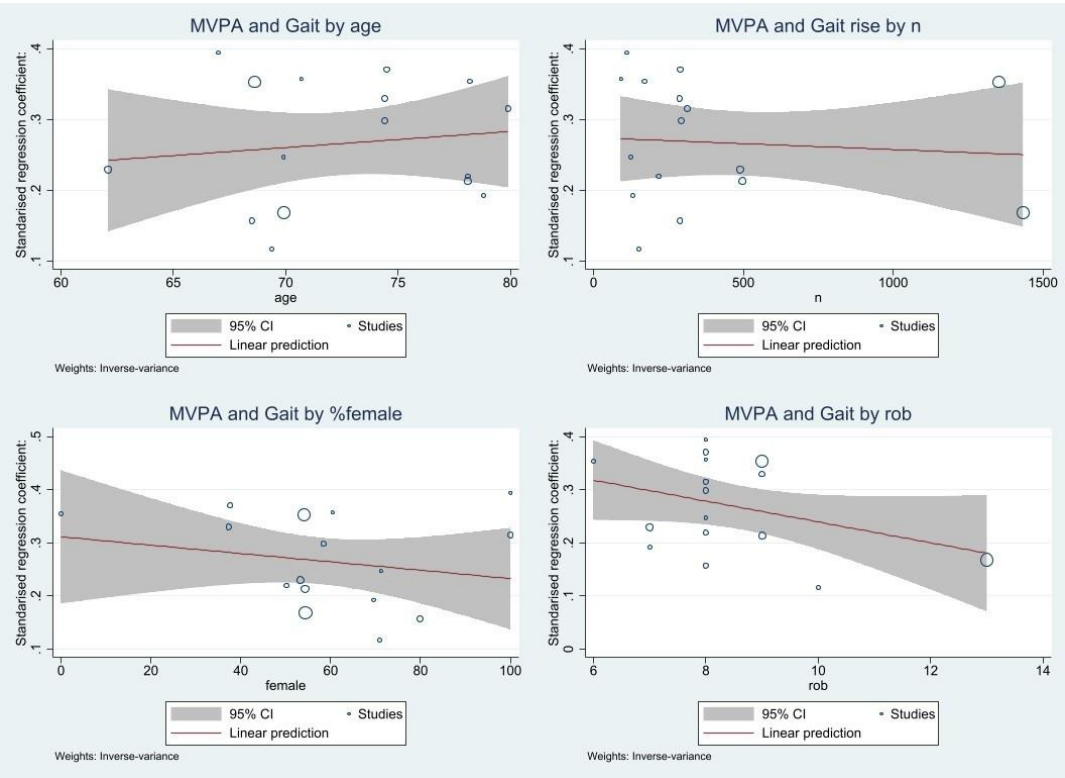
Supplementary Figure 1-5-1. Bubble plots of meta-regression for moderate-to-vigorous physical activity and handgrip strength for; age, sample size (n), percentage of females per study, and risk of bias (quality assessment score)



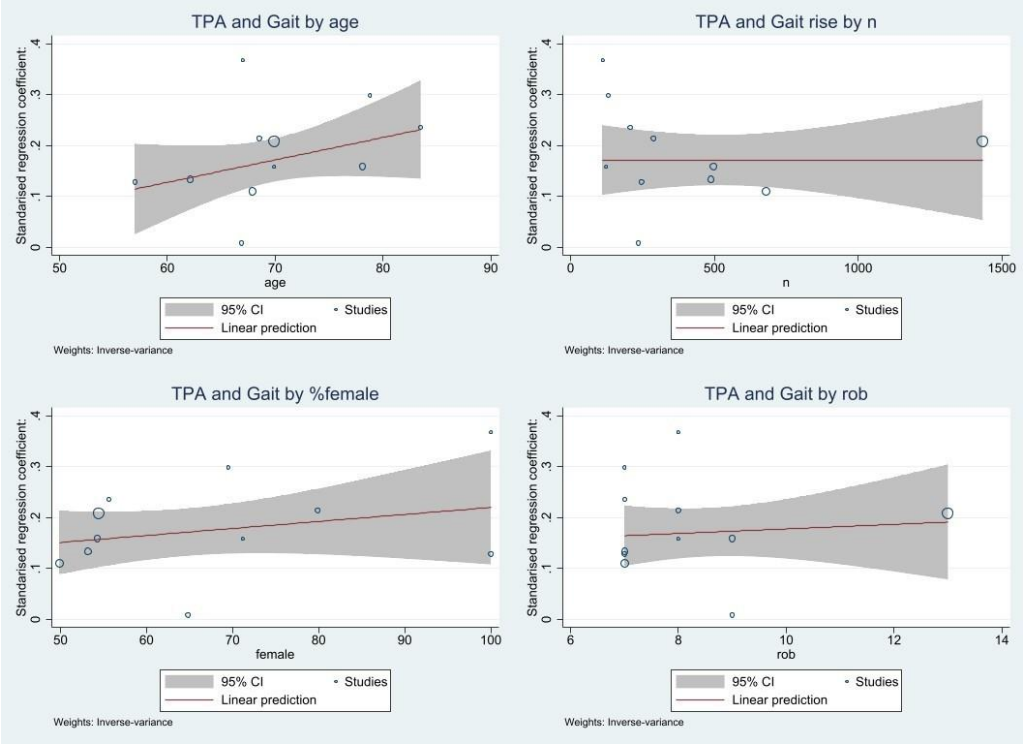
Supplementary Figure 1-5-2. Bubble plots of meta-regression for total physical activity with handgrip strength for; age, sample size (n), percentage of females per study, and risk of bias (quality assessment score)



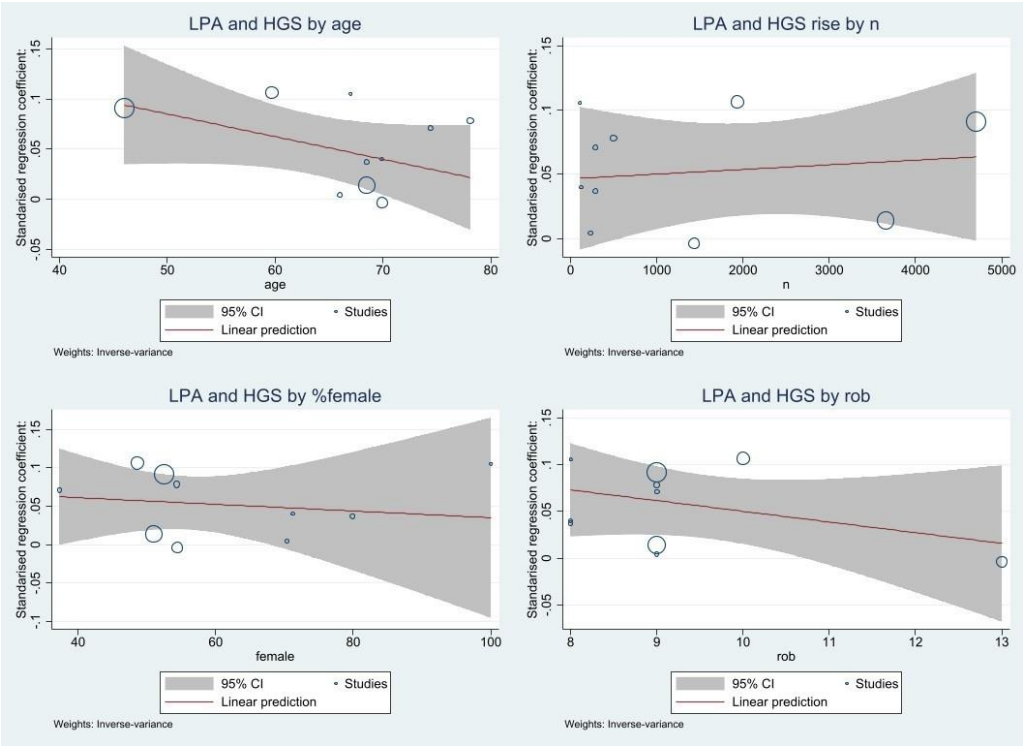
Supplementary Figure 1-5-3. Bubble plots of meta-regression for moderate-to-vigorous physical activity with chair rise for; age, sample size (n), percentage of females per study, and risk of bias (quality assessment score)



Supplementary Figure 1-5-4. Bubble plots of meta-regression for moderate-to-vigorous physical activity with gait speed for; age, sample size (n), percentage of females per study, and risk of bias (quality assessment score)



Supplementary Figure 1-5-5. Bubble plots of meta-regression for total physical activity with gait speed for; age, sample size (n), percentage of females per study, and risk of bias (quality assessment score)



Supplementary Figure 1-5-6. Bubble plots of meta-regression for light physical activity with gait speed for; age, sample size (n), percentage of females per study, and risk of bias (quality assessment score)

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(A)

Random-effects meta-regression
Method: REML

Number of obs = 13
Residual heterogeneity:
tau2 = .01019
I2 (%) = 88.20
H2 = 8.48
R-squared (%) = 0.00
Wald chi2(1) = 0.06
Prob > chi2 = 0.8063

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
age	-.0015296	.0062391	-0.25	0.806	-.0137581	.0106988
_cons	.2862545	.4227316	0.68	0.498	-.5422842	1.114793

Test of residual homogeneity: Q_res = chi2(11) = 102.16 Prob > Q_res = 0.0000

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(B)

Random-effects meta-regression
Method: REML

Number of obs = 13
Residual heterogeneity:
tau2 = .01046
I2 (%) = 87.25
H2 = 7.85
R-squared (%) = 0.00
Wald chi2(1) = 0.01
Prob > chi2 = 0.9125

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
n	-3.35e-06	.0000305	-0.11	0.912	-.0000631	.0000564
_cons	.1868621	.0469646	3.98	0.000	.0948131	.2789111

Test of residual homogeneity: Q_res = chi2(11) = 67.76 Prob > Q_res = 0.0000

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(C)

Random-effects meta-regression
Method: REML

Number of obs = 13
Residual heterogeneity:
tau2 = .009824
I2 (%) = 88.99
H2 = 9.08
R-squared (%) = 0.00
Wald chi2(1) = 0.59
Prob > chi2 = 0.4439

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
female	.0022466	.0029346	0.77	0.444	-.003505	.0079983
_cons	.0525061	.1728945	0.30	0.761	-.2863609	.3913731

Test of residual homogeneity: Q_res = chi2(11) = 100.63 Prob > Q_res = 0.0000

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(D)

Random-effects meta-regression
Method: REML

Number of obs = 13
Residual heterogeneity:
tau2 = .009458
I2 (%) = 87.73
H2 = 8.15
R-squared (%) = 0.00
Wald chi2(1) = 0.80
Prob > chi2 = 0.3724

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
rob	-.0164824	.0184773	-0.89	0.372	-.0526972	.0197323
_cons	.3284359	.1669153	1.97	0.049	.0012878	.6555839

Test of residual homogeneity: Q_res = chi2(11) = 96.46 Prob > Q_res = 0.0000

Supplementary Figure 1-5-7. Meta-regression output for moderate-to-vigorous physical activity with chair rise for; (A) age, (B) sample size, (C) percentage of females per study, and (D) risk of bias (quality assessment score)

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(A)

Random-effects meta-regression
Method: REML

Number of obs = 11
Residual heterogeneity:
tau2 = .001855
I2 (%) = 40.77
H2 = 1.69
R-squared (%) = 16.79
Wald chi2(1) = 1.94
Prob > chi2 = 0.1641

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
age	.0044013	.0031632	1.39	0.164	-.0017984	.010601
_cons	-.1362307	.221096	-0.62	0.538	-.5695709	.2971095

Test of residual homogeneity: Q_res = chi2(9) = 16.68 Prob > Q_res = 0.0539

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(B)

Random-effects meta-regression
Method: REML

Number of obs = 11
Residual heterogeneity:
tau2 = .003481
I2 (%) = 51.14
H2 = 2.05
R-squared (%) = 0.00
Wald chi2(1) = 0.00
Prob > chi2 = 0.9970

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
n	-2.22e-07	.0000593	-0.00	0.997	-.0001165	.000116
_cons	.1717266	.0397358	4.32	0.000	.0938458	.2496073

Test of residual homogeneity: Q_res = chi2(9) = 18.41 Prob > Q_res = 0.0307

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(C)

Random-effects meta-regression
Method: REML

Number of obs = 11
Residual heterogeneity:
tau2 = .002757
I2 (%) = 50.51
H2 = 2.02
R-squared (%) = 0.00
Wald chi2(1) = 0.89
Prob > chi2 = 0.3446

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
female	.0013765	.0014564	0.95	0.345	-.0014779	.0042309
_cons	.0823167	.096629	0.85	0.394	-.1070726	.271706

Test of residual homogeneity: Q_res = chi2(9) = 18.70 Prob > Q_res = 0.0279

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(D)

Random-effects meta-regression
Method: REML

Number of obs = 11
Residual heterogeneity:
tau2 = .003025
I2 (%) = 46.71
H2 = 1.88
R-squared (%) = 0.00
Wald chi2(1) = 0.15
Prob > chi2 = 0.7000

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
rob	.004495	.011664	0.39	0.700	-.018366	.027356
_cons	.132817	.1023774	1.30	0.195	-.067839	.3334729

Test of residual homogeneity: Q_res = chi2(9) = 17.18 Prob > Q_res = 0.0460

Supplementary Figure 1-5-8. Meta-regression output for total physical activity with gait speed for; (A) age, (B) sample size, (C) percentage of females per study, and (D) risk of bias (quality assessment score)

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(A)

Random-effects meta-regression
Method: REML

Number of obs = 10
Residual heterogeneity:
tau2 = .000882
I2 (%) = 42.12
H2 = 1.73
R-squared (%) = 35.33
Wald chi2(1) = 2.28
Prob > chi2 = 0.1308

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
age	-.0022516	.0014901	-1.51	0.131	-.0051721	.0006688
_cons	.197563	.0957764	2.06	0.039	.0098447	.3852814

Test of residual homogeneity: Q_res = chi2(8) = 11.76 Prob > Q_res = 0.1624

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(B)

Random-effects meta-regression
Method: REML

Number of obs = 10
Residual heterogeneity:
tau2 = .001589
I2 (%) = 60.78
H2 = 2.55
R-squared (%) = 0.00
Wald chi2(1) = 0.11
Prob > chi2 = 0.7372

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
n	3.62e-06	.0000108	0.34	0.737	-.0000175	.0000248
_cons	.0465493	.0291841	1.60	0.111	-.0106505	.1037492

Test of residual homogeneity: Q_res = chi2(8) = 22.18 Prob > Q_res = 0.0046

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(C)

Random-effects meta-regression
Method: REML

Number of obs = 10
Residual heterogeneity:
tau2 = .001434
I2 (%) = 63.50
H2 = 2.74
R-squared (%) = 0.00
Wald chi2(1) = 0.09
Prob > chi2 = 0.7636

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
female	-.0004349	.0014457	-0.30	0.764	-.0032685	.0023987
_cons	.0785198	.082466	0.95	0.341	-.0831107	.2401502

Test of residual homogeneity: Q_res = chi2(8) = 23.15 Prob > Q_res = 0.0032

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(D)

Random-effects meta-regression
Method: REML

Number of obs = 10
Residual heterogeneity:
tau2 = .001326
I2 (%) = 58.22
H2 = 2.39
R-squared (%) = 2.76
Wald chi2(1) = 0.98
Prob > chi2 = 0.3215

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
rob	-.0114224	.0115213	-0.99	0.321	-.0340036	.0111589
_cons	.1642439	.1121764	1.46	0.143	-.0556178	.3841056

Test of residual homogeneity: Q_res = chi2(8) = 20.48 Prob > Q_res = 0.0087

Supplementary Figure 1-5-8. Meta-regression output for light physical activity with handgrip strength for; (A) age, (B) sample size, (C) percentage of females per study, and (D) risk of bias (quality assessment score)

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(A)

Random-effects meta-regression
Method: REML

Number of obs = 18
Residual heterogeneity:
tau2 = .002789
I2 (%) = 69.45
H2 = 3.27
R-squared (%) = 6.45
Wald chi2(1) = 1.70
Prob > chi2 = 0.1919

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
age	.0021139	.00162	1.30	0.192	-.0010613	.005289
_cons	-.0698531	.1072536	-0.65	0.515	-.2800662	.14036

Test of residual homogeneity: Q_res = chi2(16) = 60.56 Prob > Q_res = 0.0000

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(B)

Random-effects meta-regression
Method: REML

Number of obs = 18
Residual heterogeneity:
tau2 = .002925
I2 (%) = 70.27
H2 = 3.36
R-squared (%) = 1.91
Wald chi2(1) = 1.25
Prob > chi2 = 0.2629

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
n	-.0000176	.0000157	-1.12	0.263	-.0000483	.0000132
_cons	.0926447	.0275085	3.37	0.001	.038729	.1465603

Test of residual homogeneity: Q_res = chi2(16) = 63.56 Prob > Q_res = 0.0000

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(C)

Random-effects meta-regression
Method: REML

Number of obs = 18
Residual heterogeneity:
tau2 = .002721
I2 (%) = 68.74
H2 = 3.20
R-squared (%) = 8.75
Wald chi2(1) = 1.39
Prob > chi2 = 0.2379

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
female	.0007143	.0006053	1.18	0.238	-.000472	.0019007
_cons	.0278897	.0380723	0.73	0.464	-.0467307	.1025102

Test of residual homogeneity: Q_res = chi2(16) = 56.91 Prob > Q_res = 0.0000

Effect-size label: Standarised regression coefficient:
Effect size: fisherz
Std. err.: SE

(D)

Random-effects meta-regression
Method: REML

Number of obs = 18
Residual heterogeneity:
tau2 = .003101
I2 (%) = 72.62
H2 = 3.65
R-squared (%) = 0.00
Wald chi2(1) = 1.19
Prob > chi2 = 0.2746

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
rob	-.0136958	.012535	-1.09	0.275	-.038264	.0108724
_cons	.193879	.1158183	1.67	0.094	-.0331208	.4208788

Test of residual homogeneity: Q_res = chi2(16) = 68.20 Prob > Q_res = 0.0000

Supplementary Figure 1-5-9. Meta-regression output for moderate-to-vigorous physical activity with handgrip strength for; (A) age, (B) sample size, (C) percentage of females per study, and (D) risk of bias (quality assessment score)

(A)

```
Effect-size label: Standarised regression coefficient:
      Effect size: fisherz
        Std. err.: SE

Random-effects meta-regression                  Number of obs  =        14
Method: REML                                    Residual heterogeneity:
                                                          tau2 = .002236
                                                       I2 (%) =   62.91
                                                          H2 =    2.70
                                                R-squared (%) =    0.00
                                                Wald chi2(1)  =    0.12
                                                Prob > chi2   =    0.7267
```

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
age	-.000644	.0018429	-0.35	0.727	-.004256	.0029679
_cons	.1121226	.1212493	0.92	0.355	-.1255216	.3497668

```
Test of residual homogeneity: Q_res = chi2(12) = 35.09   Prob > Q_res = 0.0005
```

(B)

```
Effect-size label: Standarised regression coefficient:
      Effect size: fisherz
        Std. err.: SE

Random-effects meta-regression                  Number of obs  =        14
Method: REML                                    Residual heterogeneity:
                                                          tau2 = .002162
                                                       I2 (%) =   64.32
                                                          H2 =    2.80
                                                R-squared (%) =    0.00
                                                Wald chi2(1)  =    0.55
                                                Prob > chi2   =    0.4572
```

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
n	-8.25e-06	.0000111	-0.74	0.457	-.00003	.0000135
_cons	.0845119	.0261942	3.23	0.001	.0331722	.1358516

```
Test of residual homogeneity: Q_res = chi2(12) = 35.15   Prob > Q_res = 0.0004
```

(C)

```
Effect-size label: Standarised regression coefficient:
      Effect size: fisherz
        Std. err.: SE

Random-effects meta-regression                  Number of obs  =        14
Method: REML                                    Residual heterogeneity:
                                                          tau2 = .002084
                                                       I2 (%) =   67.59
                                                          H2 =    3.09
                                                R-squared (%) =    0.00
                                                Wald chi2(1)  =    0.97
                                                Prob > chi2   =    0.3254
```

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
female	.0012018	.0012222	0.98	0.325	-.0011936	.0035973
_cons	-.0018811	.0751264	-0.03	0.980	-.1491262	.1453639

```
Test of residual homogeneity: Q_res = chi2(12) = 36.19   Prob > Q_res = 0.0003
```

(D)

```
Effect-size label: Standarised regression coefficient:
      Effect size: fisherz
        Std. err.: SE

Random-effects meta-regression                  Number of obs  =        14
Method: REML                                    Residual heterogeneity:
                                                          tau2 = .002052
                                                       I2 (%) =   65.50
                                                          H2 =    2.90
                                                R-squared (%) =    0.00
                                                Wald chi2(1)  =    1.57
                                                Prob > chi2   =    0.2097
```

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
rob	-.0139659	.0111327	-1.25	0.210	-.0357857	.0078538
_cons	.1984021	.1038656	1.91	0.056	-.0051707	.4019749

```
Test of residual homogeneity: Q_res = chi2(12) = 35.65   Prob > Q_res = 0.0004
```

Supplementary Figure 1-5-10. Meta-regression output for total physical activity with handgrip strength for; (A) age, (B) sample size, (C) percentage of females per study, and (D) risk of bias (quality assessment score)

(A)

```
Effect-size label: Standarised regression coefficient:
      Effect size: fisherz
        Std. err.: SE

Random-effects meta-regression                  Number of obs  =        16
Method: REML                                    Residual heterogeneity:
                                                          tau2 = .004312
                                                       I2 (%) =   60.29
                                                          H2 =    2.52
                                                R-squared (%) =    0.00
                                                Wald chi2(1)  =    0.26
                                                Prob > chi2   =    0.6098
```

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
age	.0022648	.0044372	0.51	0.610	-.006432	.0109617
_cons	.1017223	.3221858	0.32	0.752	-.5297502	.7331949

```
Test of residual homogeneity: Q_res = chi2(14) = 42.46   Prob > Q_res = 0.0001
```

(B)

```
Effect-size label: Standarised regression coefficient:
      Effect size: fisherz
        Std. err.: SE

Random-effects meta-regression                  Number of obs  =        16
Method: REML                                    Residual heterogeneity:
                                                          tau2 = .004534
                                                       I2 (%) =   59.50
                                                          H2 =    2.47
                                                R-squared (%) =    0.00
                                                Wald chi2(1)  =    0.11
                                                Prob > chi2   =    0.7366
```

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
n	-.0000167	.0000498	-0.34	0.737	-.0001143	.0000808
_cons	.2742415	.0338929	8.09	0.000	.2078127	.3406704

```
Test of residual homogeneity: Q_res = chi2(14) = 42.36   Prob > Q_res = 0.0001
```

(C)

```
Effect-size label: Standarised regression coefficient:
      Effect size: fisherz
        Std. err.: SE

Random-effects meta-regression                  Number of obs  =        16
Method: REML                                    Residual heterogeneity:
                                                          tau2 = .004089
                                                       I2 (%) =   60.08
                                                          H2 =    2.51
                                                R-squared (%) =    0.00
                                                Wald chi2(1)  =    0.58
                                                Prob > chi2   =    0.4452
```

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
female	-.0007869	.0010307	-0.76	0.445	-.0028069	.0012332
_cons	.3113835	.0638756	4.87	0.000	.1861897	.4365774

```
Test of residual homogeneity: Q_res = chi2(14) = 41.60   Prob > Q_res = 0.0001
```

(D)

```
Effect-size label: Standarised regression coefficient:
      Effect size: fisherz
        Std. err.: SE

Random-effects meta-regression                  Number of obs  =        16
Method: REML                                    Residual heterogeneity:
                                                          tau2 =  .00322
                                                       I2 (%) =   49.90
                                                          H2 =    2.00
                                                R-squared (%) =   19.09
                                                Wald chi2(1)  =    2.70
                                                Prob > chi2   =    0.1001
```

_meta_es	Coefficient	Std. err.	z	P>|z|	[95% conf.	interval]
rob	-.0196365	.0119405	-1.64	0.100	-.0430395	.0037666
_cons	.4357582	.1057488	4.12	0.000	.2284944	.643022

```
Test of residual homogeneity: Q_res = chi2(14) = 30.14   Prob > Q_res = 0.0073
```

Supplementary Figure 1-5-11. Meta-regression output for moderate-to-vigorous physical activity with gait speed for; (A) age, (B) sample size, (C) percentage of females per study, and (D) risk of bias (quality assessment score)

Appendix 8.6. Eggers and funnel plots.

```
. *Chair_mvpa
. meta bias if pa==2 & pf==1, egger

  Effect-size label: Standarised regression coefficient:
        Effect size: fisherz
          Std. err.: SE

Regression-based Egger test for small-study effects
Random-effects model
Method: REML

H0: beta1 = 0; no small-study effects
            beta1 =      1.61
      SE of beta1 =     0.974
                z =      1.65
       Prob > |z| =    0.0993
```

(A)

```
. meta bias if pa==2 & pf==2, egger

  Effect-size label: Standarised regression coefficient:
        Effect size: fisherz
          Std. err.: SE

Regression-based Egger test for small-study effects
Random-effects model
Method: REML

H0: beta1 = 0; no small-study effects
            beta1 =      0.48
      SE of beta1 =     1.023
                z =      0.47
       Prob > |z| =    0.6378
```

(C)

```
. meta bias if pa==1 & pf==0, egger

  Effect-size label: Standarised regression coefficient:
        Effect size: fisherz
          Std. err.: SE

Regression-based Egger test for small-study effects
Random-effects model
Method: REML

H0: beta1 = 0; no small-study effects
            beta1 =     -0.06
      SE of beta1 =     0.784
                z =     -0.08
       Prob > |z| =    0.9373
```

(E)

```
. meta bias if pa==0 & pf==2, egger

  Effect-size label: Standarised regression coefficient:
        Effect size: fisherz
          Std. err.: SE

Regression-based Egger test for small-study effects
Random-effects model
Method: REML

H0: beta1 = 0; no small-study effects
            beta1 =      1.26
      SE of beta1 =     1.192
                z =      1.06
       Prob > |z| =    0.2899
```

(B)

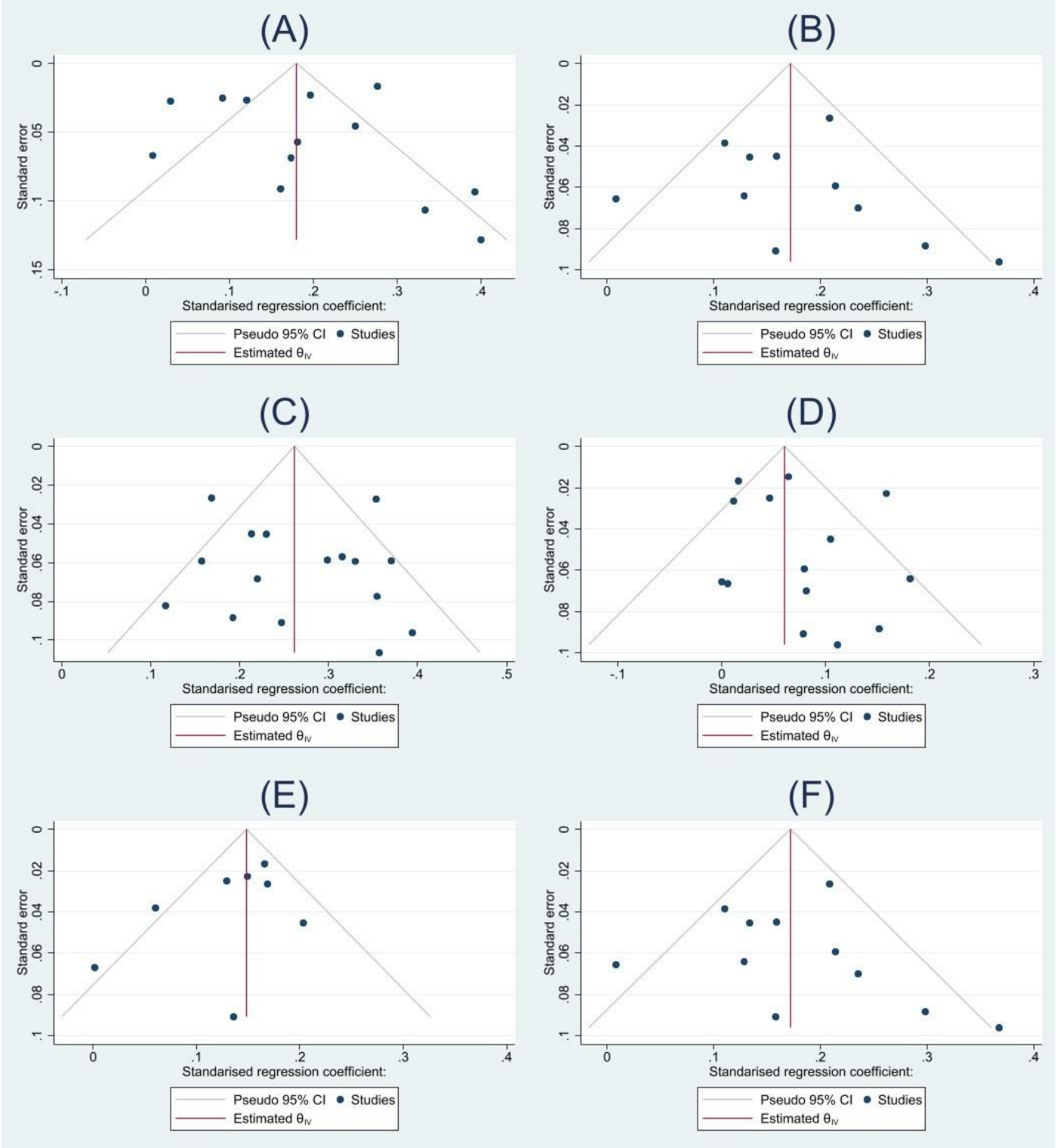
```
. meta bias if pa==0 & pf==0, egger

  Effect-size label: Standarised regression coefficient:
        Effect size: fisherz
          Std. err.: SE

Regression-based Egger test for small-study effects
Random-effects model
Method: REML

H0: beta1 = 0; no small-study effects
            beta1 =      0.53
      SE of beta1 =     0.699
                z =      0.76
       Prob > |z| =    0.4448
```

(D)

```
. meta bias if pa==2 & pf==0, egger

  Effect-size label: Standarised regression coefficient:
        Effect size: fisherz
          Std. err.: SE

Regression-based Egger test for small-study effects
Random-effects model
Method: REML

H0: beta1 = 0; no small-study effects
            beta1 =      0.69
      SE of beta1 =     0.677
                z =      1.01
       Prob > |z| =    0.3106
```

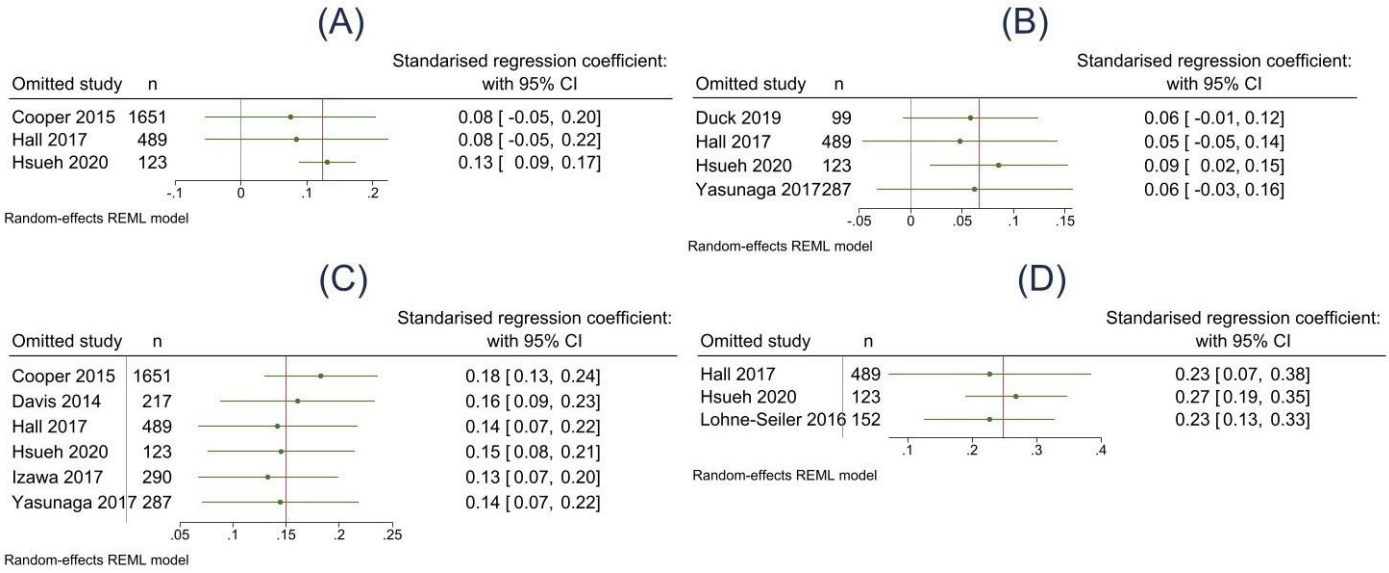
(F)

Supplementary Figure 1-6-1. Egger's test output for the associations between; (A) moderate-to-vigorous physical activity and chair rise (B) total physical activity and gait speed (C) moderate-to-vigorous physical activity and gait speed (D) total physical activity and handgrip strength (E) light physical activity and handgrip strength (F) moderate-to-vigorous physical activity and handgrip strength

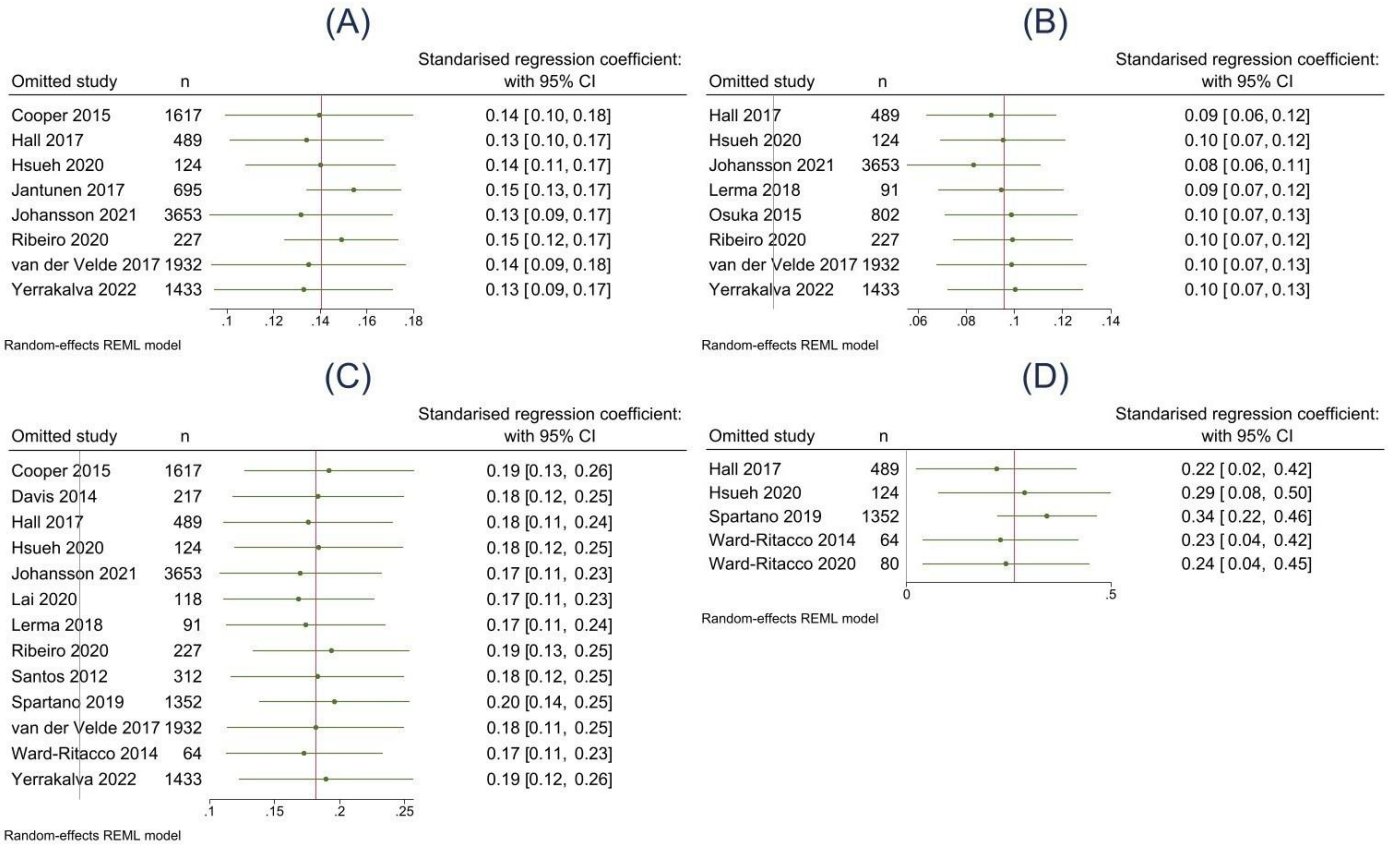


Supplementary Figure 1-6-2. Bubble plots, visual output of Egger's tests for the associations between; (A) moderate-to-vigorous physical activity and chair rise (B) total physical activity and gait speed (C) moderate-to-vigorous physical activity and gait speed (D) total physical activity and handgrip strength (E) light physical activity and handgrip strength (F) moderate-to-vigorous physical activity and handgrip strength

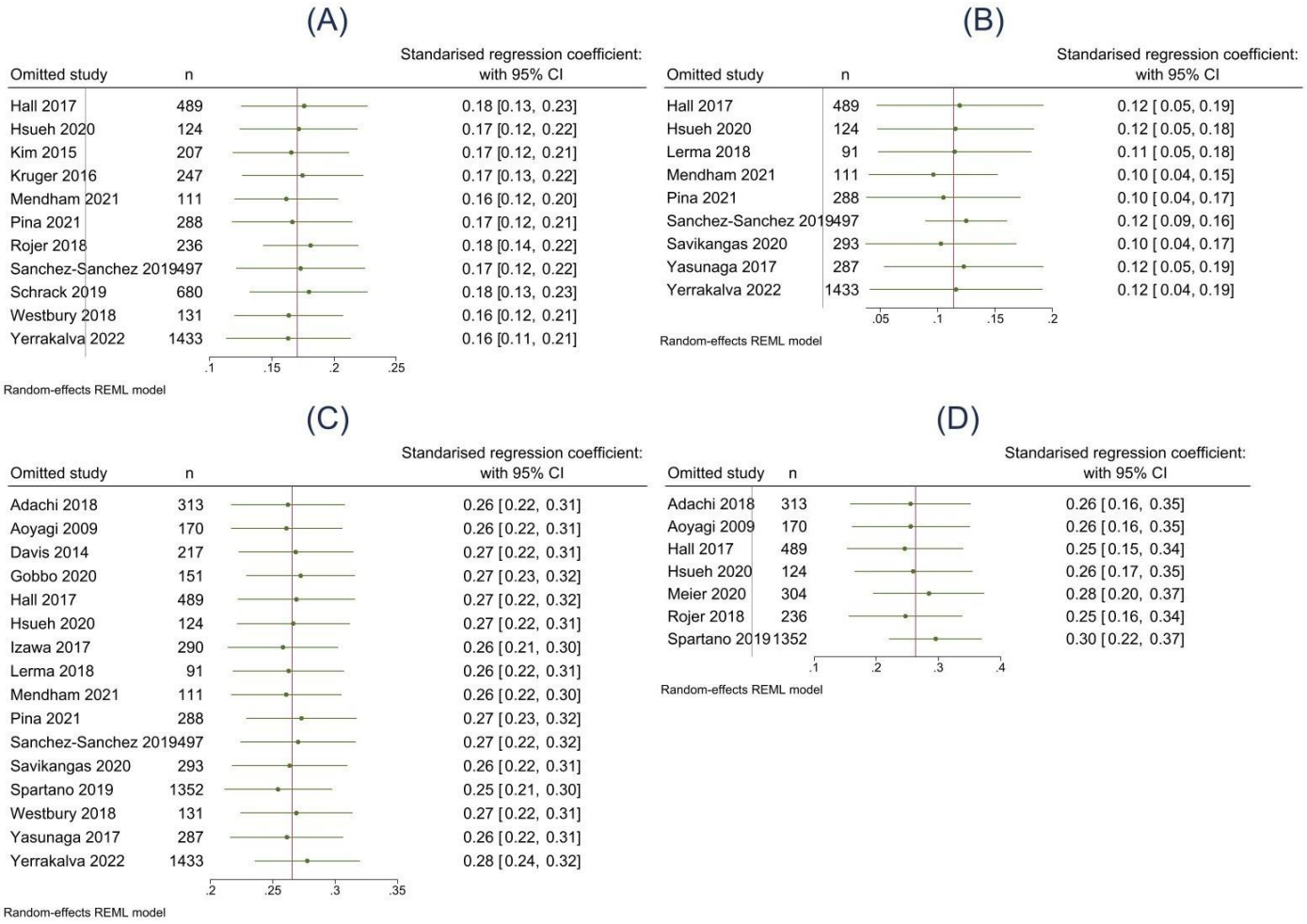
Appendix 8.7. Leave-one-out analysis.



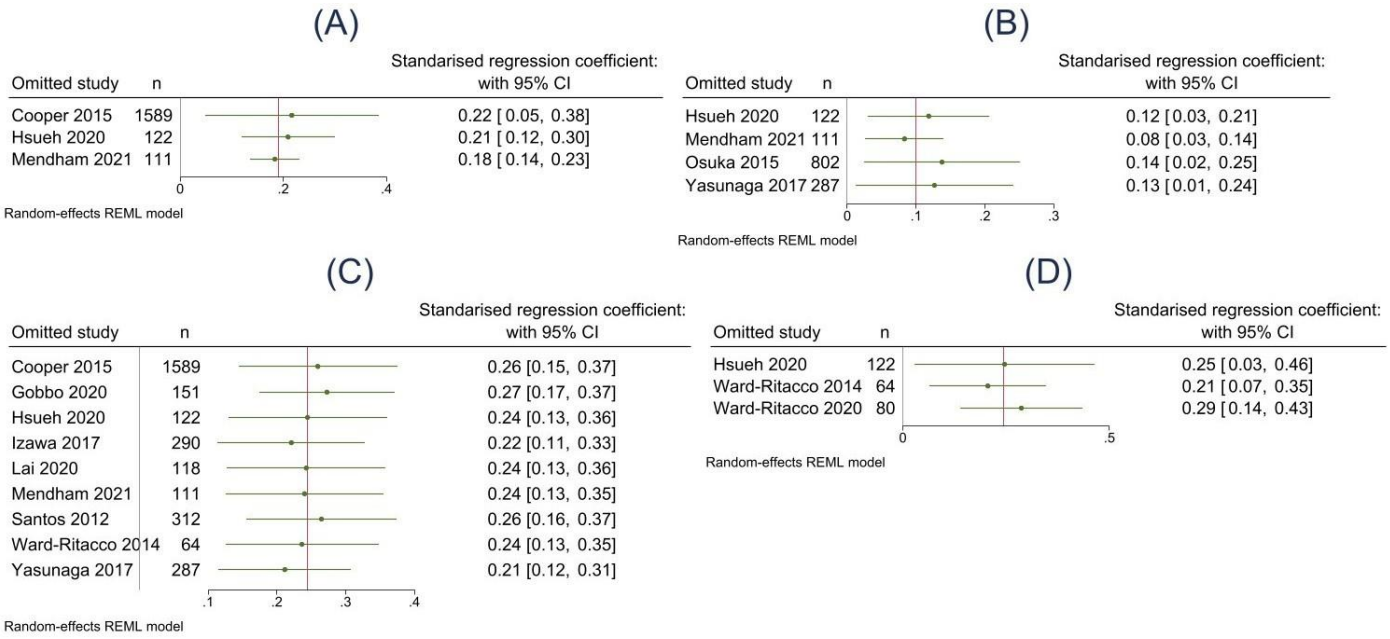
Supplementary Figure 1-7-1. Balance leave-one-out sensitivity analysis for the association with (A) total physical activity (B) light physical activity (C) moderate-to-vigorous physical activity (D) step count



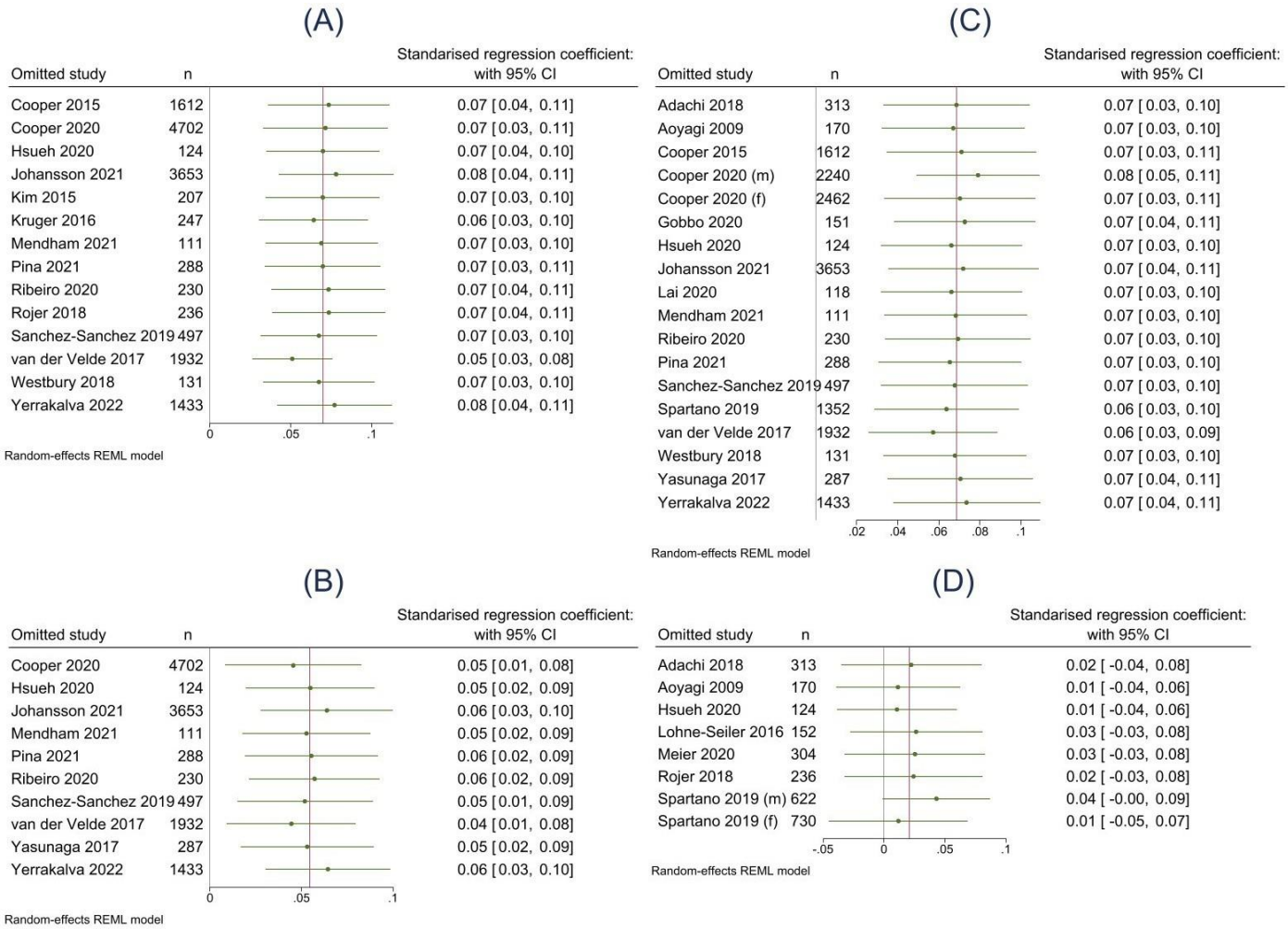
Supplementary Figure 1-7-2. Chair rise test leave-one-out sensitivity analysis for the association with (A) total physical activity (B) light physical activity (C) moderate-to-vigorous physical activity (D) step count



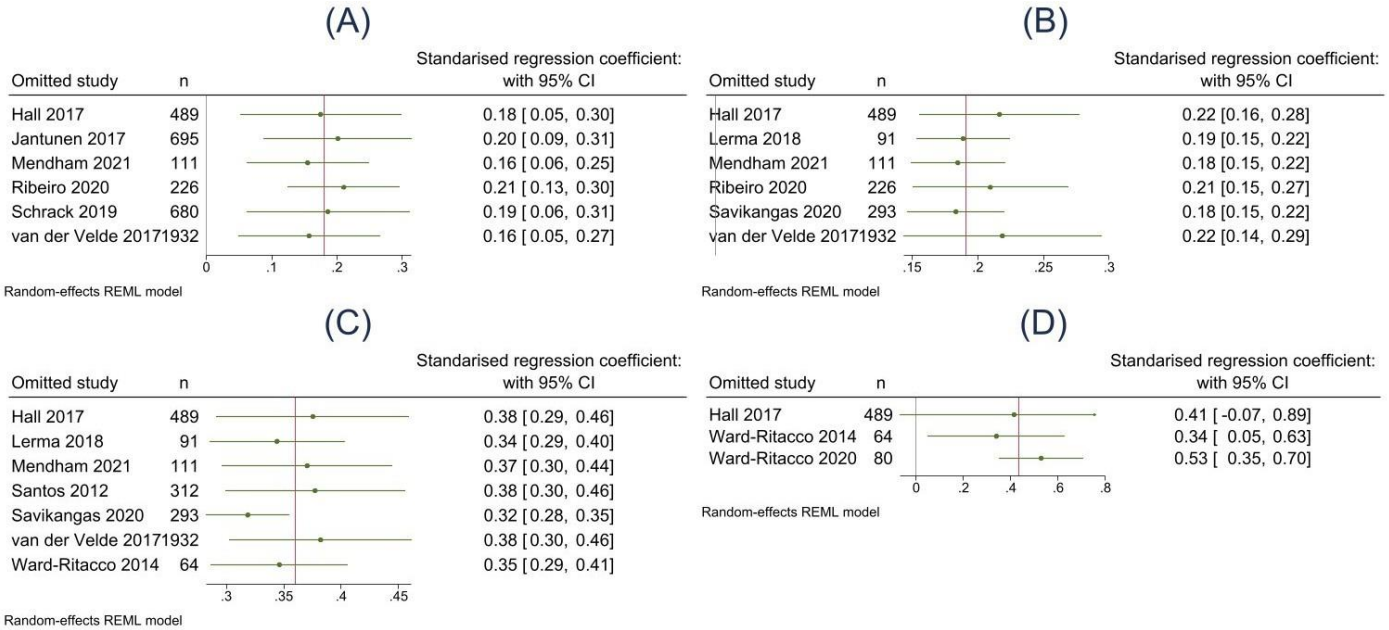
Supplementary Figure 1-7-3. Gait speed leave-one-out sensitivity analysis for the association with (A) total physical activity (B) light physical activity (C) moderate-to-vigorous physical activity (D) step count



Supplementary Figure 1-7-4. Timed up-and-go leave-one-out sensitivity analysis for the association with (A) total physical activity (B) light physical activity (C) moderate-to-vigorous physical activity (D) step count



Supplementary Figure 1-7-5. Handgrip strength leave-one-out sensitivity analysis for the association with (A) total physical activity (B) light physical activity (C) moderate-to-vigorous physical activity (D) step count



Supplementary Figure 1-7-6. Walk test leave-one-out sensitivity analysis for the association with (A) total physical activity (B) light physical activity (C) moderate-to-vigorous physical activity (D) step count

Appendix 8.8. The Maastricht Study data access application (Appendix B).

Version 4, May 2022

THE MAASTRICHT STUDY

Appendix B

Analysis Plan/Application data/materials

To be filled in by The Maastricht Study

Analysis plan #: Date received: Date approval:

Applications submitted on Tuesday in odd weeks, are in general discussed on Thursday in even weeks (with the exception of July and August).

1. Title:

Variation in the behavioural composition and temporal distribution of upright events and the associations with physical function

2. Applicant *:

Name: Joshua Culverhouse

Position: PhD student

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*** NOTE: For student projects, a different form applies. Please see appendix F.**

3. Co-applicants

Writing team: Dr Richard Pulsford, Associate Professor Melvyn Hillsdon, Associate Professor Annemarie Koster

Informed co-owner(s): yes (*strike thru or delete what is not applicable*)

Name(s) co-owner(s) that were informed:

A Koster
B de Galan
H Savelberg
GJ Dinant
P Dagnelie
C Stehouwer
C vd Kallen
H Bosma
Simone Eussen
M van Dongen

Provide list of co-owner(s) who agreed to be co-author:

A Koster
B de Galan
H Savelberg
C Stehouwer
H Bosma
Simone Eussen

4. Research questions and hypotheses:

Are the distribution and composition of upright events associated with measures of physical function?

Hypothesis:

- A higher number of majority stepping events will be associated with better physical function performance
- A higher number of majority standing events will be associated with better physical function performance
- Longer longest stepping event, and higher highest cadence events, will be associated with better physical function performance
- We are unsure of the direction of the association with temporal distribution (burstiness) metrics.

5. Background

Background and rationale for addressing the research questions and hypotheses.

Physical function is a key determinant of healthy ageing and is predictive of falls, hospitalization, morbidity, and mortality.(1-2) Physical activity has been linked with physical function, with greater levels of activity and structured exercise interventions showing improvement or delay in the loss of physical function in older adults (3-4). However, much of this evidence is based largely on self-reports of physical activity.

Device-based measures of physical activity address many of the limitations of self-report and provide precise and accurate information of physical activity behaviours, including movement, inactivity, and posture. A number of studies have begun to examine associations between device-derived metrics of physical activity and physical function outcomes, with positive associations.(5-6) However, these studies have described physical activity by summarizing steps or movement acceleration over predefined time periods, or epochs, and then aggregating these summary measures to produce broad estimates of average amounts of physical activity achieved over a day or week. This approach may miss important differences in how the physical activity is accumulated.

In free-living, physical behaviours are comprised of a series of contiguous 'events'.(7) Active behaviours begin with a transition from sitting to an upright posture, and end with a transition back to a seated posture (at which time an inactive event begins). These upright events are considered 'physically active' (or non-sedentary), but vary considerably in terms of the amount and intensity of movement that occurs within them (versus the amount of standing), their duration, frequency, and their distribution across a day or week.(5)

The variation in the composition and distribution of these events are potentially linked with physical function outcomes.(8) However, these differences are almost entirely masked by the process of summarizing behaviours over epochs and then aggregating these epochs to compute summary activity metrics for a day or week. Using the activPAL events and stepping output, we have developed a method for characterizing the composition and distribution of upright events, and have applied these

in ongoing work with the 1970 British Cohort Study to examine associations with socioeconomic and lifestyle characteristics, and basic health outcomes in a middle-aged population (age 46). In addition, we have applied these new metrics to basic physical function outcomes, including grip strength and the SF-36.

The Maastricht Study not only has activPAL data on over 8k people, it also has a more extensive range of physical function measures including the chair stand test and the 6-minute walk test. In the proposed work we aim to characterize the associations between the composition and distribution of upright events with indices of physical function.

References:

(1) Cooper R, Kuh D, Cooper C, et al. Objective measures of physical capability and subsequent health: A systematic review. *Age Ageing*. 2011;40(1):14-23. doi:10.1093/ageing/afq117
(2) Cooper R, Kuh D, Hardy R. Objectively measured physical capability levels and mortality: Systematic review and meta-analysis. *BMJ*. 2010;341(7774):639. doi:10.1136/bmj.c4467
(3) Dipietro L, Campbell WW, Buchner DM, et al. Physical Activity, Injurious Falls, and Physical Function in Aging: An Umbrella Review. *Med Sci Sports Exerc*. 2019;51(6):1303-1313. doi:10.1249/MSS.0000000000001942
(4) Chase JAD, Phillips LJ, Brown M. Physical activity intervention effects on physical function among community-dwelling older adults: A systematic review and meta-analysis. *J Aging Phys Act*. 2017;25(1):149–70. doi: 10.1123/japa.2016-0040.
(5) Culverhouse JW, Hillsdon M, Lear R, Brailey G, Metcalf B. Nunns M, Pulsford R. 'The association between device-measured physical activity and performance-based physical function outcomes in adults: a systematic review and meta-analysis' *BMJ Public Health* (*Under review*)
(6) Ramsey KA, Rojer AGM, Andrea LD, Heymans MW, Trappenburg MC, Verlaan S, et al. The association of objectively measured physical activity and sedentary behavior with skeletal muscle strength and muscle power in older adults : A systematic review and meta-analysis. 2021;67(January). doi: 10.1016/j.arr.2021.101266.
(7) Granat MH. Event-based analysis of free-living behaviour. *Physiol Meas*. 2012;33(11):1785–800. doi: 10.1088/0967-3334/33/11/1785.
(8) Park C, Mishra R, Golledge J, Najafi B. Digital biomarkers of physical frailty and frailty phenotypes using sensor-based physical activity and machine learning. *Sensors*. 2021;21(16):1–12. doi: 10.3390/s21165289.

6. Design and sample

Study design and main in- and exclusion criteria of the study sample, e.g. cross-sectional study in participants with type 2 diabetes.

Cross-sectional study in participants with activPAL accelerometer data and physical function outcomes

7. Variables

All requested variables should be listed in the Table. Please copy – paste the exact variable names from the online data dictionary of The Maastricht Study (https://demaastrichtstudie.app/data-

*dictionary**). The system is Capital sensitive.*

*** Please note that with respect to the GDPR, information about co-owners cannot be found in this data dictionary. In time, the data dictionary will be coupled to a new data request application system. As soon as this coupling is a fact, co-owners will be informed automatically after a data request has been submitted to the Maastricht Study. Until then, you can contact the data management team for information on the co-owners.*

Variable Name	General Description	"Co-owner(s)"
Main independent variable(s)		
activPAL derived variables: - Number of upright events - Upright duration - Stepping duration - Average upright event duration - Burstiness (upright) - Burstiness (non-upright) - Number of stepping upright events - Number of standing upright events - No of faster stepping upright events - Longest stepping event - Step-weighted cadence - Highest cadence step event	Either raw activPAL files – or Events output – the listed metrics will be derived by the applicant	A Koster; B de Galan; H Savelberg
accelerometry_data_available	accelerometry data available and valid	
Outcome variable(s)		
6 minute walk test vars: WTcompleted WTfinish WTdistance WTspeed	Walktest completed? Once started, did participant complete 6MWT? Distance covered 6MWT (m) Gait speed 6MWT (m/s)	H Savelberg; A Koster; GJ Dinant
		H Savelberg; A Koster
Timed chair stand test vars: TCSTdone TCSTtime	Timed chair stand test performed? TCST time (s)	H Savelberg; A Koster; GJ Dinant
GRIP_max_Overall GRIP_avg_Overall	Maximal Grip strength Overall (kg) Mean Grip strength Both hands (kg)	P Dagnelie, A Koster, GJ Dinant
SF36 vars: SF36_PF SF36_Q01 SF36_PCS SF36_GH	SF36 physical functioning General health rating SF36 Physical component summary score SF36 general health	
Confounders		
Age	Age at visit 1 (years)	
Sex	Sex of the participant	
BMI	Body mass index	
DEXA_WB_TOTAL_PFAT	Dexa total body fat percentage	C Stehouwer; C vd Kallen
N_Diabetes_WHO2; N_Diabetes_2b	Diabetes	
N_Education_3cat	Education level 3 categories	

Income_equivalent	Income level that takes household size into account	
N_OccupationalStatusGroup_ISEI08	Occupational status groups based on ISEI-08	A Koster; H Bosma
smoking_3cat	Smoking status (3 categories)	
NIT_alcoholtot	Alcohol total (g/day)	
DHD_sum; DHD_sum_min_alc	Diet	Simone Eussen; M van Dongen

8. Statistical analyses

Concisely describe the statistical analyses. This should include: 1. Statistical testing; 2. Model structure; 3. Sensitivity analyses; and 4. Interaction and stratified analyses.
If applicable, a clear distinction should be made between confounders, interactions and mediators (for statistical advice See Attachment 1).

1. Statistical testing
   The analytical sample will include all participants in the The Maastricht Study who have activPAL data and performance-based measures of physical function (listed above). Cross-sectional analyses of the association between upright event metrics (derived from the activPAL) and physical function outcomes will be examines using multivariate regression. Assumptions: Explanatory variables are continuous and will be divided into quintiles for visual inspection of linearity. Histograms of the residuals of the will be checked for normality.

   In addition to the inferential statistics, thorough descriptive summaries of the upright metrics and physical function outcomes will be produced.

2. Model structure

- Model 1: crude; each newly derived upright/stepping event metric will be regressed individually with each of the physical function measures (additionally adjusted for waking wear time)
- Model 2: as model 1 + socio-demographics (age, sex, T2DM, education, and income)
- Model 3: as model 2 + lifestyle factors (body composition, smoking, alcohol use, and diet)
- Model 4: as model 3 + adjustment for traditional stepping metrics; total step count, duration of upright time, duration of stepping

3. Interaction and stratified analyses
   Interaction of sex and type 2 diabetes will be performed.

4. Exclusions
   Analyses will be performed using a 'complete case analysis' approach. The requested confounders are common covariates that should be available for the majority of the sample, and the number of participants excluded on this basis should be minimal. Participants require activPAL data to be included. This is re-analysed by the applicants and requires participants to have a minimum number of 'valid days', determined by wear hours.

9. Mock Tables

Include mock-up of key tables.

Please see supplementary document attached with draft tables.

10. Timeline

A timeline for completion and submission of the paper.

The main applicant is currently in Maastricht and we expect that data analyses can be performed

between June and July 2023, with a draft paper produced by August, with a view to submit the paper by September 2023.

11. Compensation

What compensation is proposed by the applicant?
(for information refer to 'Procedure data materials' see https://www.demaastrichtstudie.nl/data-guidelines)

The main applicant (Joshua Culverhouse) is a visiting PhD student from the University of Exeter, UK. He is currently hosted at Maastricht University by Associate Professor Annemarie Koster, where he will be reprocessing the activPAL data to create new variables describing the composition and temporal distribution of upright events – as compensation for access to the data. These new metrics will be made available for others to utilize.

12. Agreement for the of data and/or materials of the Maastricht Study

This agreement is for the analysis plan entitled:

Variation in the behavioural composition and temporal distribution of upright events

The participating researchers are:

Joshua Culverhouse
Richard Pulsford
Melvyn Hillsdon

I certify that I am aware of the rules described in 'Procedure Data/Materials - The Maastricht Study' which include:

- The data/materials should be treated confidentially
- The data/materials may not be shared with others who are not included in this project
- I agree with the "Maastricht Study Data License Agreement" as stated in Appendix D (see below)
- The approval is valid for 1 year: After a year a written progress report should be submitted.
- For publications the rules as described in the 'Procedure Publicatie' are applicable.

Date 12/06/2023

Name main applicant and signature

Joshua Culverhouse

Appendix 8.9. Stata syntax to produce upright and stepping event metrics from activPAL stepping output .csv.


```
/*
 _____            _            ___    _____  _
(  _  )          ( )_ _       (  _`\ (  _  )( )
| (_) |   ___    | ,_)(_) _ _ | |_) )| (_) || |
|  _  | /'___)   | |  | |( ) ( )| ,__/'|  _  || |  _
| | | |( (___    | |_ | || \_/ || |    | | | || |_( )
(_) (_)`\____)   `\__)(_)`\___/'(_)    (_) (_)(____/'

 _   _                       _          _
( ) ( )                 _   ( )     ( )_
| | | | _ _    _ __  (_)  __ | |__   | ,_)
| | | |( '_`\ ( '__)| | /'_ `\|  _ `\| |
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(_____)| ,__/'(_)   (_)`\__  |(_) (_)`\__)
       | |              ( )_) |
       (_)               \___/'

              _
/'\_/`\      ( )_      _
|     |   __ | ,_) _ _(_)   ___   ___
| (_) | /'__`\| |  ( '__)| | /'___)/',__)
| | | |(  ___/| |_ | |   | |( (___ \__, \
(_) (_)`\____)`\__)(_)
(_)`\____)(____/
*/
******************************************************************************
* Project title: Upright event metrics                                       *
* Datasets used: BCS70 activPAL stepping bouts .CSV                          *
* Author: J Culverhouse                                                      *
* Date: 01/07/2023                                                           *
* Description: Stata code deriving upright event metrics from posture       *
*              data (activPAL stepping output)                               *
******************************************************************************

******************************************************************************
*** Install packages                                                       ***
******************************************************************************

* asgen for step-weight cadence
ssc install asgen

******************************************************************************
*** Importing activPAL stepping output .csv files                          ***
******************************************************************************

*** Following lines of code imports .csv files into Stata, taking the name of
the and adding it as a new variable (so ID can be extracted later), then appends
them all in the same Stata file

cd "folder_path"

local filepath = "`c(folder_path)'"

local files : dir "`filepath'" files "*.csv"

tempfile name
save `name', replace empty

```

06_11_23_activpal_code_bcs70_assoc.do - Printed on 19/05/2024 17:56:23

```
54  foreach x of local files {
55
56      qui: import delimited "`x'", delimiter(";")  case(preserve) clear
57
58      qui: gen path = subinstr("`x'", ".csv", "", .)
59
60      append using `name'
61
62      save `name', replace
63      }
64
65  ********************************************************************************
66  *** Basic set-up / importing                                                   ***
67  ********************************************************************************
68
69  *** The above method of importing imports the files 'as-is', which includes 14
    unnesscary rows at the top of each file (with activPAL software info), and
    variable names are not detected. The lines of code below rename the variables to
    match the activPAL stepping output var names, and drops the unnesscary rows.
70
71  drop v2 v6 v7 v10
72
73  rename v1 time
74  rename v3 data_count
75  rename v4 event_type
76  rename v5 duration_s
77  rename v8 num_steps
78  rename v9 cadence
79  rename id path
80
81  drop if data_count=="" & event_type=="" & num_steps=="" & cadence==""
82  drop if time == "Time"
83
84  destring _all, replace
85
86  * Converting excel time to stata time
87
88  gen double starttime = round((time+td(30dec1899))*864000)*100
89  format starttime %tcHH:MM:SS.s
90
91  gen date = dofc(starttime)
92  format date %td
93
94  ********************************************************************************
95  *** Extract numeric ID from DMS ID, destring                                   ***
96  ********************************************************************************
97
98  gen id = substr(path,1,7)
99  destring id, replace
100
101 order id date starttime
102
103 ********************************************************************************
104 *** Dropping non valid days / wear                                             ***
105 ********************************************************************************
106
```

```
*** Dropping first parital day and any days over 7

* Generates a cumulative count of bouts per day
bysort id date (data_count), sort : gen daybouts = _n
* Generates a var that with only the 1st bout of each day as 1
bysort id (data_count), sort : gen cu_days = sum(daybouts) if daybouts ==1
* Generates var with numbered days from 1
bysort id date (data_count), sort : egen days_new = max(cu_days)

* Drops day 1 and any day after 8 (which is the 7th full day)
drop if days_new ==1 | days_new >8

*** Dropping nonwear

/* The code below does the followinig
    1) Identifies the data_count values on nonwear rows
    2) Generates a column of the minimum nonwear data count per person ( the first nonwear event)
    3) Drops cases with a data count >= than the minimum nonwear datacount (which removes all data from the first nonwear period, per person)
    4) Drops generated vars

    Note: this works for cohorts where the device was applied by researcher/nurse, as there should be no non-wear. Further steps would need to be applied if devices were sent in the post and there is potential non-wear to clean before device is applied. This method assumes the first non-wear is after device is removed.
*/

* 1
gen nonwear_datacount = data_count if event_type==4
* 2
bysort id : egen nonwear_value = min(nonwear_datacount)
* 3
drop if data_count >= nonwear_value
* 4
drop nonwear_datacount nonwear_value


***Same again but for -1s
* 1
gen nonwear_datacount = data_count if event_type==-1
* 2
bysort id : egen nonwear_value = min(nonwear_datacount)
* 3
drop if data_count >= nonwear_value
* 4
drop nonwear_datacount nonwear_value

*** Calculating total wear time from day2 (first whole day)

* Genertate seconds from midnight that 1st bout starts
gen stHour = hh(starttime)
gen stMin = mm(starttime)
gen stSec = ss(starttime)
gen startsecs = (stHour*60*60) + (stMin*60) + stSec if cu_days ==2
```

```
157
158  bysort id : egen tot_dur = total(duration_s)
159
160  gen fin_dur = tot_dur + startsecs if cu_days ==2
161
162  gen tot_days_wear = fin_dur /60 / 60 / 24
163
164  *** Determining if last bout of 7th day is nonwear/invalid due to length, or
     crosses midnight into 8th day and needs to be dropped
165
166  * Generates col for each participant with the max data count vale (i.e. the
     final bout for each person)
167  bysort id (data_count), sort : egen fin_bt_data_count = max(data_count)
168
169  * Fills in all cells with total days value
170  bysort id (data_count): egen tot_days_wear_new = mean(tot_days_wear)
171
172  * Drops final bout if: over 7 days_new
173  drop if tot_days_wear_new >7 & tot_days_wear_new <. & data_count ==
     fin_bt_data_count
174
175  *** Recalculating total days for remaining participants
176  drop tot_days_wear fin_dur tot_dur tot_days_wear_new
177  bysort id : egen tot_dur = total(duration_s)
178  gen fin_dur = tot_dur + startsecs if cu_days ==2
179  gen tot_days_wear = fin_dur /60 / 60 / 24
180
181  sum tot_days_wear if tot_days_wear >7 & tot_days_wear <., detail
182
183  ********************************************************************************
184  *** Participant count                                                          ***
185  ********************************************************************************
186  *** Create a participant count (1) at their first bout - as reference for
     counting participants and creating new vars later - to get single values of
     repeated values in one consistent row
187
188  bysort id(data_count), sort : gen participantcount
189  gen participants=1 if participantcount<1
190  drop participantcount
191  sum participants
192
193  drop startsecs fin_bt_data_count tot_dur fin_dur tot_days_wear cu_days
194
195  ********************************************************************************
196  *** Day identifier (cumul count of first of each)                              ***
197  ********************************************************************************
198
199  * Uses daybouts to cumul count first bout of each day
200  bysort  id(data_count), sort : gen day_first=1 if daybouts==1
201
202  ********************************************************************************
203  *** Convert duration vars to minutes                                           ***
204  ********************************************************************************
205  gen dur=duration_s/60
206
207  ********************************************************************************
```

```
208  *** Recoding event_types                                                ***
209  ****************************************************************************
210
211  *** Needed for the CREA version output from activPAL - will be slighty different
     for VANE version as it won't have cycling, and different types of sitting, just
     0,1,2 hopefully
212
213  * Importing from SPSS changed the decimal values - below covers anything above 2
214  * Recodes cycling to stepping (as this is what the 'steps' would have been
     allocated too in the older VANE algorithm)
215  recode event_type 2.01/2.1=2
216  * Recodes all others (seated transport, types of lying, etc.) to sit/lying
217  recode event_type 3.01/5=0
218
219  ****************************************************************************
220  *** Upright event creation                                               ***
221  ****************************************************************************
222
223  *** Upright bout number across measurement period
224  * Classfies upright postures with a 1
225  gen upr_bt_num_ =.
226  bysort id (data_count) : replace upr_bt_num_ = 1 if event_type != 0
227
228  * Creates a cumulative count within upright events (upright postures between two
     sit/lying events) *NOTE* The 1 value for this var becomes the classifier for
     each upright event later on
229  gen upr_bt_num__ =.
230  bysort id (data_count): replace upr_bt_num__ = cond(missing(upr_bt_num_[_n-1]),
     upr_bt_num_, upr_bt_num_ + upr_bt_num__[_n-1])
231
232  * Cumulative count of each upright event per person
233  bysort id (data_count), sort: gen upr_bt_num___ = sum(upr_bt_num__) if
     upr_bt_num__==1
234
235  * Fills in each upright event with its respective cumulative count
236  gen upr_bt_num = upr_bt_num___
237  bysort id (data_count): replace upr_bt_num = upr_bt_num[_n-1] if missing(
     upr_bt_num) & upr_bt_num_==1
238
239  *** Upright event duration
240  * Minutes
241  bysort id upr_bt_num (data_count) : egen upr_bt_dur_min = sum(dur_min) if
     upr_bt_num !=.
242  sort id data_count
243  * Seconds
244  bysort id upr_bt_num (data_count) : egen upr_bt_dur_s = sum(duration_s) if
     upr_bt_num !=.
245  sort id data_count
246
247  *** Cumulative count of upright event per day
248  bysort id date (data_count), sort: gen upr_bt_num_day___ = sum(upr_bt_num__) if
     upr_bt_num__==1
249  * Fills in each upright event with its respective cumulative count
250  gen upr_bt_num_day = upr_bt_num_day___
251  bysort id date (data_count): replace upr_bt_num_day = upr_bt_num_day[_n-1] if
     missing(upr_bt_num_day) & upr_bt_num_==1
```

```
252
253  *** Sitting bout number across measurement period
254  gen sit_bt_num_ =.
255  bysort id (data_count) : replace sit_bt_num_ = 1 if event_type == 0
256  * Cumulative count of sit events per persn
257  bysort id (data_count), sort: gen sit_bt_num__ = sum(sit_bt_num_) if sit_bt_num_
     ==1
258  * Cumulative count of sit events per day
259  bysort id date (data_count), sort: gen sit_bt_num_day = sum(sit_bt_num_) if
     sit_bt_num_==1
260
261  ********************************************************************************
262  *** Upright 10 second MINIMUM event creation                                   ***
263  ********************************************************************************
264
265  * Upright events should not be less than 10s (if you applied the recommended
     minimums through PALbatch analysis), but this just checks. Can be used for
     events data, and change duration if you're interested in shorter/longer upright
     events.
266
267  *** Upright bout >=10sec
268  bysort id (data_count) : gen upr_bt_10sec = sum(upr_bt_num__) if upr_bt_num__==1
     & upr_bt_dur_s >=10
269
270  bysort id (data_count): replace upr_bt_10sec = upr_bt_10sec[_n-1] if missing(
     upr_bt_10sec) & upr_bt_num_==1 & upr_bt_dur_s >=10
271
272  ********************************************************************************
273  *** Sedentary bouts INCLUDING uprigths less than <10 seconds                   ***
274  ********************************************************************************
275
276  * Unlike upright bouts - sedentary bouts are only one row at a time (uprights
     can be 1s and 2s for multiple rows). The below creates count and duration
     vairbles for the time between >1min upright bouts - which can include multiple
     sedentary bouts and the upright bout/s <1min in between
277
278  * An idiots way of creating ones in the gaps between >10s upr events
279  gen sit_ = upr_bt_10sec +1
280  replace sit_ =1 if sit_==.
281  replace sit_ =. if sit_>1
282
283  * Cumulative count within these bouts - allows for next step...
284  gen sit__ =.
285  bysort id (data_count): replace sit__ = cond(missing(sit_[_n-1]), sit_, sit_ +
     sit__[_n-1])
286  * Cumulative count of 1s - therefore each sedentary bout
287  bysort id (data_count), sort: gen sit_num = sum(sit__) if sit__==1
288  * Fills in each bout with the bout number (to allow for sorting by bout number.)
289  bysort id (data_count): replace sit_num = sit_num[_n-1] if missing(sit_num) &
     sit_==1
290
291  *** Duration of gaps between >10sec upright bouts (sedentary time - but also
     with upr bts <10sec)
292  bysort id sit_num (data_count) : egen sit_and_less_10sec_upr_dur_min = sum(
     dur_min) if sit_num !=.
293  sort id data_count
```

```
295
296
297   /*
298
299   ********************************************************************************
300   ** Creating filter for waking wear based on 1st bout (>=1min) after 5am **
301   ********************************************************************************
302
303   * Putting a 1 qualifierfor waking wear time between 03:00 and 23:00, from first
      upright to last upright
304   * Cumulative count of rows between these hours per day pp
305   bysort id date (data_count) : gen wake_ = _n if stHour>=3 & stHour<24
306
307   * Replaces the last row of a waking day - if the immediate row after is the
      first row of the next day (if there was literally one sleeping bout - it will
      give this a missing value)
308   replace wake_ =. if wake_[_n+1]==1
309   * Replaces final bout with missing (this because it crosses 24:00 and can make
      the wear_time more than the 20h window (3am-11pm))
310   replace wake_=. if wake_[_n+1]==.
311
312   * This generates waking wear time from first upright bout >=10sec after 3am -
      but with gaps (puts ones in all the upright bouts)
313   bysort id date (data_count) : gen wake_time = 1 if stHour>=3 & upr_bt_10sec !=.
314   *This then replaes missing values between 3am and middnight with 1s - so that
      all time after 3am filled with 1s
315   replace wake_time =1 if wake_time[_n-1]==1 & stHour>3 & stHour<24
316   * Final step replaces the wake_tie with missing if wake_ is missing, which is
      the time after 11pm - and the final bouts that may go into the next day etc.
317   replace wake_time=. if wake_==.
318
319   // Just to clarify - wake_ is now a continous count of rows per day from 3am,
      with final bout replaced with . if immediately proceed by the first bout of the
      next day, and if the final bout is sit/lying (we don't want to count these as
      the cross to the next day - they are the 'sleeping bouts')
320   // and wake_time is now a classifier with 1s in every cell from the frist
      upright bout after 3am to the penultimate event before 11pm - because the
      last/next bout is the event that crosses into the next day, which we don;t want
      to count
321
322   drop wake_
323
324   */
325
326
327   ********************************************************************************
328   ** Experimenting with wear time from 6am to 10pm                              **
329   ********************************************************************************
330
331   * Putting a 1 qualifierfor waking wear time between 03:00 and 23:00, from first
      upright to last upright
332   * Cumulative count of rows between these hours per day pp
333   bysort id date (data_count) : gen wake_ = _n if stHour>=6 & stHour<22
334
335   * Replaces the last row of a waking day - if the immediate row after is the
```

```
first row of the next day (if there was literally one sleeping bout - it will
give this a missing value)
replace wake_ =. if wake_[_n+1]==1
* Replaces final bout with missing (this because it crosses 24:00 and can make
the wear_time more than the 20h window (3am-11pm))
replace wake_=. if wake_[_n+1]==.

* This generates waking wear time from first upright bout >=10sec after 3am -
but with gaps (puts ones in all the upright bouts)
bysort id date (data_count) : gen wake_time = 1 if stHour>=6
*This then replaes missing values between 3am and middnight with 1s - so that
all time after 3am filled with 1s
replace wake_time =1 if wake_time[_n-1]==1 & stHour>6 & stHour<22
* Final step replaces the wake_tie with missing if wake_ is missing, which is
the time after 11pm - and the final bouts that may go into the next day etc.
replace wake_time=. if wake_==.

// Just to clarify - wake_ is now a continous count of rows per day from 3am,
with final bout replaced with . if immediately proceed by the first bout of the
next day, and if the final bout is sit/lying (we don't want to count these as
the cross to the next day - they are the 'sleeping bouts')
// and wake_time is now a classifier with 1s in every cell from the frist
upright bout after 3am to the penultimate event before 11pm - because the
last/next bout is the event that crosses into the next day, which we don;t want
to count

drop wake_




*********************************************************************
***           Deriving upright event and stepping metrics             ***
*********************************************************************

*** No. upright events >10sec
bysort id date (data_count ) : egen upr_10s_bts_per_day_ = sum(upr_bt_num__) if
upr_bt_num__  ==1 & upr_bt_10sec !=. & wake_time ==1
bysort id date (data_count ) : egen upr_10s_bts_per_day = max(
upr_10s_bts_per_day_)
drop upr_10s_bts_per_day_

*** Upright duration per day
bysort id date (data_count ) : egen upr_10s_dur_day_ = sum(dur_min) if wake_time
==1 & upr_bt_10sec !=.
bysort id date (data_count ) : egen upr_10s_dur_day_min = max(upr_10s_dur_day_)
drop upr_10s_dur_day_
gen upr_10s_dur_day_h = upr_10s_dur_day_min/60

*** Standing duration per day
bysort id date (data_count ) : egen std_dur_day_ = sum(dur_min) if wake_time ==1
& upr_bt_10sec !=. & event_type==1
bysort id date (data_count ) : egen std_dur_day_min = max(std_dur_day_)
drop std_dur_day_
gen std_dur_day_h = std_dur_day_min/60

```

```
*** Stepping duration per day
bysort id date (data_count ) : egen stp_dur_day_ = sum(dur_min) if wake_time ==1 & upr_bt_10sec !=. & event_type==2
bysort id date (data_count ) : egen stp_dur_day_min = max(stp_dur_day_)
drop stp_dur_day_
gen stp_dur_day_h = stp_dur_day_min/60

*** Stepping proportion per event metric
* Stepping duration per upright evevnt
bysort id date upr_bt_num_day (data_count) : egen within_stp_dur_ = sum(dur_min) if event_type==2
bysort id date upr_bt_num_day (data_count) : egen within_stp_dur = max(within_stp_dur_) if upr_bt_num_day !=.
sort id data_count
drop within_stp_dur_
replace within_stp_dur = 0 if upr_bt_num__==1 & within_stp_dur==.
* Standing duration per upright evevnt
bysort id date upr_bt_num_day (data_count) : egen within_std_dur_ = sum(dur_min) if event_type==1
bysort id date upr_bt_num_day (data_count) : egen within_std_dur = max(within_std_dur_) if upr_bt_num_day !=.
sort id data_count
drop within_std_dur_
*** Propoertion of time stepping
gen perc_dur_stp = (within_stp_dur / upr_bt_dur_min)*100

*** Step-weighted mean cadence per upright bout
bysort id date upr_bt_num_day : asgen stpw_mean_cad_ = cadence if event_type==2, w(num_steps)
sort id data_count
bysort id date upr_bt_num_day : egen stpw_mean_cad = max(stpw_mean_cad_)
sort id data_count
replace stpw_mean_cad =0 if stpw_mean_cad==. & within_stp_dur==0
drop stpw_mean_cad_

* No. of stepping events within upright
bysort id date upr_bt_num_day (data_count) : egen within_num_stp_bts_ = sum(event_type) if event_type==2
bysort id date upr_bt_num_day (data_count) : egen within_num_stp_bts__ = max(within_num_stp_bts_) if upr_bt_num_day !=.
gen within_num_stp_bts = within_num_stp_bts__/2
sort id data_count
drop within_num_stp_bts_ within_num_stp_bts__
replace within_num_stp_bts = 0 if within_stp_dur==0

*** No. of steps within upright events
bysort id date upr_bt_num_day (data_count) : egen within_num_stps = sum(num_steps) if upr_bt_num_day !=.
sort id data_count

*** Step count per day (withing >=10sec)
bysort id date (data_count ) : egen steps_day_ = sum(num_steps) if wake_time ==1 & upr_bt_10sec !=.
bysort id date (data_count ) : egen steps_day = max(steps_day_)
drop steps_day_
* Check
```

```
list id if steps_day ==0 | steps_day ==.

*************************************************************************
** Valid day of wear (duration & no. upright events) classifier         **
*************************************************************************
* Calculate minutes of wear during wake time
bysort id date (data_count) : egen wear_ = sum(dur_min) if wake_time ==1
bysort id date (data_count) : egen wear_time_min = max(wear_)
drop wear_
* Adds a 1 classifier to wear that is valid (>=10 waking wear)
bysort id date (data_count) : gen valid_wear =1 if wear_time_min >600 &
wear_time_min <. & upr_10s_bts_per_day >3

* Count valid days per person
bysort id (data_count) : gen valid_days_ =1 if day_first_bt !=. & valid_wear==1
bysort id (data_count) : egen valid_days__ = sum(valid_days_) if valid_days_==1 &
 valid_wear==1
bysort id (data_count) : egen n_valid_days = max(valid_days__)

drop valid_days_ valid_days__

drop if valid_wear ==.

*************************************************************************
*** Burstiness - Between UPRIGHT events                                ***
*************************************************************************

*** BURSTINESS between upright events (n, mean(SD) of sit/lying bouts) ******

* n - number of upright events per day
// upr_10s_bts_per_day

* t - mean duration of sit/lyig bouts
bysort id date (data_count): egen mean_ = mean(sit_and_less_10sec_upr_dur_min) if
 sit__ ==1 & wake_time==1
bysort id date (data_count): egen mean_sed_dur_day = max(mean_)
drop mean_

* 0 - mean duration of sit/lyig bouts
bysort id date (data_count): egen sd_ = sd(sit_and_less_10sec_upr_dur_min) if
sit__ ==1 & wake_time==1
bysort id date (data_count): egen sd_sed_dur_day = max(sd_)
drop sd_

* burstiness between upright events
gen burst_between_upr_bts = (sqrt(upr_10s_bts_per_day+1)*(sd_sed_dur_day/
mean_sed_dur_day)-sqrt(upr_10s_bts_per_day-1))/((sqrt(upr_10s_bts_per_day+1)-2)*(
sd_sed_dur_day/mean_sed_dur_day)+(sqrt(upr_10s_bts_per_day-1)))

sum burst_between_upr_bts if day_first_bt !=. , detail

*************************************************************************
*** Burstiness - Between NON-UPRIGHT events                            ***
*************************************************************************

*** BURSTINESS between NON-upright events (n, mean(SD) of upright bouts) ******
```

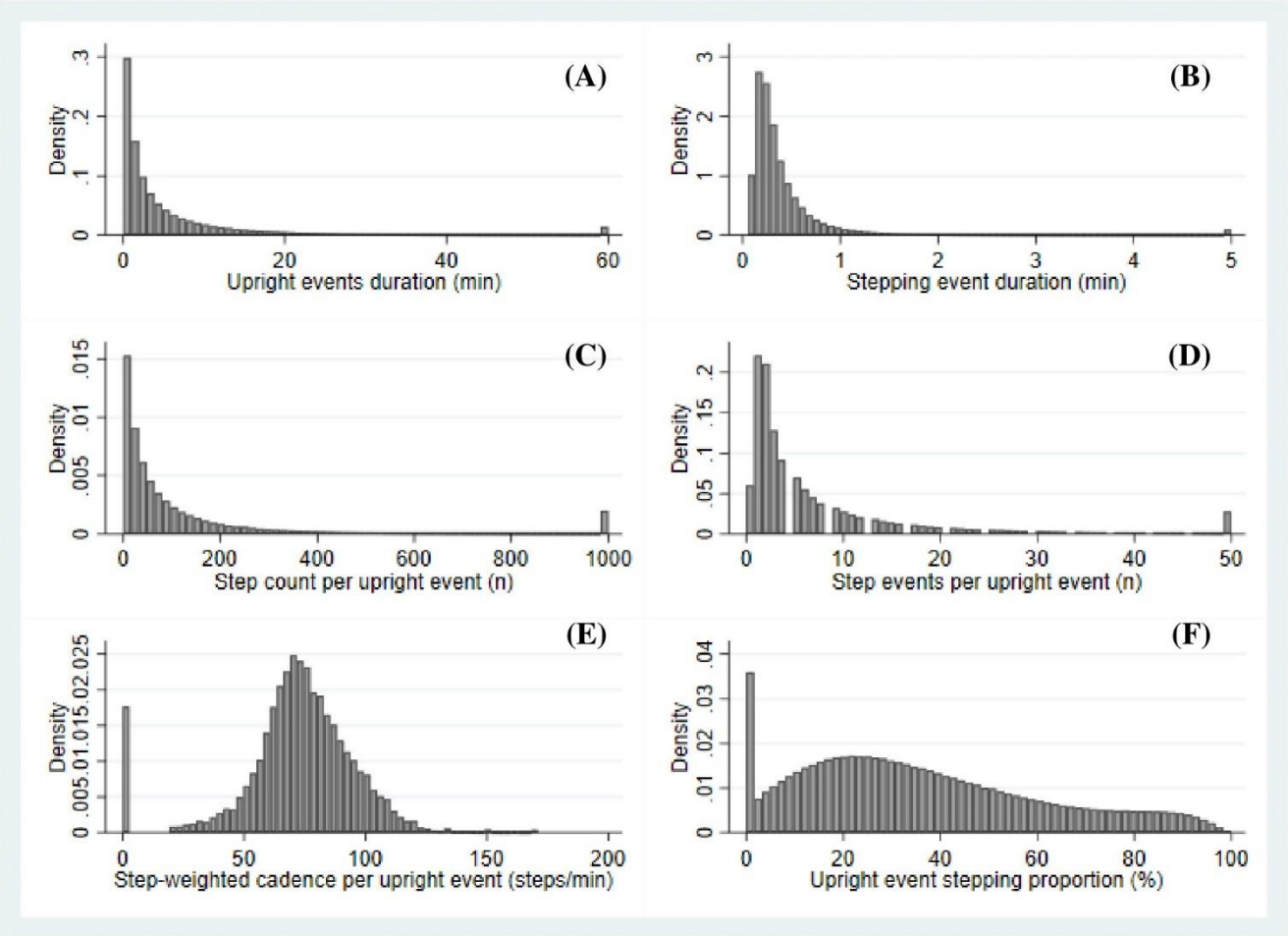
```
472
473   * n - number of upright events per day (already created)
474   bysort id date (data_count ) : egen non_upr_bts_per_day_ = sum(sit__) if sit__
      ==1 & wake_time ==1
475   bysort id date (data_count ) : egen non_upr_bts_per_day = max(non_upr_bts_per_day
476   drop non_upr_bts_per_day_
477
478   * t - mean duration of upright events per day
479   bysort id date (data_count): egen mean_ = mean(upr_bt_dur_min) if upr_bt_num__ ==
      1 & wake_time==1
480   bysort id date (data_count): egen mean_upr_dur_day = max(mean_)
481   drop mean_
482
483   * 0 - mean duration of sit/lyig bouts
484   bysort id date (data_count): egen sd_ = sd(upr_bt_dur_min) if upr_bt_num__ ==1 &
      wake_time==1
485   bysort id date (data_count): egen sd_upr_dur_day = max(sd_)
486   drop sd_
487
488   * burstiness between upright events
489   gen burst_between_sed_bts = (sqrt(non_upr_bts_per_day+1)*(sd_upr_dur_day/
      mean_upr_dur_day)-sqrt(non_upr_bts_per_day-1))/((sqrt(non_upr_bts_per_day+1)-2)*(
      sd_upr_dur_day/mean_upr_dur_day)+(sqrt(non_upr_bts_per_day-1)))
490
491   sum burst_between_sed_bts if day_first_bt !=. , detail
492
493   ********************************************************************************
494   *** ASTP (active-to-sedentary tranisition probability) Fragmentation   ***
495   ********************************************************************************
496
497   * ASTP is the reciprocal (the shortest event length over...) the mean duration
      of the events (upright events)
498
499   * 10s events (in minutes) - times by 100 to give percentage
500   gen daily_astp = ((0.16666666666/mean_upr_dur_day)*100)
501
502
503   ********************************************************************************
504   ***                                                                          ***
505   ***                 FINAL VARIABLES (1 value per person)                     ***
506   ***                                                                          ***
507   ********************************************************************************
508
509   *** Average waking wear hours
510   bysort id (data_count) : egen avg_waking_wear_ = mean(wear_time_min) if
      day_first_bt !=.
511   bysort id (data_count) : egen avg_waking_wear_h_ = max(avg_waking_wear_)
512   gen avg_waking_wear_h = avg_waking_wear_h_/60
513   drop avg_waking_wear_ avg_waking_wear_h_
514
515   ************************* DAILY SUMMARIES ******************************
516
517   *** Average number of bouts per day per person
518   bysort id (data_count) : egen avg_n_upr_bts_day_ = mean(upr_10s_bts_per_day) if
      day_first_bt !=.
519   bysort id (data_count) : egen avg_n_upr_bts_day = max(avg_n_upr_bts_day_)
```

```
drop avg_n_upr_bts_day_

*** Average upright duration per day
bysort id (data_count) : egen avg_upr_dur_day_ = mean(upr_10s_dur_day_h) if
day_first_bt !=.
bysort id (data_count) : egen avg_upr_dur_day = max(avg_upr_dur_day_)
drop avg_upr_dur_day_

*** Average standing duration per day
bysort id (data_count) : egen avg_std_dur_day_ = mean(std_dur_day_h) if
day_first_bt !=.
bysort id (data_count) : egen avg_std_dur_day = max(avg_std_dur_day_)
drop avg_std_dur_day_

*** Average stepping duration per day
bysort id (data_count) : egen avg_stp_dur_day_ = mean(stp_dur_day_h) if
day_first_bt !=.
bysort id (data_count) : egen avg_stp_dur_day = max(avg_stp_dur_day_)
drop avg_stp_dur_day_

*** Average stepping proportion per upright
bysort id (data_count) : egen avg_stp_prop_ = mean(perc_dur_stp) if upr_bt_num__
==1 & upr_bt_10sec !=. & wake_time ==1
bysort id (data_count) : egen avg_stp_prop = max(avg_stp_prop_)
drop avg_stp_prop_

*** Average stepping events per day per person (>10)
bysort id date (data_count) : egen n_stp_evnts_10_per_day_ = sum(event_type) if
event_type==2 & num_steps>=10
bysort id date (data_count) : egen n_stp_evnts_10_per_day__ = max(
n_stp_evnts_10_per_day_)
bysort id date (data_count) : gen n_stp_evnts_10_per_day___ =
n_stp_evnts_10_per_day__/2
bysort id (data_count) : egen avg_n_stp_evnts_10_per_day_ = mean(
n_stp_evnts_10_per_day___) if day_first_bt !=.
bysort id (data_count) : egen avg_n_stp_evnts_per_day_10 = max(
avg_n_stp_evnts_10_per_day_)
drop n_stp_evnts_10_per_day_ n_stp_evnts_10_per_day__
avg_n_stp_evnts_10_per_day_ avg_n_stp_evnts_10_per_day_

*** Avg. step count per day
bysort id (data_count ) : egen avg_steps_day_ = mean(steps_day) if day_first_bt
!=.
bysort id (data_count ) : egen avg_steps_day = max(avg_steps_day)
drop avg_steps_day_

*************************** COMPOSITION ********************************

*** Average duration of upright event
bysort id (data_count) : egen avg_upr_event_dur_ = mean(upr_bt_dur_min) if
upr_bt_num__ ==1 & upr_bt_10sec !=. & wake_time ==1
bysort id (data_count) : egen avg_upr_event_dur = max(avg_upr_event_dur_)
drop avg_upr_event_dur_

*** Average number of step events per upright event
bysort id (data_count) : egen avg_within_num_stp_bts_ = mean(within_num_stp_bts)
```

```
    if upr_bt_num__ ==1 & upr_bt_10sec !=. & wake_time ==1
564 bysort id (data_count) : egen avg_within_num_stp_bts = max(
    avg_within_num_stp_bts_)
565 drop avg_within_num_stp_bts_
566
567 *** Average number of steps per upright event
568 bysort id (data_count) : egen avg_within_num_stps_ = mean(within_num_stps) if
    upr_bt_num__ ==1 & upr_bt_10sec !=. & wake_time ==1
569 bysort id (data_count) : egen avg_within_num_stps = max(avg_within_num_stps_)
570 drop avg_within_num_stps_
571
572 *** Average step-weight cadence per upright event
573 bysort id (data_count) : egen avg_stpw_mean_cad_ = mean(stpw_mean_cad) if
    upr_bt_num__ ==1 & upr_bt_10sec !=. & wake_time ==1
574 bysort id (data_count) : egen avg_stpw_mean_cad = max(avg_stpw_mean_cad_)
575 drop avg_stpw_mean_cad_
576
577 ************************ PATTERN METRICS ********************************
578
579 *** Average upright burstines (inter-event-time)
580 bysort id (data_count ) : egen avg_inter_burst_ = mean(burst_between_upr_bts) if
    day_first_bt !=.
581 bysort id (data_count ) : egen avg_inter_burst = max(avg_inter_burst_)
582 drop avg_inter_burst_
583 *** Average non-upright burstiness
584 bysort id (data_count ) : egen avg_intra_burst_ = mean(burst_between_sed_bts) if
    day_first_bt !=.
585 bysort id (data_count ) : egen avg_intra_burst = max(avg_intra_burst_)
586 drop avg_intra_burst_
587
588 *** Average daily ASTP
589 bysort id (data_count ) : egen avg_daily_astp_ = mean(daily_astp) if day_first_bt
     !=.
590 bysort id (data_count ) : egen avg_daily_astp = max(avg_daily_astp_)
591 drop avg_daily_astp_
592
593 ************************ STEPPING METRICS ********************************
594
595 *** Longest continuous stepping event (>=10 steps)
596 bysort id (data_count) : egen longest_step_bt_min_ = max(dur_min) if event_type
    ==2 & wake_time ==1 & num_steps >=10
597 bysort id (data_count) : egen longest_step_bt_min = max(longest_step_bt_min_)
598 drop longest_step_bt_min_
599
600 *** Step-weighted mean cadence of every step count
601 bysort id (data_count) : asgen avg_stpw_cad_all_ = cadence if wake_time==1 &
    event_type==2 & num_steps>=10, w(num_steps)
602 bysort id (data_count) : egen avg_stpw_cad_all = max(avg_stpw_cad_all_)
603 drop avg_stpw_cad_all_
604
605 *** Average steps per stepping event (>=10 steps)
606 bysort id (data_count) : egen avg_stps_per_stp_evnt_10_ = mean(num_steps) if
    event_type==2 & wake_time ==1 & num_steps >=10
607 bysort id (data_count) : egen avg_stps_per_stp_evnt_10 = max(
    avg_stps_per_stp_evnt_10_)
608 drop avg_stps_per_stp_evnt_10_
```

```
609
610  ***Average duration per stepping event-time (>=10 steps)
611  bysort id (data_count): egen avg_dur_stpev_10_ = mean(duration_s) if wake_time ==
     1 & event_type ==2 & num_steps>=10
612  bysort id (data_count): egen avg_dur_stpev_10 = max(avg_dur_stpev_10_)
613  drop avg_dur_stpev_10_
614
615  *** Highest cadence stepping event (=10 steps)
616  bysort id (data_count) : egen highest_cad_stp_event_ = max(cadence) if wake_time
     ==1 & event_type==2 & num_steps >=10
617  bysort id (data_count) : egen highest_cad_stp_event = max(highest_cad_stp_event_)
618  drop highest_cad_stp_event_
619
620  ****************************** TIDYING UP *********************************
621
622  * Collapse to one row per person
623  drop if participants !=1
624
625  *** Dropping unneeded vars
626  drop date - valid_wear
627  drop n_stp_evnts_10_per_day___
628  drop mean_sed_dur_day - burst_between_sed_bts
629
630  ***
631
632
```

Appendix 8.10. Histograms of the composition metrics of all 1.64 million upright events



(A) upright duration (mins); (B) Stepping event duration (mins): (C) Step count per upright event (n); (D) Step events per upright event (n); (E) Step-weighted mean cadence per upright event (steps/min); (F) Upright event stepping proportion (%).

Appendix 8.11. Sensitivity analyses.

Supplementary Table 5.11-1.Sensitivity analyses regressions (excluding EU-SILC severely hampered).

	(1) N upev		(2) Upr dur_h		(3) std_ dur_h		(4) Stp dur_h		(5) N stpev		(6) Dur stpev		(7) stps_per stpev		(8) Stpw cad	
0.Sex	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.Sex	4.41***	[3.43,5.38]	0.37***	[0.28,0.46]	0.37***	[0.29,0.46]	-0.00	[-0.02,0.01]	12.75***	[9.64,15.86]	-3.05***	[-3.51,-2.59]	-4.24***	[-5.13,-3.35]	1.04***	[0.54,1.54]
0.Qual	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.Qual	0.00	[-1.24,1.25]	-0.01	[-0.13,0.11]	-0.01	[-0.13,0.10]	0.00	[-0.01,0.02]	0.05	[-3.90,4.00]	0.11	[-0.48,0.69]	0.08	[-1.06,1.21]	0.13	[-0.51,0.77]
2.Qual	-0.02	[-1.52,1.47]	-0.01	[-0.15,0.13]	-0.01	[-0.15,0.12]	0.01	[-0.01,0.02]	-1.80	[-6.56,2.95]	0.41	[-0.30,1.11]	0.40	[-0.97,1.77]	-0.09	[-0.86,0.68]
3.Qual	-0.78	[-2.16,0.60]	-0.13	[-0.26,0.00]	-0.12	[-0.24,0.00]	-0.01	[-0.03,0.01]	-7.98***	[-12.36,-3.59]	1.41***	[0.76,2.07]	2.12***	[0.86,3.38]	0.41	[-0.30,1.12]
0.Disab	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.Disab	-0.29	[-1.88,1.30]	0.06	[-0.09,0.21]	0.06	[-0.09,0.20]	0.00	[-0.02,0.02]	-2.13	[-7.17,2.91]	0.21	[-0.53,0.96]	0.27	[-1.18,1.72]	-0.18	[-0.99,0.64]
0.SRhealth	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.SRhealth	0.77	[-0.45,1.99]	0.16**	[0.04,0.27]	0.12*	[0.01,0.23]	0.03***	[0.02,0.05]	9.56***	[5.67,13.44]	-1.44***	[-2.02,-0.87]	-2.90***	[-4.02,-1.79]	-1.38***	[-2.01,-0.75]
2.SRhealth	0.79	[-0.58,2.15]	0.13*	[0.00,0.26]	0.10	[-0.02,0.23]	0.03***	[0.01,0.05]	10.60***	[6.26,14.94]	-1.61***	[-2.26,-0.97]	-3.23***	[-4.47,-1.98]	-1.61***	[-2.31,-0.91]
3.SRhealth	0.37	[-1.51,2.25]	0.18*	[0.01,0.36]	0.14	[-0.03,0.31]	0.05***	[0.02,0.07]	13.20***	[7.22,19.17]	-1.66***	[-2.55,-0.77]	-3.48***	[-5.20,-1.76]	-2.32***	[-3.29,-1.36]
4.SRhealth	-1.47	[-5.96,3.01]	-0.15	[-0.57,0.28]	-0.15	[-0.55,0.25]	0.00	[-0.06,0.06]	2.33	[-11.93,16.58]	0.03	[-2.08,2.15]	-0.16	[-4.26,3.94]	-1.30	[-3.60,1.01]
0.NSSEC_3	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.NSSEC_3	1.96***	[0.82,3.10]	0.23***	[0.12,0.33]	0.19***	[0.09,0.29]	0.04***	[0.03,0.05]	6.99***	[3.37,10.62]	-0.99***	[-1.53,-0.46]	-2.18***	[-3.22,-1.14]	-1.26***	[-1.84,-0.67]
2.NSSEC_3	-0.35	[-1.92,1.22]	0.11	[-0.04,0.26]	0.07	[-0.07,0.21]	0.04***	[0.02,0.06]	3.78	[-1.22,8.78]	-0.37	[-1.12,0.37]	-1.21	[-2.64,0.23]	-1.19**	[-2.00,-0.39]
3.NSSEC_3	-6.24	[-17.62,5.14]	-1.14*	[-2.22,-0.07]	-1.03*	[-2.04,-0.02]	-0.11	[-0.26,0.03]	-22.90	[-59.07,13.27]	2.51	[-2.86,7.88]	5.25	[-5.15,15.64]	3.35	[-2.50,9.19]
4.NSSEC_3	0.72	[-1.39,2.83]	0.26*	[0.06,0.46]	0.22*	[0.03,0.41]	0.04**	[0.02,0.07]	7.86*	[1.16,14.57]	-1.40**	[-2.39,-0.40]	-3.04**	[-4.97,-1.12]	-1.74**	[-2.83,-0.66]
0.BMIC	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.BMIC	-3.15***	[-4.26,-2.05]	-0.10	[-0.21,0.00]	-0.10	[-0.19,0.00]	-0.01	[-0.02,0.01]	-0.96	[-4.49,2.56]	0.20	[-0.32,0.73]	0.29	[-0.72,1.30]	-0.14	[-0.71,0.43]
2.BMIC	-6.48***	[-7.73,-5.22]	-0.12*	[-0.24,-0.00]	-0.11	[-0.22,0.01]	-0.01	[-0.03,0.00]	-2.67	[-6.66,1.31]	0.47	[-0.12,1.06]	0.62	[-0.52,1.77]	-0.58	[-1.22,0.07]
3.BMIC	-13.10***	[-16.08,-10.13]	-0.03	[-0.31,0.25]	-0.00	[-0.27,0.26]	-0.02	[-0.06,0.02]	-6.85	[-16.31,2.61]	1.19	[-0.22,2.59]	1.43	[-1.29,4.15]	-1.61*	[-3.14,-0.08]
4.BMIC	-8.26***	[-11.58,-4.95]	-0.08	[-0.39,0.24]	-0.07	[-0.37,0.22]	-0.01	[-0.05,0.04]	0.83	[-9.71,11.37]	0.21	[-1.36,1.77]	-0.10	[-3.13,2.93]	-1.35	[-3.05,0.36]
0.OccAct	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.OccAct	-0.60	[-1.92,0.72]	1.18***	[1.06,1.31]	1.08***	[0.96,1.20]	0.10***	[0.09,0.12]	29.10***	[24.90,33.30]	-3.97***	[-4.59,-3.35]	-7.87***	[-9.08,-6.66]	-3.76***	[-4.44,-3.08]
2.OccAct	-0.43	[-1.66,0.80]	1.06***	[0.94,1.17]	0.91***	[0.80,1.02]	0.15***	[0.13,0.16]	35.17***	[31.25,39.09]	-4.56***	[-5.15,-3.98]	-9.65***	[-10.78,-8.53]	-5.80***	[-6.44,-5.17]
3.OccAct	-0.06	[-2.44,2.31]	1.28***	[1.05,1.50]	1.03***	[0.82,1.24]	0.25***	[0.22,0.28]	51.86***	[44.31,59.41]	-6.16***	[-7.28,-5.04]	-13.51***	[-15.68,-11.34]	-8.58***	[-9.80,-7.36]
0.Smoking	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.Smoking	1.51**	[0.50,2.52]	-0.11*	[-0.20,-0.01]	-0.12*	[-0.21,-0.03]	0.01	[-0.00,0.02]	0.14	[-3.07,3.35]	-0.04	[-0.51,0.44]	-0.23	[-1.15,0.69]	-0.30	[-0.82,0.22]
2.Smoking	2.53*	[0.35,4.72]	0.24*	[0.03,0.45]	0.24*	[0.04,0.43]	0.00	[-0.03,0.03]	3.88	[-3.07,10.83]	-0.70	[-1.73,0.33]	-0.96	[-2.95,1.04]	0.01	[-1.11,1.14]
3.Smoking	2.90***	[1.38,4.41]	0.20**	[0.06,0.34]	0.18*	[0.04,0.31]	0.02*	[0.00,0.04]	9.82***	[5.00,14.64]	-1.22***	[-1.94,-0.51]	-2.20**	[-3.59,-0.82]	-1.26**	[-2.04,-0.48]
wake_time_h	2.25***	[1.74,2.76]	0.24***	[0.19,0.29]	0.22***	[0.18,0.27]	0.02***	[0.01,0.03]	7.95***	[6.33,9.57]	-0.93***	[-1.17,-0.69]	-1.69***	[-2.15,-1.22]	-0.65***	[-0.91,-0.39]
daily_n_stps	0.00***	[0.00,0.00]	0.00***	[0.00,0.00]	0.00***	[0.00,0.00]	0.00***	[0.00,0.00]	0.01***	[0.01,0.01]	0.00***	[0.00,0.00]	0.00***	[0.00,0.00]	0.00***	[0.00,0.00]
_cons	11.10**	[2.76,19.45]	-0.74	[-1.52,0.05]	-0.59	[-1.33,0.15]	-0.15**	[-0.25,-0.04]	-73.25***	[-99.76,-46.73]	38.35***	[34.41,42.29]	57.64***	[50.02,65.26]	95.15***	[90.86,99.43]
p	0.00		0.00		0.00		0.00		0.00		0.00		0.00		0.00	

95% confidence intervals in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Supplementary Table 5.11-2. Sensitivity analyses regressions (excluding EU-SILC severely hampered).

	(1) prop_stp _to_std		(2) Upev dur_min		(3) Upev n_stpev		(4) Upev n_stps		(8) Upev bursti		(9) Nonupev bursti	
0.Sex	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.Sex	-0.12	[-0.51,0.26]	-0.26*	[-0.51,-0.02]	-0.06	[-0.30,0.17]	-17.84***	[-21.95,-13.73]	0.05***	[0.04,0.05]	-0.00	[-0.01,0.00]
0.Qual	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.Qual	0.02	[-0.47,0.51]	-0.08	[-0.39,0.23]	-0.03	[-0.33,0.27]	-2.03	[-7.26,3.19]	0.00	[-0.00,0.01]	-0.01	[-0.01,0.00]
2.Qual	-0.36	[-0.95,0.23]	-0.14	[-0.52,0.23]	-0.19	[-0.55,0.17]	-2.49	[-8.78,3.80]	0.00	[-0.00,0.01]	-0.01*	[-0.02,-0.00]
3.Qual	0.00	[-0.54,0.55]	-0.17	[-0.52,0.17]	-0.32	[-0.65,0.01]	0.02	[-5.78,5.81]	-0.00	[-0.01,0.01]	-0.02***	[-0.03,-0.01]
0.Disab	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.Disab	-0.65*	[-1.28,-0.03]	0.31	[-0.09,0.71]	0.21	[-0.17,0.59]	3.30	[-3.36,9.97]	0.00	[-0.00,0.01]	-0.00	[-0.01,0.01]
0.SRhealth	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.SRhealth	0.23	[-0.25,0.72]	0.09	[-0.22,0.39]	0.32*	[0.03,0.62]	-2.58	[-7.72,2.55]	0.01	[-0.00,0.01]	0.00	[-0.00,0.01]
2.SRhealth	0.25	[-0.28,0.79]	0.05	[-0.29,0.39]	0.30	[-0.02,0.63]	-1.99	[-7.74,3.75]	0.01*	[0.00,0.02]	0.00	[-0.01,0.01]
3.SRhealth	-0.15	[-0.89,0.59]	0.45	[-0.02,0.92]	0.58*	[0.13,1.04]	0.27	[-7.63,8.17]	0.01	[-0.00,0.02]	0.00	[-0.01,0.01]
4.SRhealth	0.82	[-0.95,2.59]	-0.37	[-1.49,0.76]	-0.18	[-1.26,0.89]	2.77	[-16.08,21.61]	-0.02	[-0.05,0.00]	0.00	[-0.02,0.03]
0.NSSEC_3	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.NSSEC_3	-0.19	[-0.64,0.26]	0.15	[-0.14,0.44]	0.37**	[0.10,0.65]	-4.13	[-8.92,0.66]	0.01*	[0.00,0.01]	0.01	[-0.00,0.01]
2.NSSEC_3	0.07	[-0.55,0.69]	0.39	[-0.01,0.78]	0.52**	[0.14,0.90]	2.16	[-4.45,8.77]	0.00	[-0.01,0.01]	0.01*	[0.00,0.02]
3.NSSEC_3	1.75	[-2.74,6.24]	-0.83	[-3.69,2.02]	-0.68	[-3.42,2.05]	18.36	[-29.47,66.18]	0.00	[-0.06,0.07]	-0.03	[-0.09,0.04]
4.NSSEC_3	-0.40	[-1.24,0.43]	0.39	[-0.14,0.91]	0.59*	[0.08,1.10]	0.87	[-7.99,9.74]	0.01*	[0.00,0.02]	-0.00	[-0.01,0.01]
0.BMIC	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.BMIC	0.55*	[0.12,0.99]	0.31*	[0.03,0.58]	0.26	[-0.01,0.52]	9.92***	[5.26,14.58]	-0.02***	[-0.02,-0.01]	-0.00	[-0.01,0.01]
2.BMIC	0.87***	[0.38,1.37]	0.97***	[0.65,1.28]	0.84***	[0.54,1.14]	25.81***	[20.55,31.08]	-0.03***	[-0.04,-0.02]	-0.00	[-0.01,0.01]
3.BMIC	0.92	[-0.25,2.10]	2.41***	[1.67,3.16]	1.90***	[1.18,2.61]	49.23***	[36.72,61.73]	-0.04***	[-0.06,-0.03]	0.01	[-0.01,0.03]
4.BMIC	0.49	[-0.82,1.80]	1.44***	[0.60,2.27]	1.37***	[0.57,2.16]	30.08***	[16.15,44.02]	-0.00	[-0.02,0.01]	0.00	[-0.01,0.02]
0.OccAct	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.OccAct	-1.53***	[-2.05,-1.01]	1.79***	[1.46,2.12]	1.98***	[1.67,2.30]	2.14	[-3.42,7.70]	0.04***	[0.03,0.04]	0.02***	[0.01,0.02]
2.OccAct	-1.34***	[-1.82,-0.85]	1.46***	[1.15,1.77]	2.19***	[1.89,2.48]	3.42	[-1.76,8.60]	0.04***	[0.04,0.05]	0.02***	[0.01,0.03]
3.OccAct	-0.98*	[-1.92,-0.04]	1.80***	[1.20,2.39]	3.09***	[2.52,3.66]	6.24	[-3.74,16.22]	0.06***	[0.05,0.07]	0.03***	[0.01,0.04]
0.Smoking	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.Smoking	0.36	[-0.04,0.76]	-0.34**	[-0.60,-0.09]	-0.16	[-0.40,0.09]	-4.67*	[-8.91,-0.42]	-0.00	[-0.01,0.00]	-0.00	[-0.01,0.00]
2.Smoking	-0.71	[-1.57,0.15]	-0.10	[-0.65,0.45]	-0.14	[-0.66,0.39]	-7.69	[-16.88,1.50]	-0.01	[-0.02,0.01]	-0.00	[-0.02,0.01]
3.Smoking	-0.48	[-1.08,0.12]	0.20	[-0.18,0.58]	0.23	[-0.14,0.59]	-5.19	[-11.57,1.18]	-0.01*	[-0.02,-0.00]	-0.01*	[-0.02,-0.00]
wake_time_h	-0.33**	[-0.53,-0.13]	-0.01	[-0.13,0.12]	-0.02	[-0.15,0.10]	-8.37***	[-10.50,-6.23]	0.02***	[0.02,0.02]	0.00	[-0.00,0.01]
avg_daily_n_stps	0.00***	[0.00,0.00]	0.00***	[0.00,0.00]	0.00***	[0.00,0.00]	0.02***	[0.02,0.02]	0.00***	[0.00,0.00]	0.00***	[0.00,0.00]
_cons	35.69***	[32.40,38.99]	4.50***	[2.40,6.59]	4.30***	[2.29,6.30]	144.73***	[109.68,179.79]	-0.08**	[-0.13,-0.03]	0.19***	[0.14,0.24]
p	0.00		0.00		0.00		0.00		0.00		0.00	

95% confidence intervals in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Supplementary Table 5.11-3. Sensitivity analyses regressions (excluding EU-SILC severely hampered and some extent).

	(1) N upev		(2) upr_ ur_h		(3) Std dur_h		(4) Stp dur_h		(5) N stpev		(6) Dur stpev		(7) Stps per_stpev		(8) Stpw cad	
0.Sex	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.Sex	4.26***	[3.23,5.29]	0.36***	[0.27,0.46]	0.37***	[0.27,0.46]	-0.00	[-0.01,0.01]	13.72***	[10.42,17.01]	-3.18***	[-3.67,-2.68]	-4.48***	[-5.43,-3.52]	0.91***	[0.38,1.44]
0.Qual	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.Qual	-0.42	[-1.73,0.89]	0.02	[-0.11,0.14]	0.01	[-0.11,0.13]	0.01	[-0.01,0.02]	0.19	[-4.00,4.37]	0.11	[-0.51,0.74]	0.04	[-1.17,1.26]	0.07	[-0.60,0.75]
2.Qual	-0.07	[-1.65,1.51]	-0.01	[-0.16,0.14]	-0.02	[-0.16,0.12]	0.01	[-0.01,0.03]	-1.85	[-6.88,3.18]	0.41	[-0.34,1.17]	0.43	[-1.03,1.89]	0.01	[-0.81,0.82]
3.Qual	-0.85	[-2.30,0.59]	-0.10	[-0.23,0.04]	-0.10	[-0.22,0.03]	-0.00	[-0.02,0.02]	-6.78**	[-11.40,-2.16]	1.27***	[0.58,1.96]	1.75*	[0.41,3.09]	0.18	[-0.57,0.92]
0.Disab	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
0.SRhealth	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.SRhealth	0.62	[-0.62,1.86]	0.15*	[0.04,0.27]	0.12*	[0.01,0.23]	0.03***	[0.02,0.05]	9.52***	[5.57,13.48]	-1.47***	[-2.07,-0.88]	-2.97***	[-4.11,-1.82]	-1.40***	[-2.04,-0.76]
2.SRhealth	0.93	[-0.48,2.34]	0.15*	[0.01,0.28]	0.11	[-0.01,0.24]	0.03***	[0.01,0.05]	11.17***	[6.68,15.65]	-1.72***	[-2.40,-1.05]	-3.40***	[-4.71,-2.10]	-1.64***	[-2.36,-0.91]
3.SRhealth	0.49	[-1.61,2.58]	0.13	[-0.06,0.33]	0.10	[-0.09,0.28]	0.04**	[0.01,0.06]	12.34***	[5.66,19.02]	-1.73***	[-2.73,-0.73]	-3.53***	[-5.47,-1.59]	-2.23***	[-3.31,-1.15]
4.SRhealth	-1.02	[-7.06,5.02]	-0.01	[-0.58,0.55]	-0.03	[-0.56,0.50]	0.02	[-0.06,0.09]	4.56	[-14.70,23.83]	-1.05	[-3.93,1.84]	-2.24	[-7.83,3.35]	-2.04	[-5.15,1.07]
0.NSSEC_3	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.NSSEC_3	1.90**	[0.70,3.11]	0.25***	[0.14,0.36]	0.21***	[0.10,0.31]	0.04***	[0.03,0.06]	8.10***	[4.26,11.94]	-1.09***	[-1.67,-0.52]	-2.42***	[-3.54,-1.31]	-1.50***	[-2.12,-0.88]
2.NSSEC_3	-0.34	[-2.00,1.32]	0.11	[-0.04,0.27]	0.08	[-0.07,0.22]	0.04***	[0.02,0.06]	3.71	[-1.59,9.00]	-0.40	[-1.19,0.40]	-1.30	[-2.84,0.23]	-1.35**	[-2.20,-0.49]
3.NSSEC_3	-7.30	[-19.77,5.17]	-1.04	[-2.21,0.13]	-0.93	[-2.03,0.17]	-0.11	[-0.27,0.04]	-19.03	[-58.81,20.76]	1.72	[-4.24,7.68]	4.06	[-7.49,15.61]	3.41	[-3.01,9.83]
4.NSSEC_3	0.43	[-1.84,2.70]	0.22*	[0.01,0.43]	0.18	[-0.02,0.38]	0.04**	[0.01,0.07]	7.57*	[0.32,14.82]	-1.53**	[-2.62,-0.45]	-3.20**	[-5.31,-1.10]	-1.67**	[-2.84,-0.50]
0.BMIC	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.BMIC	-3.18***	[-4.34,-2.02]	-0.14*	[-0.25,-0.03]	-0.13*	[-0.23,-0.03]	-0.01	[-0.02,0.01]	-1.36	[-5.07,2.34]	0.28	[-0.28,0.83]	0.43	[-0.65,1.50]	-0.11	[-0.71,0.48]
2.BMIC	-6.51***	[-7.83,-5.19]	-0.14*	[-0.27,-0.02]	-0.13*	[-0.25,-0.01]	-0.01	[-0.03,0.01]	-3.29	[-7.50,0.93]	0.59	[-0.04,1.22]	0.77	[-0.45,2.00]	-0.71*	[-1.39,-0.03]
3.BMIC	-13.76***	[-17.07,-10.46]	0.06	[-0.25,0.37]	0.09	[-0.21,0.38]	-0.03	[-0.07,0.01]	-9.20	[-19.74,1.35]	1.71*	[0.13,3.29]	2.38	[-0.68,5.44]	-1.00	[-2.70,0.70]
4.BMIC	-7.91***	[-11.46,-4.35]	-0.10	[-0.43,0.23]	-0.10	[-0.41,0.22]	-0.00	[-0.05,0.04]	0.84	[-10.49,12.17]	0.18	[-1.51,1.88]	-0.08	[-3.37,3.21]	-1.18	[-3.01,0.64]
0.OccAct	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.OccAct	-0.26	[-1.65,1.13]	1.16***	[1.03,1.29]	1.06***	[0.94,1.18]	0.10***	[0.08,0.12]	28.80***	[24.37,33.23]	-3.89***	[-4.56,-3.23]	-7.75***	[-9.04,-6.46]	-3.66***	[-4.37,-2.94]
2.OccAct	-0.14	[-1.45,1.17]	1.10***	[0.98,1.23]	0.95***	[0.84,1.07]	0.15***	[0.13,0.17]	36.35***	[32.16,40.53]	-4.67***	[-5.30,-4.04]	-9.92***	[-11.14,-8.71]	-5.92***	[-6.60,-5.24]
3.OccAct	0.22	[-2.26,2.70]	1.32***	[1.09,1.56]	1.07***	[0.85,1.29]	0.25***	[0.22,0.28]	53.72***	[45.82,61.62]	-6.37***	[-7.55,-5.18]	-13.91***	[-16.20,-11.62]	-8.71***	[-9.99,-7.44]
0.Smoking	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.Smoking	1.46**	[0.39,2.52]	-0.14**	[-0.24,-0.04]	-0.14**	[-0.24,-0.05]	0.01	[-0.01,0.02]	0.24	[-3.16,3.64]	-0.01	[-0.52,0.50]	-0.16	[-1.14,0.83]	-0.20	[-0.75,0.35]
2.Smoking	2.38*	[0.09,4.68]	0.27*	[0.06,0.49]	0.27**	[0.06,0.47]	0.01	[-0.02,0.03]	4.11	[-3.21,11.43]	-0.69	[-1.79,0.40]	-1.03	[-3.15,1.09]	-0.05	[-1.23,1.13]
3.Smoking	2.84***	[1.21,4.47]	0.14	[-0.01,0.30]	0.13	[-0.02,0.27]	0.01	[-0.01,0.03]	8.03**	[2.83,13.23]	-1.04**	[-1.82,-0.26]	-1.87*	[-3.38,-0.36]	-1.23**	[-2.07,-0.40]
wake_time_h	1.98***	[1.44,2.52]	0.24***	[0.19,0.29]	0.22***	[0.17,0.27]	0.02***	[0.01,0.03]	7.91***	[6.20,9.62]	-0.92***	[-1.17,-0.66]	-1.67***	[-2.16,-1.17]	-0.65***	[-0.93,-0.37]
daily_n_stps	0.00***	[0.00,0.00]	0.00***	[0.00,0.00]	0.00***	[0.00,0.00]	0.00***	[0.00,0.00]	0.01***	[0.01,0.01]	0.00***	[0.00,0.00]	0.00***	[0.00,0.00]	0.00***	[0.00,0.00]
_cons	15.55***	[6.75,24.35]	-0.65	[-1.48,0.17]	-0.51	[-1.29,0.27]	-0.14*	[-0.25,-0.03]	-71.94***	[-100.01,-43.86]	38.24***	[34.03,42.44]	57.51***	[49.36,65.66]	95.41***	[90.88,99.94]
p	0.00		0.00		0.00		0.00		0.00		0.00		0.00		0.00	

95% confidence intervals in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Supplementary Table 5.11-4. Sensitivity analyses regressions (excluding EU-SILC severely hampered and some extent).

	(1) Prop stp_to_std		(2) upev_ ur_min		(3) Upev n_stpev		(4) Upev n_stps		(8) Upev bursti		(9) Nonupev bursti	
0.Sex	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.Sex	-0.05	[-0.46,0.35]	-0.27*	[-0.50,-0.04]	-0.01	[-0.25,0.24]	-17.71***	[-22.01,-13.42]	0.05***	[0.04,0.05]	-0.00	[-0.01,0.00]
0.Qual	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.Qual	-0.11	[-0.62,0.41]	0.10	[-0.19,0.40]	0.09	[-0.22,0.40]	0.02	[-5.43,5.48]	0.00	[-0.01,0.01]	-0.01	[-0.01,0.00]
2.Qual	-0.29	[-0.91,0.33]	-0.06	[-0.41,0.30]	-0.15	[-0.52,0.22]	-1.46	[-8.02,5.10]	0.00	[-0.01,0.01]	-0.01*	[-0.02,-0.00]
3.Qual	-0.01	[-0.58,0.55]	-0.07	[-0.39,0.26]	-0.22	[-0.56,0.12]	1.20	[-4.82,7.22]	-0.00	[-0.01,0.01]	-0.02***	[-0.03,-0.01]
0.Disab	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
0.SRhealth	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.SRhealth	0.26	[-0.23,0.74]	0.12	[-0.16,0.40]	0.36*	[0.07,0.65]	-2.04	[-7.19,3.11]	0.01	[-0.00,0.01]	0.00	[-0.00,0.01]
2.SRhealth	0.26	[-0.29,0.81]	0.12	[-0.19,0.44]	0.36*	[0.03,0.69]	-1.57	[-7.42,4.29]	0.01*	[0.00,0.02]	0.00	[-0.01,0.01]
3.SRhealth	-0.11	[-0.93,0.71]	0.17	[-0.30,0.64]	0.42	[-0.08,0.91]	-2.33	[-11.04,6.39]	0.00	[-0.01,0.02]	-0.01	[-0.02,0.01]
4.SRhealth	1.71	[-0.66,4.08]	0.04	[-1.32,1.40]	0.10	[-1.32,1.52]	1.73	[-23.39,26.85]	-0.00	[-0.04,0.03]	-0.02	[-0.06,0.01]
0.NSSEC_3	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.NSSEC_3	-0.23	[-0.70,0.25]	0.18	[-0.09,0.45]	0.42**	[0.14,0.70]	-3.85	[-8.85,1.15]	0.01*	[0.00,0.02]	0.00	[-0.00,0.01]
2.NSSEC_3	0.08	[-0.57,0.73]	0.19	[-0.18,0.57]	0.40*	[0.01,0.79]	0.59	[-6.31,7.49]	0.00	[-0.01,0.01]	0.01	[-0.00,0.02]
3.NSSEC_3	1.41	[-3.49,6.31]	-0.54	[-3.34,2.27]	-0.37	[-3.30,2.56]	23.95	[-27.91,75.81]	-0.03	[-0.10,0.05]	-0.04	[-0.12,0.03]
4.NSSEC_3	-0.32	[-1.21,0.57]	0.36	[-0.15,0.87]	0.58*	[0.04,1.11]	1.45	[-8.00,10.91]	0.01	[-0.00,0.03]	-0.01	[-0.02,0.01]
0.BMIC	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.BMIC	0.60**	[0.15,1.06]	0.23	[-0.03,0.49]	0.20	[-0.07,0.48]	9.86***	[5.04,14.69]	-0.02***	[-0.02,-0.01]	0.00	[-0.01,0.01]
2.BMIC	0.88***	[0.36,1.40]	0.86***	[0.57,1.16]	0.78***	[0.47,1.10]	25.52***	[20.02,31.01]	-0.03***	[-0.04,-0.02]	0.00	[-0.01,0.01]
3.BMIC	0.22	[-1.08,1.52]	2.77***	[2.03,3.51]	2.04***	[1.26,2.82]	53.22***	[39.47,66.96]	-0.04***	[-0.06,-0.02]	0.01	[-0.00,0.03]
4.BMIC	0.45	[-0.95,1.85]	1.33**	[0.53,2.13]	1.41***	[0.57,2.24]	27.65***	[12.88,42.42]	-0.00	[-0.02,0.02]	0.00	[-0.02,0.02]
0.OccAct	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.OccAct	-1.49***	[-2.04,-0.94]	1.58***	[1.26,1.89]	1.82***	[1.49,2.15]	0.21	[-5.57,5.98]	0.04***	[0.03,0.05]	0.01***	[0.01,0.02]
2.OccAct	-1.37***	[-1.89,-0.86]	1.57***	[1.28,1.87]	2.26***	[1.95,2.57]	3.79	[-1.66,9.25]	0.05***	[0.04,0.05]	0.02***	[0.01,0.03]
3.OccAct	-0.99*	[-1.96,-0.02]	1.93***	[1.38,2.49]	3.21***	[2.63,3.79]	6.62	[-3.68,16.91]	0.06***	[0.05,0.07]	0.03***	[0.01,0.04]
0.Smoking	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]	0.00	[0.00,0.00]
1.Smoking	0.49*	[0.07,0.91]	-0.37**	[-0.61,-0.13]	-0.16	[-0.41,0.09]	-4.81*	[-9.24,-0.38]	-0.00	[-0.01,0.00]	-0.00	[-0.01,0.00]
2.Smoking	-0.68	[-1.58,0.22]	-0.02	[-0.53,0.50]	-0.06	[-0.60,0.48]	-6.56	[-16.10,2.98]	-0.00	[-0.02,0.01]	0.00	[-0.01,0.01]
3.Smoking	-0.27	[-0.91,0.37]	-0.02	[-0.39,0.34]	0.03	[-0.35,0.42]	-6.73	[-13.51,0.05]	-0.01**	[-0.02,-0.00]	-0.01*	[-0.02,-0.00]
wake_time_h	-0.29**	[-0.50,-0.08]	0.04	[-0.08,0.16]	0.02	[-0.10,0.15]	-7.47***	[-9.71,-5.24]	0.02***	[0.02,0.02]	0.00	[-0.00,0.01]
daily_n_stps	0.00***	[0.00,0.00]	0.00***	[0.00,0.00]	0.00***	[0.00,0.00]	0.02***	[0.02,0.02]	0.00**	[0.00,0.00]	0.00***	[0.00,0.00]
_cons	34.79***	[31.33,38.25]	3.76***	[1.78,5.74]	3.56***	[1.49,5.63]	129.27***	[92.67,165.87]	-0.06*	[-0.11,-0.01]	0.18***	[0.13,0.23]
p	0.00		0.00		0.00		0.00		0.00		0.00	

95% confidence intervals in brackets

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Appendix 8.12. Associations with covariates.

Supplementary Table 6.12-1 Associations of participant characteristics with upright and stepping event outcomes.

	N	Upright events (n)	Burstiness of upright events	Burstiness of sedentary events	Stepping events (n)	Duration of step events (s)	Steps per stepping events (n)
Sex (Ref: Male)	3016	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Female	3072	0.19 [-0.46,0.85]	**0.04 [0.04,0.05]**	**-0.01 [-0.01,-0.00]**	**20.18 [17.84,22.52]**	**-3.79 [-4.13,-3.44]**	**-6.01 [-6.67,-5.36]**
Age (years)	6085	**-0.18 [-0.22,-0.14]**	0 [-0.00,0.00]	**0 [0.00,0.00]**	**-0.26 [-0.40,-0.12]**	**0.05 [0.03,0.07]**	**0.05 [0.01,0.09]**
Type 2 diabetes (Ref: No)	4906	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Yes	1179	0.16 [-0.70,1.02]	**-0.01 [-0.02,-0.01]**	0 [-0.01,0.00]	-0.48 [-3.55,2.60]	-0.09 [-0.55,0.36]	0 [-0.86,0.86]
Education (Ref: Low)	1942	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Med	1689	0.27 [-0.57,1.11]	**-0.01 [-0.01,-0.00]**	**-0.01 [-0.01,-0.00]**	**-3.13 [-6.13,-0.12]**	0.34 [-0.11,0.78]	0.62 [-0.22,1.46]
High	2454	-0.42 [-1.20,0.36]	**-0.01 [-0.02,-0.01]**	**-0.02 [-0.02,-0.01]**	**-13.51 [-16.31,-10.72]**	**2.04 [1.63,2.45]**	**4 [3.22,4.79]**
Body mass index (Ref: 18.5<25)	2385	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
25<30	2581	**-2.39 [-3.10,-1.67]**	**-0.02 [-0.02,-0.01]**	0 [-0.00,0.01]	**7.64 [5.08,10.19]**	**-0.76 [-1.14,-0.38]**	**-1.73 [-2.44,-1.01]**
30<40	1065	**-5.56 [-6.53,-4.60]**	**-0.03 [-0.04,-0.02]**	0 [-0.01,0.00]	**5.98 [2.52,9.43]**	**-0.81 [-1.32,-0.30]**	**-1.65 [-2.62,-0.69]**
≥40	54	**-9.06 [-12.46,-5.65]**	**-0.03 [-0.06,-0.01]**	-0.01 [-0.03,0.01]	-0.62 [-12.79,11.54]	-0.26 [-2.05,1.54]	-0.99 [-4.39,2.41]
Smoking status (Ref: Never)	2416	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Former	2953	**0.98 [0.30,1.66]**	**0.01 [0.00,0.01]**	**0 [0.00,0.01]**	0.58 [-1.85,3.02]	-0.13 [-0.49,0.23]	-0.26 [-0.94,0.42]
Current	716	**4.26 [3.21,5.32]**	0 [-0.01,0.01]	0 [-0.01,0.00]	**7.34 [3.57,11.10]**	**-1.18 [-1.74,-0.63]**	**-2.01 [-3.06,-0.96]**

Each upright event metric is adjusted for covariates for all covariates in the table, and daily number of steps.

Supplementary Table 6.12-2. Associations of participant characteristics with upright and stepping event outcomes.

	N	Daily step count (n)	Step-weighted cadence (steps/min)	Within upright event composition metrics			
				Duration (min)	Stepping proportion (%)	Step count (n)	Stepping events (n)
Sex (Ref: Male)	3016	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Female	3072	-115.47 [-293.64,62.71]	**-0.4 [-0.78,-0.02]**	**0.9 [0.76,1.05]**	**-0.75 [-1.03,-0.48]**	**-0.6 [-3.18,1.98]**	**1.21 [1.07,1.36]**
Age (years)	6085	**-37.00 [-47.67,-26.33]**	**-0.07 [-0.09,-0.05]**	**0.02 [0.01,0.03]**	**-0.06 [-0.08,-0.04]**	**0.65 [0.49,0.80]**	**0.02 [0.01,0.03]**
Type 2 diabetes (Ref: No)	4906	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Yes	1179	**-1159.98 [-1392.36,-927.59]**	**-0.5 [-0.99,-0.00]**	**-0.24 [-0.43,-0.05]**	0.23 [-0.13,0.59]	-0.67 [-4.07,2.72]	-0.18 [-0.37,0.01]
Education (Ref: Low)	1942	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Med	1689	-1.80 [-230.34,226.74]	**0.62 [0.13,1.10]**	**-0.22 [-0.40,-0.04]**	0.16 [-0.19,0.51]	-2.48 [-5.79,0.83]	**-0.36 [-0.55,-0.17]**
High	2454	-52.56 [-265.17,160.04]	**2.13 [1.68,2.58]**	**-0.52 [-0.69,-0.35]**	**0.78 [0.46,1.11]**	-0.31 [-3.39,2.77]	**-0.94 [-1.11,-0.77]**
Body mass index (Ref: 18.5<25)	2385	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
25<30	2581	**-790.04 [-983.55,-596.52]**	**-1.15 [-1.56,-0.73]**	**0.4 [0.24,0.55]**	**0.66 [0.36,0.96]**	**9.47 [6.65,12.28]**	**0.56 [0.40,0.72]**
30<40	1065	**-1903.04 [-2161.50,-1644.59]**	**-1.38 [-1.94,-0.83]**	**0.79 [0.58,1.00]**	**1.41 [1.00,1.81]**	**20.48 [16.67,24.28]**	**0.84 [0.63,1.06]**
≥40	54	**-3593.18 [-4514.43,-2671.94]**	**-2.87 [-4.83,-0.91]**	**1.72 [0.99,2.46]**	1.19 [-0.23,2.61]	**30.85 [17.45,44.26]**	**1.3 [0.55,2.06]**
Smoking status (Ref: Never)	2416	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
Former	2953	**-250.18 [-435.60,-64.76]**	-0.31 [-0.70,0.09]	**-0.21 [-0.36,-0.06]**	0.09 [-0.20,0.37]	**-4.01 [-6.69,-1.32]**	-0.09 [-0.24,0.06]
Current	716	**-1468.21 [-1752.47,-1183.96]**	**-1.54 [-2.15,-0.93]**	**-0.43 [-0.65,-0.20]**	0.04 [-0.40,0.48]	**-11.7 [-15.85,-7.55]**	**-0.33 [-0.56,-0.09]**

Each upright event metric is adjusted for covariates for all covariates in the table, and daily number of steps (except daily steps)

Appendix 8.13. Sensitivity analyses.

Supplementary Table 6.12-1**.** Sensitivity analyses with full sample size for grip strength (n =6426) and timed chair stand test (n =6602), model 3.

	Grip strength (kg)		TCST (s)	
	Males	*Females*	*Males*	*Females*
Upright events *(per + 13.1 n)*	-0.04 [-0.27,0.18] (0.714)	-0.03 [-0.26,0.20] (0.809)	-0.13 [-0.32,0.06] (0.187)	**-0.2 [-0.40,-0.01]** (0.044)
Burstiness of upright events *(per + 0.09)*	-0.21 [-0.44,0.02] (0.072)	0.05 [-0.20,0.30] (0.678)	0.18 [-0.02,0.37] (0.077)	-0.02 [-0.23,0.19] (0.857)
Burstiness of sedentary events *(per + 0.08)*	0.14 [-0.07,0.35] (0.198)	0.25 [-0.00,0.50] (0.052)	-0.16 [-0.34,0.02] (0.085)	**-0.25 [-0.47,-0.04]** (0.022)
Stepping events *(per + 59.1 n)*	**-0.38 [-0.64,-0.11]** (0.005)	**-0.37 [-0.64,-0.11]** (0.006)	-0.18 [-0.40,0.05] (0.124)	**-0.24 [-0.46,-0.01]** (0.041)
Duration of stepping events *(per + 8.8 sec)*	**0.41 [0.17,0.65]** (0.001)	**0.61 [0.30,0.92]** (<0.001)	**0.29 [0.09,0.50]** (0.005)	0.06 [-0.21,0.32] (0.675)
Steps per stepping event *(per + 16.7 steps)*	**0.28 [0.04,0.52]** (0.023)	**0.46 [0.15,0.77]** (0.004)	**0.24 [0.03,0.44]** (0.023)	-0.02 [-0.29,0.24] (0.868)
Step-weighted cadence *(per + 8.6 steps/min)*	0.05 [-0.17,0.28] (0.642)	0 [-0.27,0.27] (0.977)	-0.15 [-0.35,0.04] (0.125)	**-0.46 [-0.69,-0.24]** (<0.001)
Duration of upright events *(per + 2.9 min)*	-0.13 [-0.38,0.12] (0.316)	-0.11 [-0.33,0.10] (0.303)	0.03 [-0.18,0.24] (0.78)	-0.01 [-0.19,0.17] (0.924)
Stepping proportion of upright events *(per + 5.6 %)*	**0.3 [0.08,0.52]** (0.008)	0.02 [-0.22,0.26] (0.883)	-0.18 [-0.37,0.01] (0.062)	-0.01 [-0.22,0.19] (0.908)
Step count of upright events *(per + 82.3 steps)*	0.1 [-0.21,0.41] (0.525)	0.02 [-0.30,0.34] (0.898)	**0.29 [0.03,0.55]** (0.031)	0.14 [-0.13,0.41] (0.303)
Stepping events within upright events *(per + 3.0 n)*	-0.09 [-0.34,0.16] (0.481)	-0.19 [-0.41,0.04] (0.1)	-0.04 [-0.25,0.18] (0.729)	0 [-0.19,0.19] (0.998)

Model 3 adjusted for age, sex, waking wear time, type 2 diabetes, education level, body mass index, smoking status, and average daily step count. Bold indicates statistical significance p < 0.05. Green indicates coefficient became significant with sensitivity analyses. Red indicates coefficient became non-significant with sensitivity analyses.

Supplementary Table 6.12-2**.** Sensitivity analyses with full sample size for six-minute walk test (n =6426) and SF-36 physical functioning (n =6913), model 3.

	6MWT (m)		SF-36 physical functioning	
	Males	*Females*	*Males*	*Females*
Upright events *(per + 13.1 n)*	0.2 [-2.04,2.45] (0.859)	0.35 [-1.96,2.66] (0.763)	-0.45 [-0.99,0.09] (0.103)	-0.04 [-0.60,0.52] (0.89)
Burstiness of upright events *(per + 0.09)*	**-2.91 [-5.17,-0.65]** (0.012)	1 [-1.45,3.45] (0.422)	**-1.04 [-1.59,-0.48]** (<0.001)	-0.55 [-1.15,0.05] (0.071)
Burstiness of sedentary events *(per + 0.08)*	2.11 [-0.01,4.24] (0.052)	**5.5 [2.99,8.01]** (<0.001)	**0.58 [0.07,1.09]** (0.026)	**1.57 [0.96,2.18]** (<0.001)
Stepping events *(per + 59.1 n)*	**-3.08 [-5.70,-0.45]** (0.022)	**-3 [-5.64,-0.35]** (0.026)	-0.07 [-0.71,0.57] (0.829)	0.44 [-0.20,1.09] (0.178)
Duration of stepping events *(per + 8.8 sec)*	1.75 [-0.69,4.19] (0.159)	**3.26 [0.26,6.26]** (0.033)	0.28 [-0.30,0.87] (0.34)	0.68 [-0.05,1.42] (0.07)
Steps per stepping event *(per + 16.7 steps)*	**3.07 [0.67,5.48]** (0.012)	**4.6 [1.58,7.62]** (0.003)	0.39 [-0.19,0.96] (0.192)	**0.93 [0.18,1.67]** (0.015)
Step-weighted cadence *(per + 8.6 steps/min)*	**8.1 [5.83,10.37]** (<0.001)	**9.39 [6.71,12.06]** (<0.001)	**1.6 [1.06,2.15]** (<0.001)	**2.56 [1.92,3.21]** (<0.001)
Duration of upright events *(per + 2.9 min)*	-0.3 [-2.82,2.22] (0.817)	-0.45 [-2.60,1.70] (0.68)	0.23 [-0.37,0.84] (0.448)	0.15 [-0.37,0.67] (0.581)
Stepping proportion of upright events *(per + 5.6 %)*	1.29 [-0.94,3.52] (0.256)	1.55 [-0.87,3.97] (0.208)	0.27 [-0.27,0.80] (0.327)	**1.23 [0.65,1.81]** (<0.001)
Step count of upright events *(per + 82.3 steps)*	-0.96 [-4.04,2.11] (0.539)	-0.4 [-3.49,2.69] (0.8)	0.15 [-0.60,0.89] (0.701)	0.7 [-0.06,1.46] (0.07)
Stepping events within upright events *(per + 3.0 n)*	-0.7 [-3.23,1.83] (0.587)	-0.78 [-3.00,1.43] (0.488)	0.25 [-0.35,0.86] (0.411)	0.28 [-0.26,0.82] (0.312)

Model 3 adjusted for age, sex, waking wear time, type 2 diabetes, education level, body mass index, smoking status, and average daily step count. Bold indicates statistical significance p < 0.05. Green indicates coefficient became significant with sensitivity analyses. Red indicates coefficient became non-significant with sensitivity analyses.

Supplementary Table 6.12-3**.** Sensitivity analyses substituting binary type 2 classification for WHO classification with pre-diabetes. Model 3 (n =6085).

	Grip strength (kg)		TCST (s)	
	Males	*Females*	*Males*	*Females*
Upright events	-0.04 [-0.28,0.20]	0 [-0.25,0.24]	-0.12 [-0.32,0.07]	**-0.22 [-0.41,-0.02]**
(per + 13.1 n)	(0.725)	(0.989)	(0.202)	(0.03)
Burstiness of upright events	-0.22 [-0.46,0.02]	0.04 [-0.22,0.30]	0.17 [-0.03,0.36]	-0.05 [-0.25,0.16]
(per + 0.09)	(0.072)	(0.766)	(0.089)	(0.67)
Burstiness of sedentary events	0.03 [-0.19,0.26]	0.25 [-0.01,0.52]	-0.07 [-0.25,0.11]	**-0.23 [-0.44,-0.02]**
(per + 0.08)	(0.789)	(0.06)	(0.469)	(0.035)
Stepping events	**-0.45 [-0.73,-0.18]**	**-0.38 [-0.66,-0.10]**	-0.15 [-0.38,0.07]	-0.17 [-0.39,0.06]
(per + 59.1 n)	(0.001)	(0.007)	(0.184)	(0.144)
Duration of stepping events	**0.35 [0.10,0.61]**	**0.67 [0.35,0.99]**	**0.33 [0.13,0.54]**	0.12 [-0.13,0.38]
(per + 8.8 sec)	(0.007)	(<0.001)	(0.002)	(0.349)
Steps per stepping event	0.22 [-0.03,0.48]	**0.52 [0.20,0.84]**	**0.25 [0.04,0.45]**	0.03 [-0.23,0.29]
(per + 16.7 steps)	(0.08)	(0.001)	(0.017)	(0.81)
Step-weighted cadence	-0.05 [-0.29,0.20]	0.01 [-0.27,0.30]	-0.16 [-0.35,0.04]	**-0.39 [-0.62,-0.16]**
(per + 8.6 steps/min)	(0.708)	(0.933)	(0.11)	(0.001)
Duration of upright events	-0.16 [-0.43,0.10]	-0.16 [-0.38,0.07]	0.02 [-0.19,0.24]	0.06 [-0.12,0.24]
(per + 2.9 min)	(0.225)	(0.172)	(0.836)	(0.528)
Stepping proportion of upright events	0.18 [-0.05,0.42]	0.09 [-0.17,0.34]	-0.15 [-0.34,0.04]	0 [-0.20,0.21]
(per + 5.6 %)	(0.127)	(0.5)	(0.133)	(0.991)
Step count of upright events	-0.04 [-0.36,0.29]	0 [-0.33,0.32]	**0.31 [0.05,0.57]**	0.23 [-0.04,0.49]
(per + 82.3 steps)	(0.83)	(0.995)	(0.019)	(0.093)
Stepping events within upright events	-0.15 [-0.42,0.11]	-0.22 [-0.45,0.01]	-0.01 [-0.22,0.21]	0.06 [-0.12,0.25]
(per + 3.0 n)	(0.257)	(0.065)	(0.955)	(0.505)

Model 3 adjusted for age, sex, waking wear time, type 2 diabetes, education level, body mass index, smoking status, and average daily step count. Bold indicates statistical significance p < 0.05. Green indicates coefficient became significant with sensitivity analyses. Red indicates coefficient became non-significant with sensitivity analyses.

Supplementary Table 6.12-4**.** Sensitivity analyses substituting binary type 2 classification for WHO classification with pre-diabetes. Model 3 (n =6085).

	6MWT (m)		SF-36 physical functioning	
	Males	*Females*	*Males*	*Females*
Upright events	0.12 [-2.15,2.39]	0.5 [-1.82,2.83]	-0.48 [-1.00,0.05]	-0.22 [-0.76,0.31]
(per + 13.1 n)	(0.919)	(0.671)	(0.075)	(0.414)
Burstiness of upright events	-2.11 [-4.39,0.17]	1 [-1.47,3.46]	**-1.01 [-1.54,-0.49]**	-0.36 [-0.93,0.21]
(per + 0.09)	(0.069)	(0.427)	(<0.001)	(0.214)
Burstiness of sedentary events	**2.27 [0.13,4.41]**	**5.21 [2.69,7.73]**	0.09 [-0.40,0.59]	**1.24 [0.66,1.83]**
(per + 0.08)	(0.037)	(<0.001)	(0.708)	(<0.001)
Stepping events	**-3.74 [-6.39,-1.09]**	**-3.46 [-6.12,-0.81]**	**-0.63 [-1.25,-0.02]**	0.03 [-0.58,0.65]
(per + 59.1 n)	(0.006)	(0.01)	(0.043)	(0.912)
Duration of stepping events	2.12 [-0.32,4.56]	**3.44 [0.40,6.47]**	0.14 [-0.42,0.71]	**0.86 [0.16,1.56]**
(per + 8.8 sec)	(0.088)	(0.026)	(0.617)	(0.016)
Steps per stepping event	**3.62 [1.22,6.02]**	**4.9 [1.85,7.95]**	0.23 [-0.32,0.79]	**1.09 [0.39,1.80]**
(per + 16.7 steps)	(0.003)	(0.002)	(0.412)	(0.002)
Step-weighted cadence	**8.28 [5.99,10.56]**	**8.85 [6.16,11.54]**	**0.9 [0.37,1.43]**	**2.26 [1.64,2.89]**
(per + 8.6 steps/min)	(<0.001)	(<0.001)	(0.001)	(<0.001)
Duration of upright events	-0.15 [-2.68,2.39]	-0.37 [-2.52,1.79]	0.15 [-0.44,0.73]	0.27 [-0.23,0.77]
(per + 2.9 min)	(0.909)	(0.74)	(0.622)	(0.283)
Stepping proportion of upright events	1.04 [-1.21,3.28]	0.41 [-2.02,2.85]	-0.17 [-0.69,0.35]	**0.81 [0.25,1.37]**
(per + 5.6 %)	(0.365)	(0.741)	(0.527)	(0.005)
Step count of upright events	-1.03 [-4.10,2.04]	-0.62 [-3.73,2.49]	-0.14 [-0.85,0.57]	**0.73 [0.01,1.45]**
(per + 82.3 steps)	(0.511)	(0.695)	(0.699)	(0.046)
Stepping events within upright events	-0.99 [-3.53,1.55]	-0.99 [-3.20,1.23]	-0.09 [-0.68,0.50]	0.18 [-0.34,0.69]
(per + 3.0 n)	(0.444)	(0.382)	(0.767)	(0.498)

Model 3 adjusted for age, sex, waking wear time, type 2 diabetes, education level, body mass index, smoking status, and average daily step count. Bold indicates statistical significance p < 0.05. Green indicates coefficient became significant with sensitivity analyses. Red indicates coefficient became non-significant with sensitivity analyses.

Appendix 8.14. Sensitivity analyses. Different waking-wear classification.

Supplementary Table 7.5-1. Associations of upright and stepping event metrics with handgrip strength, SF-36 physical functioning, and single-leg stance balance test. Using 06:00am to 22:00h waking wear classification

	Handgrip strength (kg) - Model 3		**SF-36 physical functioning – Model 3**		**Balance – Model 3**	
	Males	***Females***	***Males***	***Females***	***Males***	***Females***
	B [95% CI] (*p*-value)	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**B [95% CI] (*p*-value)**	**OR [95% CI] (*p*-value)**	**OR [95% CI] (*p*-value)**
Daily step count	-	-	-	-	-	-
(per + 3582 steps)	-	-	-	-	-	-
Upright events	0.25 [-0.07,0.57]	0.3 [-0.03,0.62]	0.77 [-0.08,1.61]	**0.98 [0.14,1.83]**	1.0 [0.92,1.10]	**1.1 [1.01,1.21]**
(per + 13.1 n)	(0.126)	(0.074)	(0.074)	(0.022)	(0.915)	(0.036)
Stepping events	**0.65 [0.27,1.02]**	**0.49 [0.09,0.88]**	-0.48 [-1.45,0.49]	0.38 [-0.63,1.39]	**0.86 [0.78,0.96]**	0.9 [0.81,1.01]
(per + 59.1 n)	(0.001)	(0.015)	(0.336)	(0.461)	(0.006)	(0.065)
Duration of stepping events	**-1.04 [-1.36,-0.71]**	-0.04 [-0.41,0.34]	-0.19 [-1.02,0.65]	**1.24 [0.25,2.23]**	1.05 [0.96,1.15]	**1.11 [1.00,1.24]**
(per + 8.8 sec)	(<0.001)	(0.854)	(0.664)	(0.014)	(0.28)	(0.048)
Steps per stepping event	**-1.17 [-1.49,-0.85]**	-0.09 [-0.47,0.28]	0.05 [-0.77,0.87]	**1.6 [0.62,2.58]**	1.06 [0.97,1.16]	**1.12 [1.01,1.24]**
(per + 16.7 steps)	(<0.001)	(0.628)	(0.907)	(0.001)	(0.175)	(0.038)
Step-weighted cadence	**-1.3 [-1.63,-0.98]**	0.0 [-0.34,0.34]	**1.17 [0.32,2.01]**	**3.11 [2.24,3.98]**	**1.12 [1.02,1.23]**	**1.14 [1.03,1.26]**
(per + 8.6 steps/min)	(<0.001)	(0.985)	(0.007)	(<0.001)	(0.017)	(0.008)
Duration of upright events	0.21 [-0.13,0.55]	0.03 [-0.27,0.33]	-0.38 [-1.27,0.50]	-0.55 [-1.33,0.23]	0.99 [0.89,1.09]	0.97 [0.89,1.05]
(per + 2.9 min)	(0.227)	(0.841)	(0.396)	(0.169)	(0.761)	(0.408)
Stepping proportion of upright events	0.17 [-0.15,0.49]	-0.08 [-0.41,0.25]	-0.18 [-1.02,0.66]	**1.23 [0.39,2.06]**	0.93 [0.84,1.01]	0.95 [0.87,1.04]
(per + 5.6 %)	(0.294)	(0.623)	(0.674)	(0.004)	(0.097)	(0.273)
Step count of upright events	**-0.62 [-0.99,-0.25]**	-0.19 [-0.61,0.24]	**-1.13 [-2.09,-0.16]**	-0.23 [-1.34,0.88]	0.92 [0.83,1.02]	0.89 [0.79,1.01]
(per + 82.3 steps)	(0.001)	(0.392)	(0.022)	(0.689)	(0.133)	(0.066)
Stepping events within upright events	**0.39 [0.07,0.70]**	0.08 [-0.27,0.42]	-0.81 [-1.63,0.01]	-0.56 [-1.45,0.33]	0.92 [0.84,1.01]	**0.89 [0.81,0.98]**
(per + 3.0 n)	(0.017)	(0.668)	(0.052)	(0.217)	(0.065)	(0.019)
Upright event burstiness	0.30 [-0.00,0.60]	**0.42 [0.07,0.76]**	-0.24 [-1.02,0.54]	0.44 [-0.46,1.34]	1.02 [0.94,1.11]	1.02 [0.92,1.12]
(per + 0.09)	(0.053)	(0.019)	(0.545)	(0.342)	(0.621)	(0.709)
Sedentary event burstiness	0.21 [-0.09,0.52]	-0.16 [-0.50,0.17]	0.34 [-0.47,1.15]	0.32 [-0.54,1.18]	0.98 [0.89,1.07]	0.92 [0.83,1.01]
(per + 0.08)	(0.173)	(0.334)	(0.411)	(0.466)	(0.611)	(0.065)
USTP	**-0.54 [-0.88,-0.20]**	**-0.35 [-0.67,-0.03]**	-0.28 [-1.18,0.62]	**-1.20 [-2.01,-0.39]**	0.93 [0.85,1.03]	0.95 [0.87,1.05]
(per + 1.0)	(0.002)	(0.034)	(0.537)	(0.004)	(0.172)	(0.317)

Results are presented as regression coefficient (B) with 95% confidence interval [95% CI] and p-value, where the predictor is standardised and the outcome is unstandardised (a one standard deviation increase in the predictor equates to an absolute change in the physical function outcome. Associations were adjusted for the following covariates; ; Model 3: sex, waking wear time, education level, socioeconomic status, body mass index, smoking status, and average daily step count

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