

ACCURACY AND PRECISION OF WEARABLE CAMERA MEDIA ANNOTATIONS TO
ESTIMATE DIMENSIONS OF PHYSICAL ACTIVITY AND SEDENTARY BEHAVIOR

by

Julian Martinez

A Dissertation Submitted in
Partial Fulfillment of the
Requirements for the Degree of

Doctor of Philosophy
in Kinesiology

at

The University of Wisconsin-Milwaukee

May 2024

ABSTRACT

ACCURACY AND PRECISION OF WEARABLE CAMERA MEDIA ANNOTATIONS TO ESTIMATE DIMENSIONS OF PHYSICAL ACTIVITY AND SEDENTARY BEHAVIOR

by

Julian Martinez

The University of Wisconsin-Milwaukee, 2024
Under the Supervision of Professor Dr. Scott Strath

Physical activity (PA) is a complex behavior to measure given its sporadic nature and its all-encompassing definition as bodily movement produced by skeletal muscles that result in increased energy expenditure. Sedentary behavior (SB) is another complex health behavior to measure as it is more exactly defined as sitting, reclining, or lying while having an energy expenditure ≤ 1.5 metabolic equivalents (METs). For both PA and SB, it is important to measure the dimensions of frequency, intensity, duration and type of activity being performed when associating the volume of PA and SB with different health outcomes. However, commonly used measurement tools within the field do not fully capture all dimensions of PA and SB, nor are they able to do so while providing information about behavioral intent or the domain of PA and SB being performed (i.e. Household chores, Leisure activities, Occupational activities, or Transportation). The wearable camera (WC) is a tool seeing increased use for health behavior research that has the potential to fully capture all dimensions and domains of PA and SB.

The purpose of this dissertation is to establish the validity of WC still-images (IMGs) to assess all dimensions of PA and SB, as well as different domains of PA and SB. Specifically, the aims of this dissertation are to: 1) establish the convergent validity

of WC IMGs to assess posture against a validated thigh-worn accelerometer; 2) establish the criterion validity of WC IMGs to assess the frequency and duration of PA and SB domains, PA and SB behaviors, and postures against video-recorded direct observation (DO); and 3) establish the criterion validity of WC IMGs to assess the frequency and duration of PA intensity compared with indirect calorimetry (IC). Results showed that WC IMG annotations were accurate and precise when compared with a thigh-worn monitor for time spent in sitting postures, but overestimated movement time and underestimated standing time. In comparison to criterion DO video, WC IMGs were accurate and equivalent on all estimates of PA and SB domains, across 10 different PA and SB activity types, for sitting posture, for standing posture within the Household domain and movement within the Leisure and Transportation domains. Finally, in comparison to IC, WC IMGs were accurate and equivalent for sedentary, moderate, low and moderate-to-vigorous PA intensity across steady-state behaviors and postures. In conclusion, WC IMGs can be used as a criterion measure for assessing the frequency and duration for different types of PA and SB. Future work is warranted to estimate point estimates of PA intensity using WC annotations as time series data within advanced statistical methods, as well as automate annotations of WC IMG data.

© Copyright by Julian Martinez, 2024
All Rights Reserved

To Victoria Martinez, la persona más fuerte que conozco.

TABLE OF CONTENTS

LIST OF FIGURES.....	ix
LIST OF TABLES.....	x
LIST OF ABBREVIATIONS.....	xii
ACKNOWLEDGEMENTS	xiii
1. Introduction	1
1.1 What is Physical Activity & Sedentary Behavior?	1
1.2 Measuring Physical Activity and Sedentary Behavior for Health	2
1.3 Barriers to Defining the Dose-Response Relationship of Physical Activity and Sedentary Behavior to Health Outcomes.....	4
1.4 Physical Activity and Sedentary Behavior Measurement Tool Limitations.....	6
1.5 Wearable Cameras: A Tool Utilized to Comprehensively Capture a Variety of Health-Behavior Characteristics	9
References	13
2. The Use of Wearable Cameras to Capture Physical Activity and Sedentary Behavior: A Scoping Review	24
2.1 Introduction.....	24
2.2 Methods.....	28
2.2.1 Search Strategy & Source Identification.....	29
2.2.2 Screening.....	30
2.2.3 Data Extraction & Analysis	33
2.3 Results.....	34
2.3.1 Main reasons for Using Annotated Wearable Camera Media to Capture Human Physical Activity and Sedentary Behavior.....	34
2.3.2 Dimensions of Physical Activity and Sedentary Behavior Commonly Captured by Wearable Camera Media Annotations.....	41
2.3.3 Methodologies for Using Wearable Cameras and for Annotating Physical Activity and Sedentary Behavior from Wearable Camera Media.....	43
2.4 Discussion	43
2.4.1 Main reasons for Using Annotated Wearable Camera Media to Capture Human Physical Activity and Sedentary Behavior.....	47
2.4.2 Dimensions of Physical Activity and Sedentary Behavior Commonly Captured by Wearable Camera Media Annotations.....	49
2.4.3 Methodologies for Using Wearable Cameras and for Annotating Physical Activity and Sedentary Behavior from Wearable Camera Media.....	51
2.4.4 Scoping Review Strengths & Limitations.....	54
2.5 Conclusion.....	55
References	57

3. Validation of Wearable Camera Still Images to Assess Posture in Free-Living Conditions	77
3.1 Introduction.....	77
3.2 Methods.....	78
3.2.1 Study Overview	78
3.2.2 Participants	79
3.2.3 Measurement and Instrumentation.....	79
3.2.4 Data Processing	82
3.2.5 Statistical Analysis.....	83
3.3 Results.....	84
3.4 Discussion	85
3.5 Conclusion.....	92
References	94
4. Validation of Wearable Camera Still-Image Estimates of Physical Activity and Sedentary Behavior against Direct Observation.....	97
4.1 Introduction.....	97
4.2 Methods.....	100
4.2.1 Participants	100
4.2.2 Study Procedure	100
4.2.3 Measures and Instrumentation.....	100
4.2.4 Data Processing	105
4.2.5 Statistical Analysis.....	105
4.3 Results.....	108
4.4 Discussion	118
4.5 Conclusion.....	125
References	127
5. Accuracy & Precision of Wearable Camera Physical Activity Intensity Estimates against Indirect Calorimetry.....	134
5.1 Introduction.....	134
5.2 Methods.....	137
5.2.1 Participants	137
5.2.2 Study Overview	137
5.2.3 Measures and Instrumentation.....	139
5.2.4 Data Processing	141
5.2.5 Statistical Analysis.....	143
5.3 Results.....	144
5.4 Discussion	151
5.5 Conclusion.....	155

References	156
6. Conclusion	160
References	165
Appendices	168
Appendix A: Scoping Review Final Search Queries	168
Appendix B: Scoping Review Publications Per Year By Record Type.....	175
Appendix C: Scoping Review Study Characteristics.....	176
Appendix D: Extracted Dimensions of Physical Activity and Sedentary Behavior from Included Sources.....	182
Appendix E: Extracted Wearable Camera Characteristics from Included Sources..	185
Appendix F: Oxford Image Browser Behavior Annotation Codes	200
Appendix G: Behavior and Posture Domain Equivalence Plots using 90%, 95% and 99% Confidence Intervals.....	219
Appendix H: Posture Domain Equivalence Plots Using 90%, 95% and 99% Confidence Intervals Stratified by Behavior Domain.....	220
Appendix I: Intensity Category Equivalence Plots Using 90%, 95% and 99% Confidence Intervals.....	221
Appendix J: Intensity Category Equivalence Testing Using 90%, 95% and 99% Confidence Intervals.....	222

LIST OF FIGURES

Figure 2.1: PRISMA flow diagram detailing the review process.	35
Figure 2.2: Number of Publications per Year.	36
Figure 3.1: Interface of the Oxford Image Browser software used to annotate still images.....	81
Figure 3.2: Modified Bland–Altman plots with event activPAL estimates as the x-axis and difference between image and activPAL estimates within events as the y-axis.	88
Figure 4.1: Boxplots showing the distribution of direct observation video minutes in each domain across all visits.....	111
Figure 4.2: Mean percent difference of wearable camera still-image estimates minus direct observation video for each behavior and posture domain using a $\pm 15\%$ equivalence region.	114
Figure 4.3: Mean percent difference of wearable camera still-image estimates minus direct observation video for each posture domain stratified by behavior domain using a $\pm 15\%$ equivalence region.	116
Figure 5.1: Boxplots showing the distribution of COSMED K5 minutes in each physical activity intensity category across all visits.	146
Figure 5.2: Mean percent difference of wearable camera still-image estimates minus K5 measurements for each physical activity intensity by procedure using a $\pm 15\%$ equivalence region.	150

LIST OF TABLES

Table 1.1: Dimensions of Physical Activity and Sedentary Behavior.	3
Table 1.2: Domains of Physical Activity and Sedentary Behavior.	5
Table 2.1: Dimensions of Physical Activity and Sedentary Behavior.	25
Table 2.2: Domains of Physical Activity and Sedentary Behavior.	27
Table 2.3: Database-agnostic search terms used.	31
Table 2.4: Electronic databases searched for the scoping review on November 1st, 2023.	32
Table 2.5: Frequency table of included record types and publication years by identified themes of wearable camera use.	37
Table 2.6: Summary table of sample characteristics for included studies by theme of wearable camera use.	40
Table 2.7: Summary of physical activity and sedentary behavior dimensions captured from wearable camera media annotations by theme of wearable camera use.	42
Table 2.8: Summary of physical activity and sedentary behavior types captured from wearable camera media annotations by theme of wearable camera use.	44
Table 2.9: Operational definitions for categorization of physical activity and sedentary behavior types seen within the scoping review.	45
Table 2.10: Summary of wearable cameras brands, general attachment sites and media by themes of wearable camera use.	46
Table 3.1: Schema used to annotate wearable camera still-images in the Oxford Image Browser.	82
Table 3.2: Participant demographics.	86

Table 3.3: Mean image annotation and AP estimates within events that an image annotation posture code was applied.	87
Table 3.4: Confusion Matrix of Mean Total AP Estimates with Image Annotations as a Percentage of Mean Total AP Estimates.	89
Table 4.1: Behavior and posture schema domains used for analysis.	106
Table 4.2: Participant and visit descriptives.	109
Table 4.3: Confusion matrix of behavior domains between direct observation video and wearable camera still-images.	112
Table 4.4: Confusion matrix of posture domains between direct observation video and wearable camera still-images.	113
Table 4.5: Classification and equivalence testing results for wearable camera still-image annotations by activity type.	117
Table 5.1: Data Collection Visit Categories.	138
Table 5.2: Participant and visit descriptives.	145
Table 5.3: Classification metrics of Sedentary to Vigorous intensity categories by procedure.	147
Table 5.4: Classification metrics of Low to MVPA intensity categories by procedure.	148

LIST OF ABBREVIATIONS

ACC	Accelerometer
AP	activPAL
BORIS	Behavioral Observation Research Interactive Software
CI	Confidence Interval
DO	Direct Observation
EE	Energy Expenditure
FAR	First-Person Activity Recognition
GRT	Ground-Truth
IC	Indirect Calorimetry
ICC	Intra-class Correlations Coefficient
IMG	Still-Image
MET	Metabolic Equivalent
ML	Machine Learning
MVPA	Moderate to Vigorous Physical Activity
OCM	Outcome Measure
OIB	Oxford Image Browser
PA	Physical Activity
SB	Sedentary Behavior
ST	Sedentary Time
VAL	Validation
WC	Wearable Camera

ACKNOWLEDGEMENTS

There have been many instances throughout the course of my adult life where I stop the routine of my day, look at the nature around me, and think “Damn, I’m really lucky”. These moments of appreciation increased tenfold for several individuals while working on this body of work. And although words on a page will never be enough to fully show the magnitude of my appreciation, may it be proof the completion of this dissertation was made possible by these individuals.

First and foremost, I would like to thank Dr. Strath for taking me under his mentorship and shaping me into the scientist I am today. When we first talked on the phone while I was still an undergraduate, I was just happy to be offered an opportunity to visit the Physical Activity and Health Research Laboratory (PAHRL). Now six years later, I am proud to say I am the mentee of someone who values the “bigger picture” of physical activity (PA) and sedentary behavior (SB) research, and the priceless things in life such as family, friends and travel. I will keep in mind your “Strath-isms”, and let you know when I have grown my sweater vest collection to a respectable size. I will also let you know when I learn how to drive (oops). Thank you for letting me aim for the stars and ushering me towards success.

I big thank you to everyone on my dissertation committee. Dr. Swartz, thank you for making PAHRL feel like a home away from home, and being a role model for how to successfully support others. If you look in the dictionary, I am sure your name is the only thing that pops when searching the phrase “pillar of support”. Chris, thank you for meeting with me to talk statistics and mentoring me on how to best present the results of statistical analyses that is most informative to the reader. I hope to make you proud

with the statistical knowledge I will gain in my future endeavors. Dr. Kate, thank you for introducing me to the world of machine learning. Your instruction has been instrumental in my endeavors to bridge the computer science and PA and SB measurement fields.

Dr. Keadle, I will always be grateful for you starting me down this path I now take. If not for your mentorship at Cal Poly, I would not be where I am today. Because of that, I will always have the utmost respect for you. Youngster Julian never dreamed himself getting a doctorate in philosophy. You made that dream into reality.

Kat, you are the glue that holds PAHRL together, and an unsung hero who keeps many behind-the-scene processes alive and well. I am sure once you leave campus on your last day as Research Program Manager, Enderis Hall will spontaneously combust due to something failing behind the scenes. And you won't be available because you will be out frolicking through fields with a falcon on your shoulder. My friend, you deserve happiness and more.

Thank you to the Clinical and Translational Science Institute of Southeast Wisconsin and the Advanced Opportunity Program at UW-Milwaukee for their fellowships in supporting my dissertation work.

There have been many students who have come and gone during my time with PAHRL, and they all had a part in keeping me sane. Saira, Christa, Kristen, Andrew, Dr. Rowley, Dr. Tokarek, Nikki: thank you for being the first friends of a misplaced Californian in a, at the time, scary Wisconsin. Bryce and Maher, thank you for solidifying two things that I will be carrying forward with me in life: a "BANG HEAD HERE" sign and "Ain't got no more gas in it Billy". Brooke, thank you for being my personal chauffeur while I collected data for my dissertation. Julia, thank you for having such a supportive,

inquisitive nature, which has helped me be a better mentor. Avery, thank you for being an awesome first mentee and hosting a cat summer camp. Michael, thank you for always going above and beyond your responsibilities, and being a person I can depend on as a “right-hand man”. Autumn, Jake, Taylor and Garrett, thank you for being my family away from family in Wisconsin. Autumn and Jake, from experiencing Milwaukee for the first time together to late nights of playing Overcooked or watching horror movies, it felt like we’ve known each other for so long for how quickly we got along. Thank you for making my first two years here bearable. Taylor, thank you for officially being the best roommate I have ever had and supporting me when I did not have a place to live in. I will keep up with my ab rollouts, and yes, Big Frank is part of the family as well. Garrett, thank you for being such a nice human being, and making my dissertator status years bearable through Sendik’s and Breadsmith runs. You have an aura of acceptance and innocence that I hope you never lose. You four let me be my true self, and for that I will always support you.

Current PAHRL members, Charlie Benforado, Benjamin Gates, Honey Patel, Rylee Mazur, Joseph Patnode, Abigail Skirmont, and Eileen Tocco, I hope you keep the PAHRL camaraderie and quiriness alive and well. Treat the lab well and it will treat you well back. Finally, all the students who have helped with annotating the direct observation videos and wearable camera data, I literally would not have been here without your support and dedication to learning the annotation procedures. Whether it be my antics for helping you all to remember a specific coding procedure, philosophical discussions on what it means to be stepping, or appropriately naming annotations (i.e. Driving Landcraft), I truly appreciate your work and my time with you all.

I big thank you to my friends and family back in California for supporting me from afar. The Oades family, thank you for supporting me in my life endeavors and being a positive influence in my life during my formative years. William, Anthony, and Oscar, thank you for always reminding me to enjoy the smaller things in life, and not letting me forget my Californian roots. You all are amazing men and I will be there for you as you have for me. Kyle, you are in there too even though I haven't had the time to reach out to you. Tia, thank you for checking in on me sporadically during my time here. I wish I could have been there more to see Gabriela and Camilla grow up, but I am glad they remember me at all! Adrian, thank you always being there for me and for all the late-night sessions of monster hunting and exploring the lands between. I am glad I have you as an older brother and as a best friend. Mom, I don't think I will ever be able to show you just how much I appreciate the sacrifices you made for Adrian and I. Thank you for showing me the value of my health, and nurturing me to be the person I am today.

Last but not least, I have to thank a wonderful bundle of sunshine named Maricela. You reached out to me during a time when my mental and physical health was at its lowest point during my dissertation work, and made working through those days bearable. Since then, you have done nothing but support me through the thick and thin of it: delivering my poster presentation in Keystone, the research opportunity in Cambridge, the month of no sleep before defending my dissertation. I will always be thankful for you and your family. I love you Maricela and I will forever continue being thankful for having you in my life. Who would've thought huh?

Everyone, I hope to make you proud. Just watch me.

1. Introduction

1.1 What is Physical Activity & Sedentary Behavior?

Physical activity (PA) is a complex behavior that is embedded within many facets of human life and extends across multiple scientific disciplines. It can be defined as a behavior “involving people moving, acting and performing within culturally specific spaces and contexts...influenced by a unique array of interests, emotions, ideas, instructions and relationships” [1]. This holistic definition provided is a testament to the complexity of PA as a behavior, where even the most widely cited epidemiology-based definition of PA, “any bodily movements produced by skeletal muscles that result in energy expenditure (EE)” [2], is all-encompassing and covers all facets of human activity. It is easy to imagine then how PA occurs throughout many environmental settings with the accomplishments of daily tasks: moving inventory within one’s occupation, walking with friends around a museum, sweeping the floor at ones’ household or even folding laundry. Regardless of the environmental setting or intent of the PA, it has been consistently shown that increasing one’s level of PA engagement improves health and promotes longevity. So much so, that meeting recommended PA guidelines, namely engaging in 150 minutes of moderate or 75 minutes of vigorous intensity activity, is part of the American Heart Association’s “Life’s Essential 8” [3] for cardiovascular health. Opposite of PA’s positive impact, large accumulations of sedentary behavior (SB) has been consistently shown to have negative impacts on one’s health [4, 5] where SB is defined as “waking behavior characterized by an EE \leq 1.5 metabolic equivalents (METs), while in a sitting, reclining or lying posture” [6]. Due to the positive effects of maintaining a physically active lifestyle and the adverse effects

from sedentariness, it is imperative to measure one's PA and SB levels. This is done through the measurement of key characteristics, or dimensions, of PA and SB

1.2 Measuring Physical Activity and Sedentary Behavior for Health

The broadness and exactness of PA and SB can be characterized into four different dimensions, 1) frequency, 2) intensity, 3) duration and 4) type (see **Table 1.1**). Frequency refers to the occurrences or transitions into PA or SB during a set time frame, which is typically during a day, week or within a studies data collection time frame. Intensity refers to the rate of EE during bodily movement from skeletal muscle contractions which can be expressed in many ways. Units of measure include kilocalories or Metabolic Equivalent (METs), where 1 MET is the resting EE of an individual during quiet sitting [7]. METs can further be collapsed into absolute intensity categories of light (1.5-2.9 METs), moderate (3.0-5.9 METs) and vigorous (6.0+ METs) intensity, where time spent in moderate and vigorous intensity PA is part of the key PA guidelines for Americans [8]. Duration refers to the amount of time spent in PA or SB within a single bout, which can consist of any unit of time. Typically, the duration of PA and SB is measured in minutes and hours, where duration in combination with frequency and intensity is used to calculate a composite PA or SB dimension of total volume. Finally, the type of PA and SB is a qualitative measure aimed at contextualizing PA and SB into categories that are meaningful for health, daily life, or other topical areas of research. Typically, types of PA describe a combination of movement patterns while types of SB describe physical or non-physical interactions with objects or the immediate vicinity of an individual to explain the reason for the SB. Types of PA and SB can be collapsed into categories such as *ambulation* (walking, running, ascending

Table 1.1: Dimensions of Physical Activity and Sedentary Behavior.

Dimension^a	Definition	Examples
Frequency	The number of times a continuous bout of PA ^b or SB ^c occurs over a given time frame.	Walking to the bus 2 times in a day; Sweeping the floor 3 times while at work; Maintaining a vehicle once a week
Intensity	The rate of how much energy the body is expending from PA ^b or SB ^c , separate from diet-induced energy expenditure and basal energy expenditure.	50 kJ per day; 10.5 mL O ₂ /kg/min (3 METs ^d); light, moderate, vigorous intensity
Duration	The length of an activity bout or total time in a type of PA ^b or SB ^c .	30 minutes of walking; 2 hours of television watching; 30 seconds of ascending stairs
Type	Combination of movements caused by skeletal muscle movements or descriptors of object interactions during non-ambulatory movement.	Using phone; Cooking/Meal preparation; Cycling; Aerobic vs Anaerobic

^aDimensions of PA^b or SB^c are key characteristics that are essential to capture for comprehensive measurement. Two or more dimensions are commonly measured at the same time.

^bPhysical Activity

^cSedentary Behavior

^dMetabolic Equivalents; 1 MET = 3.5 mL O₂/kg/min

stairs), *activities of daily living* (caring/grooming, dressing, eating) or *screen-time* (phone-use, television watching) or be further generalized into domains of PA and SB, namely these domains are leisure, transportation, household and occupation, as a way to discriminate the intent or reasons for performing the type of PA and SB typically seen throughout daily life (Table 1.2).

1.3 Barriers to Defining the Dose-Response Relationship of Physical Activity and Sedentary Behavior to Health Outcomes

Substantial work shows a clear direction of impact linking PA and SB to non-communicable diseases. However, the doses of PA and SB necessary to confer benefits or determinants to health are unknown due to studies omitting the measurement of PA and SB type or focusing only on one type of PA and SB at a time. For example, Ahmadi et al. [11] have recently shown the impact of different PA frequency, vigorous intensity and duration combinations on all-cause mortality, incident cardiovascular disease and cancer. However, the accelerometer algorithm used was calibrated to estimate vigorous intensity during walking and running only [12], which misses other types of PA that are typically vigorous such as cycling and stair climbing [13]. When examining the impact of SB on health, the associations between sedentary television viewing and mortality have been shown separately from the associations of total SB with mortality [14, 15], as television viewing has been shown to have different confounding/mediating patterns as opposed to general SB [14, 16, 17]. This type-specific association of SB exhibits how certain types of PA and SB may have stronger/weaker associations with health outcomes. However, similar to how aerobic PA has been the primary PA type examined for health associations, screen-time SB is still

Table 1.2: Domains of Physical Activity and Sedentary Behavior.

Domain^a	Definition	Examples of PA^d/SB^e Types^f
Household^{b,c}	Activity undertaken for maintenance of a household within a domestic setting	Cleaning; Cooking; Caring for Children, Adults or Pets; Laundry
Leisure^{b,c}	Activity performed by an individual that is not required as an essential activity of daily living and is performed at the discretion of the individual.	Television watching; Reading; Sports; Exercise Conditioning; Dancing; Gardening
Occupation^{b,c}	Activity undertaken during paid or voluntary work.	Keyboard/Mouse Use; Organizing Inventory; Constructing/Repairing architecture
Transport^b	Activity performed for the purpose of getting to and from places, and refers to walking, cycling and wheeling (i.e. some form of locomotion)	Walking; Cycling; Using a Scooter; Driving; Riding the Bus

^aHigh-level descriptors of physical activity and sedentary behavior that incorporates contextual information (such as physical environment and purpose of PA/SB engagement) with type of PA/SB. These descriptors are meant to be representative of active living [9]

^bDomain definitions adapted from World Health Organization 2020 Guidelines [10]. This translation was not created by the World Health Organization (WHO). WHO is not responsible for the content or accuracy of this translation. The original English edition shall be the binding and authentic.

^cWHO does not extend these domains to encompass sedentary behavior.

^dPhysical Activity

^eSedentary Behavior

^fRepresentations of typical examples. These types of PA/SB can occur within other domains depending on the environment and/or intent of engagement. For example, Cycling can be for Leisure or for Transport depending on intent for engagement. Gardening can be for Leisure or for Household

much more researched than non-screen time SB. The focus on single types of PA and SB within the literature miss the qualitative characterization of PA and SB and is frequently noted to be recommended as future research directions [18–21]. These recommendations also extend to capturing PA and SB from multiple domains [22–24]. For example, leisure domain PA has been the focal point for epidemiological PA research [25]. This trend is worrisome as it has been shown that PA accumulation from all domains of PA can determine whether an individual is meeting recommended levels of PA [26, 27] and the domains of PA and SB were determined as areas where PA and SB interventions could occur [9, 28]. Therefore, there is a clear need to measure types of PA and SB for refining the dose-response relationship between PA and SB with different health outcomes, where the dose-response relationship are the unique combinations of PA and SB frequencies, intensities, durations and types on health. A reason for the absence of PA and SB types being captured may be due to the measurement tools themselves.

1.4 Physical Activity and Sedentary Behavior Measurement Tool Limitations

Self-report questionnaires have been used to assess population-representative levels of PA and SB due to its ease of delivery and low participant and researcher burden. Historically, the International Physical Activity Questionnaire [29] and Global Physical Activity questionnaire are widely used questionnaires with general questions that allow the capture of frequency, intensity, duration and type of PA whereas the International Sedentary Assessment Tool [30] is a more recent questionnaire that also captures all dimensions of SB. Albeit its ease of use, and the ability to capture all dimensions of PA and ease of delivery, self-report tools are limited by biases when it

comes to capturing the intensity and duration of PA and SB. When measuring PA intensity through self-report tools, it is possible that PA intensity relative to an individual's fitness level is assessed instead of PA intensity in units of a standardized measure [31, 32]. When measuring duration, shorter bouts of PA, such as incidental (non-purposeful) PA [33], and SB is also more likely to be missed by questionnaires [31, 32, 34, 35]. Finally, social desirability bias to seem more physically active or less sedentary are also likely to influence responses [36, 37]. A tool that is not afflicted from such biases are body worn accelerometers, where they have also been implemented in large-scale studies.

Whereas self-report questionnaires are considered to provide subjective measures of PA and SB due to several biases affecting their output, body worn accelerometers provide objective measures of PA and SB such that raw data from micro-electromechanical sensors that measure changes in velocity over time are used to estimate dimensions of PA and SB. As movement caused by skeletal muscle contraction is an essential component for the definition of PA and SB, measures of acceleration are used as a proxy for EE. In epidemiological studies, accelerometers are typically limited to measuring the frequency, intensity and duration of PA and SB for determining associations with health outcomes [11, 38]. As interdisciplinary collaboration becomes more commonplace, the application of more complex statistical methods, such as deep learning, has brought more utility to the use of accelerometry for PA and SB measurement. Research has also shown that accelerometer-derived features can be used to estimate PA and SB type [39–41]. However, this capability has been limited to semi-structured types of activity performed in lab settings, a limited

variety of posture or movement type being assessed within free-living settings or requiring the use of multiple accelerometers at different wear locations that are not typically used nor applicable in large-scale studies.

The use of self-report tools and accelerometry do not accurately and precisely capture the entirety of PA and SB by themselves. The concurrent use of time-use diaries, self-report tools that capture 24-hour PA and SB with more accuracy than questionnaires [42], and accelerometry has the potential to assess all four dimensions, frequency, intensity, duration and type, of PA and SB in large-scale studies. There has been work in validating PA and SB measures estimated from time-use diaries and accelerometry against criterion measures such direct observation (DO) [43, 44]. Validation research using DO however has typically been limited to observing < 3 hours of PA and SB across days, as DO places significant burden on both researchers and participants [7] which is additional participant burden to consider with the use of time-use diaries. The PA and SB measurement field is lacking a single tool that can 1) provide criterion measures of PA and SB frequency, intensity, duration and type, 2) be utilized within free-living settings to capture habitual time-series data of PA and SB, and 3) have low participant and researcher burden. The availability of such a tool will help establish the combined use of time-use diaries and accelerometry to comprehensively measure PA and SB in epidemiological studies, as well as be the primary PA and SB measurement tool in applied research studies. A tool with the potential to fill this gap are body-worn wearable cameras (WCs).

1.5 Wearable Cameras: A Tool Utilized to Comprehensively Capture a Variety of Health-Behavior Characteristics

Body-worn WCs are small, lightweight cameras worn by individuals to capture first-person still-images (IMGs) or video of the wearer's immediate environment or vicinity. The initial use of WCs in research focused on their utility to aid memory recall [45–48] where the literature now consistently shows the beneficial effects of WCs to aid in those in memory rehabilitation by providing rich contextual information [49–51]. Since then, contextual information from WC media has been utilized and applied in a variety of disciplines. For examining environmental influences in one's life, WC media from children have been annotated to provide objective measures of access to resources, built environment characteristics and exposure to household harm [52–54] and for documenting environmental determinants of obesity [55].

Wearable camera media can also assist with capturing health-related behavior. An ethical framework was developed specifically for the use of WCs in health-related research, which informs the reader on the ethical implication passive, large volume IMG capture has towards the privacy, autonomy and confidentiality of research participants [56]. The recommendation of guidelines to address these ethical implications, such as informing the participant they have the opportunity to view and delete any captured IMGs in privacy, being informed they are welcome to remove the WC if they feel uneasy wearing the device, and seeking verbal permission from cohabitants before study commencement [56], has been widely adopted in WC health research. The “Seeing is Believing Study” determined that WC IMGs can be used to capture self-management practices for individuals with heart failure [57–59]. Multiple studies have used WC media to assist with 24-hour dietary recall [60], where it has been shown to reduce dietary

under-reporting [61, 62]. The widespread use of WCs to capture health-related research, as well as the establishment of an ethical framework for WC use in health-related research and a more recent review showing little risk of adverse events concerning privacy for WC health-related research [63], all demonstrate the acceptability and appropriateness of their use for health-related research.

In capturing the wearer's vicinity, WC media can be used to provide rich contextual information of PA and SB as it captures the wearer's activity behavior, interactions with the environment and how the wearers environment may influence the wearer's activity. This information is essential to classifying an individual's PA and SB type and domain, which in turn shows the immense potential of WCs to address barriers in defining the dose-response relationship between PA and SB and several health outcomes by overcoming self-report and accelerometer tool limitations. For PA and SB research, WCs have been shown to have high wear compliance and acceptability by varying age groups [64, 65] and WC media have been used to aid understanding of PA and SB experiences. Sutherland et al. [66] used WC media to assist with semi-structured interviews on experiences with PA for individuals who receive regular hemodialysis, while Dontje et al. [67] used WC IMGs to provide a storyboard when interviewing older adults why accelerometer-defined bouts of ST occurred and reasons for breaking bouts of ST.

The utility of WCs for PA and SB research is clear, where annotations of WC media for PA and SB are already being used in four main ways:

1. In the development of machine learning (ML) models for the purpose of predicting PA and SB from annotated first-person WC media. A testament to

WCs extensive use in the field, the human activity recognition field, is the recent release of the Ego4D dataset [68], a collection of more than 3000 hours of WC media from users all across the world.

2. To provide primary and secondary outcome measures relevant to study hypothesis' and aims, such as in the Kid's Cam study [52].
3. To provide ground-truth annotated labels of PA and SB for validating other PA and SB measurement tools [64] or for training accelerometer machine learning models [69].
4. To have their validity and reliability assessed against established measures of PA and SB [70], where it is observed that no studies have assessed the criterion validity of WC media annotations to capture all dimensions of PA and SB.

A recent scoping review from Maddison et al. [71] briefly covered the aims of studies using WC media annotations to provide outcome measures of PA and SB or validate other PA and SB measurement tools. However, the purpose of the Maddison et al. scoping review was to determine the extent of use for WCs to aid chronic disease self-management behaviors, and not the extent of use for WCs to capture PA and SB. Due to the lack of a comprehensive, systematic review detailing the extent of use of WC media annotations to capture PA and SB, and no studies having assessed the criterion validity of WC PA and SB annotations being a clear scientific knowledge gap due to its variety in use within the literature, this dissertation aims to fill these needs from the scientific community. Specifically, the scope and structure of this dissertation proposal is as follows:

- Chapter 2 is a scoping review on the use of WC media to measure PA and SB. Specifically, themes of study purposes for use of WC media annotations to capture PA and SB, the dimensions of PA and SB captured by WC media annotations and the methodologies for WC utilization for PA and SB measurement is explored. From the results of this scoping review, I highlight a significant gap in the literature: the lack of validity research surrounding PA and SB annotations from WC IMGs and video, despite its widespread use to provide ground-truth labels.
- Chapter 3 details preliminary efforts in establishing the validity of WC IMGs to assess posture. More concretely, the convergent validity for WC IMG annotations of sitting, standing and movement. This is determined by direct comparison to activPAL accelerometer posture classifications, output that has been determined to be an accurate measurement of posture.
- Chapter 4 is a more comprehensive evaluation of WC IMG annotations to measure frequency, duration and type of PA and SB, where DO video PA and SB annotations will be used as the criterion measure. As part of a larger study, 260 hours of free-living DO video & WC IMG data will be analyzed from 51 healthy individuals.
- Chapter 5 establishes the criterion validity of WC IMG annotations to classify PA intensity by comparing PA intensity estimations from WC IMGs to the COSMED K5 portable metabolic system, a pseudo gold-standard measure of PA EE.
- Finally, a summary of key results from the preceding chapters is provided, along with a discussion of future research opportunities.

References

1. Piggin J (2020) What Is Physical Activity? A Holistic Definition for Teachers, Researchers and Policy Makers. *Frontiers in Sports and Active Living* 2:
2. Caspersen CJ, Powell KE, Christenson GM (1985) Physical activity, exercise, and physical fitness: Definitions and distinctions for health-related research. *Public Health Rep* 100:126–131
3. Lloyd-Jones DM, Allen NB, Anderson CAM, et al (2022) Life’s Essential 8: Updating and Enhancing the American Heart Association’s Construct of Cardiovascular Health: A Presidential Advisory From the American Heart Association. *Circulation* 146:e18–e43
4. Dempsey PC, Biddle SJH, Buman MP, et al (2020) New global guidelines on sedentary behaviour and health for adults: Broadening the behavioural targets. *International Journal of Behavioral Nutrition and Physical Activity* 17:151
5. Park JH, Moon JH, Kim HJ, Kong MH, Oh YH (2020) Sedentary Lifestyle: Overview of Updated Evidence of Potential Health Risks. *Korean J Fam Med* 41:365–373
6. Tremblay MS, Aubert S, Barnes JD, et al (2017) Sedentary Behavior Research Network (SBRN) – Terminology Consensus Project process and outcome. *International Journal of Behavioral Nutrition and Physical Activity* 14:75
7. Strath SJ, Kaminsky LA, Ainsworth BE, Ekelund U, Freedson PS, Gary RA, Richardson CR, Smith DT, Swartz AM, American Heart Association Physical Activity Committee of the Council on Lifestyle and Cardiometabolic Health and Cardiovascular, Exercise, Cardiac Rehabilitation and Prevention Committee of

- the Council on Clinical Cardiology, and Council (2013) Guide to the assessment of physical activity: Clinical and research applications: A scientific statement from the American Heart Association. *Circulation* 128:2259–2279
8. Piercy KL, Troiano RP, Ballard RM, Carlson SA, Fulton JE, Galuska DA, George SM, Olson RD (2018) The Physical Activity Guidelines for Americans. *JAMA* 320:2020–2028
 9. Sallis JF, Cervero RB, Ascher W, Henderson KA, Kraft MK, Kerr J (2006) An Ecological Approach to Creating Active Living Communities. *Annual Review of Public Health* 27:297–322
 10. Organization WH (2020) Guidelines on physical activity and sedentary behaviour. World Health Organization, Geneva
 11. Ahmadi MN, Clare PJ, Katzmarzyk PT, del Pozo Cruz B, Lee IM, Stamatakis E (2022) Vigorous physical activity, incident heart disease, and cancer: How little is enough? *European Heart Journal* 43:4801–4814
 12. Pavey TG, Gilson ND, Gomersall SR, Clark B, Trost SG (2017) Field evaluation of a random forest activity classifier for wrist-worn accelerometer data. *Journal of Science and Medicine in Sport* 20:75–80
 13. Matthews CE, Saint-Maurice PF (2022) The hare and the tortoise: Physical activity intensity and scientific translation. *European Heart Journal* 43:4815–4816
 14. Patterson R, McNamara E, Tainio M, de Sá TH, Smith AD, Sharp SJ, Edwards P, Woodcock J, Brage S, Wijndaele K (2018) 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* 33:811–829
15. Xu C, Furuya-Kanamori L, Liu Y, et al (2019) Sedentary Behavior, Physical Activity, and All-Cause Mortality: Dose-Response and Intensity Weighted Time-Use Meta-analysis. *Journal of the American Medical Directors Association* 20:1206–1212.e3
 16. Bowman SA (2006) Television-Viewing Characteristics of Adults: Correlations to Eating Practices and Overweight and Health Status. *Prev Chronic Dis* 3:A38
 17. Hamer M, Yates T, Demakakos P (2017) Television viewing and risk of mortality: Exploring the biological plausibility. *Atherosclerosis* 263:151–155
 18. Barisic A, Leatherdale ST, Kreiger N (2011) Importance of Frequency, Intensity, Time and Type (FITT) in Physical Activity Assessment for Epidemiological Research. *Can J Public Health* 102:174–175
 19. Atkin AJ, Gorely T, Clemes SA, Yates T, Edwardson C, Brage S, Salmon J, Marshall SJ, Biddle SJH (2012) Methods of Measurement in epidemiology: Sedentary Behaviour. *Int J Epidemiol* 41:1460–1471
 20. Thompson D, Peacock O, Western M, Batterham AM (2015) Multidimensional Physical Activity: An Opportunity, Not a Problem. *Exercise and Sport Sciences Reviews* 43:67
 21. Kelly P, Fitzsimons C, Baker G (2016) Should we reframe how we think about physical activity and sedentary behaviour measurement? Validity and reliability reconsidered. *Int J Behav Nutr Phys Act* 13:32

22. Marshall AL, Miller YD, Burton NW, Brown WJ (2010) Measuring Total and Domain-Specific Sitting: A Study of Reliability and Validity. *Med Sci Sports Exerc* 42:1094–1102
23. Kraus WE, Powell KE, Haskell WL, et al (2019) Physical Activity, All-Cause and Cardiovascular Mortality, and Cardiovascular Disease. *Med Sci Sports Exerc* 51:1270–1281
24. Ding D, Varella AR, Bauman AE, Ekelund U, Lee I-M, Heath G, Katzmarzyk PT, Reis R, Pratt M (2020) Towards better evidence-informed global action: Lessons learnt from the Lancet series and recent developments in physical activity and public health. *Br J Sports Med* 54:462–468
25. Quinn TD, Gibbs BB (2023) Context Matters: The Importance of Physical Activity Domains for Public Health. *Journal for the Measurement of Physical Behaviour* - 1:1–5
26. Whitfield GP (2020) Combining Data From Assessments of Leisure, Occupational, Household, and Transportation Physical Activity Among US Adults, NHANES 2011–2016. *Prev Chronic Dis*.
<https://doi.org/10.5888/pcd17.200137>
27. Whitfield GP, Ussery EN, Saint-Maurice PF, Carlson SA (2021) Trends in Aerobic Physical Activity Participation Across Multiple Domains Among US Adults, National Health and Nutrition Examination Survey 2007/2008 to 2017/2018. *Journal of Physical Activity and Health* 18:S64–S73
28. King AC, Jeffery RW, Fridinger F, Dusenbury L, Provence S, Hedlund SA, Spangler K (1995) Environmental and Policy Approaches to Cardiovascular

- Disease Prevention Through Physical Activity: Issues and Opportunities. *Health Education Quarterly* 22:499–511
29. Craig CL, Marshall AL, Sjöström M, et al (2003) International Physical Activity Questionnaire: 12-Country Reliability and Validity. *Medicine & Science in Sports & Exercise* 35:1381
 30. Prince SA, LeBlanc AG, Colley RC, Saunders TJ (2017) Measurement of sedentary behaviour in population health surveys: A review and recommendations. *PeerJ* 5:e4130
 31. Shephard RJ (2003) Limits to the measurement of habitual physical activity by questionnaires. *British Journal of Sports Medicine* 37:197–206
 32. Matthews CE, Moore SC, George SM, Sampson J, Bowles HR (2012) Improving Self-Reports of Active and Sedentary Behaviors in Large Epidemiologic Studies. *Exercise and Sport Sciences Reviews* 40:118
 33. Tremblay MS, Esliger DW, Tremblay A, Colley R (2007) Incidental movement, lifestyle-embedded activity and sleep: New frontiers in physical activity assessment. *Appl Physiol Nutr Metab* 32:S208–S217
 34. Owen N, Healy GN, Matthews CE, Dunstan DW (2010) Too Much Sitting: The Population Health Science of Sedentary Behavior. *Exerc Sport Sci Rev* 38:105–113
 35. Healy GN, Clark BK, Winkler EAH, Gardiner PA, Brown WJ, Matthews CE (2011) Measurement of Adults' Sedentary Time in Population-Based Studies. *Am J Prev Med* 41:216–227

36. Adams SA, Matthews CE, Ebbeling CB, Moore CG, Cunningham JE, Fulton J, Hebert JR (2005) The Effect of Social Desirability and Social Approval on Self-Reports of Physical Activity. *American Journal of Epidemiology* 161:389–398
37. Prince SA, Cardilli L, Reed JL, Saunders TJ, Kite C, Douillette K, Fournier K, Buckley JP (2020) A comparison of self-reported and device measured sedentary behaviour in adults: A systematic review and meta-analysis. *Int J Behav Nutr Phys Act* 17:31
38. Dempsey PC, Rowlands AV, Strain T, et al (2022) Physical activity volume, intensity, and incident cardiovascular disease. *European Heart Journal* 43:4789–4800
39. Zhang S, Rowlands AV, Murray P, Hurst TL (2012) Physical activity classification using the GENEActiv wrist-worn accelerometer. *Med Sci Sports Exerc* 44:742–748
40. Skotte J, Korshoj M, Kristiansen J, Hanisch C, Holtermann A (2014) Detection of Physical Activity Types Using Triaxial Accelerometers. *J Phys Act Health* 11:76–84
41. Bach K, Kongsvold A, Bårdstu H, Bardal EM, Kjærnli HS, Herland S, Logacjov A, Mork PJ (2022) A Machine Learning Classifier for Detection of Physical Activity Types and Postures During Free-Living. *Journal for the Measurement of Physical Behaviour* 5:24–31
42. Bakker EA, Hartman YAW, Hopman MTE, Hopkins ND, Graves LEF, Dunstan DW, Healy GN, Eijsvogels TMH, Thijssen DHJ (2020) Validity and reliability of subjective methods to assess sedentary behaviour in adults: A systematic review and meta-analysis. *Int J Behav Nutr Phys Act* 17:75

43. Keadle SK, Patel S, Berrigan D, Christopher CN, Huang J, Saint-Maurice PF, Lofffield E, Matthews CE (2023) Validation of ACT24 Version 2.0 for Estimating Behavioral Domains, Active and Sedentary Time. *Med Sci Sports Exerc* 55:1054–1062
44. Marcotte RT, Petrucci GJJ, Cox MF, Freedson PS, Staudenmayer JW, Sirard JR (2020) Estimating Sedentary Time from a Hip- and Wrist-Worn Accelerometer. *Medicine & Science in Sports & Exercise* 52:225
45. Hodges S, Williams L, Berry E, Izadi S, Srinivasan J, Butler A, Smyth G, Kapur N, Wood K (2006) SenseCam: A Retrospective Memory Aid. In: Dourish P, Friday A (eds) *UbiComp 2006: Ubiquitous Computing*. Springer, Berlin, Heidelberg, pp 177–193
46. Berry E, Hampshire A, Rowe J, Hodges S, Kapur N, Watson P, Browne G, Smyth G, Wood K, Owen AM (2009) The neural basis of effective memory therapy in a patient with limbic encephalitis. *J Neurol Neurosurg Psychiatry* 80:1202–1205
47. Berry E, Kapur N, Williams L, Hodges S, Watson P, Smyth G, Srinivasan J, Smith R, Wilson B, Wood K (2007) The use of a wearable camera, SenseCam, as a pictorial diary to improve autobiographical memory in a patient with limbic encephalitis: A preliminary report. *Neuropsychol Rehabil* 17:582–601
48. Muhlert N, Milton F, Butler CR, Kapur N, Zeman AZ (2010) Accelerated forgetting of real-life events in Transient Epileptic Amnesia. *Neuropsychologia* 48:3235–3244

49. Allé MC, Manning L, Potheegadoo J, Coutelle R, Danion J-M, Berna F (2017) Wearable Cameras Are Useful Tools to Investigate and Remediate Autobiographical Memory Impairment: A Systematic PRISMA Review. *Neuropsychol Rev* 27:81–99
50. Silva AR, Pinho MS, Macedo L, Moulin CJA (2018) A critical review of the effects of wearable cameras on memory. *Neuropsychol Rehabil* 28:117–141
51. Mateo-Fernández PV, García-Silva J, Caparrós-González RA (2021) Utilización de SenseCam para rehabilitación de memoria tras un Daño Cerebral Adquirido: revisión sistemática de estudios experimentales. *Revista Española de Salud Pública* 95:e1–e16
52. Signal LN, Smith MB, Barr M, et al (2017) Kids’Cam: An Objective Methodology to Study the World in Which Children Live. *Am J Prev Med* 53:e89–e95
53. Robinson A, Hulme-Moir S, Puloka V, Smith M, Stanley J, Signal L (2017) Housing as a Determinant of Tongan Children’s Health: Innovative Methodology Using Wearable Cameras. *International Journal of Environmental Research and Public Health* 14:1170
54. Gage R, Chambers T, Smith M, McKerchar C, Puloka V, Pearson A, Kawachi I, Signal L (2022) Children’s perspectives on the wicked problem of child poverty in Aotearoa New Zealand: A wearable camera study. *N Z Med J* 135:95–111
55. Barr M, Signal L, Jenkin G, Smith M (2015) Capturing exposures: Using automated cameras to document environmental determinants of obesity. *Health Promotion International* 30:56–63

56. Kelly P, Marshall SJ, Badland H, Kerr J, Oliver M, Doherty AR, Foster C (2013) An ethical framework for automated, wearable cameras in health behavior research. *Am J Prev Med* 44:314–319
57. Gemming L, Ni Mhurchu C (2016) Dietary under-reporting: What foods and which meals are typically under-reported? *Eur J Clin Nutr* 70:640–641
58. Cartledge S, Rogerson M, Singh T, Huynh V, Phung D, Neil C, Ball K, Maddison R (2018) Seeing is Believing: Can Wearable Cameras Enhance Self-Management for People with Heart Failure? *Heart, Lung and Circulation* 27:S129
59. Nourse R, Cartledge S, Tegegne T, Gurrin C, Maddison R (2022) Now you see it! Using wearable cameras to gain insights into the lived experience of cardiovascular conditions. *EUROPEAN JOURNAL OF CARDIOVASCULAR NURSING* 21:750–755
60. Chan V, Davies A, Wellard-Cole L, et al (2021) Using Wearable Cameras to Assess Foods and Beverages Omitted in 24 Hour Dietary Recalls and a Text Entry Food Record App. *Nutrients* 13:1806
61. Gemming L, Utter J, Ni Mhurchu C (2015) Image-Assisted Dietary Assessment: A Systematic Review of the Evidence. *Journal of the Academy of Nutrition and Dietetics* 115:64–77
62. Gemming L, Rush E, Maddison R, Doherty A, Gant N, Utter J, Mhurchu CN (2015) Wearable cameras can reduce dietary under-reporting: Doubly labelled water validation of a camera-assisted 24 h recall. *British Journal of Nutrition* 113:284–291

63. Meyer LE, Porter L, Reilly ME, Johnson C, Safir S, Greenfield SF, Silverman BC, Hudson JI, Javaras KN (2022) Using Wearable Cameras to Investigate Health-Related Daily Life Experiences: A Literature Review of Precautions and Risks in Empirical Studies. *Res Ethics* 18:64–83
64. Kelly P, Thomas E, Doherty A, Harms T, Burke Ó, Gershuny J, Foster C (2015) Developing a Method to Test the Validity of 24 Hour Time Use Diaries Using Wearable Cameras: A Feasibility Pilot. *PLOS ONE* 10:e0142198
65. Harvey JA, Skelton DA, Chastin SFM, Harvey JA, Skelton DA, Chastin SFM (2016) Acceptability of novel lifelogging technology to determine context of sedentary behaviour in older adults. *AIMSPH* 3:158–171
66. Sutherland S, Penfold R, Doherty A, Milne Z, Dawes H, Pugh C, Boulton M, Newton JL (2021) A cross-sectional study exploring levels of physical activity and motivators and barriers towards physical activity in haemodialysis patients to inform intervention development. *Disability & Rehabilitation* 43:1675–1681
67. Dontje ML, Leask CF, Harvey J, Skelton DA, Chastin SFM (2018) Why Older Adults Spend Time Sedentary and Break Their Sedentary Behavior: A Mixed-Methods Approach Using Life-Logging Equipment. *J Aging Phys Act* 26:259–266
68. Grauman K, Westbury A, Byrne E, et al (2022) Ego4D: Around the World in 3,000 Hours of Egocentric Video. In: 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). pp 18973–18990
69. Willetts M, Hollowell S, Aslett L, Holmes C, Doherty A (2018) Statistical machine learning of sleep and physical activity phenotypes from sensor data in 96,220 UK Biobank participants. *Sci Rep* 8:7961

70. Martinez J, Decker A, Cho CC, Doherty A, Swartz AM, Staudenmayer JW, Strath SJ (2021) Validation of Wearable Camera Still Images to Assess Posture in Free-Living Conditions. *J Meas Phys Behav* 4:47–52
71. Maddison R, Cartledge S, Rogerson M, Goedhart NS, Ragbir Singh T, Neil C, Phung D, Ball K (2019) Usefulness of Wearable Cameras as a Tool to Enhance Chronic Disease Self-Management: Scoping Review. *JMIR mHealth uHealth* 7:e10371

2. The Use of Wearable Cameras to Capture Physical Activity and Sedentary Behavior: A Scoping Review

2.1 Introduction

Over the last 70 years substantial evidence has shown that engaging in physical activity (PA) contributes to better health, improved functionality and increased longevity [1–4]. Recent evidence has also started to accumulate to highlight the deleterious health effects of spending too much time engaged in sedentary behaviors (SB), such as sitting and television viewing [5–9]. Subsequently, public health recommendations have evolved over the years and now state that all adults should strive to minimally accumulate 150 minutes per week of moderate intensity PA or 75 minutes a week of vigorous intensity PA to confer associated health benefits [10] while minimizing time in SB [11]. Measuring PA and SB remains paramount for public health surveillance, but given that both PA and SB can be sporadic and are subject to large inter- and intra-individual variability, they remain very complex behaviors to accurately and precisely measure.

Physical activity is defined as “any bodily movements produced by skeletal muscles that result in energy expenditure” [12] which can be characterized by four dimensions (i.e., key characteristics) [13]: the frequency of activity, the intensity of the activity, the duration of the activity and the actual type of activity engaged in (see **Table 2.1**). These four dimensions also characterize SB which, in contrast to the definition of PA, is much more exact, such that SB is defined as “waking behavior characterized by an energy expenditure ≤ 1.5 metabolic equivalents (METs), while in a sitting, reclining or lying posture” [14]. Both PA and SB can be planned during one’s leisure-time or be the

Table 2.1: Dimensions of Physical Activity and Sedentary Behavior.

Dimension^a	Definition	Examples
Frequency	The number of times a continuous bout of PA ^b or SB ^c occurs over a given time frame.	Walking to the bus 2 times in a day; Sweeping the floor 3 times while at work; Maintaining a vehicle once a week
Intensity	The rate of how much energy the body is expending from PA ^b or SB ^c , separate from diet-induced energy expenditure and basal energy expenditure.	50 kj per day; 10.5 mL O ₂ /kg/min (3 METs ^d); light, moderate, vigorous intensity
Duration	The length of an activity bout or total time in a type of PA ^b or SB ^c .	30 minutes of walking; 2 hours of television watching; 30 seconds of ascending stairs
Type	Combination of movements caused by skeletal muscle movements or descriptors of object interactions during non-ambulatory movement.	Using phone; Cooking/Meal preparation; Cycling; Aerobic vs Anaerobic

^aDimensions of PA^b or SB^c are key characteristics that are essential to capture for comprehensive measurement. Two or more dimensions are commonly measured at the same time.

^bPhysical Activity

^cSedentary Behavior

^dMetabolic Equivalents; 1 MET = 3.5 mL O₂/kg/min

result of daily activities during household duties, at one's occupation or during transportation, where these "domains" of PA and SB help us further characterize these health-behaviors (see **Table 2.2**).

The measurement of all dimensions and domains of PA and SB is necessary, where the focus has been limited to leisure-time PA [17], television viewing [9, 18], or no specification of SB. The lack of PA and SB types being measured in conjunction with other dimensions of PA and SB does not allow us to fully understand the complex relationship between PA or SB with health outcomes [19], which is partially due to limitations in currently used PA and SB measurement tools. Historically, self-reported measures of PA and SB were essential for public health surveillance, but are affected by biases such as recall and social desirability [20]. This has seen increased use of accelerometers, which are sensors that provide objective estimates of PA and SB as they directly measure motion. The nature of accelerometers, however, mean they cannot provide any contextual information on what the types of PA and SB are being performed or the domains in which they are occurring in [17].

There is a need for an objective tool to capture all dimensions of PA and SB and provide contextual information on the domains in which PA and SB occurs. Wearable cameras (WCs) have the potential to fill this need, as they have seen extensive use in capturing lived experiences [21, 22] and several health behaviors [23] such as diet [24] and feeding behavior [25]. They have also been used to characterize PA and SB. Within the human activity recognition field, WCs have been used to train machine learning (ML) models developed for predicting PA and SB from WC first-person media, with WC media annotations serving as the ground-truth [26]. WC media annotations have also

Table 2.2: Domains of Physical Activity and Sedentary Behavior.

Domain^a	Definition	Examples of PA^d/SB^e Types^f
Household^{b,c}	Activity undertaken for maintenance of a household within a domestic setting	Cleaning; Cooking; Caring for Children, Adults or Pets; Laundry
Leisure^{b,c}	Activity performed by an individual that is not required as an essential activity of daily living and is performed at the discretion of the individual.	Television watching; Reading; Sports; Exercise Conditioning; Dancing; Gardening
Occupation^{b,c}	Activity undertaken during paid or voluntary work.	Keyboard/Mouse Use; Organizing Inventory; Constructing/Repairing architecture
Transport^b	Activity performed for the purpose of getting to and from places, and refers to walking, cycling and wheeling (i.e. some form of locomotion)	Walking; Cycling; Using a Scooter; Driving; Riding the Bus

^aHigh-level descriptors of physical activity and sedentary behavior that incorporates contextual information (such as physical environment and purpose of PA/SB engagement) with type of PA/SB. These descriptors are meant to be representative of active living [15]

^bDomain definitions adapted from World Health Organization 2020 Guidelines [16]. This translation was not created by the World Health Organization (WHO). WHO is not responsible for the content or accuracy of this translation. The original English edition shall be the binding and authentic.

^cWHO does not extend these domains to encompass sedentary behavior.

^dPhysical Activity

^eSedentary Behavior

^fRepresentations of typical examples. These types of PA/SB can occur within other domains depending on the environment and/or intent of engagement. For example, Cycling can be for Leisure or for Transport depending on intent for engagement. Gardening can be for Leisure or for Household

served as the ground truth for training accelerometer algorithms [27] or other PA and SB measurement tools [28].

Despite the extensive use of WCs for health behaviors and the use of WC media to understand PA and SB-related variables, few systematic investigations have reported on the use of WCs to directly capture PA and SB within the scientific literature. This knowledge will help determine the utility of WCs to be a tool to characterize all dimensions of PA and SB, where it has the potential to address recommendations for the comprehensive measurement of PA and SB. Therefore, the purpose of this study is to determine the extent of WC media use for detailing PA and SB. In achieving this objective, we aim to answer three key questions:

- Key Question 1: What are the main reasons for using annotated WC media to capture human PA and SB in any setting in relation to study purposes within the scientific literature?
- Key Question 2: What dimensions of PA and SB are commonly captured by WC media annotations in the scientific literature?
- Key Question 3: What are the methodologies for using WCs and for annotating PA and SB from WC media?

The answers to these key questions will provide readers with a common knowledge base of WC use for capturing PA and SB and highlight any gaps in the scientific literature.

2.2 Methods

A scoping review was determined to be the most appropriate systematic investigation to conduct for answering the key questions set forth, as the use of WC

media to capture PA and SB involves a variety of different scientific disciplines. A previous systematic review has described the study aims of using WCs for PA and SB research [29]. However, with the focus of the review being on the use of WC media to assist with self-management of chronic diseases, it is unclear why, what and how WCs measure PA and SB. As such, there is no comprehensive review on the use of WC media to capture different dimensions of PA and SB within the scientific literature. Guidelines from the Joanna Briggs Institute Manual for Evidence Synthesis were followed and the Preferred Reporting Items for Systematic Reviews (PRISMA) extension for Scoping Reviews were consulted for conducting this scoping review [30, 31].

2.2.1 Search Strategy & Source Identification

The following inclusion and exclusion criteria for sources of evidence were used to guide the comprehensive search strategy:

Inclusion:

- Sources of evidence are in the English language.
- Sources of evidence use WC media within a human population sample.
- A WC was used to capture egocentric media, such that a WC was placed in such a way to capture first-person views of the wearer's immediate environment.
- WC media (images or video) were annotated to detail a dimension of PA or SB (frequency, intensity, duration, type), either as part of a record's purpose for conducting the study or as a necessary step for accomplishing the study purpose.
- No country-based or study setting-based restrictions are applied.

Exclusion:

- The use of WC media to describe PA or SB in a non-human population.
- The use of WC media from multiple wearers to detail one instance of PA or SB from one wearer.
- The WC media viewpoint is not something the wearer's eye's would be able to see (i.e. the camera is worn on the chest but is pointed directly towards the face).
- The WC media annotations do not capture a dimension of PA or SB.

Preliminary searches were conducted on PubMed and Web of Science Core Collection with search-terms that are PA and SB focused (“physical activity”, “behavior”, “sedentary”) and WC focused (“wearable camera”, “first-person camera”, “body-worn camera”) to establish terms that would clearly eliminate records following exclusion criteria. After exclusion terms were finalized, database “Title” and “Abstract” fields were searched using finalized terms seen in **Table 2.3**.

Table 2.4 lists the electronic databases searched, as well as search settings used for each database in order to adhere to inclusion and exclusion criteria (see Appendix A for the final database-specific search queries). Final database searches were conducted on November 1st, 2023, had “English language only” setting applied, with date ranges spanning the database inception to October 31st, 2023. Types of sources included were peer-reviewed journal articles, conference abstracts, conference preceding papers, theses and dissertations. No restriction was set on study types.

2.2.2 Screening

Sources of evidence were uploaded into the Zotero Reference Manager software. Duplicated sources were first identified using Zotero's built-in algorithm as it

Table 2.3: Database-agnostic search terms used.

Group	Terms^a
1^b (Physical Activity & Sedentary Behavior Terms)	ADL OR activit* OR “daily living” OR driving OR “aerobic training” OR conditioning OR “endurance training” OR exercis* OR exergam* OR jog* OR “resistance training” OR run* OR swim* OR walk* OR weightlift* OR “weight lift*” OR leisure OR camping OR danc* OR gardening OR play OR athlet* OR badminton OR baseball OR basketball OR bicycl* OR boating OR boxing OR canoeing OR climb* OR cycl* OR diving OR football OR golf OR gym* OR hockey OR kayaking OR lacrosse OR “martial art*” OR mountaineering OR netball OR powerlifting OR racketball OR racquetball OR rowing OR rugby OR skat* OR skiing OR sledding OR snowboard* OR soccer OR softball OR sport* OR squash OR surf* OR “track and field” OR tennis OR volleyball OR “water polo” OR wrestling OR “electronic use” OR “screen time” OR “screen use” OR commut* OR transport* OR travel* OR movement OR behavior* OR behaviour* OR inactivit* OR lifestyle* OR “life style*” OR seden*
2^b (Wearable Camera Terms)	“action camera*” OR “action image*” OR “action wearable camera*” OR autographer OR “automatic ingestion monitor” OR “body-worn camera*” OR “body-worn image*” OR “body-worn video*” OR brinno OR ebutton OR “egocentric camera*” OR “egocentric image*” OR “egocentric video*” OR “egocentric wearable camera*” OR “first-person camera*” OR “first-person image*” OR “first-person video*” OR “first-person wearable camera*” OR gopro OR “go pro” OR “narrative clip” OR sensecam OR “sense cam” OR “vicon revue” OR “wearable camera*” OR “wearable image*” OR “wearable video*”
3^c (Exclusion Terms)	memor* OR kinematic* OR kinetic* OR robot* OR crim* OR law* OR officer* OR diet OR drinking OR eating OR fasting OR feeding OR food* OR nutrition OR mastication OR animal OR arthropod OR bird OR cattle OR fish* OR horse*

^aTerms within each group were collapsed inside parenthesis for database search queries.

^bFinal search queries consisted of an AND boolean phrase between Group 1 and 2 collapsed terms.

^cFinal search queries consisted of an NOT boolean phrase between Group 1 + 2 collapsed terms and Group 3 collapsed terms.

Table 2.4: Electronic databases searched for the scoping review on November 1st, 2023.

Database	Settings^a
PubMed	-
Web of Science Core Collection	-
SPORTDiscus	<ul style="list-style-type: none">• Search Mode = Boolean/Phrase• Publication Type = Academic Journal
CINAHL	<ul style="list-style-type: none">• Search Mode = Boolean/Phrase• Exclude Medline Records = YES
ACM Guide to Computing Literature	-
IEEE Xplore Digital Library^b	-
ProQuest	<ul style="list-style-type: none">• Source Type = Dissertations & Theses

^a“Language = English” and “up to date October 31st, 2023” settings applied to all databases.

^bIEEE Xplore Digital Library was searched twice due to webpage failing to load when including “Document Title” and “Abstract” fields for all search terms at once.

has been shown to have high specificity [32] and then manually merged and checked by Julian Martinez. Afterwards, duplicate sources were manually searched by comparing source title, authors, abstract and source type. “Deduplicated” records were exported from Zotero into the online systematic review platform PICO Portal for title and abstract screening. Sources that were sought for retrieval were then manually re-imported into Zotero for full-text review. The full-text review was manually conducted by Julian Martinez and Garrett Steinbrink, with Scott Strath consulted for second opinions for source eligibility. From eligible sources, forward and backward citation searching was conducted to screen sources not identified through database searches.

2.2.3 Data Extraction & Analysis

The latest recommendations for data extraction, analysis and presentation from sources were additionally consulted [33]. For eligible sources, a Microsoft Excel (Redmond, Washington, USA) spreadsheet was used for data extraction. The entire text of each included source was searched for data, as well as supplementary material and cited references if a reference was stated to contain more detail on the data collection protocol.

For analyses, the PRISMA 2020 flow diagram is used to detail source identification and screening process [34]. Data relevant to each key question will be presented in tabular format. For key question #1, themes of WC use are presented with the number of sources under each theme. For key question #2, the frequency of each PA and SB dimension measured from included source are presented within identified themes of WC use, with types of PA and SB extracted from included sources summarized into general categories. For key question #3, frequencies for WC brands

used, location of WC, and type of media used will be summarized under each theme. For key questions #2 and #3, sources that were observed to be from the same dataset with the same WC uses, but different study aims, were excluded for frequency calculation. Analyses were performed using Microsoft Excel (Redmond, Washington, USA).

2.3 Results

Figure 2.1 is a PRISMA 2020 flow diagram detailing the review process. Conference abstracts, conference proceeding papers, theses and dissertations were excluded if one or more peer-reviewed articles were published from the same author or similar set of authors on similar objectives, methods, analyses and data. Out of a total 1473 identified sources of evidence, 73 met the inclusion criteria. Types of sources included were journal articles (44/73, 60%), conference papers (20/73, 27%), theses (4/73, 5.5%), conference abstracts (4/73, 5.5%) and one technical report. The earliest publication included in the review is from 2008.

Figure 2.2 illustrates the publication year for each included source. The highest number of publications within a year was 8 (2016, 2017, 2022). From 2015 - 2023, 3-6 journal articles, focused on using WC media annotations to capture PA and SB, have been published per year, with a conference paper published every single year from 2008 - 2023 (see **Appendix B**).

2.3.1 Main reasons for Using Annotated Wearable Camera Media to Capture Human Physical Activity and Sedentary Behavior

Table 2.5: Frequency table of included record types and publication years by identified themes of wearable camera use. provides a summary of source types and year of publication by central themes of WC use identified from included records. Four

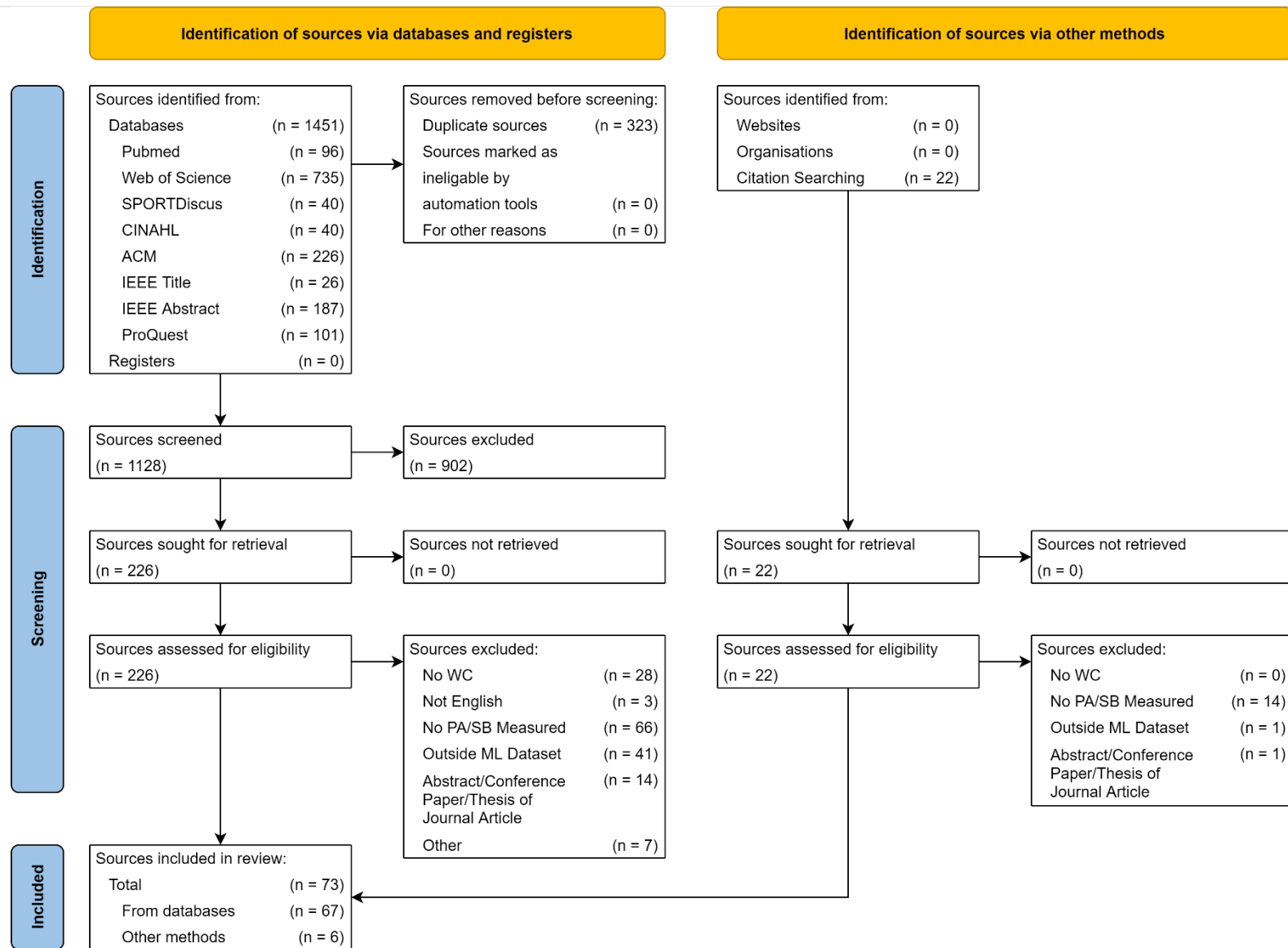


Figure 2.1: PRISMA flow diagram detailing the review process.

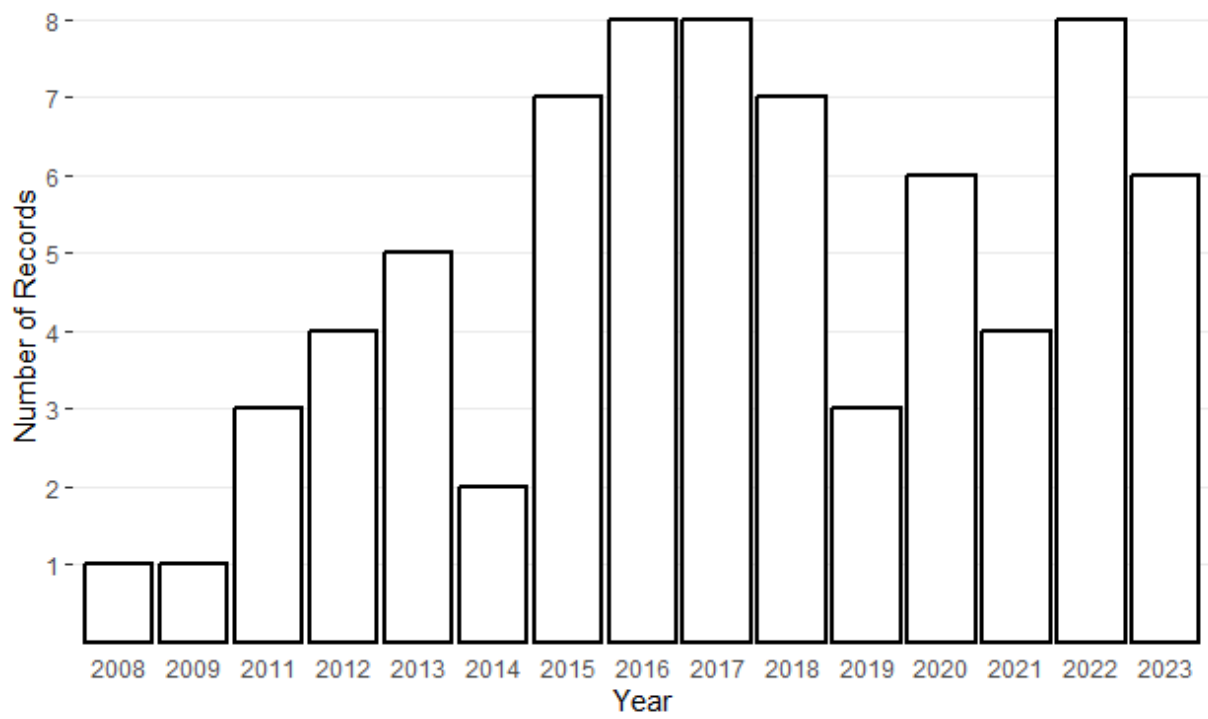


Figure 2.2: Number of Publications per Year.

Table 2.5: Frequency table of included record types and publication years by identified themes of wearable camera use.

Characteristic	Overall N = 73	FAR^a [35–65] N = 31	OCM^b [86–95] N = 10	GRT^c [27, 28, 66–85] N = 22	VAL^d [96–105] N = 10
Record Type					
Journal Article	44 (60%)	10 (32%)	10 (100%)	20 (91%)	4 (40%)
Conference Paper	20 (27%)	18 (58%)	0 (0%)	1 (4.5%)	1 (10%)
Thesis	4 (5.5%)	2 (6.5%)	0 (0%)	1 (4.5%)	1 (10%)
Abstract	4 (5.5%)	0 (0%)	0 (0%)	0 (0%)	4 (40%)
Report	1 (1.4%)	1 (3.2%)	0 (0%)	0 (0%)	0 (0%)
Year					
2008	1 (1.4%)	1 (3.2%)	0 (0%)	0 (0%)	0 (0%)
2009	1 (1.4%)	1 (3.2%)	0 (0%)	0 (0%)	0 (0%)
2011	3 (4.1%)	2 (6.5%)	1 (10%)	0 (0%)	0 (0%)
2012	4 (5.5%)	3 (9.7%)	0 (0%)	0 (0%)	1 (10%)
2013	5 (6.8%)	1 (3.2%)	0 (0%)	1 (4.5%)	3 (30%)
2014	2 (2.7%)	1 (3.2%)	0 (0%)	1 (4.5%)	0 (0%)
2015	7 (9.6%)	1 (3.2%)	2 (20%)	3 (14%)	1 (10%)
2016	8 (11%)	5 (16%)	0 (0%)	3 (14%)	0 (0%)
2017	8 (11%)	4 (13%)	0 (0%)	3 (14%)	1 (10%)
2018	7 (9.6%)	3 (9.7%)	1 (10%)	3 (14%)	0 (0%)
2019	3 (4.1%)	1 (3.2%)	1 (10%)	1 (4.5%)	0 (0%)
2020	6 (8.2%)	2 (6.5%)	1 (10%)	2 (9.1%)	1 (10%)
2021	4 (5.5%)	0 (0%)	2 (20%)	1 (4.5%)	1 (10%)
2022	8 (11%)	2 (6.5%)	2 (20%)	2 (9.1%)	2 (20%)
2023	6 (8.2%)	4 (13%)	0 (0%)	2 (9.1%)	0 (0%)

Note: References are included within the themes of wearable camera use column headers.

^aFirst-person Activity Recognition, the use of machine learning models to predict PA^e and SB^f from annotated wearable camera media.

^bOutcome Measure, the use of PA^e and SB^f annotations as an outcome measure (OCM) in relation to the study purpose.

^cGround-Truth, the use of PA^e and SB^f annotations as the ground truth for validating or training other PA^e and SB^f measurement tools.

^dValidation, testing the validity or reliability of wearable camera PA and SB annotations.

^ePhysical Activity

^fSedentary Behavior

main themes of WC use were identified within this scoping review: 1) first-person activity recognition, which is the use of ML models to predict PA and SB from annotated WC media (31/73, 45%), 2) outcome measure, which is WC media annotations of PA and SB used in relation to a study purpose (22/73, 30%), 3) ground-truth, which is WC media annotations of PA and SB used as the criterion for validating or training other PA and SB measurement tools (10/73, 14%), and 4) validation, which is a study aimed to assess the validity, reliability or responsiveness of WC media annotations to assess PA and SB (10/73, 14%).

The most common source type included were journal articles, which is the only source type seen within the outcome measure (20/22, 91%) and the ground-truth (10/10, 100%) themes, whereas journal articles and conference abstracts were evenly seen within the validation theme (4/10, 40% and 4/10, 40% respectively). A mixture of source types was seen within the first-person activity recognition theme with conference papers being the most common (18/31, 58%), which makes up the bulk of all conference papers included within the review (18/20, 90%). Looking at yearly number of publications by WC theme, studies focused on describing approaches for first-person activity recognition have been published at least once every year between 2008 - 2023 with 2016 (5/31, 16%), 2017 (4/31, 13%) and 2023 (4/31, 13%) seeing the highest years of publication. The publication of sources within the outcome measure and ground-truth themes were spread throughout the years in this review, with the use of WC media annotations to provide ground-truth labels not consistently appearing in the literature until 2013. WC validation studies are published more sparsely, with the most studies being published in 2013 (3/10, 30%) and 2022 (2/10, 20%). **Appendices C, D and E**

outline the population characteristics, dimensions/outcome measures of PA and SB and WC methodology data extracted from each included record respectively.

2.3.1.1 Study Characteristics Within Each Theme of Wearable Camera Use

Table 2.6 summarizes the characteristics of unique participant samples by WC theme. To aid the advancement of first-person activity recognition, a notable number of sources provide publicly available annotated WC datasets [35, 36, 38, 41–44, 46, 47, 53, 54, 57, 59, 63] (14/31, 45%), with a few sources re-annotating publicly available datasets to provide more study-specific annotations of PA [37, 45, 51] (4/31, 13%). Within the first-person activity recognition theme, on average 10 participants were recruited with females recruited for only 6/26 (23%) sources. Within the first-person activity recognition theme, only one sample reported the average age of participants and no studies reported BMI. One study recruited community-dwelling individuals with Type 2 Diabetes [62] and another recruited individuals with dementia [46]. Within the outcome measure theme, 6/10 (60%) used PA and SB measures from WC annotations as the sole PA and SB measure [86, 88–90, 94, 95] while 4/10 (40%) used WC annotations to supplement PA and SB measures from another measurement tool [87, 91–93]. On average, 40 participants were recruited with both males and females recruited for 8/10 (80%) sources. The median average age was 20yrs, with the median average BMI of participants being 23.75 kg/m². Special populations recruited for this theme consist of measuring the environmental pollutant exposure of e-Waste workers while documenting their PA and SB [91] and determining patterns of PA and SB for community-dwelling individuals with persistent pain [95]. Within the ground-truth theme, participants were recruited to determine the validity of PA and SB estimates from a variety of PA and SB measurement tools or to calibrate algorithms using features

Table 2.6: Summary table of sample characteristics for included studies by theme of wearable camera use.

Characteristic	Overall N = 67 ^a	FAR^b N = 26	OCM^c N = 10	GRT^d N = 21	VAL^e N = 10
Sample Size (mean (SD) [range])	30 (33) [1-141]	10 (8) [1-26]	40 (44) [4-141]	40 (36) [10-132]	30 (22) [1-62]
Unknown	13	11	0	0	2
Included Females (n, (%))	35 (52%)	6 (23%)	8 (80%)	17 (81%)	4 (40%)
Average Age (median [range])	34 [10-76]	29 [29-29]	20 [10-68]	36 [21-76]	37 [34-47]
Unknown	41	25	4	5	7
Average BMI (median [range])	25.00 [21.90-32.00]	NA [Inf-Inf]	23.75 [21.90-25.60]	25.10 [22.40-32.00]	24.90 [24.90-24.90]
Unknown	57	26	8	14	9

^aStudies that 1) reference out data collection procedures with exactly the same sample characteristics as the referenced study or 2) re-annotate publicly available datasets were excluded.

^bFirst-person Activity Recognition

^cOutcome Measure

^dGround-Truth

^eValidation

derived from physical sensors, using WC PA and SB annotations as the GRT labels. Specifically, WC annotations have been used as the criterion measure for training accelerometer algorithms [27, 66, 67, 70, 72, 76] (6/21, 29%), to validate existing PA and SB accelerometer algorithms [71, 75, 77, 79, 80, 82–85] (9/21, 43%), and to validate other measures (e.g. time-use diaries, self-report questionnaires) of PA and SB [28, 69, 73, 74, 78, 81] (6/21, 29%). One source used a WC to capture the ground-truth of semi-structured activity within free-living settings to establish an external dataset for validating accelerometer algorithms [68]. On average approximately 40 participants were typically recruited for sources within this theme with both males and females recruited in 17/21 (81%) sources. Average age ranged between 21 years to 76 years and BMI ranging from 25.1 kg/m² to 23.0 kg/m². A wide range of populations were sampled, including individuals who require maintenance kidney dialysis [80], individuals who were admitted cardiac rehabilitation patients [71], individuals who engaged in sport [76, 81], individuals who were pregnant (at all trimesters) [28], factory workers [84], and older adults [68, 82, 85]. Within the validation theme, 4/10 (40%) sources conducted preliminary work to determine if WC media annotations were feasible to measure PA and SB [97, 98, 100, 102], 2/10 (20%) used existing tools to determine the convergent validity of WC PA and SB annotations [96, 103] and 4/10 (40%) used gold-standard measures for validating WC annotations [99, 101, 104, 105].

2.3.2 Dimensions of Physical Activity and Sedentary Behavior Commonly Captured by Wearable Camera Media Annotations

The number of times each dimension of PA and SB was measured by theme is summarized in **Table 2.7**. For each dimension, frequency was assessed 18/73 (25%) times, intensity (6/73, 8%) times, duration of PA and SB 26/73 (36%) times, and PA and

Table 2.7: Summary of physical activity and sedentary behavior dimensions captured from wearable camera media annotations by theme of wearable camera use.

Dimension	Overall N = 73	FAR^a	OCM^b	GRT^c	VAL^d
Frequency	18	5 (28%)	4 (22%)	7 (39%)	2 (11%)
Intensity	6	1 (17%)	0 (0%)	3 (50%)	2 (33%)
Duration	26	2 (8%)	4 (15%)	13 (50%)	7 (27%)
Type	73	31 (42%)	10 (14%)	22 (30%)	10 (14%)

^aFirst-person Activity Recognition

^bOutcome Measure

^cGround-Truth

^dValidation

SB type measured 73/73 (100%) times. More studies captured PA (41/73, 56%) than SB (6/73, 8%), with 26/73 (36%) studies examining both PA and SB (**Appendix D**).

Table 2.8 further breaks down the aspects of PA and SB activity types seen for included studies into 6 general categories: posture (37/73, 51%), movement (40/73, 55%), behavior (42/73, 58%), action (11/73, 15%), context (13/73, 18%) and domain (4/73, 5%) with definitions and examples for each category shown in **Table 2.9**.

2.3.3 Methodologies for Using Wearable Cameras and for Annotating Physical Activity and Sedentary Behavior from Wearable Camera Media

A variety of WC brands and models were used for capturing egocentric media.

Table 2.10 summarizes the major brands of WCs, attachment locations and media for included studies that were unique. The most popular WC brand for research has been the SenseCam/Autographer (26/66, 39%), with GoPro second (11/66, 17%). When looking at models of WCs, the SenseCam was still the most popular (14/66, 21%) with the OMG Life Autographer second (12/66, 18%). For general attachment sites, the chest was the most popular location (44/66, 67%) with the general head location the second most popular location (8/66, 12%). Looking at specific attachment sites, the sternum was the most popular (41/66, 62%) with the eyeline location the second most popular (5/66, 8%). The most common media used from WCs were still-images (IMG) (40/66, 67%) with videos only used (20/66, 30%) in studies.

2.4 Discussion

Wearable camera media is being used in a wide range of academic disciplines to characterize human behavior. The results of this scoping review show the extent of WC media use to capture PA and SB in academic literature, highlighting its extensive use in

Table 2.8: Summary of physical activity and sedentary behavior types captured from wearable camera media annotations by theme of wearable camera use.

Type	Overall N = 73	FAR^a	OCM^b	GRT^c	VAL^d
Posture	37	10 (27%)	7 (19%)	13 (35%)	7 (19%)
Movement	40	13 (33%)	4 (10%)	15 (38%)	8 (20%)
Behavior	42	14 (33%)	9 (21%)	13 (31%)	6 (14%)
Action	11	10 (91%)	1 (9.1%)	0 (0%)	0 (0%)
Context	13	5 (38%)	5 (38%)	1 (7.7%)	2 (15%)
Domain	4	0 (0%)	1 (25%)	0 (0%)	3 (75%)

^aFirst-person Activity Recognition

^bOutcome Measure

^cGround-Truth

^dValidation

Table 2.9: Operational definitions for categorization of physical activity and sedentary behavior types seen within the scoping review.

Category	Definition	Examples
Posture	<ul style="list-style-type: none"> • Descriptors of one’s body position in space where either skeletal muscles are not being used to maintain the position in space or skeletal muscles are being contracted the position in space. • Operational definitions for postures typically specify lower limb and torso positioning to describe posture. 	<ul style="list-style-type: none"> • Standing • Sitting • Lying
Movement	<ul style="list-style-type: none"> • Descriptors of one’s combined movement pattern of multiple limbs or the entire body itself through space. • Operational definitions typically specify the combined movement patterns of lower limbs and the torso for ambulatory movement, or in conjunction with the upper limbs as well. 	<ul style="list-style-type: none"> • Walking • Running • Cycling • Climbing • Ascending Stairs
Behavior	<ul style="list-style-type: none"> • Descriptors of repeated interaction with physical objects. • Further definitions of what an “interaction” with objects is required for each descriptor. • Is made up of multiple “Action” descriptors. 	<ul style="list-style-type: none"> • Cooking • Cleaning • Typing • Eating • Washing Hands
Action	<ul style="list-style-type: none"> • Specific descriptors Elementary • Are limb movements described by one verb in the present tense. • Operational definitions typically specify are typically focused on upper-limb movement only or lower limb movement only 	<ul style="list-style-type: none"> • Chop • Stir • Kick • Pull • Push
Context	<ul style="list-style-type: none"> • Descriptors of where, when and why in relation to behavior to further describe physical activity & sedentary behavior. • Descriptors must be used in combination with another type category, and not be by itself. 	<ul style="list-style-type: none"> • Shopping • Riding a Bus • Socializing
Domain	<ul style="list-style-type: none"> • Broad descriptors of behavior that use Behavioral and Contextual information together. • These broad descriptors are still easily distinguishable from one another. 	<ul style="list-style-type: none"> • Household • Occupation • Leisure • Transportation

Table 2.10: Summary of wearable cameras brands, general attachment sites and media by themes of wearable camera use.

Characteristic	Overall^a N = 66	FAR^b	OCM^c	GRT^d	VAL^e
Camera					
SenseCam ^f	26	2 (7.7%)	7 (27%)	11 (42%)	6 (23%)
GoPro	11	4 (36%)	1 (9.1%)	6 (55%)	0 (0%)
Other	18	13 (72%)	2 (11%)	3 (17%)	0 (0%)
Unknown	11	8 (73%)	0 (0%)	0 (0%)	3 (27%)
Location					
Chest ^g	44	12 (27%)	9 (20%)	16 (36%)	7 (16%)
Head ^h	8	8 (100%)	0 (0%)	0 (0%)	0 (0%)
Other	2	1 (50%)	0 (0%)	1 (50%)	0 (0%)
Unknown	12	6 (50%)	1 (8.3%)	3 (25%)	2 (17%)
Media					
Still-Image	40	8 (20%)	10 (25%)	14 (35%)	8 (20%)
Video	20	14 (70%)	0 (0%)	6 (30%)	0 (0%)
Unknown	6	5 (83%)	0 (0%)	0 (0%)	1 (17%)

^aStudies that 1) reference out data collection procedures or 2) re-annotate publicly available datasets were excluded.

^bFirst-person Activity Recognition

^cOutcome Measure

^dGround-Truth

^eValidation

^fConsists of SenseCam and Autographer cameras.

^gConsists of Chest and Shoulder locations.

^hConsists of Forehead and Eyeline locations.

the computer science field for developing ML models to predict PA and SB for applied and clinical research and within applied research studies.

2.4.1 Main reasons for Using Annotated Wearable Camera Media to Capture Human Physical Activity and Sedentary Behavior

Studies focusing on WC first-person activity recognition have been consistently published from 2008-2023, ranging from journal articles to theses. The highest years of publication (2016, 2017 and 2023) follows major advances within the first-person activity recognition [106, 107] and the human activity recognition field as a whole [108]. The proliferation of publicly available WC datasets also promotes this advancement, where it is not uncommon to incorporate a multitude of sensor modalities such as accelerometers, gyroscopes and magnetometers. However, a large number of first-person activity recognition studies did not give any characteristics of the individuals who participated. This is a concern for end users who wish to use WC first-person activity recognition algorithms in applied PA and SB research as the lack of participant characteristics can lead to unaccounted for limitations from study results. For example, Gjoreski et al. [42] detail a multimodal dataset on transportation behaviors, having 8 categories of “Still”, “Walk”, “Run”, “Bike”, “Car”, “Bus”, “Train”, and “Subway”. In detailing the number of hours within each transportation mode, they note one participant “had difficulties with running” [42] which led to less “Run” transportation in the dataset compared to other transportation modes. From an applied research lens, this detail is of significant importance as it is a sign that a potential medical condition or health ailment may have impacted the distribution of frequency and types of behavior seen in the WC media dataset. Therefore, this information is essential for other researchers pushing the

frontiers of first-person activity recognition and eventual end-users of first-person activity recognition models.

Included records focused on validation of WC PA and SB annotations consist of the highest number of conference abstracts compared to other WC themes identified. Sources within this theme are more sparsely published compared to the publication rate for sources within other themes. Within the first half of the publication years observed (2012 - 2015), four sources were focused on establishing the feasibility of WCs to capture PA and SB. This foundational research paved the way for future studies to start assessing the measurement properties of WC media annotations for PA and SB, such as content validity, structural validity and reliability. However, little advancement has been made in comparing WC estimates in each dimension of PA and SB against gold standard measures. The first observed mention of a gold standard measure to validate WC PA and SB annotations was seen in one thesis [99], where a preliminary exploration was detailed. One individual wore the SenseCam for 20 journeys of varying length by walking, transportation by car or cycling while being directly monitored. Journey times and type were all seen to be highly agreeable with direct observation (DO) data. Few studies have expanded upon this initial step, with the next record to use DO as the gold standard measure to assess WC estimated PA and SB occurring 4 years later [104]. The reason for the low number of validation themed sources is likely due to the high face validity of WC media, as it is difficult to say a PA or SB has not occurred for a certain frequency, intensity, duration or type when it is clearly seen within the media. This is more so true for WC video, which provides a constant view of the PA and SB being observed and is made apparent when noting that all validation studies

focused on WC IMGs, and not WC video. However, differences in annotation platforms between studies and attachment sites may still affect the ability of WC video to estimate certain PAs and SBs.

2.4.2 Dimensions of Physical Activity and Sedentary Behavior Commonly Captured by Wearable Camera Media Annotations

The second most common PA and SB dimension captured was frequency, where around half of studies measuring frequency also measured duration of PA only or PA and SB. Of studies measuring frequency, none of them were focused on capturing SB only. This could be due to current observational research associating the total time of SB per day with health outcomes [6, 9, 109–112]. Breaks in SB, therefore measuring frequency of SB, have been extensively measured in trials focused on determining the physiological outcomes of SB [113–117]. For observational research, the measurement of frequency and SB type can help researchers understand what causes people to break from their SB. For example, although Dontje et al. [118] did not annotate WC IMGs for SB, they used WC IMGs to facilitate interviews with older adults as to why breaks from SB occurred. As WC media annotations were observed to capture frequency in studies assessing PA and SB, and are extensively used to measure type, the absence of WC use to capture all dimensions of SB is a missed opportunity.

The dimension of intensity was captured the least from included sources. MET values for PA annotations in these sources were linked to the Compendium of Physical Activities [119] in order to provide some estimate of PA intensity, which is not an uncommon procedure for contextual measurement tools. For example, it is also typically used in DO annotation platforms where annotation codes are linked to Taylor codes from the Compendium as well [120–122]. In both uses, the linkage is typically not to

provide point estimates, but to collapse MET estimations into intensity categories of sedentary, light, moderate and vigorous PA. A difference between DO and the use of WCs however is the duration of time participants are directly observed or asked to wear the camera. From the included sources assessing intensity, the longest wear time was noted to be 10-14 hours where participants were asked to wear a GoPro pointed towards their feet [66]. This resulted in 750 - 1050 hours of video, with an unstated but assumable significant amount of time for annotation. The longest DO session noted from the literature was for 10 hours [123], where 3 different observers in 2-4 hour shifts annotated a participant's behavior in-person. For video-recorded DO, the longest session has been 3-hours [124]. Depending on a research team's resources, the use of WC's to provide an estimate of PA intensity and PA type for long hours of a day may be more beneficial compared to DO. However, the use of video-recorded DO to estimate intensity has been validated against a criterion measure [120], whereas no study has tested the criterion validity of WC media annotations to estimate PA intensity.

Across all themes, a broad range of PA and SB types were captured. Cartas et al. [38] categorized the activities to be recognized as proposed by Lara & Labrador [125] in order to match the activities typically seen in the human activity recognition literature. In 2013, Lara & Labrador [125] provided a comprehensive survey of the human activity recognition field, where it was stated that ambulation, transportation, phone usage, daily activities, exercise/fitness, military activities and upper body activities (chewing speaking, swallowing) were the types of activities being recognized by human activity recognition systems. Outside of recommendations provided by publications, some sources included in this review, across all themes, derived their PA

and SB annotation codes from established frameworks of activity, such as the Compendium of Physical Activities [119], the Harmonized European Time Use Survey-UK Version, and the Sedentary Behavior International Taxonomy [126]. However, only 12 unique studies used this approach, with the rest of included studies focusing on a limited schema of posture and movement (e.g. sit, stand, move). The use of published/established frameworks should be used to derive study-specific annotations, making sure that a connection between study-specific annotation codes and original framework codes is established whenever possible. Such efforts will help advance all scientific disciplines interested in measuring PA and SB, as the adoption of study-specific annotation platforms using this approach will still allow for cross-comparisons of study results. Regardless if an existing taxonomy is used or not, an annotation platform should still be documented and disseminated for WC PA and SB research. The complexity of PA and SB can make it difficult for end-users of WC media annotations to know how to define when an activity starts and when it stops. With the creation of an annotation platform, which consists of an annotation protocol describing scoring procedures and a schema/taxonomy of annotation codes with operational definitions and examples for each code provided, research teams will be more prepared to use WC media for their study purposes.

2.4.3 Methodologies for Using Wearable Cameras and for Annotating Physical Activity and Sedentary Behavior from Wearable Camera Media

A variety of WC models and manufacturing companies were observed from included sources. The SenseCam and its derivatives were the only WCs developed for research, with all other WC models created for commercial purposes. The SenseCam

and Autographer camera was the most common WC model observed, most likely due to the early SenseCam research showing how WC IMGs can provide rich contextual information [127], which has immense transferable utility in other areas of health-research [23]. Unfortunately, SenseCam and its derivative Autographer have not been in production since 2016. Since its last year in production, a multitude of other cameras have seen more use within the literature, with improvements in technology that addresses noted shortcomings of the SenseCam such as low battery life on a high capture rate [89]. For example, the Brinno TLC120 has been noted to have the capability of a 6-day battery life with a 10-second IMG capture rate [86] with the manufacturer-provided manual stating a capture rate of 1 IMG per second is possible, albeit with an unstated battery life. The improvements in battery life and IMG capture rate has the potential to address concerns about WC IMGs not being able to capture more spontaneous bouts of activity [77]. For capturing egocentric videos, GoPro was the most common brand of WCs. As the target consumers of GoPro use the action cameras in a variety of sports and high intensity movements, it is no wonder the cameras provide immense utility for researchers to measure all types of PA and SB. However, the low battery life of these cameras, even on the lowest resolution and fps settings, do not allow longer periods of video capture without the use of battery packs [83]. No included studies have used this methodology to capture whole-day PA and SB.

Wearable cameras were observed to be commonly placed at the head or around chest level, with studies utilizing forehead straps and glasses for the head and lanyards around the neck and adjustable harnesses for the chest as the apparatus for attachment. First-person activity recognition focused studies placed WCs at the head

location more than the chest, where stated reasons were to capture physical interactions with objects for activity recognition. As quite a few first-person activity recognition feature representations rely on detecting the presence of objects and/or hands to classify the annotated activity label [106, 107], it seems the head attachment location may better capture PA and SB that require constant visual attention for engagement. Examples of such activities are repairing an overhead light fixture, squatting or kneeling down to obtain cookware, and watching a screen-based electronic device. The use of WC media at this location site has the potential to address shortcomings of using chest-worn WC media to estimate adult SB, where it has been noted that screen-based SB often results in IMGs that are unable to be coded due to participant “slouching or lying, all of which may leave the camera pointed away” [128]. Research comparing paired head-worn and chest-worn WC media in comparison to 3rd-person DO is needed to address this. Despite this, out of sources that stated a wear location, all but one source not within the first-person activity recognition theme used chest-worn WCs. This may be due to the lower perceived social burden when wearing a chest-worn WC compared to wearing a head-worn WC, as it is less likely to lead to a confrontational situation with a third-party [129]. For studies utilizing chest-worn WCs, 77% of them included statements of ethical/IRB approval or adherence to an ethical framework [130] compared to 0% of head-worn WC studies. Although it is important to note that all but one of the sources using head-worn WCs were conference papers, reports and a thesis publication, where explicit ethical/IRB approval is not required for publication.

Sources within the outcome measure theme utilized IMGs from WCs more often than video. Interestingly, all sources using WC video were within the first-person activity recognition and ground-truth themes. All 6 studies in the ground-truth theme used downward-facing chest-worn WC video to either validate step estimates from a variety of activity monitors [71, 79, 83], train a ACC ML classifier [67] and train a ACC and plantar pressure classifier [66] for posture detection, or to create a transition-labeled dataset for public use [68]. A downward facing WC recording video is noted then to be highly valuable for validating/calibrating models that estimate steps.

2.4.4 Scoping Review Strengths & Limitations

The identification, screening and full-text review of sources was completed following standardized recommendations. This approach, when searching through databases from a variety of scientific disciplines, allowed an extensive summary of research to be conducted from two fields using WCs for similar outcomes but in different approaches: the human activity recognition field and PA and SB measurement field. Results from this review will be beneficial for researchers from both fields. However, sources using WC media as a tool to assist qualitative research focused on PA and SB factors were excluded, as these studies did not explicitly detail the annotation of WC media for PA or SB within the text of the record or through tables or figures. There is also research utilizing “activity oriented” WCs to capture health-related behavior [131], but these records were excluded for not capturing a true first-person view of the wearer’s immediate environment.

2.5 Conclusion

This scoping review was conducted to determine the extent of use for PA and SB WC media annotations. From data extraction and analysis, we expand upon four main themes of WC use across various scientific disciplines, quantified what dimensions of PA and SB are being measured, and detailed the various WC methodologies utilized. Our exploration of WC media annotations for PA and SB highlights the following scientific knowledge gaps:

- Participant characteristics are not being reported in studies exploring novel feature extractions of WC media or novel model architectures for FAR.
- Limited work in establishing the criterion validity of WC PA and SB annotations.

The following are recommendations for addressing these gaps:

- Age and sex of participants should be reported at the bare minimum. Anthropometric information such as height, weight, and BMI and demographic information such as gender, race/ethnicity, educational status, income levels and occupation is highly recommended. For clinical or special populations, such as individuals with degenerative neuromuscular diseases, additional characteristics of health are necessary such as a measure for physical functioning. Summary statistics should be utilized for sample sizes > 10.
- Validation studies utilizing criterion measures of PA and SB frequency, intensity, duration and type, such as DO and indirect calorimetry, should be used to determine the construct validity of WC media annotations.

As PA and SB are behaviors that humans engage in throughout daily life, the capture of their frequency, intensity, duration and type are essential for public health surveillance

due to their independent impacts on mortality, cardiovascular disease and non-communicable disease risk. Tools currently used to measure the associations between PA and SB and several outcomes are limited by their capability to comprehensively capture these dimensions of PA and SB. WCs are tools that can measure all of these key characteristics of PA and SB, where it is currently being used in a variety of scientific disciplines. Research towards filling current scientific knowledge gaps will greatly advance the use of WCs for translational health research and help ascertain the dose-response relationship of PA and SB with various health outcomes.

References

1. Ahmadi MN, Clare PJ, Katzmarzyk PT, del Pozo Cruz B, Lee IM, Stamatakis E (2022) Vigorous physical activity, incident heart disease, and cancer: How little is enough? *European Heart Journal* 43:4801–4814
2. Dempsey PC, Rowlands AV, Strain T, et al (2022) Physical activity volume, intensity, and incident cardiovascular disease. *European Heart Journal* 43:4789–4800
3. Kraus WE, Powell KE, Haskell WL, et al (2019) Physical Activity, All-Cause and Cardiovascular Mortality, and Cardiovascular Disease. *Med Sci Sports Exerc* 51:1270–1281
4. Wasfy MM, Lee I-M (2022) Examining the Dose–Response Relationship between Physical Activity and Health Outcomes. *NEJM Evidence* 1:EVIDra2200190
5. Grøntved A, Hu FB (2011) Television viewing and risk of type 2 diabetes, cardiovascular disease, and all-cause mortality: A meta-analysis. *JAMA* 305:2448–2455
6. Matthews CE, George SM, Moore SC, Bowles HR, Blair A, Park Y, Troiano RP, Hollenbeck A, Schatzkin A (2012) Amount of time spent in sedentary behaviors and cause-specific mortality in US adults. *Am J Clin Nutr* 95:437–445
7. Dempsey PC, Biddle SJH, Buman MP, et al (2020) New global guidelines on sedentary behaviour and health for adults: Broadening the behavioural targets. *International Journal of Behavioral Nutrition and Physical Activity* 17:151

8. Park JH, Moon JH, Kim HJ, Kong MH, Oh YH (2020) Sedentary Lifestyle: Overview of Updated Evidence of Potential Health Risks. *Korean J Fam Med* 41:365–373
9. Patterson R, McNamara E, Tainio M, de Sá TH, Smith AD, Sharp SJ, Edwards P, Woodcock J, Brage S, Wijndaele K (2018) 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* 33:811–829
10. Piercy KL, Troiano RP, Ballard RM, Carlson SA, Fulton JE, Galuska DA, George SM, Olson RD (2018) The Physical Activity Guidelines for Americans. *JAMA* 320:2020–2028
11. Bull FC, Al-Ansari SS, Biddle S, et al (2020) World Health Organization 2020 guidelines on physical activity and sedentary behaviour. *Br J Sports Med* 54:1451–1462
12. Caspersen CJ, Powell KE, Christenson GM (1985) Physical activity, exercise, and physical fitness: Definitions and distinctions for health-related research. *Public Health Rep* 100:126–131
13. Strath SJ, Kaminsky LA, Ainsworth BE, Ekelund U, Freedson PS, Gary RA, Richardson CR, Smith DT, Swartz AM, American Heart Association Physical Activity Committee of the Council on Lifestyle and Cardiometabolic Health and Cardiovascular, Exercise, Cardiac Rehabilitation and Prevention Committee of the Council on Clinical Cardiology, and Council (2013) Guide to the assessment

- of physical activity: Clinical and research applications: A scientific statement from the American Heart Association. *Circulation* 128:2259–2279
14. Tremblay MS, Aubert S, Barnes JD, et al (2017) Sedentary Behavior Research Network (SBRN) – Terminology Consensus Project process and outcome. *International Journal of Behavioral Nutrition and Physical Activity* 14:75
 15. Sallis JF, Cervero RB, Ascher W, Henderson KA, Kraft MK, Kerr J (2006) An Ecological Approach to Creating Active Living Communities. *Annual Review of Public Health* 27:297–322
 16. Organization WH (2020) Guidelines on physical activity and sedentary behaviour. World Health Organization, Geneva
 17. Quinn TD, Gibbs BB (2023) Context Matters: The Importance of Physical Activity Domains for Public Health. *Journal for the Measurement of Physical Behaviour* - 1:1–5
 18. Hamer M, Yates T, Demakakos P (2017) Television viewing and risk of mortality: Exploring the biological plausibility. *Atherosclerosis* 263:151–155
 19. Kelly P, Fitzsimons C, Baker G (2016) Should we reframe how we think about physical activity and sedentary behaviour measurement? Validity and reliability reconsidered. *Int J Behav Nutr Phys Act* 13:32
 20. Matthews CE, Moore SC, George SM, Sampson J, Bowles HR (2012) Improving Self-Reports of Active and Sedentary Behaviors in Large Epidemiologic Studies. *Exercise and Sport Sciences Reviews* 40:118

21. Gage R, Chambers T, Smith M, McKerchar C, Puloka V, Pearson A, Kawachi I, Signal L (2022) Children's perspectives on the wicked problem of child poverty in Aotearoa New Zealand: A wearable camera study. *N Z Med J* 135:95–111
22. Nourse R, Cartledge S, Tegegne T, Gurrin C, Maddison R (2022) Now you see it! Using wearable cameras to gain insights into the lived experience of cardiovascular conditions. *EUROPEAN JOURNAL OF CARDIOVASCULAR NURSING* 21:750–755
23. Doherty AR, Hodges SE, King AC, Smeaton AF, Berry E, Moulin CJA, Lindley S, Kelly P, Foster C (2013) Wearable cameras in health: The state of the art and future possibilities. *Am J Prev Med* 44:320–323
24. Gemming L, Utter J, Ni Mhurchu C (2015) Image-Assisted Dietary Assessment: A Systematic Review of the Evidence. *Journal of the Academy of Nutrition and Dietetics* 115:64–77
25. Alshurafa N, Zhang S, Romano C, Zhang H, Pfammatter AF, Lin AW (2021) Association of number of bites and eating speed with energy intake: Wearable technology results under free-living conditions. *Appetite* 167:105653
26. Grauman K, Westbury A, Byrne E, et al (2022) Ego4D: Around the World in 3,000 Hours of Egocentric Video. In: 2022 IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR). pp 18973–18990
27. Willetts M, Hollowell S, Aslett L, Holmes C, Doherty A (2018) Statistical machine learning of sleep and physical activity phenotypes from sensor data in 96,220 UK Biobank participants. *Sci Rep* 8:7961

28. Chasan-Taber L, Park S, Marcotte RT, Staudenmayer J, Strath S, Freedson P (2023) Update and Novel Validation of a Pregnancy Physical Activity Questionnaire. *Am J Epidemiol* 192:1743–1753
29. Maddison R, Cartledge S, Rogerson M, Goedhart NS, Ragbir Singh T, Neil C, Phung D, Ball K (2019) Usefulness of Wearable Cameras as a Tool to Enhance Chronic Disease Self-Management: Scoping Review. *JMIR mHealth uHealth* 7:e10371
30. Peters MD, Godfrey C, McInerney P, Munn Z, Tricco AC, Khalil H (2020) Chapter 11: Scoping reviews. *JBIMES-20-12*. <https://doi.org/10.46658/JBIMES-20-12>
31. Tricco AC, Lillie E, Zarin W, et al (2018) PRISMA Extension for Scoping Reviews (PRISMA-ScR): Checklist and Explanation. *Ann Intern Med* 169:467–473
32. McKeown S, Mir ZM (2021) Considerations for conducting systematic reviews: Evaluating the performance of different methods for de-duplicating references. *Syst Rev* 10:38
33. Pollock D, Peters MDJ, Khalil H, et al (2023) Recommendations for the extraction, analysis, and presentation of results in scoping reviews. *JBIMES-20-12* 21:520–532
34. Page MJ, McKenzie JE, Bossuyt PM, et al (2021) The PRISMA 2020 statement: An updated guideline for reporting systematic reviews. *BMJ* 372:n71
35. Abebe G, Cavallaro A, Parra X (2016) Robust multi-dimensional motion features for first-person vision activity recognition. *Computer Vision and Image Understanding* 149:229–248

36. Bokhari SZ, Kitani KM (2017) Long-Term Activity Forecasting Using First-Person Vision. In: Lai S-H, Lepetit V, Nishino K, Sato Y (eds) Computer Vision – ACCV 2016. Springer International Publishing, Cham, pp 346–360
37. Cartas A, Marín J, Radeva P, Dimiccoli M (2018) Batch-based activity recognition from egocentric photo-streams revisited. PATTERN ANALYSIS AND APPLICATIONS 21:953–965
38. Cartas A, Radeva P, Dimiccoli M (2020) Activities of Daily Living Monitoring via a Wearable Camera: Toward Real-World Applications. IEEE Access 8:77344–77363
39. Cho Y, Nam Y, Choi Y-J, Cho W-D (2008) SmartBuckle: Human activity recognition using a 3-Axis accelerometer and a wearable camera. In: Proceedings of the 2nd International Workshop on Systems and Networking Support for Health Care and Assisted Living Environments. Association for Computing Machinery, New York, NY, USA, pp 1–3
40. Chou C-K, Lin C-C, Chen M-S (2016) Context-aware daily activity summarization with adaptive transmission. In: Proceedings of the 31st Annual ACM Symposium on Applied Computing. Association for Computing Machinery, New York, NY, USA, pp 560–565
41. Gao Q, Pei M, Shen H (2022) Do You Live a Healthy Life? Analyzing Lifestyle by Visual Life Logging. In: ICASSP 2022 - 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). pp 1845–1849
42. Gjoreski H, Ciliberto M, Wang L, Ordonez Morales FJ, Mekki S, Valentin S, Roggen D (2018) The University of Sussex-Huawei Locomotion and

- Transportation Dataset for Multimodal Analytics With Mobile Devices. IEEE
Access 6:42592–42604
43. Hao Y, Uto K, Kanezaki A, Sato I, Kawakami R, Shinoda K (2023) EvIs-Kitchen: Egocentric Human Activities Recognition with Video and Inertial Sensor Data. In: Dang-Nguyen D-T, Gurrin C, Larson M, Smeaton AF, Rudinac S, Dao M-S, Trattner C, Chen P (eds) MultiMedia Modeling. Springer International Publishing, Cham, pp 373–384
 44. Hipiny I, Mayol-Cuevas W (2012) Recognising Egocentric Activities from Gaze Regions with Multiple-Voting Bag of Words. CTIT technical reports series
 45. Hipiny I (2013) Egocentric activity recognition using gaze. PhD thesis, University of Bristol (United Kingdom)
 46. Karaman S, Benois-Pineau J, Mégret R, Pinquier J, Gaëstel Y, Dartigues J-F (2011) Activities of daily living indexing by hierarchical HMM for dementia diagnostics. In: 2011 9th International Workshop on Content-Based Multimedia Indexing (CBMI). pp 79–84
 47. Kitani KM, Okabe T, Sato Y, Sugimoto A (2011) Fast unsupervised ego-action learning for first-person sports videos. In: CVPR 2011. pp 3241–3248
 48. Kode KA (2017) Recognizing Manual Actions from Egocentric Videos. M.S., University of Maryland, Baltimore County
 49. Li Z, Wei Z, Yue Y, Wang H, Jia W, Burke L, Baranowski T, Sun M (2015) An Adaptive Hidden Markov Model for Activity Recognition Based on a Wearable Multi-Sensor Device. Journal of Medical Systems 39:1–10

50. Liu Z, Chihara T, Tan JK (2020) Ego-Posture Estimation for a Pedestrian Using a Monocular Wearable Camera. In: 2020 5th International Conference on Computer and Communication Systems (ICCCS). pp 409–412
51. Liu X, Zhou S, Lei T, Jiang P, Chen Z, Lu H (2023) First-Person Video Domain Adaptation with Multi-Scene Cross-Site Datasets and Attention-Based Methods. *IEEE Transactions on Circuits and Systems for Video Technology* 1–1
52. Moghimi M, Wu W, Chen J, Godbole S, Marshall S, Kerr J, Belongie S (2014) Analyzing sedentary behavior in life-logging images. In: 2014 IEEE International Conference on Image Processing (ICIP). IEEE, Paris, France, pp 1011–1015
53. Nakamura K, Yeung S, Alahi A, Fei-Fei L (2017) Jointly Learning Energy Expenditures and Activities Using Egocentric Multimodal Signals. In: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp 6817–6826
54. Ohnishi K, Kanehira A, Kanezaki A, Harada T (2016) Recognizing Activities of Daily Living with a Wrist-Mounted Camera. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp 3103–3111
55. Oliveira-Barra G, Dimiccoli M, Radeva P (2017) Leveraging Activity Indexing for Egocentric Image Retrieval. In: Alexandre LA, Salvador Sánchez J, Rodrigues JMF (eds) *Pattern Recognition and Image Analysis*. Springer International Publishing, Cham, pp 295–303
56. Possas R, Caceres SP, Ramos F (2018) Egocentric Activity Recognition on a Budget. In: 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp 5967–5976

57. Ragusa F, Furnari A, Farinella G (2023) MECCANO: A multimodal egocentric dataset for humans behavior understanding in the industrial-like domain. COMPUTER VISION AND IMAGE UNDERSTANDING. <https://doi.org/10.1016/j.cviu.2023.103764>
58. Sanal Kumar KP, Bhavani R (2019) Human activity recognition in egocentric video using PNN, SVM, kNN and SVM+kNN classifiers. Cluster Comput 22:10577–10586
59. Song S, Cheung N-M, Chandrasekhar V, Mandal B, Liri J (2016) Egocentric activity recognition with multimodal fisher vector. In: 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). pp 2717–2721
60. Sundaram S, Mayol Cuevas WW (2009) High level activity recognition using low resolution wearable vision. In: 2009 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops. pp 25–32
61. Wang P (2016) Investigating Factorizations in Everyday Activity Recognition. Tsinghua University. <https://doi.org/10.1117/12.2243847>
62. Xiong H, Phan HN, Yin K, Berkovsky S, Jung J, Lau AYS (2022) Identifying daily activities of patient work for type 2 diabetes and co-morbidities: A deep learning and wearable camera approach. J Am Med Inform Assoc 29:1400–1408
63. Xu L, Wu Q, Pan L, Meng F, Li H, He C, Wang H, Cheng S, Dai Y (2023) Towards Continual Egocentric Activity Recognition: A Multi-Modal Egocentric Activity Dataset for Continual Learning. IEEE Transactions on Multimedia 1–15

64. Yin B, Qi W, Wei Z, Nie J (2012) Indirect human activity recognition based on optical flow method. In: 2012 5th International Congress on Image and Signal Processing. pp 99–103
65. Zhan K, Ramos F, Faux S (2012) Activity recognition from a wearable camera. In: 2012 12th International Conference on Control Automation Robotics & Vision (ICARCV). IEEE, Guangzhou, China, pp 365–370
66. Aguilar Grajeda R (2018) Using plantar pressure for free-living posture recognition and sedentary behaviour monitoring. PhD thesis, Loughborough University (United Kingdom)
67. Bach K, Kongsvold A, Bårdstu H, Bardal EM, Kjærnli HS, Herland S, Logacjov A, Mork PJ (2022) A Machine Learning Classifier for Detection of Physical Activity Types and Postures During Free-Living. *Journal for the Measurement of Physical Behaviour* 5:24–31
68. Bourke AK, Ihlen EAF, Bergquist R, Wik PB, Vereijken B, Helbostad JL (2017) A Physical Activity Reference Data-Set Recorded from Older Adults Using Body-Worn Inertial Sensors and Video Technology-The ADAPT Study Data-Set. *Sensors (Basel)*. <https://doi.org/10.3390/s17030559>
69. Carlson JA, Jankowska MM, Meseck K, Godbole S, Natarajan L, Raab F, Demchak B, Patrick K, Kerr J (2015) Validity of PALMS GPS Scoring of Active and Passive Travel Compared with SenseCam. *Medicine & Science in Sports & Exercise* 47:662–667

70. Ellis K, Kerr J, Godbole S, Staudenmayer J, Lanckriet G (2016) Hip and Wrist Accelerometer Algorithms for Free-Living Behavior Classification. *Medicine & Science in Sports & Exercise* 48:933–940
71. Femiano R, Werner C, Wilhelm M, Eser P (2022) Validation of open-source step-counting algorithms for wrist-worn tri-axial accelerometers in cardiovascular patients. *Gait & Posture* 92:206–211
72. Fullerton E, Heller B, Munoz-Organero M (2017) Recognizing Human Activity in Free-Living Using Multiple Body-Worn Accelerometers. *IEEE Sensors Journal* 17:5290–5297
73. Gershuny J, Harms T, Doherty A, Thomas E, Milton K, Kelly P, Foster C (2020) Testing Self-Report Time-Use Diaries against Objective Instruments in Real Time. *Sociological Methodology* 50:318–349
74. Kelly P, Doherty A, Mizdrak A, Marshall S, Kerr J, Legge A, Godbole S, Badland H, Oliver M, Foster C (2014) High group level validity but high random error of a self-report travel diary, as assessed by wearable cameras. *Journal of Transport & Health* 1:190–201
75. Kerr J, Marshall S, Godbole S, Chen J, Legge A, Doherty A, Kelly P, Oliver M, Badland H, Foster C (2013) Using the SenseCam to Improve Classifications of Sedentary Behavior in Free-Living Settings. *AMERICAN JOURNAL OF PREVENTIVE MEDICINE* 44:290–296
76. Kerr J, Patterson RE, Ellis K, Godbole S, Johnson E, Lanckriet G, Staudenmayer J (2016) Objective Assessment of Physical Activity: Classifiers for Public Health. *Med Sci Sports Exerc* 48:951–957

77. Kim Y, Barry VW, Kang M (2015) Validation of the ActiGraph GT3X and activPAL Accelerometers for the Assessment of Sedentary Behavior. *Measurement in Physical Education and Exercise Science* 19:125–137
78. Kim H, Kang M (2019) Validation of Sedentary Behavior Record Instrument as a Measure of Contextual Information of Sedentary Behavior. *J Phys Act Health* 16:623–630
79. Lynn R, Pfitzer R, Rogers RR, Ballmann CG, Williams TD, Marshall MR (2020) Step-Counting Validity of Wrist-Worn Activity Monitors During Activities With Fixed Upper Extremities. *Journal for the Measurement of Physical Behaviour* 3:197–203
80. Nawab KA, Storey BC, Staplin N, et al (2021) Accelerometer-measured physical activity and functional behaviours among people on dialysis. *Clinical Kidney Journal* 14:950–958
81. O. Connor S, McCaffrey N, Whyte E, Moran K (2016) The novel use of a SenseCam and accelerometer to validate training load and training information in a self-recall training diary. *Journal of Sports Sciences* 34:303–310
82. Rosenberg D, Godbole S, Ellis K, Di C, Lacroix A, Natarajan L, Kerr J (2017) Classifiers for Accelerometer-Measured Behaviors in Older Women. *Medicine & Science in Sports & Exercise* 49:610–617
83. Toth LP, Park S, Springer CM, Feyerabend MD, Steeves JA, Bassett DR (2018) Video-Recorded Validation of Wearable Step Counters under Free-living Conditions. *Medicine & Science in Sports & Exercise* 50:1315

84. Tsutsui T, Tsutsui Y, Tsukamoto M, Nakamura E (2023) Validation of foot plantar pressure sensor data used to estimate standing, sitting, and moving durations in one working day. *J Orthop Sci* 28:217–221
85. Zhao Q, Wang J, Feng W, Jia W, Burke LE, Zgibor JC, Sun M (2015) Assessing physical performance in free-living older adults with a wearable computer. In: 2015 41st Annual Northeast Biomedical Engineering Conference (NEBEC). pp 1–2
86. Andriyani FD, Biddle SJH, Priambadha AA, Thomas G, De Cocker K (2022) Physical activity and sedentary behaviour of female adolescents in Indonesia: A multi-method study on duration, pattern and context. *Journal of Exercise Science & Fitness* 20:128–139
87. Davies A, Chan V, Bauman A, Signal L, Hosking C, Gemming L, Allman-Farinelli M (2021) Using wearable cameras to monitor eating and drinking behaviours during transport journeys. *Eur J Nutr* 60:1875–1885
88. Freeman N, Gage R, Chambers T, Blaschke P, Cook H, Stanley J, Pearson A, Smith M, Barr M, Signal L (2021) Where do the children play? An objective analysis of children’s use of green space. *Health Promotion International* 36:846–853
89. Hänggi JM, Spinnler S, Christodoulides E, Gramespacher E, Taube W, Doherty A (2020) Sedentary Behavior in Children by Wearable Cameras: Development of an Annotation Protocol. *Am J Prev Med* 59:880–886

90. Kelly P, Doherty A, Berry E, Hodges S, Batterham AM, Foster C (2011) Can we use digital life-log images to investigate active and sedentary travel behaviour? Results from a pilot study. *Int J Behav Nutr Phys Act* 8:44
91. Laskaris Z, Milando C, Batterman S, Mukherjee B, Basu N, O’neill MS, Robins TG, Fobil JN (2019) Derivation of Time-Activity Data Using Wearable Cameras and Measures of Personal Inhalation Exposure among Workers at an Informal Electronic-Waste Recovery Site in Ghana. *Annals of Work Exposures and Health* 63:829–841
92. Leask C, Harvey J, Skelton D, Chastin S (2015) Exploring the context of sedentary behaviour in older adults (what, where, why, when and with whom). *European Reviews of Aging & Physical Activity* 12:1–8
93. Li W, Long Y, Kwan M-P, Liu N, Li Y, Zhang Y (2022) Measuring individuals’ mobility-based exposure to neighborhood physical disorder with wearable cameras. *Applied Geography* 145:102728
94. Rieken J, Garcia-Sanchez E, Trujillo M, Bear D (2015) Digital Ethnography and the Social Dimension of Introspection: An Empirical Study in Two Colombian Schools. *INTEGRATIVE PSYCHOLOGICAL AND BEHAVIORAL SCIENCE* 49:253–274
95. Wilson G, Jones D, Schofield P, Martin DJ (2018) The use of a wearable camera to explore daily functioning of older adults living with persistent pain: Methodological reflections and recommendations. *Journal of Rehabilitation and Assistive Technologies Engineering* 5:2055668318765411

96. Davies A, Allman-Farinelli M, Owen K, Signal L, Hosking C, Wang L, Bauman A (2020) Feasibility Study Comparing Physical Activity Classifications from Accelerometers with Wearable Camera Data. *INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH*.
<https://doi.org/10.3390/ijerph17249323>
97. Doherty A, Marshall S, Kelly P, Hamilton A, Oliver M, Badland H, Kerr J, Foster C (2012) Identifying sedentary behaviour types using SenseCam: A pilot study. *Journal of Science and Medicine in Sport* 15:S296–S297
98. Doherty AR, Kelly P, Kerr J, Marshall S, Oliver M, Badland H, Hamilton A, Foster C (2013) Using wearable cameras to categorise type and context of accelerometer-identified episodes of physical activity. *Int J Behav Nutr Phys Act* 10:22
99. Kelly P (2013) Assessing the utility of wearable cameras in the measurement of walking and cycling. PhD thesis, University of Oxford (United Kingdom)
100. Kelly P, Thomas E, Doherty A, Harms T, Burke Ó, Gershuny J, Foster C (2015) Developing a Method to Test the Validity of 24 Hour Time Use Diaries Using Wearable Cameras: A Feasibility Pilot. *PLOS ONE* 10:e0142198
101. Kneiert MF, Martinez J, Steinbrink GM, Strath SJ (2022) Comparison Of Wearable Camera Image Physical Activity Behavior Estimates To Direct Observation. *Medicine & Science in Sports & Exercise* 54:175–176
102. Marinac C, Merchant G, Godbole S, Chen J, Kerr J, Clark B, Marshall S (2013) The feasibility of using SenseCams to measure the type and context of daily sedentary behaviors. In: *Proceedings of the 4th International SenseCam &*

- Pervasive Imaging Conference. Association for Computing Machinery, New York, NY, USA, pp 42–49
103. Martinez J, Decker A, Cho CC, Doherty A, Swartz AM, Staudenmayer JW, Strath SJ (2021) Validation of Wearable Camera Still Images to Assess Posture in Free-Living Conditions. *J Meas Phys Behav* 4:47–52
 104. Miller N, Welch W, Doherty A, Strath S (2017) Accuracy Of Behavioral Assessment With A Wearable Camera in Semi-structured And Free Living Conditions In Older Adults. *MEDICINE AND SCIENCE IN SPORTS AND EXERCISE* 49:651–651
 105. Steinbrink GM, Martinez J, Kneiort MF, Strath SJ (2022) Assessing Posture And Activity Intensity Agreement Between Wearable Camera Images And Criterion Direct Observation. *Medicine & Science in Sports & Exercise* 54:176–177
 106. Bandini A, Zariffa J (2023) Analysis of the hands in egocentric vision: A survey. *IEEE Trans Pattern Anal Mach Intell* 45:6846–6866
 107. Núñez-Marcos A, Azkune G, Arganda-Carreras I (2022) Egocentric Vision-based Action Recognition: A survey. *NEUROCOMPUTING* 472:175–197
 108. Zhang S, Li Y, Zhang S, Shahabi F, Xia S, Deng Y, Alshurafa N (2022) Deep Learning in Human Activity Recognition with Wearable Sensors: A Review on Advances. *Sensors* 22:1476
 109. Matthews CE, Keadle SK, Troiano RP, et al (2016) Accelerometer-measured dose-response for physical activity, sedentary time, and mortality in US adults. *Am J Clin Nutr* 104:1424–1432

110. Ekelund U, Steene-Johannessen J, Brown WJ, Fagerland MW, Owen N, Powell KE, Bauman A, Lee I-M, Lancet Physical Activity Series 2 Executive Committee, Lancet Sedentary Behaviour Working Group (2016) Does physical activity attenuate, or even eliminate, the detrimental association of sitting time with mortality? A harmonised meta-analysis of data from more than 1 million men and women. *Lancet* 388:1302–1310
111. Ekelund U, Tarp J, Fagerland MW, et al (2020) Joint associations of accelerometer-measured physical activity and sedentary time with all-cause mortality: A harmonised meta-analysis in more than 44 000 middle-aged and older individuals. *Br J Sports Med* 54:1499–1506
112. Hu R, Zheng H, Lu C (2021) The Association Between Sedentary Screen Time, Non-screen-based Sedentary Time, and Overweight in Chinese Preschool Children: A Cross-Sectional Study. *Frontiers in Pediatrics*.
<https://doi.org/10.3389/fped.2021.767608>
113. Latouche C, Jowett JBM, Carey AL, Bertovic DA, Owen N, Dunstan DW, Kingwell BA (2013) Effects of breaking up prolonged sitting on skeletal muscle gene expression. *Journal of Applied Physiology* 114:453–460
114. Bailey DP, Locke CD (2015) Breaking up prolonged sitting with light-intensity walking improves postprandial glycemia, but breaking up sitting with standing does not. *J Sci Med Sport* 18:294–298
115. Thosar SS, Bielko SL, Mather KJ, Johnston JD, Wallace JP (2015) Effect of Prolonged Sitting and Breaks in Sitting Time on Endothelial Function. *Medicine & Science in Sports & Exercise* 47:843

116. Larsen RN, Kingwell BA, Sethi P, Cerin E, Owen N, Dunstan DW (2014) Breaking up prolonged sitting reduces resting blood pressure in overweight/obese adults. *Nutrition, Metabolism and Cardiovascular Diseases* 24:976–982
117. Chen Y-C, Betts JA, Walhin J-P, Thompson D (2018) Adipose Tissue Responses to Breaking Sitting in Men and Women with Central Adiposity. *Medicine & Science in Sports & Exercise* 50:2049
118. Dontje ML, Leask CF, Harvey J, Skelton DA, Chastin SFM (2018) Why Older Adults Spend Time Sedentary and Break Their Sedentary Behavior: A Mixed-Methods Approach Using Life-Logging Equipment. *J Aging Phys Act* 26:259–266
119. Ainsworth BE, Haskell WL, Herrmann SD, Meckes N, Bassett DRJ, Tudor-Locke C, Greer JL, Vezina J, Whitt-Glover MC, Leon AS (2011) 2011 Compendium of Physical Activities: A Second Update of Codes and MET Values. *Medicine & Science in Sports & Exercise* 43:1575
120. Lyden K, Petruski N, Staudenmayer J, Freedson P (2014) Direct observation is a valid criterion for estimating physical activity and sedentary behavior. *J Phys Act Health* 11:860–863
121. Cox MF, Petrucci GJ, Marcotte RT, Masteller BR, Staudenmayer J, Freedson PS, Sirard JR (2020) A Novel Video-Based Direct Observation System for Assessing Physical Activity and Sedentary Behavior in Children and Young Adults. *Journal for the Measurement of Physical Behaviour* 3:50–57
122. Keadle SK, Martinez J, Strath SJ, et al (2023) Evaluation of Within- and Between-Site Agreement for Direct Observation of Physical Behavior Across

- Four Research Groups. *Journal for the Measurement of Physical Behaviour* 6:176–184
123. Lyden K, Kozey Keadle SL, Staudenmayer JW, Freedson PS (2012) Validity of Two Wearable Monitors to Estimate Breaks from Sedentary Time. *Medicine & Science in Sports & Exercise* 44:2243
124. Keadle SK, Patel S, Berrigan D, Christopher CN, Huang J, Saint-Maurice PF, Lofffield E, Matthews CE (2023) Validation of ACT24 Version 2.0 for Estimating Behavioral Domains, Active and Sedentary Time. *Med Sci Sports Exerc* 55:1054–1062
125. Lara OD, Labrador MA (2013) A Survey on Human Activity Recognition using Wearable Sensors. *IEEE Communications Surveys & Tutorials* 15:1192–1209
126. Chastin SFM, Schwarz U, Skelton DA (2013) Development of a Consensus Taxonomy of Sedentary Behaviors (SIT): Report of Delphi Round 1. *PLOS ONE* 8:e82313
127. Hodges S, Williams L, Berry E, Izadi S, Srinivasan J, Butler A, Smyth G, Kapur N, Wood K (2006) SenseCam: A Retrospective Memory Aid. In: Dourish P, Friday A (eds) *UbiComp 2006: Ubiquitous Computing*. Springer, Berlin, Heidelberg, pp 177–193
128. Loveday A, Sherar LB, Sanders JP, Sanderson PW, Esliger DW (2016) Novel technology to help understand the context of physical activity and sedentary behaviour. *Physiol Meas* 37:1834
129. Meyer LE, Porter L, Reilly ME, Johnson C, Safir S, Greenfield SF, Silverman BC, Hudson JI, Javaras KN (2022) Using Wearable Cameras to Investigate Health-

Related Daily Life Experiences: A Literature Review of Precautions and Risks in Empirical Studies. *Res Ethics* 18:64–83

130. Kelly P, Marshall SJ, Badland H, Kerr J, Oliver M, Doherty AR, Foster C (2013) An ethical framework for automated, wearable cameras in health behavior research. *Am J Prev Med* 44:314–319
131. Alharbi R, Stump T, Vafaie N, Pfammatter A, Spring B, Alshurafa N (2018) I Can't Be Myself: Effects of Wearable Cameras on the Capture of Authentic Behavior in the Wild. *Proc ACM Interact Mob Wearable Ubiquitous Technol* 2:90:1–90:40

3. Validation of Wearable Camera Still Images to Assess Posture in Free-Living Conditions

3.1 Introduction

Wearable cameras (WCs) are body-worn devices that can capture different media formats such as still-images (IMGs) in defined periods of time. IMGs from a WC provide an objective first-person view of what a wearer engages in throughout the day, making it a valuable instrument in determining lifestyle behaviors with a low burden of use [1]. The most often utilized WC within research has been the Microsoft SenseCam (Microsoft Corp., Redmond, WA), first developed as a retrospective recall aid for individuals with memory problems [2]. Outside of its originally intended use, the SenseCam has been used to provide contextual information in a variety of fields. For example, it has been used to improve dietary reporting [3, 4], determine the validity of time-use diaries [5–7], and assist autobiographical memory and well-being for individuals with Alzheimer's [8, 9].

The WCs have also been used to provide contextual information for different physical activity (PA) behaviors within the field of PA and behavioral measurement. Doherty et al. [10] determined WCs can be used to determine contextual information during bouts of PA defined by body-worn accelerometer (ACC) measurements. As a result, they have been used as a proxy for direct observation when determining the convergent validity of commonly used ACC measures in estimating sedentary behavior [11] and for developing an ACC machine learning algorithm [12]. Exploratory work has also been done using WCs to classify the relationship between PA type and frequency and physical function of older adults [13]. All the results from the briefly described

aforementioned studies show a growth in the use of WCs for PA research and highlight its potential as a feasible tool for providing contextual information to individual free-living PA behavior. Notably, all of the previously mentioned studies relied on the use of a WC to accurately classify posture.

To date, limited studies have compared the accuracy and precision of WC IMGs to a known criterion standard. Given that the estimation of posture has been a focus in PA measurement using WCs, the purpose of this study was to assess the convergent validity of body-worn WC IMGs for determining posture compared with a pseudo gold-standard measure.

3.2 Methods

3.2.1 Study Overview

Following recruitment, the participants were asked to visit a laboratory at a major midwestern university where an informed consent document was signed, and height and weight measurements were collected. After the initial laboratory visit, the participants were scheduled to be evaluated in a free-living naturalistic environment. Three 2-hr free-living visits were scheduled for each participant on separate days, where possible settings included the participant's residence; social venues, such as a shopping mall, grocery store, or library; or recreational venues, such as a local park. During each evaluation, the participants were asked to wear a WC and an activPAL (AP), which served as the criterion measure. All data collected from the visits were time matched.

3.2.2 Participants

Individuals were recruited through phone calls and media advertisements online and in person. Eligible participants were aged ≥ 18 years and had no functional limitations and no chronic diseases or major health conditions that may cause a restriction in PA. The eligible participants came to a laboratory, where the study was explained to them and each signed an informed consent document approved by the University of Wisconsin-Milwaukee Institutional Review Board (Protocol Number 17.127).

3.2.3 Measurement and Instrumentation

3.2.3.1 Height and weight

Body mass (in kilograms, measured to the nearest 0.01 kg) and height (in centimeters, measured to the nearest 0.1 cm) were taken with a 3PHTROD-WM stadiometer and Model 439 weight beam physician's scale (DETECTO, Webb City, MO). Body mass index was calculated by dividing the body mass (in kilograms) by height squared (in meters square).

3.2.3.2 Wearable cameras

An Autographer (OMG Life, Oxford, England) WC was placed just above the participant's xyphoid process with a lanyard that went around their neck and a belt strap attached to the back of the Autographer with Velcro, which went around the upper torso. The Autographer is a derivative of the SenseCam; as such, it features a multitude of sensors (ACC, thermometer, passive infrared sensor, light-level sensor, and magnetometer) to inform the camera when to take a picture and has a 119° wide-angle fisheye lens [2]. The Autographers were set at a high capture rate so a time-stamped IMG would be taken on average 8.47 ± 4.41 s apart, with the shortest interval between

IMGs being 5 s. The IMGs from the Autographer were annotated using the Oxford Image Browser (OIB) [12, 14]. The OIB allows users, or coders, to click and drag annotation codes to a sequence of IMGs within an IMG set (**Figure 3.1**). For this study, one IMG set consisted of all the IMGs taken from one free-living visit.

3.2.3.3 Postural criterion

The criterion measure for determining posture within the study was the activPAL4 (PAL Technologies Ltd., Glasgow, Scotland). AP is a 2.0 × 1.4 × 0.3-in. (20.1 g) triaxial ACC that collects data at a frequency of 15 Hz. AP has been validated in a free-living setting and has been shown to be sensitive to changes in posture [15, 16]. The AP was placed midhigh on their right side and affixed to each participant with medical cloth tape.

The IMG sets from each free-living visit were loaded into the OIB. Three coders then annotated the IMG set with the schema shown in **Table 3.1**. To determine which code to apply, a coder would look for points of reference that appear between IMGs to determine changes in the participants' orientation and proximity relative to the points of reference and environmental changes. All coders were extensively trained on the annotation schema and evaluated for interrater reliability on a specified training data set, which was assessed by computing the intraclass correlations coefficient (ICC) between all three coders. All coders had to achieve an ICC of .90 prior to coding study data, and 20% of the study data were also randomly selected to be coded by all three coders to check for interrater reliability as a quality check.

The coders achieved an ICC of .97 prior to coding study data and achieved an ICC of .90 for the quality check. The annotation codes applied to a visit's IMG set were exported to a CSV file that denotes the beginning and end of each annotation code with

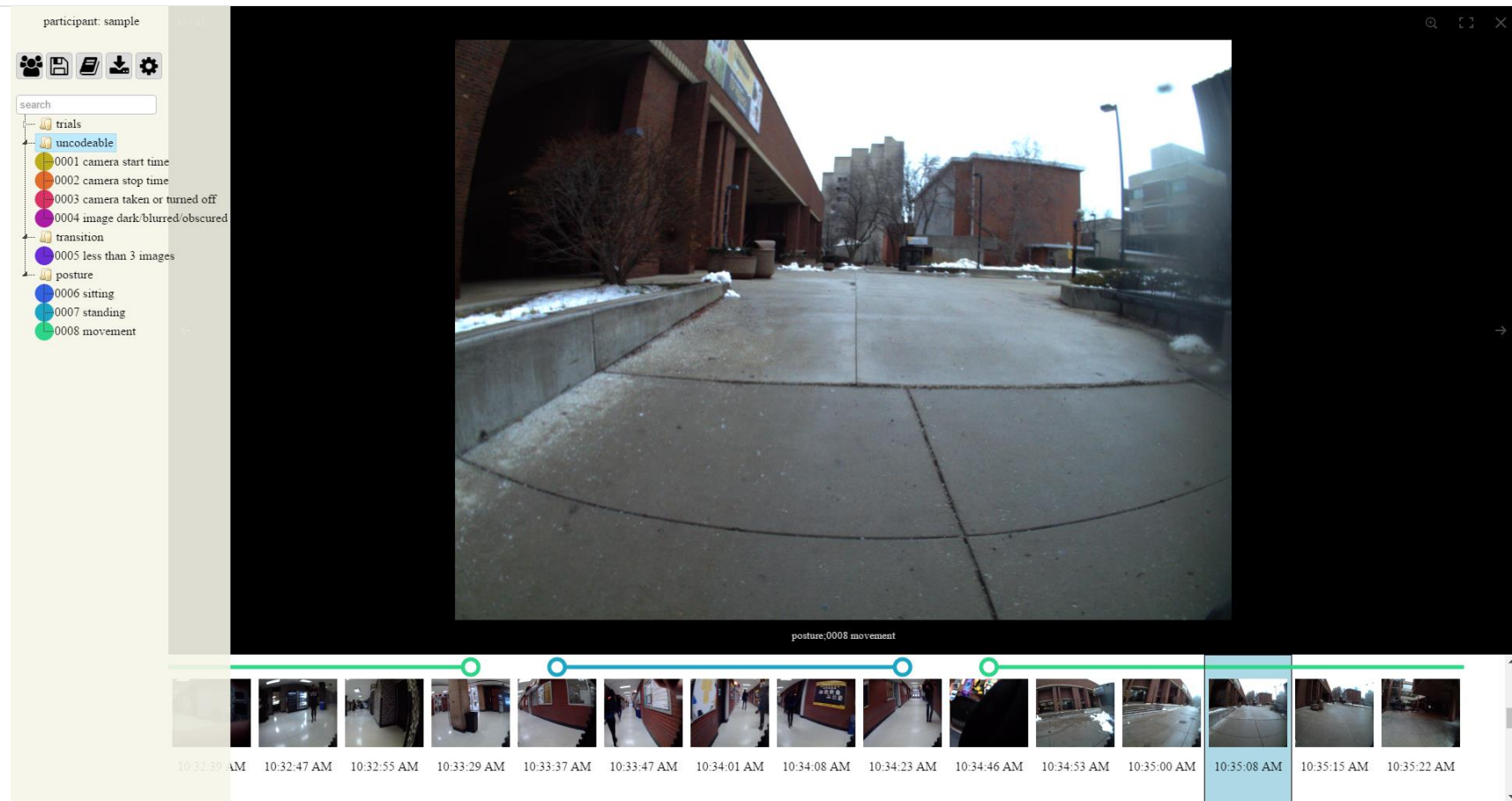


Figure 3.1: Interface of the Oxford Image Browser software used to annotate still images.

Note: Annotations (left) are applied to a sequence of images that are grouped into an event (bottom) where selected images can be enlarged (center).

3.2.4 Data Processing

Table 3.1: Schema used to annotate wearable camera still-images in the Oxford Image Browser.

Annotation Code	Type	Operational Definition
Sitting	Posture	Continuous period of being seated or sedentary by supporting body weight with buttocks or back (lying). Requires a sequence of at least three images.
Standing	Posture	Continuous period of standing in a place, less than three steps between images. Requires a sequence of at least three images.
Movement	Posture	Continuous period of movement at least three steps between images. Requires a sequence of at least three images.
Fewer than three images	Transitory State	Posture code that is only seen for two images.
Camera taken or turned off	Unknown	Camera is taken off by participant/research assistant or lens on Autographer turned on.
Image dark/blurred/obscured	Unknown	No contextual information from image cannot be determined due to image being too dark, image being too blurry, or an object obscuring the camera.

the corresponding Autographer timestamps and the duration of each code in seconds. A limitation from the OIB is that the time between two sequences of IMGs is not considered. Therefore, the end of one annotation code was not the beginning of the next annotation code. Annotation files were then converted into a continuous second-by-second time series, with the time between annotation codes labeled as “gaps.” Raw AP data were downloaded using PAL Studio (version 8.9.1.24; PAL Technologies Ltd., Glasgow, Scotland) and output into an events file where the R package *activpalProcessing* (version 1.0.2) was adapted to make the events file second by second [16–18]. The AP events file outputs posture into three types, sit, stand, and move, which match the WC OIB schema posture codes.

The annotation file and AP events file were then matched by visit start and stop time to create a visit file. A visit file was split into four groups as follows: event, gap, transitory state, and unknown. The events were annotations that described the participants’ posture, the time between annotations were gaps, the transitory states were posture annotations fewer than three IMGs, and the unknowns were IMGs that could not be accurately classified or were “uncodeable”.

3.2.5 Statistical Analysis

Descriptive characteristics of the participants’ demographic and anthropometric measures were compiled. The total visit, event, gap, transitory state, and unknown times are provided, along with the average length of a visit. The average length, along with the average percentage of the event, gap, transitory state, and unknown times within a visit, given as a reference, provide an overall picture of how much of a visit can be confidently coded with a posture (events), how much of a visit is missed due to OIB

and Autographer limitations (gap), how much of a visit consisted of transitory states, and how much cannot be determined following the schema (unknown). To determine the accuracy and precision of IMG annotations in determining total posture times within a visit, a repeated-measures model was used to calculate the bias, SE, and 95% confidence intervals (CIs) between IMG and AP estimates. Bias represents the systematic error of the IMG annotations, while the CIs, $SE \pm \text{bias}$, represent the random error of IMG annotations or the variability between visits. Bias was calculated within events because including the transitory state time and gaps artificially inflates IMG bias. Modified Bland–Altman plots were constructed using the AP estimates from visit files as the x-axis and the difference between IMG annotations and AP estimates on the y-axis to visualize the variability between visits. Confusion matrices using total AP estimates were computed to determine IMG underestimations and overestimations and where gaps, transitory states, and unknown annotations commonly occurred. Confusion matrix outputs were then averaged and represented as a percentage of the mean total AP posture times. Finally, to determine whether annotations can differentiate between sedentary and non-sedentary behavior, confusion matrices were made with stand and move codes collapsed into “upright.” All analyses for time were done in seconds, but the results were output in minutes for meaningfulness. The analyses were performed using R (version 3.6.3) in RStudio (version 1.2.5042), with the lme4 (version 1.1.23) package used to create the repeated-measures model [18–20].

3.3 Results

Sixteen participants completed all three free-living visits, for a total of 48 visits. Five visits (two from one participant and three from different participants) were excluded

from analysis due to missing AP data, leaving 43 visit files for analysis. **Table 3.2** shows the compiled demographic information. The total free-living time was 5027.73 min, where 4237.23 min were events, 567.73 min were gaps, 207.28 min were labeled as transitory states, and 15.48 min were labeled as unknown. The average visit time captured was 116.92 ± 9.15 min, with 84.28% of the visit time being events, 11.29% gaps, 4.12% transitory states, and 0.31% unknown. **Table 3.3** provides the mean IMG and AP posture estimates within events, with corresponding bias, SE, and 95% CI. The bias (CI) for sitting, standing, and moving were 0.84 [-2.34, 4.06], -6.87 [-10.76, -3.02], and 6.04 [2.77, 9.32] min, respectively. Only the CI for the sitting bias included zero. The modified Bland–Altman plots for each posture are shown in **Figure 3.2**. **Table 3.4** shows the confusion matrices from each visit averaged and as a percentage of the mean total AP posture times. Sitting, standing, and movement were correctly identified 85.69%, 54.87%, and 69.41% of the total AP time, respectively. Collapsing stand and move posture estimations into an “upright” category led to IMG estimates correctly classifying 70.46% of the total AP upright time (76.23 min), with 15.61% of the total AP upright time misclassified as gaps.

3.4 Discussion

The aim of this study was to determine the convergent validity of WC IMGs for assessing posture compared with a pseudo gold-standard measure. The results highlight that, in using the OIB software to annotate IMGs, 88.71% of a 116.92-min visit were annotated with a code from the developed schema. Furthermore, bias from the IMG estimates was shown to not be significant in estimating sitting time, but the bias was shown to significantly underestimate standing time and significantly overestimate

Table 3.2: Participant demographics.

Demographics	Overall	Male	Female
N	16	7	9
Age			
mean (SD)	46.7 (23.8)	51.8 (24.5)	42.7 (23.8)
median	39.5	70	32
range	18-76	25-73	18-76
Body Mass Index			
mean (SD)	24.9 (4.1)	27.8 (3.9)	23.8 (2.6)
median	24.3	29.0	22.7
range	17.8-33.7	22.5-33.7	17.8-25.6
Race, n (%)			
White	14 (88%)	5 (71%)	9 (100%)
Black or African American	1 (6%)	1 (14%)	0 (0%)
Asian	0 (0%)	0 (0%)	0 (0%)
Other	1 (6%)	1 (14%)	0 (0%)
Hispanic, n (%)			
Non-Hispanic	15 (94%)	6 (86%)	9 (100%)
Hispanic or Latino	1 (6%)	1 (14%)	0 (0%)

Table 3.3: Mean image annotation and AP estimates within events that an image annotation posture code was applied.

Posture	Image minutes \pm SD	AP^a minutes mean \pm SD	Bias	SE	Lower 95% CI^b	Higher 95% CI^b
Sit	38.67 \pm 25.77	37.91 \pm 26.99	0.84	7.29	-2.34	4.06
Stand	31.57 \pm 20.99	38.32 \pm 18.53	-6.87	8.25	-10.76	-3.02
Move	28.29 \pm 20.93	22.31 \pm 20.34	6.04	5.74	2.77	9.32

Note: 4,237.23 min (84% of observed time) were coded as events, defined as annotations that were classified as sit, stand or move. The square root variance of bias is the SE.

^aactivPAL

^bConfidence Interval

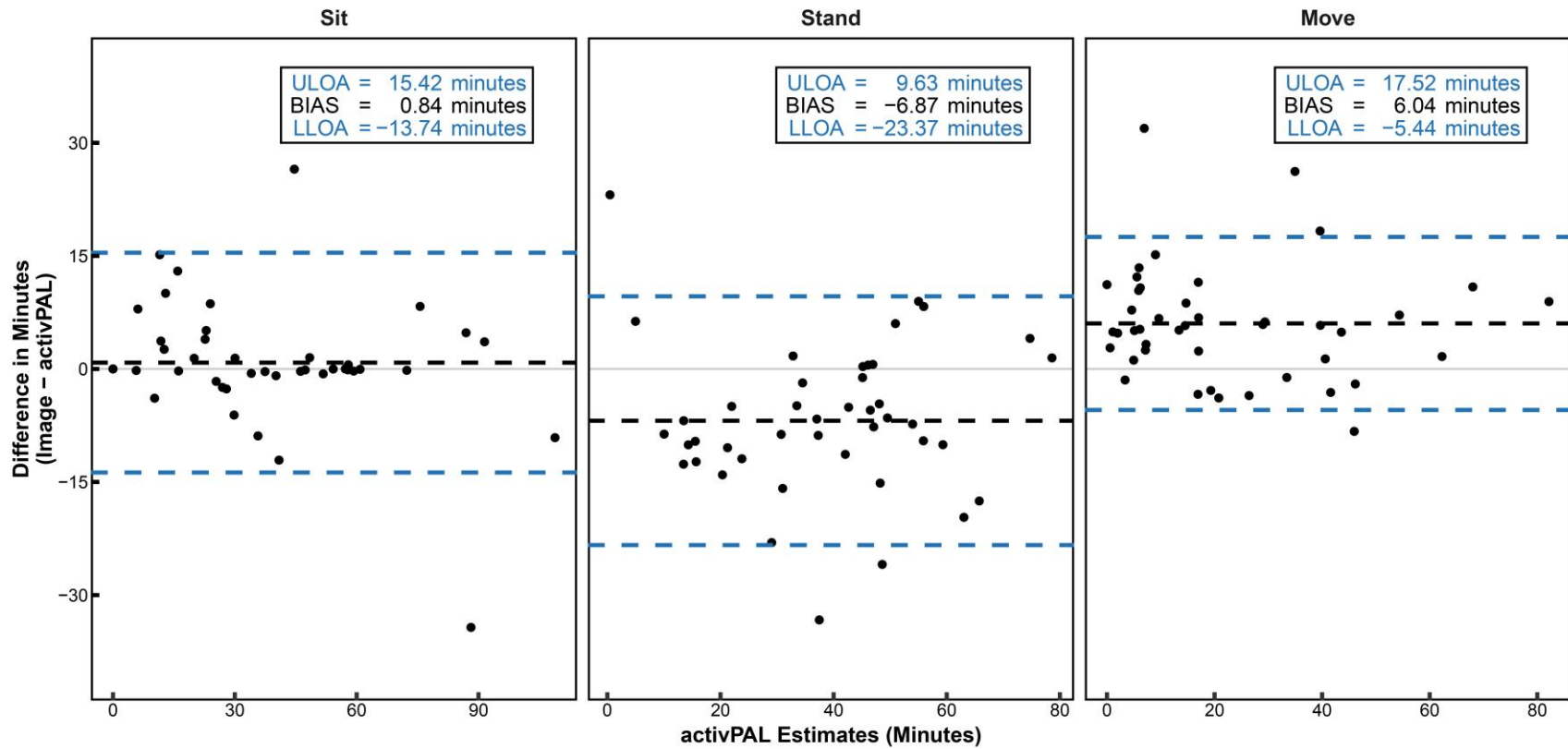


Figure 3.2: Modified Bland-Altman plots with event activPAL estimates as the x-axis and difference between image and activPAL estimates within events as the y-axis.

Note: LOA were made using ± 2 SDs of bias.

Note: LOA = limits of agreement; ULOA = upper LOA; LLOA = lower LOA

Table 3.4: Confusion Matrix of Mean Total AP Estimates with Image Annotations as a Percentage of Mean Total AP Estimates.

		Image					
Minutes		Sit (%)	Stand (%)	Move (%)	Gap (%)	Transitory State (%)	Unknown (%)
activPAL	Sit (40.70)	85.69	4.40	3.06	5.16	1.41	0.28
	Stand (48.93)	6.92	54.87	16.55	15.83	5.48	0.35
	Move (27.30)	1.53	10.76	69.41	12.31	5.72	0.26

Note: Mean total AP estimates in minutes for each posture are shown in the left-hand column. Gap is the time between Image annotations. Bold values indicate percentage of Image annotations that match activPAL posture classifications.

movement time from AP. When comparing the estimates second by second with confusion matrices, the standing and movement postures seem to be misclassified the most, where 16.55% of standing determined by AP was misclassified as movement, while 10.76% of AP movement was coded as standing. Collapsing standing and movement into an “upright” category of posture shows that WC IMGs can differentiate non-sedentary behavior 70.46% of time. However, it is also worth noting that gaps comprised 15.83% of the standing time, 12.31% of the movement time, and 15.61% of the upright time. Because gaps occur when a new annotation code is applied that is different from the previous annotation code, reducing breaks between codes may improve IMG classifications.

In previous research, WC IMGs have been annotated with specific schemas created to answer a designated question. Doherty et al. [10] matched 10-min episodes of ACC-defined PA to WC IMGs to establish whether PA behavior was able to be determined, using the 2011 Compendium of Physical Activities [21] as the basis of the behavior annotation schema. From a sample of 49 participants, 386 episodes were determined, from which, 81% of the data were able to be annotated with a PA behavior. Although the schema used in [10] was not dependent on the number of IMGs to apply an annotation, we found that a similar percentage (81%) of IMGs were able to be annotated with a code describing PA behavior. Within Kerr et al. [11], the annotation schema was developed with the “System for Observing Fitness Instruction Time” protocol used as a base [22]. The schema is more similar to the one used in the current study, as an annotation behavior code is applied when at least five consecutive IMGs with the same behavior is seen. With annotation codes aggregated to minutes, only

8,546 of 86,109 min (8.2%) were “uncodeable,” meaning 91.8% of the codes were annotated with a behavior code. This holds promise, collectively revealing that >80% of IMGs could be usable to assess both posture and PA behavior type.

The WC schema used to annotate the IMGs within Willetts et al. [12], where the WC IMGs served as the ground truth for the ACC algorithm to predict PA behavior, has similarities to the schema used in Doherty, et al. [10] and in the current study. Their approach is grounded within the Compendium of Physical Activities and requires that at least three IMGs constitute an event. However, no actual “transitory states” or “gaps” were recorded between the events; annotations fewer than two IMGs and gaps were labeled the same as the preceding event. This is different from the current study, where, if we found fewer than three IMGs to designate an event, they were labeled as a “transitory state.” The different approaches to account for transitory states and gaps may affect the ability of WC IMG annotations to estimate posture time, as gaps accounted for 12–15% of the criterion posture time in the current study. Future work comparing these approaches would be helpful both in determining the total time spent in a PA behavior, as well the ability to detect changes in a PA behavior type.

In the current study, we found that WC IMG time for standing and movement were often misclassified for one another. One potential reason for this misclassification may be due to when standing typically occurs within the context of a given day. Environments where it was hard to differentiate standing and movement occurred when a participant was within a confined space and limited stepping was common. Examples of such spaces include the kitchen when household activities were taking place. Given limited literature in this area, it is difficult to determine whether this misclassification in

determining posture is common. However, it appears that the exploratory study by Wilson et al. [13] seems to address this by including a “stepping” annotation code within their schema to define movement that was not purposeful walking (i.e., taking steps while cooking). The study found that approximately 5% of all IMGs, from a total of 221,783 IMGs representing one hundred and one 9.25-hr days, were annotated with the stepping code. Including this code would most likely account for when stand and move misclassifications occur. For example, rather than deciding between standing and movement for subtle movements in confined spaces, the stepping code can be applied.

This study is not without limitation. Only 16 participants were recruited for this study. However, 43 free-living visits were included in the analysis, permitting approximately 84 hours of WC IMG annotations to be compared with a validated pseudo-criterion measure, which has not previously been reported in the literature. Another limitation is that we created a WC IMG schema to answer a designated scientific question, just as others have done [10, 12, 13]. At present, there has been no consistent procedure in annotating IMGs within the PA measurement field, limiting across-study comparisons. More research is needed in harmonizing annotation procedures.

3.5 Conclusion

The WCs are devices that have the ability to provide contextual information on a wide number of behaviors. For PA, WCs can provide context on an individual’s posture throughout the day, as well as different types of activities performed. This study sought to determine the accuracy of WC IMGs in determining posture by comparing estimates to a known pseudo-criterion. In comparison with AP estimates, WC IMGs can accurately

determine the overall time spent sitting, but underestimate standing and overestimate moving. Improvement is needed when using IMG estimates to determine when changes in posture occur. Future directions include comparing IMG estimates to video-recorded direct observation, expanding the schema to include more contextual information such as PA behavior type, and determining when misclassifications occur.

References

1. Doherty AR, Hodges SE, King AC, Smeaton AF, Berry E, Moulin CJA, Lindley S, Kelly P, Foster C (2013) Wearable cameras in health: The state of the art and future possibilities. *Am J Prev Med* 44:320–323
2. Hodges S, Williams L, Berry E, Izadi S, Srinivasan J, Butler A, Smyth G, Kapur N, Wood K (2006) SenseCam: A Retrospective Memory Aid. In: Dourish P, Friday A (eds) *UbiComp 2006: Ubiquitous Computing*. Springer, Berlin, Heidelberg, pp 177–193
3. O’Loughlin G, Cullen SJ, McGoldrick A, O’Connor S, Blain R, O’Malley S, Warrington GD (2013) Using a Wearable Camera to Increase the Accuracy of Dietary Analysis. *Am J Prev Med* 44:297–301
4. Gemming L, Rush E, Maddison R, Doherty A, Gant N, Utter J, Mhurchu CN (2015) Wearable cameras can reduce dietary under-reporting: Doubly labelled water validation of a camera-assisted 24 h recall. *British Journal of Nutrition* 113:284–291
5. Kelly P, Thomas E, Doherty A, Harms T, Burke Ó, Gershuny J, Foster C (2015) Developing a Method to Test the Validity of 24 Hour Time Use Diaries Using Wearable Cameras: A Feasibility Pilot. *PLOS ONE* 10:e0142198
6. Harms T, Gershuny J, Doherty A, Thomas E, Milton K, Foster C (2019) A validation study of the Eurostat harmonised European time use study (HETUS) diary using wearable technology. *BMC Public Health* 19:455

7. Gershuny J, Harms T, Doherty A, Thomas E, Milton K, Kelly P, Foster C (2020) Testing Self-Report Time-Use Diaries against Objective Instruments in Real Time. *Sociological Methodology* 50:318–349
8. Woodberry E, Browne G, Hodges S, Watson P, Kapur N, Woodberry K (2015) The use of a wearable camera improves autobiographical memory in patients with Alzheimer’s disease. *Memory* 23:340–349
9. Silva AR, Pinho MS, Macedo L, Moulin C, Caldeira S, Firmino H (2017) It is not only memory: Effects of sensecam on improving well-being in patients with mild alzheimer disease. *International Psychogeriatrics* 29:741–754
10. Doherty AR, Kelly P, Kerr J, Marshall S, Oliver M, Badland H, Hamilton A, Foster C (2013) Using wearable cameras to categorise type and context of accelerometer-identified episodes of physical activity. *Int J Behav Nutr Phys Act* 10:22
11. Kerr J, Marshall S, Godbole S, Chen J, Legge A, Doherty A, Kelly P, Oliver M, Badland H, Foster C (2013) Using the SenseCam to Improve Classifications of Sedentary Behavior in Free-Living Settings. *AMERICAN JOURNAL OF PREVENTIVE MEDICINE* 44:290–296
12. Willetts M, Hollowell S, Aslett L, Holmes C, Doherty A (2018) Statistical machine learning of sleep and physical activity phenotypes from sensor data in 96,220 UK Biobank participants. *Sci Rep* 8:7961
13. Wilson G, Jones D, Schofield P, Martin DJ (2018) The use of a wearable camera to explore daily functioning of older adults living with persistent pain:

- Methodological reflections and recommendations. *Journal of Rehabilitation and Assistive Technologies Engineering* 5:2055668318765411
14. Doherty AR, Moulin CJA, Smeaton AF (2011) Automatically assisting human memory: A SenseCam browser. *Memory* 19:785–795
 15. Kozey-Keadle S, Libertine A, Lyden K, Staudenmayer J, Freedson PS (2011) Validation of wearable monitors for assessing sedentary behavior. *Med Sci Sports Exerc* 43:1561–1567
 16. Lyden K, Kozey Keadle SL, Staudenmayer JW, Freedson PS (2012) Validity of Two Wearable Monitors to Estimate Breaks from Sedentary Time. *Medicine & Science in Sports & Exercise* 44:2243
 17. Lyden K (2016) *activpalProcessing: Process activPAL Events Files*.
 18. R Core Team (2020) *R: A language and environment for statistical computing*. Vienna, Austria
 19. Bates D, Mächler M, Bolker B, Walker S (2015) Fitting Linear Mixed-Effects Models Using Lme4. *Journal of Statistical Software* 67:1–48
 20. RStudio Team (2020) *RStudio: Integrated development environment for R*. RStudio, PBC, Boston, MA
 21. Ainsworth BE, Haskell WL, Herrmann SD, Meckes N, Bassett DRJ, Tudor-Locke C, Greer JL, Vezina J, Whitt-Glover MC, Leon AS (2011) 2011 Compendium of Physical Activities: A Second Update of Codes and MET Values. *Medicine & Science in Sports & Exercise* 43:1575
 22. McKenzie TL, Sallis JF, Nader PR (1992) SOFIT: System for Observing Fitness Instruction Time. *Journal of Teaching in Physical Education* 11:195–205

4. Validation of Wearable Camera Still-Image Estimates of Physical Activity and Sedentary Behavior against Direct Observation

4.1 Introduction

A key characteristic of physical activity (PA) and sedentary behavior (SB) is the type of activity that is being engaged in, where the frequency and time spent in different types of PA and SB has been associated with health [1–3]. For example, Ahmadi et al. [4] show how small bouts of vigorous walking and running can significantly reduce one's risk of developing cardiovascular disease using UK Biobank data, while Kelly et al. [5] have shown the beneficial effects of cycling and walking through a meta-analysis of 21 studies. For SB, prolonged television viewing has been extensively shown to increase one's risk for all-cause and cause-specific mortality [6, 7] and increased risk of developing non-communicable diseases [8, 9]. Capturing the type of PA and SB being performed is a clearly a key characteristic needed for understanding the impact PA and SB have on health. However, contextualizing PA and SB can be complicated as they are both accumulated throughout the day within multiple environmental settings and for different purposes.

Domains [10, 11] of PA and SB help categorize these daily behaviors by classifying whether the type of activity was performed for accomplishing household duties, occupational tasks, for leisure or for transportation [12]. The domain of PA and SB performed can also help describe the associations of these two behaviors with health. For example, long-term leisure-time PA has been shown to reduce one's risk for all-cause mortality and cardiovascular disease mortality [13], whereas cross-sectional associations of SB have been shown to impact cognitive functioning differently

depending on the domain of SB engagement [14]. Although the domain in which PA and SB occurs in helps provide clarity, some concerns exist because there is a lack of research on PA and SB across multiple domains. Other domains of PA such as household PA have an unclear impact on health outcomes [15] but have been shown to encompass a greater percentage of daily moderate-vigorous PA compared to leisure PA [16]. The same concerns exist for the types of PA and SB being researched, where ambulation (walking, running) is typically assessed [4, 5] instead of behaviors such as resistance-training, cooking, dog-walking and gardening. Television viewing and health has been examined due to the confounding/mediating patterns of this type of SB being different from other types of SB [17–19]. However, the joint or independent associations of screen-based SB and non-screen-based SB are not clear [20, 21]. From the lack of variety in PA and SB domains and types examined, researchers have noted the need for assessing the multitude of PA and SB types across all domains [16, 22–24] to better understand the full associations between PA and SB and health. To capture this data mandates the use of a PA and SB assessment tool able to measure the complex nature of these behaviors in a real-world context.

There are numerous methods available to assess PA and SB, with other review papers dedicated to this topic [25]. Of late, there has been a growing interest in the use of wearable cameras (WCs) as this is a tool able to capture the rich contextual information of the wearer's immediate environment through first-person media. The media from WCs can be annotated to describe the wearer's activity, their posture, and their immediate environment. These annotations are then used to determine the frequency and duration of engagement within different types and domains of PA and

SB. Wearable camera data has been used for capturing ground-truth labels of PA and SB types and domains for the development of machine learning models [26, 27], to validate self-report measurement tools [28] and to contextualize wearable monitor-defined episodes of activity [29, 30]. Despite the growing use of annotated WC media for ground-truth labels, escalating the field of PA and SB domain and activity type research, very little research has been done in validating WC-derived PA and SB measures. Therefore, the purpose of this study is to determine the criterion validity of WC still-images (IMGs) for PA and SB assessment in comparison to video-recorded direct observation (DO). Specifically, our aims and hypotheses are:

- Determine the criterion validity of WC IMGs to capture the frequency of engagement in household, leisure, occupation and transportation domains of PA and SB, as well as the frequency of engaging in sitting, standing and movement. We hypothesize that WC IMGs will have sensitivity, specificity, precision and F1 scores above 0.800 across all PA and SB domains and for sitting when compared to video-recorded DO.
- Determine the criterion validity of WC IMGs to capture the duration of time spent in household, leisure, occupation and transportation domains of PA and SB, as well as the duration of time spent in sitting, standing and movement. We hypothesize that WC IMGs will be statistically equivalent to DO for determining the average time spent within each PA and SB domain, as well as for sitting when compared to video-recorded DO.

4.2 Methods

4.2.1 Participants

Eligible participants were recruited through research contact lists, web advertisements, phone calls and word of mouth. Participants were required to be ≥ 18 years of age, have the ability to walk 50 feet unassisted and have no cardiorespiratory, neurological, or musculoskeletal diseases or conditions that would affect their physical movement. The study was explained to participants at an initial laboratory visit where enrolled participants signed an informed consent document guided by an ethical framework for WC use in health-related research [31]. The study was approved by the University of Wisconsin-Milwaukee Institutional Review Board (Protocol Number 17.127).

4.2.2 Study Procedure

During the initial laboratory visit, demographic and anthropometric information was gathered. Afterwards, participants were scheduled for three 2-hour visits within a free-living setting of their choosing, such as their place of residence, a shopping center, or other public places. During each of these 2-hour visits, participants were fitted with a WC and were video-recorded while they engaged in their normal everyday activities. Participants were encouraged to engage in different activities of daily living for each visit such that multiple domains and types of PA and SB could be observed.

4.2.3 Measures and Instrumentation

4.2.3.1 Demographics and Anthropometrics

During the initial laboratory visit self-reported age, gender and ethnicity information was collected. Height was measured using a 3PHTROD-WM stadiometer

(DETECTO, Webb City, MO) and weight was measured with a calibrated Model 439 weight beam physician's scale (DETECTO, Webb City, MO).

4.2.3.2 Direct Observation Videos

Direct observation videos were recorded using the front-facing camera of a Surface Pro 4 (Microsoft, Redmond, WA) using Open Broadcaster Software Studio v19.0.3. Snaz (v1.12.6.0) software was used to timestamp the internal clock of the Surface Pro 4 onto the video. Videos were recorded in the .flv format, which were then converted into the MP4 format for upload into annotation software. Research assistants placed the Surface Pro 4 within a chest harness to maintain video stability during video recordings. During free-living visits, research assistants were trained to unobtrusively record the participant approximately 6-10ft away and to capture the entire front body of the participant within the video frame whenever possible. In situations where this was not possible, research assistants were instructed to prioritize capturing at least the front torso and upper extremities of the participant during instances of low movement (i.e. cooking within a kitchen) and at least the lower extremities during instances of high movement (i.e. walking upstairs to apartment).

Videos were downloaded and then uploaded into the Observer XT 14 (Noldus Information Technology Inc.; Wageningen, Netherlands) software to be annotated by research assistants. Annotators were trained for 30-45 hours across a 2-3 week-period where they learned the annotation platform used for this study, consisting of the annotation protocol and operational definitions for codes within two annotation schemas. One schema was termed the "behavior" schema where types of PA and SB engaged by the participant and environment were annotated. The other was a "posture" schema focused on describing participant body position, and whole-body movement

patterns. To ensure a high inter-rater reliability, annotators needed to achieve a kappa score ≥ 0.90 compared to an experienced annotator on training videos to pass the training phase. Periodic quality checks were also implemented where annotators had to achieve a kappa ≥ 0.90 on a 10-minute video to be considered in “good standing”. If an annotator failed to achieve this score for a quality check, a review session lead by an experienced coder was conducted to cover areas for improvement, where annotators then had to achieve a kappa ≥ 0.90 on an additional 10-minute video specific to the coding procedures or operational definitions covered in the review session. Finally, all annotated data from DO videos were also spot checked by an experienced annotator to ensure annotations were applied in a manner consistent with the annotation protocol and correct annotation codes were used.

More information on the exact annotation procedure and operational definitions for codes used within the DO video annotation platform is listed elsewhere [32]. Briefly, the annotation codes for the behavior schema were developed to describe activity PA and SB type with environment as a separate modifier code while the posture schema annotation codes were split into two categories of annotation codes: one for describing whole-body movement and one for describing their body position during no whole-body movement. The annotation platform used within this study followed a “threshold” approach, such that the participant had to fulfill the operational definition for a behavior or posture annotation code for a certain length of time before the annotator could apply the annotation code to the video. In this study, Behavior schema annotation codes all followed a threshold of 5 seconds. If a behavior occurred for less than 5 seconds, the previous annotation code would be “rolled” forward. This would continue until the

participant fulfilled the operational definition for an annotation code for 5 seconds or more. Within the Posture schema, annotation codes within the posture category had a threshold of 1 second as between posture transitions typically occur in a second or less, while annotation codes describing ambulatory movement had a threshold of 5 seconds as to capture distinct and intentional whole-body movement patterns.

4.2.3.3 Wearable Camera Still-Images

The Autographer® (OMG Life, Oxford, England) WC was placed on participants with a lanyard that went around their neck and positioned at the xyphoid process. A strip of Velcro was placed on the backside of the Autographer WCs to attach the WCs to a chest belt strap for stability. The Autographer uses input from many built-in sensors for detecting color-shift, infrared, temperature, directional changes, and motion to determine image capture rate. The high-capture rate setting was enabled, resulting in IMGs being captured every 5-10 seconds.

For annotation, the Oxford Image Browser (OIB) software [33] was used for WC IMG sets. Similar to DO video annotator training, IMG annotators different from the DO video annotators were trained for 30-45 hours across a 2-3 week-period on the IMG annotation platform which also consisted of “behavior” and “posture” schemas. IMG annotators followed the same procedure for passing the training phase as video annotators and were also given periodic quality checks with review sessions if warranted.

Within the behavior schema, IMG annotation codes were directly derived from the 2011 Compendium of Physical Activities [33]. As Compendium of Physical Activities codes varied in describing behavior type only (i.e. 05043: *vacuuming, general, moderate effort*) to describing behavior type with assumed behavioral intent (i.e. 11129:

custodial work - vacuuming, moderate effort) between compendium categories, behavior schema annotation codes were split into three categories of Domestic, Non-Domestic and Independent. Domestic annotation codes represented codes under the compendium categories of Home Activities (05), Home Repair (06), Lawn & Garden (08) and Self Care (13), which typically described behavior type only. Non-Domestic annotation codes represented codes under the compendium categories of Occupation (11), Religious Activities (20), Volunteer Activities (21), shopping codes under the Home Activities (05) compendium category and some of the Miscellaneous (09) codes. Independent annotation codes matched codes within all other compendium categories. Domestic annotation codes could only be applied if the participant was deemed to be at their residence while Non-Domestic annotation codes could only be applied if the participant was not at their place of residence. Independent annotation codes could be applied regardless of environmental setting. **Appendix F** lists the annotation codes used within the behavior schema.

The posture schema used three annotation codes of sitting, standing and movement [35]. Briefly, the operational definitions for annotation codes within the Behavior schema revolve around objects of interaction and visual engagement. Depending on 1) the object the participant is physically or visually engaged with, and 2) how the participant physically manipulates the object through space. Operational definitions within the Posture schema utilize the concept of “point of reference”, how proximal the participant is to this point of reference, and the vertical and horizontal orientation of the point of reference in relation to the WC. Different combinations of

proximity and changes in orientation relative to the point of reference informed annotators on what posture annotation code to apply.

4.2.4 Data Processing

Annotations from the DO videos and WC IMGs were time-matched by showing a stopwatch time-synced with the clock of the Surface Pro 4 to the Autographer. The difference between the stopwatch time and IMG timestamp was then factored into the WC IMG annotations.

The annotation protocol and codes used within the IMG annotation platform differs from the DO video annotation platform due to the constraint of the OIB not allowing modifier annotation codes, while the operational definitions for annotation codes were similar. Behavior and posture schema annotations were collapsed into broader domains for equal comparison (**Table 4.1**). For the behavior schema, annotation codes were collapsed into domains of Household, Leisure, Occupation and Transportation (behavior domains) while DO posture schema annotations were collapsed into Sit, Stand and Movement (posture domains). The behavior domains are representative of World Health Organization domains of PA and SB [36], which are meant to be categories for discriminating the intent of performing different types of PA and SB typically seen throughout daily life. Types of PA and SB without intent for engagement (i.e. not factoring environment for DO video and only Domestic and Independent WC IMG annotation codes) were also directly compared between WC IMG annotations and DO video annotations.

4.2.5 Statistical Analysis

Descriptive statistics of participant age, sex, body mass index (BMI; weight

Table 4.1: Behavior and posture schema domains used for analysis.

Schema	Domain	Activities	
Behavior	Household	<ul style="list-style-type: none">• Caring/Grooming• Cleaning• Cooking• Grocery Shopping• Laundry• Lawn & Garden	
	Leisure	<ul style="list-style-type: none">• Electronics• Sport & Exercise	
	Occupation	<ul style="list-style-type: none">• Household activities but in a non-domestic environment	
	Transportation	<ul style="list-style-type: none">• Driving Automobile• Riding Automobile• Riding Public Transportation	
Posture	Sit	<ul style="list-style-type: none">• Crouching• Lying• Reclining• Sitting	
	Stand	<ul style="list-style-type: none">• Standing	
	Movement	<ul style="list-style-type: none">• Cycling• Walking• Running• Ascending/Descending Stairs	

(kg)/height² (m)), race/ethnicity are provided. The average duration of study visits is also provided, along with median and range of visit duration. As the capture rate for the Autographer WC is variable, the mean capture rate is calculated. A boxplot showing the distribution of Behavior Domains and Posture Domains within the data is also provided.

To determine if Autographer WC IMGs can capture the frequency of Behavior Domains and Posture Domains, confusion matrices are shown for each domain, along with classification metrics of overall accuracy and sensitivity, specificity, precision and F1 scores for each domain. Sensitivity is the ability of the WC IMGs to capture all the true positives for a given domain relative to all DO video-measured positives. Specificity is the ability of the WC IMGs to capture all the true negatives for a given domain relative to DO video-measured negatives. Precision is the ability of the WC IMGs to capture true positives for a given domain relative to all WC IMG-measured positives, which is also known as the Positive Predictive Value. F1 scores are the harmonic mean of sensitivity and precision, which takes into account the distribution of true positives, true negatives, false positives and false negatives.

To determine if Autographer WC IMGs can capture time spent within behavior domains and posture domains, equivalence testing using the confidence interval method [37] with an equivalence region that is $\pm 15\%$ of the DO video mean for a domain is performed. The null hypothesis of equivalency testing is the mean difference of IMG-derived minutes minus video-derived minutes for a domain is $\geq 15\%$ of the DO video mean or $\leq -15\%$ of the DO video mean. The null hypothesis is rejected at α if the $100(1 - 2\alpha)\%$ confidence interval (CI) for the mean difference is entirely within the $\pm 15\%$ equivalence region. Therefore, in using level $\alpha=5\%$, we reject the null hypothesis

of nonequivalence if the 90% CI is entirely within the $\pm 15\%$ equivalence region. As there were multiple visits per person, a linear mixed effects model is used to calculate mean difference and 90% CI's, treating each participant as a random effect.

Independent of PA and SB domains, classification metrics and equivalence testing results are also presented for PA and SB types.

For all statistical analyses, the DO video annotations are treated as the criterion measure. For behavior domain and behavior type analyses, data annotated as no behavior (i.e. only engaging in a posture or movement pattern or interacting with objects in a non-meaningful way), or unable to be annotated due to video/image obstruction of object interaction or visual engagement were removed. For posture domain analyses, data unable to be annotated due to video obstruction of the participant's lower extremities or torso (preventing accurate assessment of posture or movement pattern) or image blur/obstruction that prevent any points of references or a changing environment to be established were removed. Total minutes removed for analyses is presented. The R programming language (R version 4.3.1 (2023-06-16 ucrt)) and Rstudio integrated development environment (2023.06.0+421) was used for statistical analyses. The nlme package (version 3.1.162) was used to calculate mean difference and 90% CIs for equivalence tests.

4.3 Results

Table 4.2 lists participant descriptives as well as visit descriptives. Video and IMG data from 51 participants across 135 visits were collected. 15,627.4 minutes of data were collected from free-living visits, with an average visit duration of 115.8 ± 10.3 minutes. The IMG capture rate for the Autographer WC was on average 8.6 ± 6.4

Table 4.2: Participant and visit descriptives.

Characteristic	Value
N	51
Age, mean (SD)	
mean (SD)	50 (26)
median (IQR)	61 (24, 75)
range	18, 88
Weight (kg), mean (SD)	76 (13)
Height (m), mean (SD)	1.71 (0.09)
BMI (kg/m²), mean (SD)	
mean (SD)	25.8 (3.9)
median (IQR)	25.3 (23.0, 28.0)
range	17.8, 35.0
Gender, n (%)	
Woman	21 (41%)
Man	30 (59%)
Race, n (%)	
White	43 (84%)
Black or African American	1 (2.0%)
Asian	3 (5.9%)
Other	4 (7.8%)
Hispanic, n (%)	
Non-Hispanic	44 (86%)
Hispanic or Latino	7 (14%)
Visits	
n	135
Total Duration (minutes)	15,627
Duration, mean (SD) (minutes)	116 (10)
Duration, median (IQR) (minutes)	120 (118, 120)
Duration, range (minutes)	74, 132

seconds. **Figure 4.1** shows the distribution of each domain across all visits from DO video data. On average, 30.1 (37%), 35.8 (43%), 10.5 (11%) and 7.25 (8%) minutes of DO video data was Household, Leisure, Occupation and Transportation, respectively. For posture domains, 47.7 (44%), 39.8 (37%) and 21.5 (20%) minutes of DO video data were Sit, Stand and Movement, respectively. 4414.3, 909.6 and 6544.5 minutes of data were removed for behavior domain, posture domain and behavior type analyses, respectively.

Table 4.3 and **Table 4.4** list the confusion matrices between the DO video and WC IMG annotations for behavior and posture domains, respectively. Out of 11,213.0 total minutes across all behavior domains, WC IMGs had an accuracy of 89%. Sensitivity scores were above 0.860 except within the Occupation domain (0.676), specificity scores were above 0.900, and F1 scores were above 0.800 for WC IMG annotations. The lowest precision score was seen in the Leisure domain (0.876) and the lowest F1 score was seen in the Occupation domain (0.801). For posture domains, WC IMGs had an overall accuracy of 89% over the 14,717.8 total valid minutes recorded. Sensitivity was the lowest for Stand (0.786) while Sit and Movement have sensitivity scores of 0.963 and 0.915, respectively. Specificity for all posture domains was above 0.900. WC IMG Movement had the lowest F1 score (0.796), while Sit and Stand had F1 scores of 0.967 and 0.850, respectively.

Figure 4.2 is the mean percent difference of WC IMG estimates minus DO video for each behavior and posture domain across all visits, with 90% CIs from using $\alpha = 5\%$ equivalence tests. For the behavior domains, the mean difference and 90% CI's was 2.1 (0.9, 3.3) minutes for Household, 0.5 (-2.3, 1.4) for Leisure, -4.2 (-7.6, -0.8) for

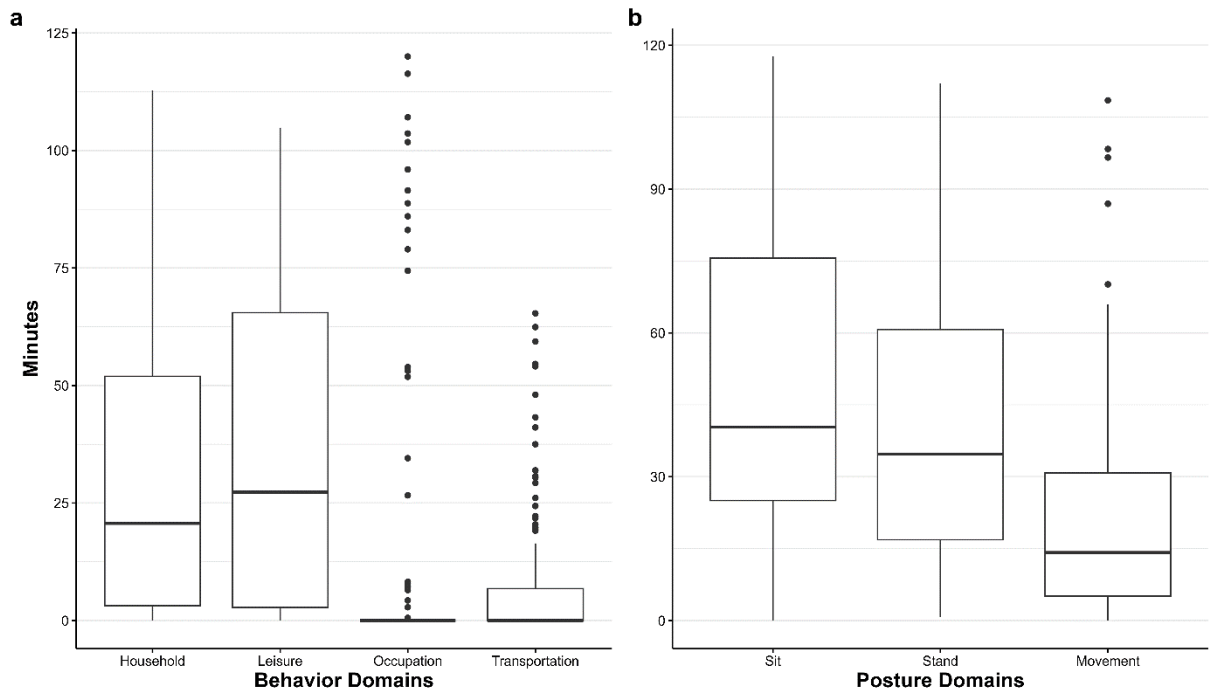


Figure 4.1: Boxplots showing the distribution of direct observation video minutes in each domain across all visits.

¹Average visit duration for valid behavior domain minutes was 83.7 minutes.

²Average visit duration for valid posture domain minutes was 109.0 minutes.

Table 4.3: Confusion matrix of behavior domains between direct observation video and wearable camera still-images.

		Image				Total (minutes)
		Household	Leisure	Occupation	Transportation	
Video	Household	3,821.8 (95%)	170.7 (4%)	11.9 (0%)	24.4 (1%)	4,028.8 (36%)
	Leisure	354.1 (7%)	4,416.1 (92%)	0.4 (0%)	29.8 (1%)	4,800.4 (43%)
	Occupation	101.6 (7%)	340.3 (24%)	954.6 (68%)	15.6 (1%)	1,412.1 (13%)
	Transportation	17.3 (2%)	114.2 (12%)	4.0 (0%)	836.2 (86%)	971.7 (9%)
	Total (minutes)	4,294.8 (38%)	5,041.3 (45%)	970.9 (9%)	906.0 (8%)	11,213.0 (100%)
Accuracy						89%
Sensitivity		0.949	0.920	0.676	0.861	
Specificity		0.934	0.903	0.998	0.993	
Precision		0.890	0.876	0.983	0.923	
F1		0.918	0.897	0.801	0.891	

Table 4.4: Confusion matrix of posture domains between direct observation video and wearable camera still-images.

		Image			Total (minutes)
		Sit	Stand	Movement	
Video	Sit	6,204.8 (96%)	133.6 (2%)	107.6 (2%)	6,446.0 (44%)
	Stand	142.3 (3%)	4,221.6 (79%)	1,004.6 (19%)	5,368.5 (36%)
	Movement	35.0 (1%)	213.1 (7%)	2,655.2 (91%)	2,903.3 (20%)
	Total (minutes)	6,382.1 (43%)	4,568.3 (31%)	3,767.4 (26%)	14,717.8 (100%)
Accuracy					89%
Sensitivity		0.963	0.786	0.915	
Specificity		0.979	0.963	0.906	
Precision		0.972	0.924	0.705	
F1		0.967	0.850	0.796	

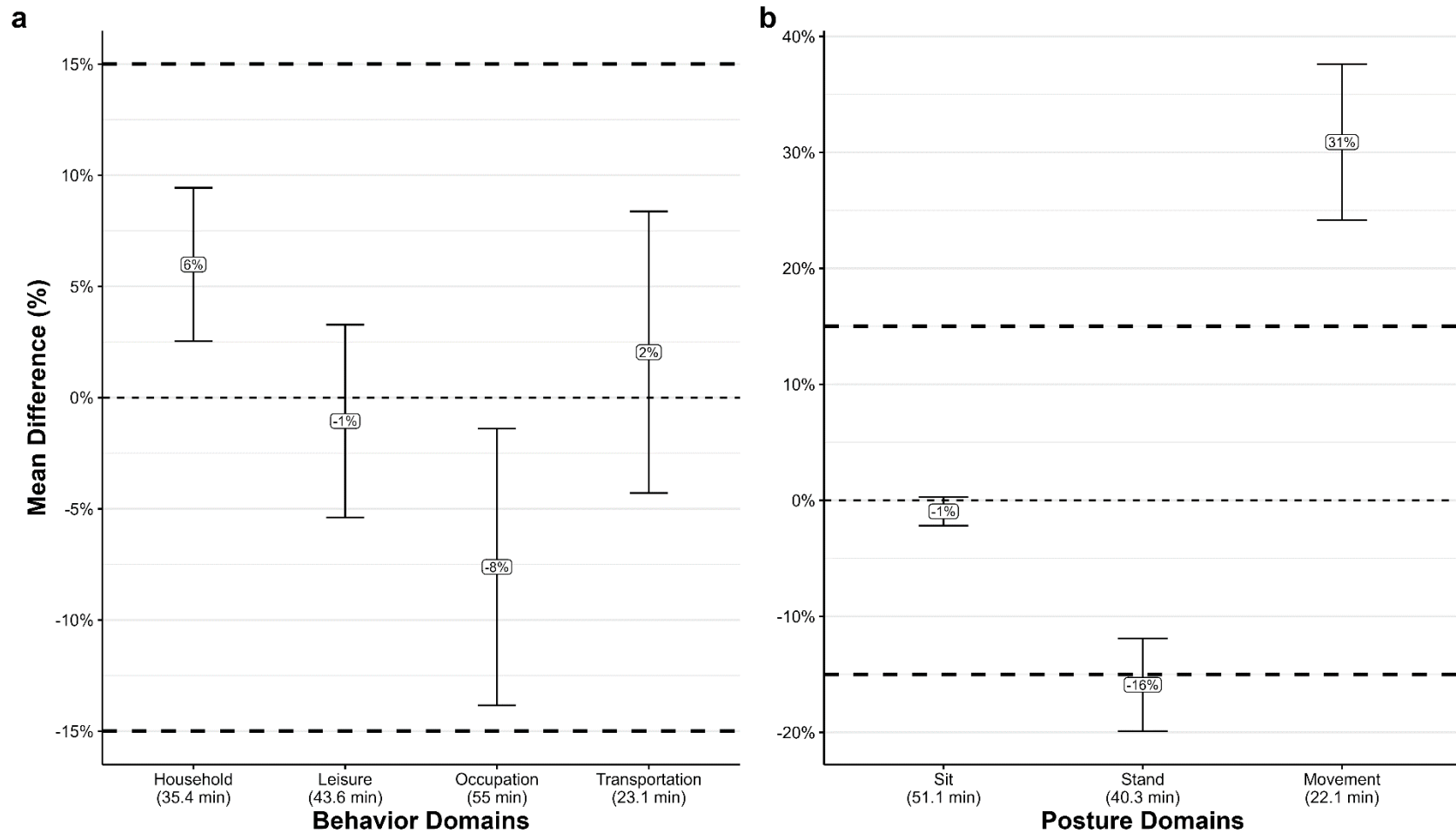


Figure 4.2: Mean percent difference of wearable camera still-image estimates minus direct observation video for each behavior and posture domain using a $\pm 15\%$ equivalence region.

¹Percentages are relative to mean direct observation video measured minutes, listed below each domain in parenthesis.

²The null hypothesis of nonequivalence is rejected at $\alpha = 5\%$ if the 90% [100(1 - 2 α)%] confidence interval for the mean percent difference is entirely within the equivalence region.

Occupation and 0.5 (-1, 1.9) for Transportation with all 90% CI's contained within $\pm 15\%$ of mean DO video minutes. Across the posture domains the mean difference and 90% CI's was -0.5 (-1.1, 0.1) for Sit, -6.4 (-8, -4.8) for Stand and 6.8 (5.4, 8.3) for Movement with only the Sit 90% CI entirely within $\pm 15\%$ of mean DO video minutes. **Figure 4.3** shows the mean percent difference and 90% CIs of WC IMG estimates minus DO video for posture domains stratified by each behavior domain. For all behavior domains, the mean WC IMG difference for Sit was between -1.1 and 0.4 minutes, with all 90% CI's within $\pm 15\%$ of mean video minutes. The mean IMGs difference for Stand varied among behavior domains, with mean WC IMG Stand equivalent to DO video only within the Household behavior domain (mean difference of -1.6 minutes, (-2.3, -1.0) 90% CI) and mean WC IMG Movement equivalent to DO video within the Leisure (mean difference of -1.1 minutes, (0.5, 1.8) 90% CI) and Transportation (mean difference of 0.5 minutes, (0.2, 0.8) 90% CI) behavior domains.

Finally, **Table 4.5** shows the classification metrics and equivalence testing results by 13 different PA and SB types independent of domain. The overall accuracy of WC IMGs to the 13 activity types was 92%. Caring or grooming for animals was the activity with the lowest amount of data, being only seen for 89.9 minutes. Caring or grooming for oneself had the lowest sensitivity (0.480) and F1 score (0.636). Other than caring or grooming for oneself, sensitivity scores were greater than 0.720 across all behaviors, and F1 scores ranged from 0.804 to 0.993. Using $\alpha=5\%$ and $\pm 15\%$ equivalence testing, WC IMG annotations for 10 behaviors are shown to be equivalent to DO video annotations. Caring or grooming an animal, caring or grooming oneself and eating were not statistically equivalent to DO video.

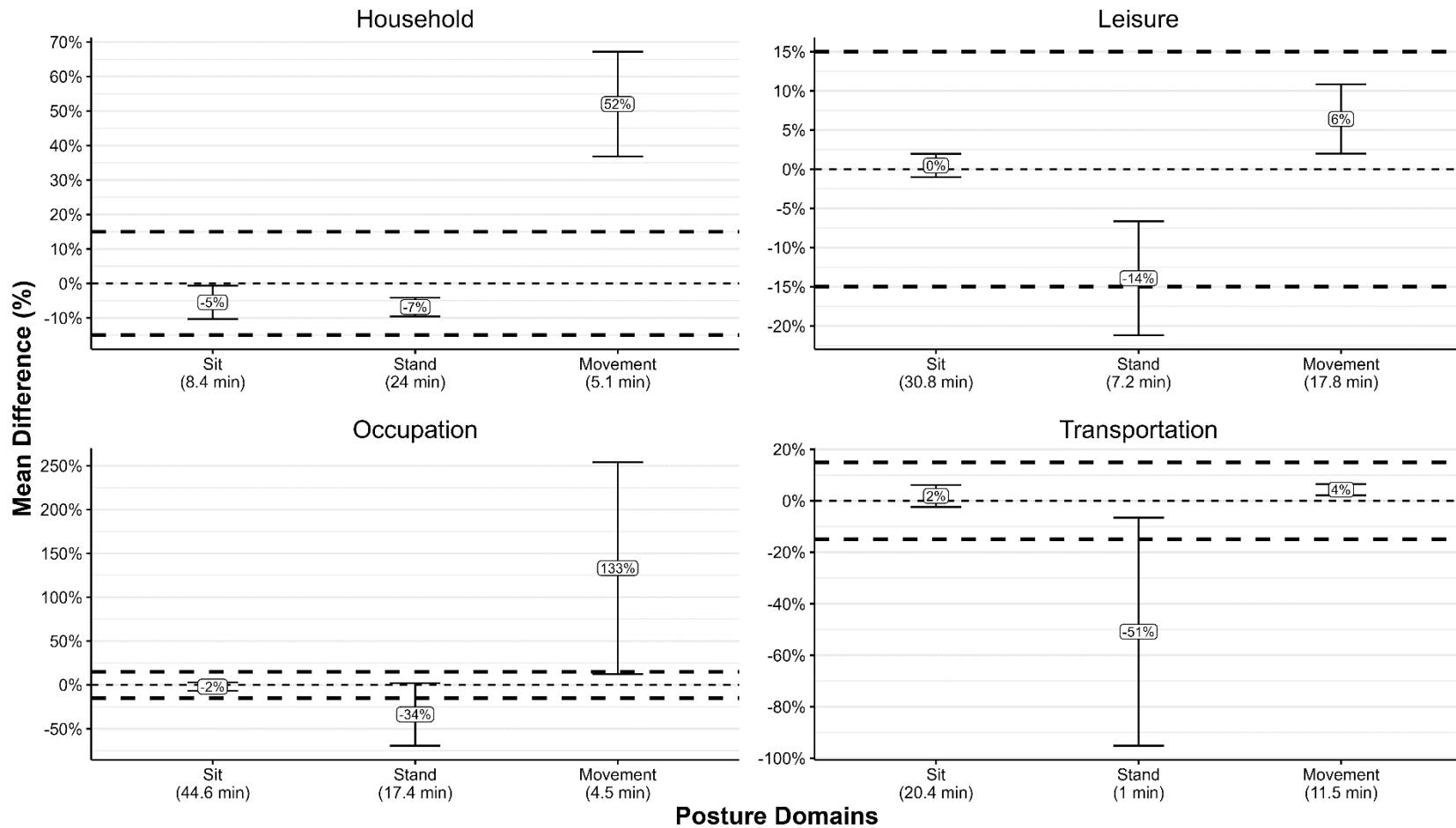


Figure 4.3: Mean percent difference of wearable camera still-image estimates minus direct observation video for each posture domain stratified by behavior domain using a $\pm 15\%$ equivalence region.

¹Percentages are relative to mean direct observation video measured minutes, listed below each posture domain in parenthesis.

²The null hypothesis of nonequivalence is rejected at $\alpha = 5\%$ if the 90% [100(1 - 2 α)%] confidence interval for the mean percent difference is entirely within the equivalence region.

Table 4.5: Classification and equivalence testing results for wearable camera still-image annotations by activity type.

Behavior	Classification Metrics				Equivalence					
	Total ^a (Min)	Sensitivity	Specificity	Precision	F1	IMG ^b Mean (min)	Video ^c Mean (min)	Bias ^d	90% CI	Reject Null ^e
Ambulatory Travel	444.8	0.722	0.996	0.906	0.804	13.0	13.2	-1.1%	(-14.8%, 12.6%)	Yes
Caring (Animal)	89.9	0.838	0.998	0.798	0.818	5.2	4.7	12.2%	(-19.7%, 44.1%)	No
Caring (Self)	117.3	0.480	1.000	0.944	0.636	2.2	2.6	14.9%	(-22.0%, -7.8%)	No
Cleaning	1,047.8	0.924	0.988	0.907	0.915	19.4	18.9	2.9%	(-1.0%, 6.9%)	Yes
Cooking	609.7	0.955	0.994	0.919	0.937	16.6	16.0	3.8%	(-0.3%, 8.0%)	Yes
Eating	234.0	0.786	0.998	0.906	0.842	6.3	6.8	-6.9%	(-19.8%, 6.0%)	No
Electronics	1,762.9	0.971	0.984	0.938	0.954	21.2	20.4	3.7%	(1.0%, 6.4%)	Yes
Laundry	304.4	0.983	0.999	0.962	0.972	10.0	9.7	3.6%	(-1.9%, 9.1%)	Yes
Lawn/Garden	721.4	0.923	0.993	0.914	0.919	36.4	33.5	8.9%	(3.0%, 14.7%)	Yes
Maintenance	555.7	0.810	0.997	0.940	0.870	31.9	30.6	4.3%	(-2.0%, 10.5%)	Yes
Other Leisure	965.5	0.938	0.987	0.899	0.918	17.9	17.3	1.0%	(-8.4%, 10.4%)	Yes
Sports/Exercise	1,705.5	0.968	0.980	0.917	0.942	34.5	33.5	3.3%	(0.2%, 6.3%)	Yes
Vehicle Travel	516.7	0.990	1.000	0.997	0.993	22.3	22.5	-0.7%	(-1.3%, 0.0%)	Yes

^aFrom direct observation video.

^bWearable camera still-image.

^cDirect observation video.

^dMean percent difference of IMG estimates minus video.

^eReject null hypothesis of non-equivalence using an $\alpha=5\%$ level.

4.4 Discussion

To our knowledge, this is the first study within the PA and SB literature focused on establishing the criterion validity of WC IMGs to capture the frequency and duration of PA and SB in healthy adults. The results from this study show WC IMGs are accurate and precise for capturing the frequency of Household, Leisure and Transportation behavior domains, posture domains of sedentary posture, and for 10 types of activity when compared to DO video. WC IMGs are also equivalent to DO video for capturing the average duration within all PA and SB domains, sedentary posture and 10 types of activity.

In examining the capability of WC IMG annotations to capture PA and SB frequency from WC IMGs, we found that WC IMG annotations are able to capture 95%, 92%, and 86% of all Household, Leisure and Transportation behavior as classified by DO video, respectively. Given that the sensitivity, specificity, precision and F1 score for these domains were greater than 0.800, we consider WC IMG annotations to be a suitable criterion for measuring the frequency of these behavior domains. Within the Occupation domain, WC IMG annotations captured only 68% of DO video estimates, with sensitivity, specificity, and F1 scores of 0.676, 0.998 and 0.801 respectively and a high precision score of 0.983. Wearable camera IMGs are able to be used for capturing the frequency of household, leisure and transportation activity in studies requiring exact measures, such as in randomized control trials. Given the high precision for all behavior domains, WC IMG estimates can be used to provide descriptives of PA and SB domain engagement.

We note that 24% of DO video-classified Occupation was erroneously annotated as Leisure by WC IMG annotations, which is the biggest misclassification from the WC IMG annotations within the behavior domains. This may be due to the subjectivity of attempting to discern a participant's intent for engaging with electronics in a non-domestic setting from WC IMGs, and not being able to separate environment and behavior within the Oxford Image Browser annotation codes. For example, we observed some participants using desktop computers in a cafe-like setting, where the WC IMGs were annotated only as "electronics". The corresponding DO video annotations also stated "electronics" but were annotated to be within an occupational environment as these participants were within the cafe area of their occupational setting where they continued to work on their laptop. Other instances where this misclassification occurred was when visits would start and end within a library, where it would be unknown from WC IMGs if the library was on a university campus, which would be annotated as an occupational environment from DO video, or if it was a public library, which would be annotated as a social/leisure environment from DO video. In such cases, the actual behavior of electronics was annotated correctly by the WC IMG annotations. However, without being able to annotate for the intent for behavior engagement in non-domestic settings, which is necessary to determine PA and SB domain type, the WC IMG annotation codes that describe behavior and intent together will understandably fail. As determining behavioral intent is of importance relating domain-specific PA and SB with health [15, 24, 38–41] and for PA and SB interventions [10, 11], separating behavioral intent from behavior type annotation codes may be more beneficial for accurately

capturing the frequency and duration of specific types of PA and SB *and* domains of PA and SB.

The underestimation of standing and overestimation of movement as seen in **Table 4.4** and **Figure 4.2** is likely due to the differences in WC IMG and DO video annotation procedures. For the posture domains, it was in the DO video annotation protocol for movement annotation codes to have a threshold ≥ 5 seconds and to roll the previous code until the threshold was met for a new posture or movement code. This procedure is likely to have movement bouts that occurred over a large distance < 5 seconds be classified as movement by WC IMGs but be classified as standing by the DO video. This is evident by examining the posture domain equivalence test results stratified by behavior domains in **Figure 4.3**. We can still see that DO video Stand is consistently underestimated while DO video Movement is overestimated across behavior domains by WC IMGs, consistent with non-stratified results. However, within the Household domain, Stand estimated by WC IMGs is statistically equivalent to DO video and Movement estimated by WC IMGs in the Leisure and Transportation domains is statistically equivalent to DO video. This is likely due to the longer duration bouts of “pure” standing that typically occurs for behaviors included within the Household domain and longer duration bouts of “pure” movement in the Leisure and Transportation domains. For example, behavior types typically seen in the Household domain, such as cooking, and laundry, will typically involve individuals to stay standing within the same room for long durations, with small steps taken around a central location. From the perspective of WC IMGs, the immediate environment will appear to be the same between IMGs. Annotators will therefore be more likely to place a Stand annotation

code. For Leisure and Transportation behaviors, such as Exercise and Ambulatory Travel, the opposite is true where these behaviors are typically done in long duration movement bouts. The immediate environment will constantly appear to be changing between WC IMGs, making it clear that Movement is occurring.

Within the Occupation domain, both WC IMG Stand and Movement annotations were not equivalent to DO video annotations. Although the WC annotation platform did not include annotation codes for specific environmental characteristics, such as whether the participant was indoors/outdoors and the type of building/room the participant was in when they were indoors, we observed from this dataset that point of references were difficult to ascertain in indoor occupational environments. In office settings, it is common for the indoor architecture to be all the same color or repetitive across rooms. For example, when annotating the WC IMGs from a participant who performed custodial duties in a community-based building, IMGs were annotated as Movement when the participant was cleaning restrooms. As there were many bathroom stalls and wash basins in each restroom the participant cleaned, the participant would be seen to be “purely” standing when cleaning a toilet or wash basin but slight differentiations between IMGs, with no points of reference, led to these IMGs being annotated as Movement.

Within the PA and SB measurement field there are no established guidelines for choosing an equivalence region when conducting equivalence tests. This is understandable and perhaps necessary as what is considered to be of clinical or practical importance will vary depending on the purpose for using the PA & SB measurement tool. Therefore, we scaled the equivalence plots to be a percentage of the DO video mean, allowing researchers to determine if the use of WC IMGs is suitable for

their study aims if they were to use a larger or smaller equivalence region. In **Appendix G**, we also provide 95% and 99% CI's for the WC IMG mean difference across all domains for researchers who require a lower type I error rate. For example, if we were to interpret the equivalence testing using 99% CI's and a $\pm 15\%$ equivalence region, we see that WC IMGs remain equivalent to DO videos within the Household, Leisure and Sit domains. We also provide 95% and 99% CIs for the mean WC IMG posture domain difference stratified by behavior domain (**Appendix H**).

Within the scientific literature, there has been little validation work of WC IMGs to estimate the frequency and duration of PA and SB. Preliminary work from our team used the activPAL (AP) accelerometer to determine the convergent validity of WC IMG posture annotations of sit, stand and movement [35]. Within that study, which used the same posture annotation schema as this study, WC IMGs had percent mean differences of 2%, -17% and 27% off of 37.9, 38.3, and 22.3 minutes of AP-derived sit, stand and move, respectively. The direction of percent mean differences within this study is similar for Stand and Movement, where percent mean differences were -16% and 31% off of 40.3 and 22.1 DO video-derived minutes, respectively. However, within this preliminary work, gaps in time between applied WC IMG annotations were removed from analysis. For studies utilizing the OIB software for WC IMG annotation, there has been no statement on the data processing procedure for filling in these gaps between applied annotation codes. Given that gaps made up approximately 11% of study data in [35] using a WC with a capture rate of 8.47 seconds, studies using the OIB software and a lower capture rate of 30 seconds or above should perform sensitivity analyses to

see if main study findings differ based on the data processing procedure for gaps between OIB annotations.

In-person DO has been used to assess the criterion validity of travel journeys from the SenseCam WC and in a small sample of older adults. In Kelly 2013 [42], 20 simulated free-living travel journeys were performed by two individuals, where they walked, cycled, drove and were a car passenger. The mode of transport from the SenseCam IMGs agreed perfectly with DO, and mean difference in duration for the journeys were < 0.1 minutes across multiple annotators. In the current study, 99% of 516.7 Vehicle Travel minutes were correctly classified by the WC IMGs, with an F1 score of 0.993. The mean percent difference and 90% CI of WC IMG Vehicle Travel was -1% (-1%, 0%) out of the average 22.5 minutes seen from DO video annotations. These results support the preliminary conclusions on Vehicle Travel within Kelly 2013 [42]. However, WC IMG annotations only classified 72% of 444.8 Ambulatory Travel correctly, with an F1 score of 0.804 and mean percent difference and 90% CI of -1% (-15%, 13%) out of DO video estimated average of 13.2 minutes. The reason for the lower accuracy, precision and nonequivalence for Ambulatory Travel from WC IMGs is related to determining behavioral intent from WC IMGs. In the current study, 24% of Ambulatory Travel was misclassified as Sport/Exercise, where the specific WC IMG behavior annotation code was outdoor movement assumed to be for exercise. When annotating the WC IMGs, annotators are instructed to assume the participant's behavioral intent for the outdoor movement journey is for exercise if they return to the start of their outdoor movement journey without attending any specific environment. In a sample size of 5 older adults for one 3-hour free-living visit, Miller et al. [43] used video-

recorded DO to determine if WC IMGs could identify posture (sedentary, standing, movement), behavior categories (sedentary, walking, household, exercise/sport) and behavior type (laundry, dishes, cooking, general, cleaning). The overall accuracy for behavior categories, posture and behavior type were 95%, 93% and 100%, respectively whereas in this study, for behavior domains, posture domains, and behavior type, the overall accuracy was 89%, 89% and 92%, respectively. Aside from the limitations in sample size and unknown WC features such as model and capture rate in Miller and colleagues work [43], it is likely that the use of WCs to measure the dimensions of PA and SB in an older adult population will be more accurate as opposed to a younger adult population assuming there is less variability in PA and SB types performed in the older adult population. Confirmation of WC IMG annotation to provide valid dimensions and domains of PA and SB in an older adult population is needed to extend current findings on when older adults break from prolonged SB and the type of PA that follows SB disruption [44, 45].

There are a few important points to consider when interpreting the results of this study. First, we used two different annotation platforms for annotating the DO video and WC IMGs due to limitations in WC IMG annotation software, limiting the comparability of some activity types between these two measures. For example, the Non-Domestic annotation codes within the WC IMG annotation platform capture both activity type and behavioral intent in one annotation code, which did not allow for a one-to-one comparison to DO video behavior annotation codes which capture activity type alone with behavioral intent captured separately through modifier codes. Still, in approximately 151 hours of data, we show WC IMG annotations can accurately capture the frequency

and duration of 10 different activity types. Second, the design of the DO video annotation protocol to roll forward standing for movement bouts < 5 seconds does not provide a true ground-truth measure of Standing and Movement. However, we were able to address this limitation by stratifying the stand and movement equivalence tests by PA and SB domains, showing WC IMG annotations can capture longer durations of “pure” standing and movement. Third, Occupation and Transportation behavior domains were not seen in every visit, leading to low mean WC IMG and DO video estimates. This is due to participants being asked to perform their usual activities of daily living between study visits, which is a strength of the study design that allows us to extrapolate our results to free-living PA and SB.

4.5 Conclusion

In this study we aimed to establish the criterion validity of WC IMGs to capture the frequency and duration of PA and SB. In comparison to video-recorded DO, we established WC IMGs were able to capture frequency and duration of PA and SB domains, as well as capture sedentary postures regardless of PA and SB engagement. For standing and movement, they are conditionally equivalent to DO video depending on the type of PA and SB behavior domain of interest (i.e. Household standing will be equivalent to DO video but not Leisure standing). Future directions include establishing the criterion validity of WC IMGs to assess other metrics of PA and SB, such as intensity classifications, and total daily energy expenditure. This next step, along with the results of this study, will solidify the use of WCs to be a criterion measure for providing ground-truth labels in validation and calibration studies, and be a valid tool for

assessing PA and SB as an outcome measure for descriptive, intervention, cross-sectional and longitudinal studies.

References

1. Piercy KL, Troiano RP, Ballard RM, Carlson SA, Fulton JE, Galuska DA, George SM, Olson RD (2018) The Physical Activity Guidelines for Americans. *JAMA* 320:2020–2028
2. Dempsey PC, Biddle SJH, Buman MP, et al (2020) New global guidelines on sedentary behaviour and health for adults: Broadening the behavioural targets. *International Journal of Behavioral Nutrition and Physical Activity* 17:151
3. Park JH, Moon JH, Kim HJ, Kong MH, Oh YH (2020) Sedentary Lifestyle: Overview of Updated Evidence of Potential Health Risks. *Korean J Fam Med* 41:365–373
4. Ahmadi MN, Clare PJ, Katzmarzyk PT, del Pozo Cruz B, Lee IM, Stamatakis E (2022) Vigorous physical activity, incident heart disease, and cancer: How little is enough? *European Heart Journal* 43:4801–4814
5. Kelly P, Kahlmeier S, Goetschi T, Orsini N, Richards J, Roberts N, Scarborough P, Foster C (2014) Systematic review and meta-analysis of reduction in all-cause mortality from walking and cycling and shape of dose response relationship. *Int J Behav Nutr Phys Act* 11:132
6. Dunstan DW, Barr ELM, Healy GN, Salmon J, Shaw JE, Balkau B, Magliano DJ, Cameron AJ, Zimmet PZ, Owen N (2010) Television Viewing Time and Mortality The Australian Diabetes, Obesity and Lifestyle Study (AusDiab). *Circulation* 121:384–391

7. Matthews CE, George SM, Moore SC, Bowles HR, Blair A, Park Y, Troiano RP, Hollenbeck A, Schatzkin A (2012) Amount of time spent in sedentary behaviors and cause-specific mortality in US adults. *Am J Clin Nutr* 95:437–445
8. Grøntved A, Hu FB (2011) Television viewing and risk of type 2 diabetes, cardiovascular disease, and all-cause mortality: A meta-analysis. *JAMA* 305:2448–2455
9. Schmid D, Leitzmann MF (2014) Television viewing and time spent sedentary in relation to cancer risk: A meta-analysis. *J Natl Cancer Inst* 106:dju098
10. King AC, Jeffery RW, Fridinger F, Dusenbury L, Provence S, Hedlund SA, Spangler K (1995) Environmental and Policy Approaches to Cardiovascular Disease Prevention Through Physical Activity: Issues and Opportunities. *Health Education Quarterly* 22:499–511
11. Sallis JF, Cervero RB, Ascher W, Henderson KA, Kraft MK, Kerr J (2006) An Ecological Approach to Creating Active Living Communities. *Annual Review of Public Health* 27:297–322
12. Bull FC, Al-Ansari SS, Biddle S, et al (2020) World Health Organization 2020 guidelines on physical activity and sedentary behaviour. *Br J Sports Med* 54:1451–1462
13. Lee DH, Rezende LFM, Joh H-K, Keum N, Ferrari G, Rey-Lopez JP, Rimm EB, Tabung FK, Giovannucci EL (2022) Long-Term Leisure-Time Physical Activity Intensity and All-Cause and Cause-Specific Mortality: A Prospective Cohort of US Adults. *Circulation* 146:523–534

14. Major L, Simonsick EM, Napolitano MA, DiPietro L (2023) Domains of Sedentary Behavior and Cognitive Function: The Health, Aging, and Body Composition Study, 1999/2000 to 2006/2007. *The Journals of Gerontology: Series A* 78:2035–2041
15. Quinn TD, Gibbs BB (2023) Context Matters: The Importance of Physical Activity Domains for Public Health. *Journal for the Measurement of Physical Behaviour* - 1:1–5
16. Saint-Maurice PF, Berrigan D, Whitfield GP, Watson KB, Patel S, Lofffield E, Sampson JN, Fulton JE, Matthews CE (2021) Amount, Type, and Timing of Domain-Specific Moderate to Vigorous Physical Activity Among US Adults. *J Phys Act Health* 18:S114–S122
17. Bowman SA (2006) Television-Viewing Characteristics of Adults: Correlations to Eating Practices and Overweight and Health Status. *Prev Chronic Dis* 3:A38
18. Hamer M, Yates T, Demakakos P (2017) Television viewing and risk of mortality: Exploring the biological plausibility. *Atherosclerosis* 263:151–155
19. Patterson R, McNamara E, Tainio M, de Sá TH, Smith AD, Sharp SJ, Edwards P, Woodcock J, Brage S, Wijndaele K (2018) 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* 33:811–829
20. Cabanas-Sánchez V, Martínez-Gómez D, Esteban-Cornejo I, Pérez-Bey A, Castro Piñero J, Veiga OL (2019) Associations of total sedentary time, screen

- time and non-screen sedentary time with adiposity and physical fitness in youth: The mediating effect of physical activity. *J Sports Sci* 37:839–849
21. Hu R, Zheng H, Lu C (2021) The Association Between Sedentary Screen Time, Non-screen-based Sedentary Time, and Overweight in Chinese Preschool Children: A Cross-Sectional Study. *Frontiers in Pediatrics*.
<https://doi.org/10.3389/fped.2021.767608>
 22. Thompson D, Peacock O, Western M, Batterham AM (2015) Multidimensional Physical Activity: An Opportunity, Not a Problem. *Exercise and Sport Sciences Reviews* 43:67
 23. Kelly P, Fitzsimons C, Baker G (2016) Should we reframe how we think about physical activity and sedentary behaviour measurement? Validity and reliability reconsidered. *Int J Behav Nutr Phys Act* 13:32
 24. Kraus WE, Powell KE, Haskell WL, et al (2019) Physical Activity, All-Cause and Cardiovascular Mortality, and Cardiovascular Disease. *Med Sci Sports Exerc* 51:1270–1281
 25. Strath SJ, Kaminsky LA, Ainsworth BE, Ekelund U, Freedson PS, Gary RA, Richardson CR, Smith DT, Swartz AM, American Heart Association Physical Activity Committee of the Council on Lifestyle and Cardiometabolic Health and Cardiovascular, Exercise, Cardiac Rehabilitation and Prevention Committee of the Council on Clinical Cardiology, and Council (2013) Guide to the assessment of physical activity: Clinical and research applications: A scientific statement from the American Heart Association. *Circulation* 128:2259–2279

26. Willetts M, Hollowell S, Aslett L, Holmes C, Doherty A (2018) Statistical machine learning of sleep and physical activity phenotypes from sensor data in 96,220 UK Biobank participants. *Sci Rep* 8:7961
27. Núñez-Marcos A, Azkune G, Arganda-Carreras I (2022) Egocentric Vision-based Action Recognition: A survey. *NEUROCOMPUTING* 472:175–197
28. Gershuny J, Harms T, Doherty A, Thomas E, Milton K, Kelly P, Foster C (2020) Testing Self-Report Time-Use Diaries against Objective Instruments in Real Time. *Sociological Methodology* 50:318–349
29. Doherty AR, Kelly P, Kerr J, Marshall S, Oliver M, Badland H, Hamilton A, Foster C (2013) Using wearable cameras to categorise type and context of accelerometer-identified episodes of physical activity. *Int J Behav Nutr Phys Act* 10:22
30. Li W, Long Y, Kwan M-P, Liu N, Li Y, Zhang Y (2022) Measuring individuals' mobility-based exposure to neighborhood physical disorder with wearable cameras. *Applied Geography* 145:102728
31. Kelly P, Marshall SJ, Badland H, Kerr J, Oliver M, Doherty AR, Foster C (2013) An ethical framework for automated, wearable cameras in health behavior research. *Am J Prev Med* 44:314–319
32. Martinez J, Staudenmayer J, Strath SJ (2023) Impact of Continuous Focal Sampling Time Thresholds on Physical Activity Metrics When Using Video-Recorded Direct Observation. *Journal for the Measurement of Physical Behaviour* -1:1–8

33. Doherty AR, Moulin CJA, Smeaton AF (2011) Automatically assisting human memory: A SenseCam browser. *Memory* 19:785–795
34. Ainsworth BE, Haskell WL, Herrmann SD, Meckes N, Bassett DRJ, Tudor-Locke C, Greer JL, Vezina J, Whitt-Glover MC, Leon AS (2011) 2011 Compendium of Physical Activities: A Second Update of Codes and MET Values. *Medicine & Science in Sports & Exercise* 43:1575
35. Martinez J, Decker A, Cho CC, Doherty A, Swartz AM, Staudenmayer JW, Strath SJ (2021) Validation of Wearable Camera Still Images to Assess Posture in Free-Living Conditions. *J Meas Phys Behav* 4:47–52
36. Organization WH (2020) Guidelines on physical activity and sedentary behaviour. World Health Organization, Geneva
37. Dixon PM, Saint-Maurice PF, Kim Y, Hibbing P, Bai Y, Welk GJ (2018) A Primer on the Use of Equivalence Testing for Evaluating Measurement Agreement. *Med Sci Sports Exerc* 50:837–845
38. Marshall AL, Miller YD, Burton NW, Brown WJ (2010) Measuring Total and Domain-Specific Sitting: A Study of Reliability and Validity. *Med Sci Sports Exerc* 42:1094–1102
39. Ding D, Varela AR, Bauman AE, Ekelund U, Lee I-M, Heath G, Katzmarzyk PT, Reis R, Pratt M (2020) Towards better evidence-informed global action: Lessons learnt from the Lancet series and recent developments in physical activity and public health. *Br J Sports Med* 54:462–468
40. Whitfield GP (2020) Combining Data From Assessments of Leisure, Occupational, Household, and Transportation Physical Activity Among US

Adults, NHANES 2011–2016. *Prev Chronic Dis*.

<https://doi.org/10.5888/pcd17.200137>

41. Whitfield GP, Ussery EN, Saint-Maurice PF, Carlson SA (2021) Trends in Aerobic Physical Activity Participation Across Multiple Domains Among US Adults, National Health and Nutrition Examination Survey 2007/2008 to 2017/2018. *Journal of Physical Activity and Health* 18:S64–S73
42. Kelly P (2013) Assessing the utility of wearable cameras in the measurement of walking and cycling. PhD thesis, University of Oxford (United Kingdom)
43. Miller N, Welch W, Doherty A, Strath S (2017) Accuracy Of Behavioral Assessment With A Wearable Camera in Semi-structured And Free Living Conditions In Older Adults. *MEDICINE AND SCIENCE IN SPORTS AND EXERCISE* 49:651–651
44. Dontje ML, Leask CF, Harvey J, Skelton DA, Chastin SFM (2018) Why Older Adults Spend Time Sedentary and Break Their Sedentary Behavior: A Mixed-Methods Approach Using Life-Logging Equipment. *J Aging Phys Act* 26:259–266
45. Leask C, Harvey J, Skelton D, Chastin S (2015) Exploring the context of sedentary behaviour in older adults (what, where, why, when and with whom). *European Reviews of Aging & Physical Activity* 12:1–8

5. Accuracy & Precision of Wearable Camera Physical Activity Intensity Estimates against Indirect Calorimetry

5.1 Introduction

There is substantial evidence supporting the impact physical activity (PA) has on reducing one's risk of all-cause mortality, risk of cardiovascular disease and risk for developing certain types of cancer [1]. The culmination of this work has made it clear that PA engagement is a public health priority, such that international guidelines on the recommended volume of PA needed to promote health and quality of life exist. Currently, 150 minutes of moderate intensity PA, 75 minutes of vigorous intensity PA, or a combination of both within a week [2] is recommended. Whether it's an individual who wishes to meet these guidelines or the researcher detailing the causal effects of their intervention on PA volume and health, PA intensity is clearly an important characteristic of PA to measure. Physical activity intensity is defined as the net rate of energy expended during bodily movement from skeletal muscle contractions. This rate of energy expenditure (EE) can be expressed using many different physiological measures, such as heart rate, the rate of oxygen uptake or in metabolic equivalents (METs) where 1 MET represents an average resting EE of 3.5 mL O₂/kg/min. As METs can be used to describe PA intensity relative to rest, it is a convenient unit of measurement widely used by researchers who wish to measure PA intensity.

The measurement of PA intensity through METs allows one to easily determine if they are meeting recommended guidelines through feasible PA measurement tools. Through the use of METs, one can categorize their PA intensity into four different groups: Sedentary (≤ 1.5 METs and in a sitting, lying or reclining posture), Light (≤ 1.5

METs in a non sitting, lying or reclining posture or 1.5 – 3.0 METs), Moderate (3.0 - 6.0 METs) and Vigorous (≥ 6.0 METs). By using a tool that can measure the frequency and time spent in different PA intensities, one can then evaluate their level of PA by determining the time spent engaging in moderate and vigorous PA. This has historically been done through the use of self-report questionnaires, which was facilitated by the formation of a database called the Compendium of Physical Activities [3]. The compendium lists the metabolic cost of several types of PA, allowing one to estimate PA intensity if you are able to measure the type of PA being performed. However, limitations present in questionnaires such as social desirability bias [4, 5] has led the PA measurement field to adopt the use of body-worn motion sensors, notably accelerometers. These mechanical sensors directly measure the acceleration of PA movement, where the magnitude of acceleration unit is typically used as a proxy for PA intensity. The use of accelerometers for capturing PA intensity has helped bring new insight in the associations between PA and health outcomes [6–9]. The volume of PA is typically reported using accelerometers. However, in order to fully describe the dose-response relationship between PA and health, type of PA must also be captured [10]. The lack of contextual information from current accelerometer use limits its capability for measuring PA type whereas the biases that affect self-report measures limits its capability to measure intensity. Current tools therefore are not able to provide new insights into the dose-response relationship between PA and SB with health, necessitating the search for a tool that can both accurately and precisely capture the intensity and type of PA and SB.

Wearable cameras (WCs) are tools that have been shown to measure all key characteristics of PA and SB (Chapter 2). Recent research carried out by Martinez et al. [11] determined the convergent validity of posture estimates from annotated WC media compared to accelerometry (Chapter 3), with follow-up work focused on describing the criterion validity of posture and activity behavior estimates compared with direct observation (Chapter 4). In the final step to determine if WC still-image (IMG) annotations can be used to holistically capture the intensity and volume of PA and SB, WC IMG annotations will be compared to indirect calorimetry (IC) which is a criterion measure of PA intensity. Therefore, the purpose of this study is to determine the criterion validity of WC IMG annotations to capture the frequency and duration of PA intensity in comparison to IC. Specifically, our aims and hypotheses are:

- Determine the criterion validity of WC IMGs to capture the frequency and duration of sedentary, light, moderate, vigorous, low (sedentary and light) and moderate-to-vigorous physical activity (MVPA) intensities. We hypothesize that WC IMGs will have sensitivity, specificity, precision and F1 scores above 0.800 for sedentary, low and MVPA intensity categories.
- Determine the criterion validity of WC IMGs to capture the duration of time spent in sedentary, light, moderate, vigorous, low and MVPA intensities. We hypothesize that WC IMGs will be statistically equivalent to DO for determining the average time spent within the sedentary, low and MVPA intensity categories.

5.2 Methods

5.2.1 Participants

Potential participants were contacted by phone calls and word of mouth through a convenience sampling method. Inclusion criteria were being between 18-65 years of age. Exclusion criteria were the use of any assistive devices for mobility or physical limitations, mobility or physical limitations that prevent the completion of activities of daily living such as household cleaning or laundry, being diagnosed with or take medication for any pulmonary, thyroid or metabolic diseases, and being currently pregnant or plan to become pregnant within two weeks from participant screening.

5.2.2 Study Overview

Participants completed two data collection visits as part of study participation. For the first visit, participants were first read and signed an informed consent document, completed a short form where they self-reported demographic information and had their anthropometrics measured. Afterwards, participants were fitted with a harness to hold a portable metabolic system with a facemask and a WC. To get a range of PA intensity levels, participants were instructed to do 1-hour of free-living activity that fell under one of four visit categories: Household, Active, Inactive and Community (**Table 5.1**) in a place of their choosing, such as their place of residence or in a communal setting. These four visit categories were chosen to ensure a wide range of PA and sedentary behavior (SB) types would be observed. For the second data collection visit, participants were weighed again, fitted with study equipment, then were required to perform free-living activities in a category different from their first data collection visit. The categories for each visit was agreed upon during the first visit.

Table 5.1: Data Collection Visit Categories

Visit Category	Example Behaviors
Household	<ul style="list-style-type: none">• Cooking• Cleaning dishes• Folding laundry• Sweeping the floor• Vacuuming• Gardening• Car maintenance• House maintenance
Active	<ul style="list-style-type: none">• Using a treadmill• Using an elliptical machine• Using a stationary bike
Inactive	<ul style="list-style-type: none">• Using the computer• Arts & crafts• Reading• Watching TV• Playing video games• Solving a puzzle
Community	<ul style="list-style-type: none">• Grocery shopping• Dropping mail off into a mailbox• Walking in a mall• Attending a farmers' market

All study procedures were approved by the University of Wisconsin-Milwaukee Institutional Review Board (Protocol Number 23.223).

5.2.3 Measures and Instrumentation

5.2.3.1 Demographics and Anthropometrics

Self-reported age, gender, sex, race, ethnicity, and height was collected. For both visits, weight was measured with a Model 880KL Digital Floor Scale (Health o meter® Professional, Illinois, USA).

5.2.3.2 Portable Indirect Calorimetry

The K5 (COSMED, Rome, Italy) is a portable metabolic system capable of measuring O₂ uptake, CO₂ production, ventilation, heart rate and energy expenditure. K5 measurements are taken via an optoelectronic reader and gas sampling line that are connected to the device, attached to a bidirectional turbine with a wind cap, and finally a facemask that covers the wearer's nose and mouth.

Prior to the start of data collection, the K5 was warmed-up for approximately 60 minutes before going through flowmeter, CO₂ scrubber, breath-by-breath reference gas, and breath-by-breath delay calibrations to ensure accurate gas measurements. Once calibrations were finished, the device was secured onto the participant's upper back via the harness worn by the participant. After determining the appropriate facemask size by measuring the distance between the participant's nasal bridge and the most anterior point of their mental protuberance, a leak test was performed to ensure the facemask with headgear were snug. The optoelectronic reader and turbine were then attached to the facemask. Participants were instructed to breathe normally while wearing the facemask and to not talk.

After all study equipment was adjusted to the participant's comfort, the K5 was initialized to collect breath-by-breath data.

5.2.3.3 Wearable Camera Still-Images

The TLC130 (Brinno®, Taipei City, Taiwan) WC was fitted on participants with a lanyard that went around their neck and connected to a chest belt via Velcro. The TLC130, positioned at the xyphoid process, was set to take a timestamped picture every 5 seconds. As the pictures from the TLC130 are exported as a timelapse video in .AVI format, the open-source software FFmpeg (version 5.0) was used to convert each video frame into an IMG.

The Behavioral Observation Research Interactive Software [12] (BORIS, version 8.22.15) was used to annotate TLC130 IMGs. As the BORIS uses the exchangeable image file format (EXIF) tag "DateTimeOriginal" to determine the time between IMGs, which is lost when IMGs are extracted from timelapse video, the "tesseract"(version 5.2.1) [13] and "exiftoolr"(version 0.2.3) [14] R packages were used to add the timestamp from each IMG into the "DateTimeOriginal" EXIF tag. Once these IMGs were corrected they were annotated using an annotation platform, which consists of a scoring protocol and annotation codes with operational definitions. The annotation platform was derived from the Compendium of Physical Activities [15], the American Time Use Survey [16] and Activities Completed over Time in 24 Hours [17] previous-day recall survey. IMGs were coded in two passes, once for participant PA and SB type and once for posture and whole-body movement. Within the PA and SB type schema, objects that the participants were directly interacting with or would be visually engaged with would be looked for. These objects of interaction, along with the upper extremity movement or absence of movement, comprise the operational definitions for the behavior type

annotation codes. For the posture/movement schema, points of reference (i.e. objects in the background of the environment that would appear from one IMG to the next) and the participant's proximity and orientation to the point of reference comprised the operational definitions for the posture/movement schema.

Two annotators were trained on the annotation platform for approximately 25 hours over 2-3 weeks, with annotators needing to achieve a kappa score ≥ 0.90 with an experienced annotator on a 10-minute IMG set to test out of training. To ensure a high inter-rater reliability, one quality check was also implemented halfway through the data collection period where annotators had to achieve a kappa ≥ 0.90 on a 10-minute IMG set to be considered in "good standing". If an annotator failed to achieve this score for a quality check, a review session lead by an experienced annotator was conducted to cover areas for improvement. Annotators then had to achieve a kappa ≥ 0.90 on an additional 10-minute IMG set specific to the review session.

5.2.4 Data Processing

Annotations from the TLC130 IMGs and K5 metabolic data were time-matched by starting data collection on the K5 to a stopwatch time-synced with the TLC130. Breath-by-breath O_2 measured by the K5 was averaged to the minute. Oxygen consumed per minute was converted into METs by transforming $L O_2/min$ into $mL O_2/kg^{-1}/min^{-1}$, which was then divided by the standard conversion of $3.5 mL O_2/kg^{-1}/min^{-1}$. The combination of behavior and posture/movement TLC130 IMG annotations were matched with corresponding Compendium of Physical Activities MET values. Behaviors and postures were then collapsed into categories of similar metabolic cost: Household, Inactive, Active and Transportation for behavior and Sit, Stand, Movement, and Stand &

Move for posture. It is important to note that these behavior categories do not incorporate behavioral intent, and should not be confused with domains of PA.

Due to the nature of O₂ kinetics in free-living behavior such as the delayed increase in O₂ consumption in performing higher intensity PA and O₂ debt when reducing the intensity of PA, data were pre-processed before analysis in 4 different procedures:

1. BASE: A straight minute-by-minute comparison between K5 and TLC130 IMG intensity categories,
2. STEADY-BEH: Sedentary behavior that has been associated with detriments in health (i.e. electronics use) and sedentary leisure behavior (i.e. reading) were categorized as Sedentary intensity regardless of MET value. Data was then filtered to only include behavior category bouts ≥ 5 minutes in duration, with the first 2 minutes and last 2 minutes removed from each bout. The K5 METs and TLC130 METs were then averaged for each behavior category bout.
3. STEADY-POS: The same as STEADY BEH, except posture category bouts were used instead.
4. STEADY-COMB: The same as STEADY BEH, except bouts where behavior categories and posture categories combined were ≥ 5 minutes in duration.

METs from both the K5 and TLC130 IMGs for each procedure were then collapsed into the following categories: Sedentary (≤ 1.5 METs and in a sitting, lying or reclining posture), Light (≤ 1.5 METs and in a non sitting, lying or reclining posture or 1.5-3.0 METs), Moderate (3.0-6.0 METs), and Vigorous (≥ 6.0 METs). Low (< 3.0 METs) and moderate-to-vigorous (MVPA, ≥ 3.0 METs) categories were also created.

5.2.5 Statistical Analysis

Descriptive statistics of participant age, gender, body mass index (BMI; average weight between the two visits (kg) /height² (m)), race/ethnicity, average study visit duration, median visit duration and range of visit duration are provided. A boxplot showing the distribution of PA intensity categories are plotted.

To determine if TLC130 IMGs can capture the frequency of PA intensity categories, confusion matrices were calculated for each PA intensity category by procedure, with measures of accuracy, sensitivity, specificity, precision and F1 scores for each procedure presented.

To determine if TLC130 IMGs can capture the duration of time spent within PA intensity categories, equivalence testing using the confidence interval method [18] and an equivalence region that is $\pm 15\%$ of the K5 mean time spent in each PA intensity category was done. The null hypothesis of equivalency testing within this study is the mean difference of TLC130 IMG-derived minutes minus K5-derived minutes for a PA intensity category is $\geq 15\%$ of the K5 mean or $\leq -15\%$ of the K5 mean, which is rejected at α if the $100(1 - 2\alpha)\%$ confidence interval (CI) for the mean difference is entirely within the $\pm 15\%$ equivalence region. Therefore, we reject the null hypothesis of nonequivalence if the 90% CI is entirely within the $\pm 15\%$ equivalence region in using a level $\alpha=5\%$. As there were multiple visits per person, a linear mixed effects model was used to calculate mean difference and 90% CI's, treating each participant as a random effect.

For all statistical analyses, the K5 intensity measurements are treated as the criterion measure. The R programming language (R version 4.3.1 (2023-06-16 ucrt))

and Rstudio integrated development environment (2023.06.0+421) was used for statistical analyses. The nlme package (version 3.1.162) and equivalence package (version 0.7.2) was used to calculate mean difference and 90% CIs for equivalence tests.

5.3 Results

Table 5.2 lists participant descriptives as well as visit descriptives. K5 and TLC130 IMG data from 19 participants across 38 visits were collected. Data from one visit was excluded due to a corrupted video exported from the TLC130, resulting in 37 visits from 19 participants. The numbers in each Household, Active, Inactive and Community visit categories out of included visits was 10, 9, 9 and 9, respectively. 2,126.7 minutes of data were collected from free-living visits, with an average visit duration of 57.5 ± 13.8 minutes. **Figure 5.1** shows the distribution of each PA intensity category across all visits from K5 data. On average, 8.2 (14%), 21.8 (41%), 23.3 (38%), 3.9 (6%) minutes of K5 data was Sedentary, Light, Moderate, Vigorous, respectively. For the broader PA intensities, 30.0 (55%) and 27.2 (45%) of K5 data was Low and MVPA, respectively.

Table 5.3 and **Table 5.4** list the classification metrics between the K5 and TLC130 IMG annotations for Sedentary to Vigorous and Low to MVPA PA intensity categories, respectively. The total number of minutes available for analysis was 2,117.7, 1,027.7, 861.4, and 740.2 minutes for the BASE, STEADY-BY, STEADY-POS and STEADY-COMB procedures, respectively.

Wearable camera IMGs had an overall accuracy of 54%, 77%, 88% and 87% for BASE, STEADY-BY, STEADY-POS and STEADY-COMB procedures for Sedentary

Table 5.2: Participant and visit descriptives.

Characteristic	N = 19
N	19
Age, mean (SD)	
mean (SD)	27 (9)
median (IQR)	23 (21, 29)
range	18, 53
Height (m), mean (SD)	1.71 (0.10)
Weight (kg), mean (SD)	77 (18)
BMI (kg/m²), mean (SD)	
mean (SD)	26.2 (4.9)
median (IQR)	26.3 (22.6, 28.3)
range	20.5, 40.3
Gender, n (%)	
Woman	10 (53%)
Man	9 (47%)
Race, n (%)	
White	19 (100%)
Black or African American	0 (0%)
Asian	0 (0%)
Other	0 (0%)
Hispanic, n (%)	
Non Hispanic	17 (89%)
Hispanic or Latino	2 (10%)
Visits	
n	37
Total Duration (minutes)	2,127
Duration, mean (SD) (minutes)	57 (14)
Duration, median (IQR) (minutes)	60 (60, 60)
Duration, range (minutes)	1, 72

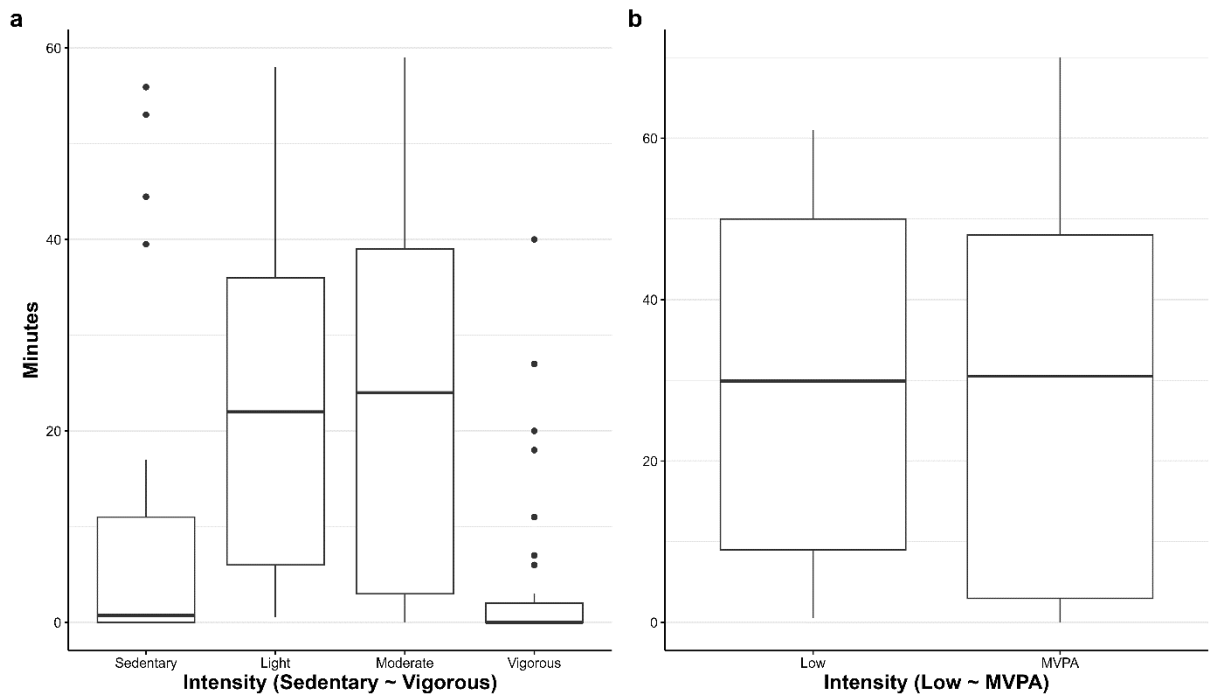


Figure 5.1: Boxplots showing the distribution of COSMED K5 minutes in each physical activity intensity category across all visits.

¹MVPA: Moderate to Vigorous Physical Activity

²Average visit duration for valid COSMED K5 minutes was 57.2 minutes.

Table 5.3: Classification metrics of Sedentary to Vigorous intensity categories by procedure.

Behavior	Total (Min)	Accuracy	Sensitivity	Specificity	Precision	F1
BASE		54%				
Sedentary	303.6		0.918	0.803	0.438	0.593
Light	806.3		0.431	0.695	0.465	0.447
Moderate	862.8		0.562	0.836	0.702	0.624
Vigorous	145.0		0.262	0.997	0.865	0.402
STEADY-BEH		77%				
Sedentary	436.4		0.980	0.993	0.991	0.985
Light	257.5		0.626	0.847	0.578	0.601
Moderate	254.0		0.570	0.849	0.554	0.562
Vigorous	79.8		0.702	1.000	1.000	0.825
STEADY-POS		88%				
Sedentary	482.1		0.978	0.980	0.984	0.981
Light	188.4		0.724	0.958	0.828	0.772
Moderate	136.4		0.870	0.905	0.634	0.733
Vigorous	54.5		0.560	1.000	1.000	0.718
STEADY-COMB		87%				
Sedentary	444.4		0.969	0.987	0.991	0.980
Light	151.1		0.712	0.951	0.789	0.749
Moderate	91.2		0.836	0.903	0.549	0.662
Vigorous	53.5		0.570	1.000	1.000	0.726

Table 5.4: Classification metrics of Low to MVPA intensity categories by procedure.

Behavior	Total (Min)	Accuracy	Sensitivity	Specificity	Precision	F1
BASE		76%				
Low	1,110.0		0.882	0.600	0.708	0.786
MVPA	1,007.9		0.600	0.882	0.822	0.694
STEADY-BEH		80%				
Low	693.9		0.866	0.673	0.846	0.856
MVPA	333.8		0.673	0.866	0.707	0.689
STEADY-POS		93%				
Low	670.4		0.933	0.907	0.972	0.953
MVPA	190.9		0.907	0.933	0.795	0.848
STEADY-COMB		93%				
Low	595.6		0.933	0.896	0.974	0.953
MVPA	144.8		0.896	0.933	0.766	0.826

MVPA: Moderate to Vigorous Physical Activity

through Vigorous intensity classifications, respectively. Classification metrics for Sedentary and Vigorous intensities were higher for STEADY-BEH while classification metrics for Light and Moderate intensities were higher for STEADY-POS. Classification metrics in the STEADY-COMB analysis procedure were second best. In looking at the Low and MVPA intensity categories, TLC130 IMGs had an overall accuracy of 75%, 80%, 93% and 93% for BASE, STEADY-BY, STEADY-POS and STEADY-COMB procedures, respectively. Classification metrics in the STEADY-POS and STEADY-COMB procedures were similar. The F1 scores for both procedures are the same for the Low intensity category (0.953) with STEADY-POS having a slightly higher F1 score than STEADY-COMP (0.848 and 0.826).

Figure 5.2 is the mean percent difference of TLC130 IMG estimates minus K5 measurements for each PA intensity category by procedure across all visits, with 90% CIs from using $\alpha = 5\%$ equivalence tests. Through the BASE procedure, no WC IMG estimates of PA intensity were equivalent to the K5. For Sedentary intensity, WC IMG annotations were equivalent to K5 by all STEADY procedures. No TLC130 IMG annotations of Light intensity were statistically equivalent to K5 in any STEADY procedure. For Moderate intensity, TLC130 IMG annotations were equivalent to K5 estimates in the STEADY-COMB procedure (0.4 mins, 90% CI (-0.4, 1.2)). Within the Low intensity category, TLC130 IMG annotations were equivalent to K5 only in the STEADY-POS procedure (-1 minute, 90% CI (-3.6, 1.6)), while TLC130 IMGs were equivalent to mean K5 minutes of MVPA (0.3 minutes, 90% CI) only in the STEADY-COMB approach.

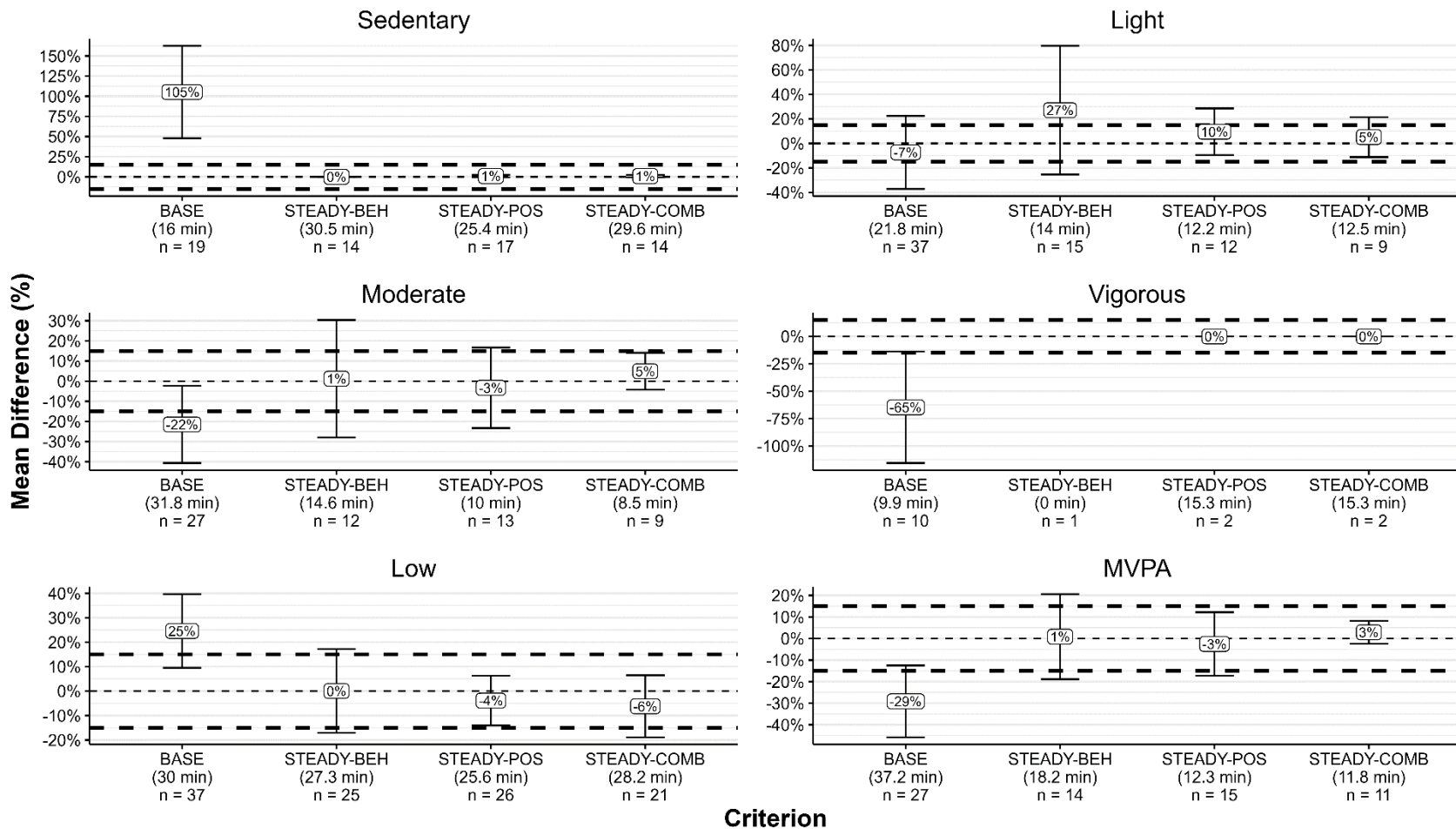


Figure 5.2: Mean percent difference of wearable camera still-image estimates minus K5 measurements for each physical activity intensity by procedure using a $\pm 15\%$ equivalence region.

¹MVPA: Moderate to Vigorous Physical Activity

²Percentages are relative to mean K5 measured minutes, listed below each procedure in parenthesis.

³ The number of visits with available data for mean percent difference calculation is listed below K5 measured minutes.

⁴The null hypothesis of nonequivalence is rejected at $\alpha = 5\%$ if the 90% $[100(1 - 2\alpha)\%]$ confidence interval for the mean percent difference is entirely within the equivalence region.

5.4 Discussion

The main findings from this analysis are WC IMG annotations are able to capture the frequency of sedentary intensity categories within across all steady-state PA, while WC IMG classification metrics of light and moderate intensities for steady-state posture were close to meeting our definition of being accurate and precise. Wearable camera IMGs are equivalent to criterion measures of indirect calorimetry for Sedentary, Moderate, and Low intensity categories depending on the procedure for filtering out non-steady-state PA and SB. Only within combined steady-state behavior and posture were WC IMG annotations equivalent to K5 for time spent in MVPA intensity.

Wearable camera IMGs in general had high specificities across all approaches for all intensity categories, while sensitivity and precision varied across intensity category and approach. In translating the results of this study, researchers can be confident in the practical usefulness of the annotation platform's ability to capture true instances of sedentary, light or low intensity bouts for posture and combined posture and behavior given the high specificity and precision metrics for these intensity categories. This is useful in cases where a new SB intervention is being evaluated, where knowing exactly how many times individuals engage in SB pre and post intervention is necessary to evaluate intervention effectiveness.

As the posture schema annotation codes within this study focused on describing lower extremity and/or torso stature or movement through space, it is reasonable to conclude these annotation codes, and posture/movement in general, are significant influences on one's energy expenditure. This is most likely due to an individual's mass being more distributed through their lower extremities and the torso. Given that more

energy is required to move more mass, annotation codes that describe the movement or absence of movement for these body regions are then more likely to be representative of a person's energy expenditure throughout one's day. For example, the driver in EE difference between a person watching television while walking on a treadmill versus watching television while lying on the couch is their difference in posture/movement, not the fact that they are watching television. Despite this, capturing upper extremity movement is also important, especially for long durations of stationary posture. For these reasons, we recommend annotation platforms capturing PA and SB to form separate behavior and posture codes to accurately measure PA intensity. Utilizing a two-pass annotation protocol allows researchers to fully describe the PA and SB patterns of participants. However, the significant burden of person-hours and infrastructure needed for collecting, annotating and processing WC IMG data should be weighed against these added benefits. Separate from deciding the protocol for holistically annotating PA and SB to accurately measure intensity, the approach for processing WC IMG annotations is also important to keep in mind.

For this study, it was decided to match behavior and posture annotation codes to 2024 Compendium of Physical Activities MET values, as these values are also representative of steady state PA and SB [3]. However, the compendium was not designed to provide accurate point estimates of METs. Rather it was designed to be connected to PA questionnaires that would be administered within large-scale studies, such as the National Health and Nutrition Examination Survey. As such, compendium MET values were truncated to facilitate ease of use [3], which may factor into the ability of this annotation platform to estimate PA intensity. In studies using rich contextual data

such as WC IMGs, the dissemination of data processing procedures for estimating PA intensity is just as important as describing the “pre-processing” annotation protocol of rich contextual data. This is analogous to PA intensity estimation from activity monitors, as the data procession methods can severely impact estimations.

Within the literature, only one study has examined the feasibility of WC IMG annotations to estimate PA intensity. Davies et al. [19], examined the agreement between Autographer WC IMGs and a wrist worn ActiGraph GT9X accelerometer for PA intensity across 3 days of wear in 53 participants. Annotations were directly based of the 2011 Compendium of Physical Activities [20], with accompanying MET values used to derive the three intensity categories of Sedentary, Light and MVPA from PA and SB annotations. Cut points from Montoye et al. [21] were used to process accelerometer data for the same intensity categories. Using mean minutes per hour as the unit of measure, WC IMGs were found to not be equivalent to accelerometer estimates for any intensity category when using a 10% equivalence region and 95% CI. If we were to use a 95% CI with a $\pm 10\%$ equivalence region of mean K5 minutes, only the STEADY BEH & POS MVPA category is considered statistically equivalent to the K5 (3% Mean Difference, (-4%, 9%), **Appendix J**). As Davies et al. [19] mentioned there was difficulty in differentiating between Moderate and Vigorous Intensities from the Autographer IMGs, the medium capture rate of approximately 30 seconds is likely to be explain the difference in equivalence test results. As this study used a consistent 5 second capture rate, we were more likely to associate different levels of blur with high levels of movement and thus, annotate a movement pattern with a higher associated metabolic cost.

This study is not without limitations. First, as the study was purposefully designed to capture a wide range free-living PA and SB, there were no restrictions on bout length. Therefore, this study design had the potential to not capture any steady-state behavior or posture as free-living PA is naturally sporadic. This was seen in the lack of visits that had any steady-state behavior or posture data that was in the vigorous intensity category. However, at least 12.3 hours of combined steady state behavior and posture were still able to be analyzed. Second, the small sample size could be of concern for generalization of study results, given that our sample primarily consisted of young healthy adults. With data reductions for equivalence testing, for example, it is important to take into consideration not all 37 visits had all intensity categories. As a result, 95% and 99% CI's were also calculated to determine if lower levels of α , would drastically change study results. At a 99% CI, WC IMG annotations are still considered statistically equivalent to K5 intensity estimates for combined behavior and posture steady state. Finally, the annotation platform estimated METs using the Compendium of Physical Activities, which was designed to be connected with self-report questionnaires and not contextually rich data. With knowledge that Compendium of Physical Activities MET values are truncated, however, efforts were made to have more accurate MET value estimations of intensity by 1) correcting sedentary behaviors to have sedentary intensity for both the K5 and WC IMGs and 2) incorporating MET values from recent publications examining the metabolic cost of different types of PA and SB [22], such as driving while sitting [23],

5.5 Conclusion

To our knowledge, this is the first study within the PA literature to establish the criterion validity of a WC IMG annotation platform to capture the frequency and duration of PA intensity. We established that WC IMG annotations are able to capture the frequency and duration of sedentary intensity and are acceptable in determining frequency within different intensity categories depending on the procedure for filtering out non-steady-state data for analyses. In the most restrictive procedure of only looking at steady-state bouts that had the same behavior and posture for the entire duration, WC IMGs are equivalent to IC for estimating time spent in the MVPA intensity category. Future work is warranted to explore more advanced data processing methods to estimate METs from tools that provide PA type time-series data.

References

1. Wasfy MM, Lee I-M (2022) Examining the Dose–Response Relationship between Physical Activity and Health Outcomes. *NEJM Evidence* 1:EVIDra2200190
2. Bull FC, Al-Ansari SS, Biddle S, et al (2020) World Health Organization 2020 guidelines on physical activity and sedentary behaviour. *Br J Sports Med* 54:1451–1462
3. Ainsworth BE, Haskell WL, Leon AS, Jacobs DR, Montoye HJ, Sallis JF, Paffenbarger RS (1993) Compendium of Physical Activities: Classification of energy costs of human physical activities. *Medicine & Science in Sports & Exercise* 25:71
4. Adams SA, Matthews CE, Ebbeling CB, Moore CG, Cunningham JE, Fulton J, Hebert JR (2005) The Effect of Social Desirability and Social Approval on Self-Reports of Physical Activity. *American Journal of Epidemiology* 161:389–398
5. Prince SA, Cardilli L, Reed JL, Saunders TJ, Kite C, Douillette K, Fournier K, Buckley JP (2020) A comparison of self-reported and device measured sedentary behaviour in adults: A systematic review and meta-analysis. *Int J Behav Nutr Phys Act* 17:31
6. Matthews CE, Keadle SK, Troiano RP, et al (2016) Accelerometer-measured dose-response for physical activity, sedentary time, and mortality in US adults. *Am J Clin Nutr* 104:1424–1432
7. Ahmadi MN, Clare PJ, Katzmarzyk PT, del Pozo Cruz B, Lee IM, Stamatakis E (2022) Vigorous physical activity, incident heart disease, and cancer: How little is enough? *European Heart Journal* 43:4801–4814

8. Dempsey PC, Rowlands AV, Strain T, et al (2022) Physical activity volume, intensity, and incident cardiovascular disease. *European Heart Journal* 43:4789–4800
9. Tarp J, Rossen J, Ekelund U, Dohrn I-M (2023) Joint associations of physical activity and sedentary time with body mass index: A prospective study of mortality risk. *Scandinavian Journal of Medicine & Science in Sports* 33:693–700
10. Herold F, Müller P, Gronwald T, Müller NG (2019) Dose–Response Matters! – A Perspective on the Exercise Prescription in Exercise–Cognition Research. *Front Psychol* 10:2338
11. Martinez J, Decker A, Cho CC, Doherty A, Swartz AM, Staudenmayer JW, Strath SJ (2021) Validation of Wearable Camera Still Images to Assess Posture in Free-Living Conditions. *J Meas Phys Behav* 4:47–52
12. Friard O, Gamba M (2016) BORIS: A free, versatile open-source event-logging software for video/audio coding and live observations. *Methods in Ecology and Evolution* 7:1325–1330
13. Ooms J (2023) Tesseract; Open Source OCR Engine.
14. O'Brien J (2023) Exiftoolr: ExifTool Functionality from R.
15. Herrmann SD, Willis EA, Ainsworth BE, et al (2024) 2024 Adult Compendium of Physical Activities: A third update of the energy costs of human activities. *Journal of Sport and Health Science* 13:6–12
16. Labor. Bureau of Labor Statistics. USD of American Time Use Survey.
17. Keadle SK, Patel S, Berrigan D, Christopher CN, Huang J, Saint-Maurice PF, Lofffield E, Matthews CE (2023) Validation of ACT24 Version 2.0 for Estimating

- Behavioral Domains, Active and Sedentary Time. *Med Sci Sports Exerc* 55:1054–1062
18. Dixon PM, Saint-Maurice PF, Kim Y, Hibbing P, Bai Y, Welk GJ (2018) A Primer on the Use of Equivalence Testing for Evaluating Measurement Agreement. *Med Sci Sports Exerc* 50:837–845
 19. Davies A, Allman-Farinelli M, Owen K, Signal L, Hosking C, Wang L, Bauman A (2020) Feasibility Study Comparing Physical Activity Classifications from Accelerometers with Wearable Camera Data. *INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH*.
<https://doi.org/10.3390/ijerph17249323>
 20. Ainsworth BE, Haskell WL, Herrmann SD, Meckes N, Bassett DRJ, Tudor-Locke C, Greer JL, Vezina J, Whitt-Glover MC, Leon AS (2011) 2011 Compendium of Physical Activities: A Second Update of Codes and MET Values. *Medicine & Science in Sports & Exercise* 43:1575
 21. Montoye AHK, Clevenger KA, Pfeiffer KA, Nelson MB, Bock JM, Imboden MT, Kaminsky LA (2020) Development of cut-points for determining activity intensity from a wrist-worn ActiGraph accelerometer in free-living adults. *Journal of Sports Sciences* 38:2569–2578
 22. Mansoubi M, Pearson N, Clemes SA, Biddle SJ, Bodicoat DH, Tolfrey K, Edwardson CL, Yates T (2015) Energy expenditure during common sitting and standing tasks: Examining the 1.5 MET definition of sedentary behaviour. *BMC Public Health* 15:516

23. Barnett RK, Greever C, Yagi K, Rhoan B, Keadle SK (2021) Reexamining the Energy Cost of Sedentary Behaviors From the 2011 Adult Compendium. *Journal of Physical Activity and Health* 18:206–211

6. Conclusion

Physical activity (PA) is deeply rooted within the human experience. From when we start learning how to walk as infants to having to carry grocery bags from the car to the house as adults, we all engage in PA behavior one way or the other. Given that the most widely used definition of PA is, “any bodily movements produced by skeletal muscles that result in energy expenditure” [1], it is clear to see PA may occur in different domains such as when you are doing Household chores, when you are relaxing and in Leisure, when you are at your Occupation or when you are Transporting somewhere. Through years of measuring different characteristics of PA in cross-sectional, longitudinal and population-wide studies, we can conclusively say that engaging in PA is good for your wellbeing and will improve your quality of life [2]. Opposite of PA’s all-encompassing definition, sedentary behavior (SB) is another health behavior that is deeply rooted in human life as a way for us to engage in leisurely activities. Defined as “waking behavior characterized by an energy expenditure ≤ 1.5 metabolic equivalents (METs), while in a sitting, reclining or lying posture” [3], prolonged bouts of SB have been shown to negatively impact one’s health [4]. Whether it be for meeting health goals in one’s personal life or for public health surveillance, the accurate measurement of both of these health behaviors is needed. In order to fully elucidate the full impact of PA and SB on health, measurement tools able to capture the key characteristic dimensions of frequency, intensity, duration and type of PA and SB are warranted. [5].

The most commonly used tools for PA and SB assessment have been self-report questionnaires and wearable motion sensors. Self-report questionnaires are subject to recall and social desirability bias and are not able to accurately capture PA intensity.

Wearable motion sensors on the other hand, are not able to capture the type of PA and SB being performed due to the lack of any contextual input. There is a clear need for a measurement tool that can provide rich contextual information on the type of PA or SB being performed, and accurately capture key characteristic dimensions of frequency, intensity and duration of said behaviors. A wearable camera (WC) has the potential to address the shortcomings of commonly used PA and SB measurement tools.

Although not a new technology [11], WCs have seen increased use within the scientific literature for capturing human behavior due to technological advancements of longer battery life and higher resolution media. Guided by an ethical framework for WC use [12], this has resulted in the successful adoption of WCs for health-related research, such as measuring dietary behavior [13], self-management practices for individuals with heart failure [14] and detailing the lived experiences for children living in poverty [15]. While there was a clear use of WCs to capture a variety of health behaviors, there was limited research in how WCs have been used to specifically capture PA and SB.

To address this, Chapter 2 details a scoping review performed to understand how WC's are being used to capture PA and SB, what dimensions of PA and SB have been captured in studies using WCs, and the methodologies of WC use such as media type, wear location and WC models used. From this systematic investigation, it was discovered that WC's were being used interdisciplinary when capturing PA and SB. Namely, the computer science field have been using WCs media as input for machine learning models to predict PA or SB. Outside of the computer science field, researchers were also using WCs as the tool of choice to measure PA or SB within studies were PA

or SB was the primary outcome measure, and to validate and calibrate other PA and SB measurement tools. Despite the growing use of WC's, it was found that very little work has been done in assessing the criterion validity of WC's to measure what PA and SB. Accordingly, the remainder of this dissertation aimed to fill this significant knowledge gap.

In Chapter 3, the convergent validity of WC still-images (IMGs) to a thigh worn monitor for assessing posture was examined. Participants were asked to wear the thigh-worn monitor and chest-worn WC for three 2-hour visits while performing their usual activities of daily living, either at their home or another place of their choosing. In computing statistical bias and 95% confidence intervals (CIs), it was found that WC's were accurate and precise for measuring sitting, but significantly underestimated standing and significantly overestimated movement. However, given that the thigh-worn monitor was only considered to be a criterion measure for sitting, a true criterion measure for all types of PA was required.

In Chapter 4, the criterion validity of WC IMGs to capture both behavior and posture was assessed by using video-recorded direct observation (DO) as the criterion measure. Similar in design to the study in Chapter 3, participants were asked to perform their free-living behavior across three 2-hour visits. WC IMGs and DO video were annotated for behavior, behavioral intent and posture. From these measures, study results showed that WC IMG annotations were accurate and precise in capturing the frequency of all PA and SB domains (i.e. Household, Leisure, Occupation and Transportation), the time spent in all PA and SB domains except for Occupation, and the frequency and duration for 10 different behavior types such as cleaning, cooking,

laundry, electronics, and vehicle travel. For posture, results showed that WC IMGs can capture the frequency and time spent sitting across all domains of PA and SB and were able to capture time spent within Household standing, Leisure movement and Transportation movement. After this finding, the criterion validity of WCs to assess the intensity dimension of PA and SB intensity was assessed.

In Chapter 5, the criterion validity of WC IMGs to capture the frequency of and time spent in sedentary, light, moderate and vigorous intensity categories, as well as the broader intensity categories of low (sedentary and light) and moderate to vigorous (MVPA), within free-living behavior was assessed. Participants were asked to wear a WC and a portable metabolic system for two 1-hour visits within a free-living setting, while being asked to perform their usual activities of daily living. Indirect calorimetry from the COSMED K5 portable metabolic system was used as the criterion measure in this study, which required estimates between the two measures to be compared during steady-state behavior, steady-state posture or a combined steady-state behavior and posture to remove the effects of delayed increase in O₂ consumption in performing higher intensity PA and O₂ debt when returning back to a resting state. Results showed that WC IMGs were accurate and precise for capturing the frequency of sedentary across all steady-state PA, and the frequency of low intensity within steady-state posture and combined steady-state behavior and posture. WC IMGs were equivalent to IC for determining time spent in sedentary intensity across all steady-state PA, moderate intensity within combined steady-state behavior and posture, low intensity within steady-state posture, and MVPA within combined steady-state behavior and posture.

In conclusion, WC IMGs using the annotation platforms described within this dissertation are able to capture all key characteristic dimensions of PA and SB. As annotation platforms and data processing methods can significantly influence the estimations of PA and SB from measurement tools that capture rich contextual information, such as the WC, the criterion validity of WC IMGs will depend on the annotation platforms and data processing methods used. Researchers using the WC to estimate different PA metrics are encouraged to disseminate annotation and data processing methods to ensure reproducibility and transparency. From our results, we comprehensively show that WC IMGs can be used to assess different behaviors, postures, PA and SB domains and PA intensity. This will give confidence to researchers using the WC that it is a measurement tool capable of what it is currently being used for within PA and SB research, while also being able to provide rich contextual information that no other PA and SB measurement tool currently has.

References

1. Caspersen CJ, Powell KE, Christenson GM (1985) Physical activity, exercise, and physical fitness: Definitions and distinctions for health-related research. *Public Health Rep* 100:126–131
2. Bull FC, Al-Ansari SS, Biddle S, et al (2020) World Health Organization 2020 guidelines on physical activity and sedentary behaviour. *Br J Sports Med* 54:1451–1462
3. Tremblay MS, Aubert S, Barnes JD, et al (2017) Sedentary Behavior Research Network (SBRN) – Terminology Consensus Project process and outcome. *International Journal of Behavioral Nutrition and Physical Activity* 14:75
4. Park JH, Moon JH, Kim HJ, Kong MH, Oh YH (2020) Sedentary Lifestyle: Overview of Updated Evidence of Potential Health Risks. *Korean J Fam Med* 41:365–373
5. Strath SJ, Kaminsky LA, Ainsworth BE, Ekelund U, Freedson PS, Gary RA, Richardson CR, Smith DT, Swartz AM, American Heart Association Physical Activity Committee of the Council on Lifestyle and Cardiometabolic Health and Cardiovascular, Exercise, Cardiac Rehabilitation and Prevention Committee of the Council on Clinical Cardiology, and Council (2013) Guide to the assessment of physical activity: Clinical and research applications: A scientific statement from the American Heart Association. *Circulation* 128:2259–2279
6. Barisic A, Leatherdale ST, Kreiger N (2011) Importance of Frequency, Intensity, Time and Type (FITT) in Physical Activity Assessment for Epidemiological Research. *Can J Public Health* 102:174–175

7. Atkin AJ, Gorely T, Clemes SA, Yates T, Edwardson C, Brage S, Salmon J, Marshall SJ, Biddle SJH (2012) Methods of Measurement in epidemiology: Sedentary Behaviour. *Int J Epidemiol* 41:1460–1471
8. Thompson D, Peacock O, Western M, Batterham AM (2015) Multidimensional Physical Activity: An Opportunity, Not a Problem. *Exercise and Sport Sciences Reviews* 43:67
9. Kelly P, Fitzsimons C, Baker G (2016) Should we reframe how we think about physical activity and sedentary behaviour measurement? Validity and reliability reconsidered. *Int J Behav Nutr Phys Act* 13:32
10. Quinn TD, Gibbs BB (2023) Context Matters: The Importance of Physical Activity Domains for Public Health. *Journal for the Measurement of Physical Behaviour* - 1:1–5
11. Mann S (1997) Wearable computing: A first step toward personal imaging. *Computer* 30:25–32
12. Kelly P, Marshall SJ, Badland H, Kerr J, Oliver M, Doherty AR, Foster C (2013) An ethical framework for automated, wearable cameras in health behavior research. *Am J Prev Med* 44:314–319
13. Gemming L, Ni Mhurchu C (2016) Dietary under-reporting: What foods and which meals are typically under-reported? *Eur J Clin Nutr* 70:640–641
14. Nourse R, Cartledge S, Tegegne T, Gurrin C, Maddison R (2022) Now you see it! Using wearable cameras to gain insights into the lived experience of cardiovascular conditions. *EUROPEAN JOURNAL OF CARDIOVASCULAR NURSING* 21:750–755

15. Gage R, Chambers T, Smith M, McKerchar C, Puloka V, Pearson A, Kawachi I, Signal L (2022) Children's perspectives on the wicked problem of child poverty in Aotearoa New Zealand: A wearable camera study. *N Z Med J* 135:95–111

Appendices

Appendix A: Scoping Review Final Search Queries

Database (Hyperlink)	Final Query Syntax
PubMed	<p>((("Human Activities"[MeSH Terms] OR "Movement"[MeSH Terms] OR "Behavior"[MeSH Terms]) AND ("action camera*" [All Fields] OR "action image*" [All Fields] OR ("action" [All Fields] OR "action s" [All Fields] OR "actions" [All Fields]) AND ("wearability" [All Fields] OR "wearable" [All Fields] OR "wearables" [All Fields]) AND "camera*" [All Fields]) OR "autographer" [All Fields] OR "automatic ingestion monitor" [All Fields] OR "body worn camera*" [All Fields] OR ("body worn" [All Fields] AND "image*" [All Fields]) OR "body worn video*" [All Fields] OR "brinno" [All Fields] OR "ebutton" [All Fields] OR "egocentric camera*" [All Fields] OR "egocentric image*" [All Fields] OR "egocentric video*" [All Fields] OR "egocentric wearable camera*" [All Fields] OR ("first person" [All Fields] AND "camera*" [All Fields]) OR "first person image*" [All Fields] OR "first person video*" [All Fields])) NOT ("memor*" [All Fields] OR "kinematic*" [All Fields] OR "kinetic*" [All Fields] OR "robot*" [All Fields] OR "crim*" [All Fields] OR ("jurisprudence" [MeSH Terms] OR "jurisprudence" [All Fields] OR "law" [All Fields]) OR ("law s" [All Fields] OR "lawful" [All Fields] OR "lawfulness" [All Fields]) OR "officer*" [All Fields] OR ("diet" [MeSH Terms] OR "diet" [All Fields]) OR ("drink" [All Fields] OR "drinking" [MeSH Terms] OR "drinking" [All Fields] OR "alcohol drinking" [MeSH Terms] OR "alcohol" [All Fields] AND "drinking" [All Fields]) OR "alcohol drinking" [All Fields] OR "drinkings" [All Fields] OR "drinks" [All Fields]) OR ("eating" [MeSH Terms] OR "eating" [All Fields]) OR ("fasted" [All Fields] OR "fasting" [MeSH Terms] OR "fasting" [All Fields] OR "fastings" [All Fields] OR "fasts" [All Fields]) OR ("feeding" [All Fields] OR "feedings" [All Fields] OR "feeds" [All Fields]) OR "food*" [All Fields] OR ("nutrition s" [All Fields] OR "nutritional status" [MeSH Terms] OR ("nutritional" [All Fields] AND "status" [All Fields]) OR "nutritional status" [All Fields] OR "nutrition" [All Fields] OR "nutritional sciences" [MeSH Terms] OR ("nutritional" [All Fields] AND "sciences" [All Fields]) OR "nutritional sciences" [All Fields] OR "nutritional" [All Fields] OR "nutritious" [All Fields] OR "nutritions" [All Fields] OR "nutritive" [All Fields]) OR ("masticated" [All Fields] OR "masticates" [All Fields] OR "masticating" [All Fields] OR "mastication" [MeSH Terms] OR "mastication" [All Fields] OR "masticate" [All Fields] OR "mastications" [All Fields] OR "masticator" [All Fields]) OR ("animals" [MeSH Terms:noexp] OR "animal" [All Fields]) OR ("arthropode" [All Fields] OR "arthropodes" [All Fields] OR "arthropods" [MeSH Terms] OR "arthropods" [All Fields] OR "arthropod" [All Fields]) OR ("birds" [MeSH Terms] OR "birds" [All Fields] OR "bird" [All Fields]) OR ("cattle" [MeSH Terms] OR "cattle" [All Fields] OR "cattle s" [All Fields] OR "cattles" [All Fields]) OR "fish*" [All Fields] OR "horse*" [All Fields])) AND (english[Filter])</p>
Web of Science Core Collection	<p>(TI=((ADL OR activit* OR "daily living" OR driving OR "aerobic training" OR conditioning OR "endurance training" OR exercis* OR exergam* OR jog* OR "resistance training" OR run* OR swim* OR walk* OR weightlift* OR "weight lift*" OR leisure OR camping OR danc* OR gardening OR play OR athlet* OR badminton OR baseball OR basketball OR bicycl* OR boating OR boxing OR canoeing OR climb* OR cycl* OR diving OR football OR golf OR gym* OR hockey OR kayaking OR lacrosse OR "martial art*" OR mountaineering OR netball OR powerlifting OR racketball OR racquetball OR rowing OR rugby OR skat* OR skiing OR sledding OR snowboard* OR soccer OR softball OR sport* OR squash OR surf* OR "track and field" OR tennis OR volleyball OR "water polo" OR wrestling OR "electronic use" OR "screen time" OR "screen use" OR commut* OR transport* OR travel* OR movement OR behavior* OR behaviour*</p>

OR inactivit* OR lifestyle* OR "life style*" OR seden*) AND ("action camera*" OR "action image*" OR "action wearable camera*" OR autographer OR "automatic ingestion monitor" OR "body-worn camera*" OR "body-worn image*" OR "body-worn video*" OR brinno OR ebutton OR "egocentric camera*" OR "egocentric image*" OR "egocentric video*" OR "egocentric wearable camera*" OR "first-person camera*" OR "first-person image*" OR "first-person video*" OR "first-person wearable camera*" OR gopro OR "go pro" OR "narrative clip" OR sensecam OR "sense cam" OR "vicon revue" OR "wearable camera*" OR "wearable image*" OR "wearable video*") NOT (memor* OR kinematic* OR kinetic* OR robot* OR crim* OR law* OR officer* OR diet OR drinking OR eating OR fasting OR feeding OR food* OR nutrition OR mastication OR animal OR arthropod OR bird OR cattle OR fish* OR horse*)) OR AB=((ADL OR activit* OR "daily living" OR driving OR "aerobic training" OR conditioning OR "endurance training" OR exercis* OR exergam* OR jog* OR "resistance training" OR run* OR swim* OR walk* OR weightlift* OR "weight lift*" OR leisure OR camping OR danc* OR gardening OR play OR athlet* OR badminton OR baseball OR basketball OR bicycl* OR boating OR boxing OR canoeing OR climb* OR cycl* OR diving OR football OR golf OR gym* OR hockey OR kayaking OR lacrosse OR "martial art*" OR mountaineering OR netball OR powerlifting OR racketball OR racquetball OR rowing OR rugby OR skat* OR skiing OR sledding OR snowboard* OR soccer OR softball OR sport* OR squash OR surf* OR "track and field" OR tennis OR volleyball OR "water polo" OR wrestling OR "electronic use" OR "screen time" OR "screen use" OR commut* OR transport* OR travel* OR movement OR behavior* OR behaviour* OR inactivit* OR lifestyle* OR "life style*" OR seden*) AND ("action camera*" OR "action image*" OR "action wearable camera*" OR autographer OR "automatic ingestion monitor" OR "body-worn camera*" OR "body-worn image*" OR "body-worn video*" OR brinno OR ebutton OR "egocentric camera*" OR "egocentric image*" OR "egocentric video*" OR "egocentric wearable camera*" OR "first-person camera*" OR "first-person image*" OR "first-person video*" OR "first-person wearable camera*" OR gopro OR "go pro" OR "narrative clip" OR sensecam OR "sense cam" OR "vicon revue" OR "wearable camera*" OR "wearable image*" OR "wearable video*") NOT (memor* OR kinematic* OR kinetic* OR robot* OR crim* OR law* OR officer* OR diet OR drinking OR eating OR fasting OR feeding OR food* OR nutrition OR mastication OR animal OR arthropod OR bird OR cattle OR fish* OR horse*))

SPORTDiscus

TI ((ADL OR activit* OR "daily living" OR driving OR "aerobic training" OR conditioning OR "endurance training" OR exercis* OR exergam* OR jog* OR "resistance training" OR run* OR swim* OR walk* OR weightlift* OR "weight lift*" OR leisure OR camping OR danc* OR gardening OR play OR athlet* OR badminton OR baseball OR basketball OR bicycl* OR boating OR boxing OR canoeing OR climb* OR cycl* OR diving OR football OR golf OR gym* OR hockey OR kayaking OR lacrosse OR "martial art*" OR mountaineering OR netball OR powerlifting OR racketball OR racquetball OR rowing OR rugby OR skat* OR skiing OR sledding OR snowboard* OR soccer OR softball OR sport* OR squash OR surf* OR "track and field" OR tennis OR volleyball OR "water polo" OR wrestling OR "electronic use" OR "screen time" OR "screen use" OR commut* OR transport* OR travel* OR movement OR behavior* OR behaviour* OR inactivit* OR lifestyle* OR "life style*" OR seden*) AND ("action camera*" OR "action image*" OR "action wearable camera*" OR autographer OR "automatic ingestion monitor" OR "body-worn camera*" OR "body-worn image*" OR "body-worn video*" OR brinno OR ebutton OR "egocentric camera*" OR "egocentric image*" OR "egocentric video*" OR "egocentric wearable camera*" OR "first-person camera*" OR "first-person image*" OR "first-person video*" OR "first-person wearable camera*" OR gopro OR "go pro" OR "narrative clip" OR sensecam OR "sense cam" OR "vicon revue" OR "wearable camera*" OR "wearable image*" OR "wearable video*") NOT (memor* OR kinematic* OR kinetic*

Database (Hyperlink)

Final Query Syntax

OR robot* OR crim* OR law* OR officer* OR diet OR drinking OR eating OR fasting OR feeding OR food* OR nutrition OR mastication OR animal OR arthropod OR bird OR cattle OR fish* OR horse*) OR AB ((ADL OR activit* OR "daily living" OR driving OR "aerobic training" OR conditioning OR "endurance training" OR exercis* OR exergam* OR jog* OR "resistance training" OR run* OR swim* OR walk* OR weightlift* OR "weight lift*" OR leisure OR camping OR danc* OR gardening OR play OR athlet* OR badminton OR baseball OR basketball OR bicycl* OR boating OR boxing OR canoeing OR climb* OR cycl* OR diving OR football OR golf OR gym* OR hockey OR kayaking OR lacrosse OR "martial art*" OR mountaineering OR netball OR powerlifting OR racketball OR racquetball OR rowing OR rugby OR skat* OR skiing OR sledding OR snowboard* OR soccer OR softball OR sport* OR squash OR surf* OR "track and field" OR tennis OR volleyball OR "water polo" OR wrestling OR "electronic use" OR "screen time" OR "screen use" OR commut* OR transport* OR travel* OR movement OR behavior* OR behaviour* OR inactivit* OR lifestyle* OR "life style*" OR seden*) AND ("action camera*" OR "action image*" OR "action wearable camera*" OR autographer OR "automatic ingestion monitor" OR "body-worn camera*" OR "body-worn image*" OR "body-worn video*" OR brinno OR ebutton OR "egocentric camera*" OR "egocentric image*" OR "egocentric video*" OR "egocentric wearable camera*" OR "first-person camera*" OR "first-person image*" OR "first-person video*" OR "first-person wearable camera*" OR gopro OR "go pro" OR "narrative clip" OR sensecam OR "sense cam" OR "vicon revue" OR "wearable camera*" OR "wearable image*" OR "wearable video*") NOT (memor* OR kinematic* OR kinetic* OR robot* OR crim* OR law* OR officer* OR diet OR drinking OR eating OR fasting OR feeding OR food* OR nutrition OR mastication OR animal OR arthropod OR bird OR cattle OR fish* OR horse*)

170

CINAHL

TI ((ADL OR activit* OR "daily living" OR driving OR "aerobic training" OR conditioning OR "endurance training" OR exercis* OR exergam* OR jog* OR "resistance training" OR run* OR swim* OR walk* OR weightlift* OR "weight lift*" OR leisure OR camping OR danc* OR gardening OR play OR athlet* OR badminton OR baseball OR basketball OR bicycl* OR boating OR boxing OR canoeing OR climb* OR cycl* OR diving OR football OR golf OR gym* OR hockey OR kayaking OR lacrosse OR "martial art*" OR mountaineering OR netball OR powerlifting OR racketball OR racquetball OR rowing OR rugby OR skat* OR skiing OR sledding OR snowboard* OR soccer OR softball OR sport* OR squash OR surf* OR "track and field" OR tennis OR volleyball OR "water polo" OR wrestling OR "electronic use" OR "screen time" OR "screen use" OR commut* OR transport* OR travel* OR movement OR behavior* OR behaviour* OR inactivit* OR lifestyle* OR "life style*" OR seden*) AND ("action camera*" OR "action image*" OR "action wearable camera*" OR autographer OR "automatic ingestion monitor" OR "body-worn camera*" OR "body-worn image*" OR "body-worn video*" OR brinno OR ebutton OR "egocentric camera*" OR "egocentric image*" OR "egocentric video*" OR "egocentric wearable camera*" OR "first-person camera*" OR "first-person image*" OR "first-person video*" OR "first-person wearable camera*" OR gopro OR "go pro" OR "narrative clip" OR sensecam OR "sense cam" OR "vicon revue" OR "wearable camera*" OR "wearable image*" OR "wearable video*") NOT (memor* OR kinematic* OR kinetic* OR robot* OR crim* OR law* OR officer* OR diet OR drinking OR eating OR fasting OR feeding OR food* OR nutrition OR mastication OR animal OR arthropod OR bird OR cattle OR fish* OR horse*) OR AB ((ADL OR activit* OR "daily living" OR driving OR "aerobic training" OR conditioning OR "endurance training" OR exercis* OR exergam* OR jog* OR "resistance training" OR run* OR swim* OR walk* OR weightlift* OR "weight lift*" OR leisure OR camping OR danc* OR gardening OR play OR athlet* OR badminton OR baseball OR basketball OR bicycl* OR boating OR boxing OR canoeing OR climb* OR cycl* OR diving OR football OR golf OR gym* OR hockey OR kayaking OR lacrosse OR

Database (Hyperlink)

Final Query Syntax

ACM Guide to
Computing Literature

“martial art*” OR mountaineering OR netball OR powerlifting OR racketball OR racquetball OR rowing OR rugby OR skat* OR skiing OR sledding OR snowboard* OR soccer OR softball OR sport* OR squash OR surf* OR “track and field” OR tennis OR volleyball OR “water polo” OR wrestling OR “electronic use” OR “screen time” OR “screen use” OR commut* OR transport* OR travel* OR movement OR behavior* OR behaviour* OR inactivit* OR lifestyle* OR “life style*” OR seden*) AND (“action camera*” OR “action image*” OR “action wearable camera*” OR autographer OR “automatic ingestion monitor” OR “body-worn camera*” OR “body-worn image*” OR “body-worn video*” OR brinno OR ebutton OR “egocentric camera*” OR “egocentric image*” OR “egocentric video*” OR “egocentric wearable camera*” OR “first-person camera*” OR “first-person image*” OR “first-person video*” OR “first-person wearable camera*” OR gopro OR “go pro” OR “narrative clip” OR sensecam OR “sense cam” OR “vicon revue” OR “wearable camera*” OR “wearable image*” OR “wearable video*”) NOT (memor* OR kinematic* OR kinetic* OR robot* OR crim* OR law* OR officer* OR diet OR drinking OR eating OR fasting OR feeding OR food* OR nutrition OR mastication OR animal OR arthropod OR bird OR cattle OR fish* OR horse*))

Title:((ADL OR activit* OR “daily living” OR driving OR “aerobic training” OR conditioning OR “endurance training” OR exercis* OR exergam* OR jog* OR “resistance training” OR run* OR swim* OR walk* OR weightlift* OR “weight lift*” OR leisure OR camping OR danc* OR gardening OR play OR athlet* OR badminton OR baseball OR basketball OR bicycl* OR boating OR boxing OR canoeing OR climb* OR cycl* OR diving OR football OR golf OR gym* OR hockey OR kayaking OR lacrosse OR “martial art*” OR mountaineering OR netball OR powerlifting OR racketball OR racquetball OR rowing OR rugby OR skat* OR skiing OR sledding OR snowboard* OR soccer OR softball OR sport* OR squash OR surf* OR “track and field” OR tennis OR volleyball OR “water polo” OR wrestling OR “electronic use” OR “screen time” OR “screen use” OR commut* OR transport* OR travel* OR movement OR behavior* OR behaviour* OR inactivit* OR lifestyle* OR “life style*” OR seden*) AND (“action camera*” OR “action image*” OR “action wearable camera*” OR autographer OR “automatic ingestion monitor” OR “body-worn camera*” OR “body-worn image*” OR “body-worn video*” OR brinno OR ebutton OR “egocentric camera*” OR “egocentric image*” OR “egocentric video*” OR “egocentric wearable camera*” OR “first-person camera*” OR “first-person image*” OR “first-person video*” OR “first-person wearable camera*” OR gopro OR “go pro” OR “narrative clip” OR sensecam OR “sense cam” OR “vicon revue” OR “wearable camera*” OR “wearable image*” OR “wearable video*”) NOT (memor* OR kinematic* OR kinetic* OR robot* OR crim* OR law* OR officer* OR diet OR drinking OR eating OR fasting OR feeding OR food* OR nutrition OR mastication OR animal OR arthropod OR bird OR cattle OR fish* OR horse*)) OR Abstract:((ADL OR activit* OR “daily living” OR driving OR “aerobic training” OR conditioning OR “endurance training” OR exercis* OR exergam* OR jog* OR “resistance training” OR run* OR swim* OR walk* OR weightlift* OR “weight lift*” OR leisure OR camping OR danc* OR gardening OR play OR athlet* OR badminton OR baseball OR basketball OR bicycl* OR boating OR boxing OR canoeing OR climb* OR cycl* OR diving OR football OR golf OR gym* OR hockey OR kayaking OR lacrosse OR “martial art*” OR mountaineering OR netball OR powerlifting OR racketball OR racquetball OR rowing OR rugby OR skat* OR skiing OR sledding OR snowboard* OR soccer OR softball OR sport* OR squash OR surf* OR “track and field” OR tennis OR volleyball OR “water polo” OR wrestling OR “electronic use” OR “screen time” OR “screen use” OR commut* OR transport* OR travel* OR movement OR behavior* OR behaviour* OR inactivit* OR lifestyle* OR “life style*” OR seden*) AND (“action camera*” OR “action image*” OR “action wearable camera*” OR autographer OR “automatic ingestion monitor” OR “body-worn camera*” OR “body-worn image*” OR “body-worn video*” OR brinno OR

Database (Hyperlink)	Final Query Syntax
IEEE Xplore Digital Library Document Title	<p>ebutton OR "egocentric camera*" OR "egocentric image*" OR "egocentric video*" OR "egocentric wearable camera*" OR "first-person camera*" OR "first-person image*" OR "first-person video*" OR "first-person wearable camera*" OR gopro OR "go pro" OR "narrative clip" OR sensecam OR "sense cam" OR "vicon revue" OR "wearable camera*" OR "wearable image*" OR "wearable video*") NOT (memor* OR kinematic* OR kinetic* OR robot* OR crim* OR law* OR officer* OR diet OR drinking OR eating OR fasting OR feeding OR food* OR nutrition OR mastication OR animal OR arthropod OR bird OR OR cattle OR fish* OR horse*))</p> <p>("Document Title":ADL OR "Document Title":activit* OR "Document Title":daily living" OR "Document Title":driving OR "Document Title":aerobic training" OR "Document Title":conditioning OR "Document Title":endurance training" OR "Document Title":exercise OR "Document Title":exercising OR "Document Title":exergame OR "Document Title":jogging OR "Document Title":resistance training" OR "Document Title":running OR "Document Title":swimming OR "Document Title":walking OR "Document Title":weightlifting OR "Document Title":weight lifting" OR "Document Title":leisure OR "Document Title":camping OR "Document Title":dance OR "Document Title":dancing OR "Document Title":gardening OR "Document Title":play OR "Document Title":athlete OR "Document Title":badminton OR "Document Title":baseball OR "Document Title":basketball OR "Document Title":bicycling OR "Document Title":boating OR "Document Title":boxing OR "Document Title":canoeing OR "Document Title":climbing OR "Document Title":cycling OR "Document Title":diving OR "Document Title":football OR "Document Title":golf OR "Document Title":gymnastics OR "Document Title":hockey OR "Document Title":kayaking OR "Document Title":lacrosse OR "Document Title":martial art" OR "Document Title":mountaineering OR "Document Title":netball OR "Document Title":powerlifting OR "Document Title":racketball OR "Document Title":racquetball OR "Document Title":rowing OR "Document Title":rugby OR "Document Title":skating OR "Document Title":skiing OR "Document Title":sledding OR "Document Title":snowboarding OR "Document Title":soccer OR "Document Title":softball OR "Document Title":sport OR "Document Title":squash OR "Document Title":surfing OR "Document Title":track and field" OR "Document Title":tennis OR "Document Title":volleyball OR "Document Title":water polo" OR "Document Title":wrestling OR "Document Title":electronic use" OR "Document Title":screen time" OR "Document Title":screen use" OR "Document Title":commuting OR "Document Title":transportation OR "Document Title":travel OR "Document Title":traveling OR "Document Title":movement OR "Document Title":behavior OR "Document Title":behaviour OR "Document Title":inactivit* OR "Document Title":lifestyle OR "Document Title":life style" OR "Document Title":seden*) AND ("Document Title":action camera" OR "Document Title":action image" OR "Document Title":action wearable camera" OR "Document Title":autographer OR "Document Title":automatic ingestion monitor" OR "Document Title":body-worn camera" OR "Document Title":body-worn image" OR "Document Title":body-worn video" OR "Document Title":brinno OR "Document Title":ebutton OR "Document Title":egocentric camera" OR "Document Title":egocentric image" OR "Document Title":egocentric video" OR "Document Title":egocentric wearable camera" OR "Document Title":first-person camera" OR "Document Title":first-person image" OR "Document Title":first-person video" OR "Document Title":first-person wearable camera" OR "Document Title":gopro OR "Document Title":go pro" OR "Document Title":narrative clip" OR "Document Title":sensecam OR "Document Title":sense cam" OR "Document Title":vicon revue" OR "Document Title":wearable camera" OR "Document Title":wearable image" OR "Document Title":wearable video") NOT ("Document Title":memory OR "Document Title":memories OR "Document Title":kinematic OR "Document Title":kinetic OR "Document Title":robot* OR "Document Title":crime OR "Document Title":criminal OR "Document Title":law OR</p>

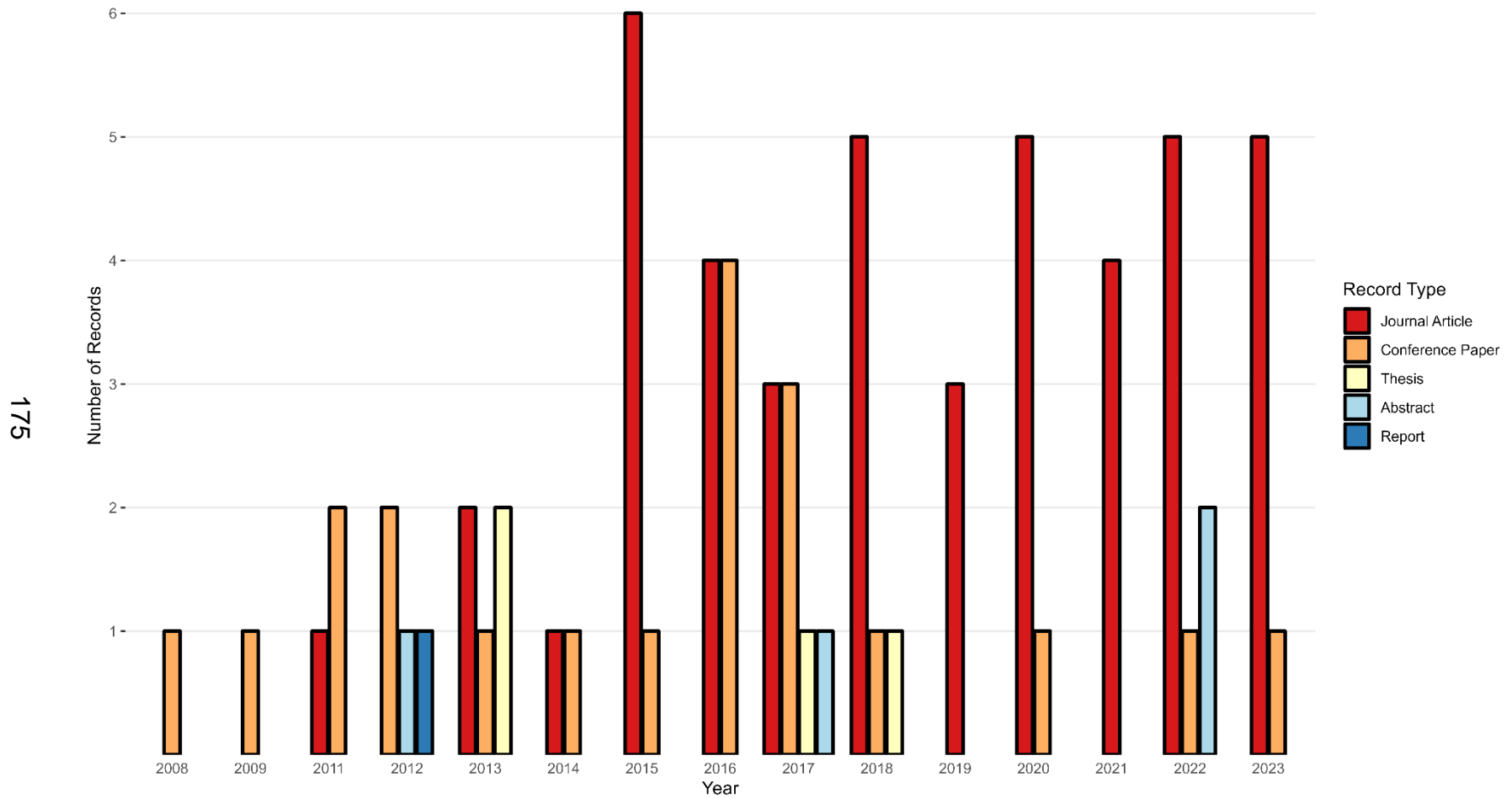
Database (Hyperlink)	Final Query Syntax
IEEE Xplore Digital Library Abstract	<p>“Document Title”:lawful OR “Document Title”:officer OR “Document Title”:diet OR “Document Title”:drinking OR “Document Title”:eating OR “Document Title”:fasting OR “Document Title”:feeding OR “Document Title”:food OR “Document Title”:nutrition OR “Document Title”:mastication OR “Document Title”:animal OR “Document Title”:arthropod OR “Document Title”:bird OR “Document Title”:cattle OR “Document Title”:fish OR “Document Title”:horse)</p> <p>(“Abstract”:ADL OR “Abstract”:activit* OR “Abstract”:“daily living” OR “Abstract”:driving OR “Abstract”:“aerobic training” OR “Abstract”:conditioning OR “Abstract”:“endurance training” OR “Abstract”:exercise OR “Abstract”:exercising OR “Abstract”:exergame OR “Abstract”:jogging OR “Abstract”:“resistance training” OR “Abstract”:running OR “Abstract”:swimming OR “Abstract”:walking OR “Abstract”:weightlifting OR “Abstract”:“weight lifting” OR “Abstract”:leisure OR “Abstract”:camping OR “Abstract”:dance OR “Abstract”:dancing OR “Abstract”:gardening OR “Abstract”:play OR “Abstract”:athlete OR “Abstract”:badminton OR “Abstract”:baseball OR “Abstract”:basketball OR “Abstract”:bicycling OR “Abstract”:boating OR “Abstract”:boxing OR “Abstract”:canoeing OR “Abstract”:climbing OR “Abstract”:cycling OR “Abstract”:diving OR “Abstract”:football OR “Abstract”:golf OR “Abstract”:gymnastics OR “Abstract”:hockey OR “Abstract”:kayaking OR “Abstract”:lacrosse OR “Abstract”:“martial art” OR “Abstract”:mountaineering OR “Abstract”:netball OR “Abstract”:powerlifting OR “Abstract”:racketball OR “Abstract”:racquetball OR “Abstract”:rowing OR “Abstract”:rugby OR “Abstract”:skating OR “Abstract”:skiing OR “Abstract”:sledding OR “Abstract”:snowboarding OR “Abstract”:soccer OR “Abstract”:softball OR “Abstract”:sport OR “Abstract”:squash OR “Abstract”:surfing OR “Abstract”:“track and field” OR “Abstract”:tennis OR “Abstract”:volleyball OR “Abstract”:“water polo” OR “Abstract”:wrestling OR “Abstract”:“electronic use” OR “Abstract”:“screen time” OR “Abstract”:“screen use” OR “Abstract”:commuting OR “Abstract”:transportation OR “Abstract”:travel OR “Abstract”:traveling OR “Abstract”:movement OR “Abstract”:behavior OR “Abstract”:behaviour OR “Abstract”:inactivit* OR “Abstract”:lifestyle OR “Abstract”:“life style” OR “Abstract”:seden*) AND (“Abstract”:“action camera” OR “Abstract”:“action image” OR “Abstract”:“action wearable camera” OR “Abstract”:autographer OR “Abstract”:“automatic ingestion monitor” OR “Abstract”:“body-worn camera” OR “Abstract”:“body-worn image” OR “Abstract”:“body-worn video” OR “Abstract”:brinno OR “Abstract”:ebutton OR “Abstract”:“egocentric camera” OR “Abstract”:“egocentric image” OR “Abstract”:“egocentric video” OR “Abstract”:“egocentric wearable camera” OR “Abstract”:“first-person camera” OR “Abstract”:“first-person image” OR “Abstract”:“first-person video” OR “Abstract”:“first-person wearable camera” OR “Abstract”:gopro OR “Abstract”:“go pro” OR “Abstract”:“narrative clip” OR “Abstract”:sensecam OR “Abstract”:“sense cam” OR “Abstract”:“vicon revue” OR “Abstract”:“wearable camera” OR “Abstract”:“wearable image” OR “Abstract”:“wearable video”) NOT (“Abstract”:memory OR “Abstract”:memories OR “Abstract”:kinematic OR “Abstract”:kinetic OR “Abstract”:robot* OR “Abstract”:crime OR “Abstract”:criminal OR “Abstract”:law OR “Abstract”:lawful OR “Abstract”:officer OR “Abstract”:diet OR “Abstract”:drinking OR “Abstract”:eating OR “Abstract”:fasting OR “Abstract”:feeding OR “Abstract”:food OR “Abstract”:nutrition OR “Abstract”:mastication OR “Abstract”:animal OR “Abstract”:arthropod OR “Abstract”:bird OR “Abstract”:cattle OR “Abstract”:fish OR “Abstract”:horse)</p>
ProQuest	<p>abstract((ADL OR activit* OR “daily living” OR driving OR “aerobic training” OR conditioning OR “endurance training” OR exercis* OR exergam* OR jog* OR “resistance training” OR run* OR swim* OR walk* OR weightlift* OR “weight lift*” OR leisure OR camping OR danc* OR gardening OR play OR athlet* OR badminton OR baseball OR basketball OR bicycl* OR boating OR boxing OR canoeing OR climb* OR cycl* OR diving OR football OR golf OR gym* OR</p>

Database (Hyperlink)

Final Query Syntax

hockey OR kayaking OR lacrosse OR "martial art*" OR mountaineering OR netball OR powerlifting OR racketball OR racquetball OR rowing OR rugby OR skat* OR skiing OR sledding OR snowboard* OR soccer OR softball OR sport* OR squash OR surf* OR "track and field" OR tennis OR volleyball OR "water polo" OR wrestling OR "electronic use" OR "screen time" OR "screen use" OR commut* OR transport* OR travel* OR movement OR behavior* OR behaviour* OR inactivit* OR lifestyle* OR "life style*" OR seden*) AND ("action camera*" OR "action image*" OR "action wearable camera*" OR autographer OR "automatic ingestion monitor" OR "body-worn camera*" OR "body-worn image*" OR "body-worn video*" OR brinno OR ebutton OR "egocentric camera*" OR "egocentric image*" OR "egocentric video*" OR "egocentric wearable camera*" OR "first-person camera*" OR "first-person image*" OR "first-person video*" OR "first-person wearable camera*" OR gopro OR "go pro" OR "narrative clip" OR sensecam OR "sense cam" OR "vicon revue" OR "wearable camera*" OR "wearable image*" OR "wearable video*") NOT (memor* OR kinematic* OR kinetic* OR robot* OR crim* OR law* OR officer* OR diet OR drinking OR eating OR fasting OR feeding OR food* OR nutrition OR mastication OR animal OR arthropod OR bird OR cattle OR fish* OR horse*)) OR title((ADL OR activit* OR "daily living" OR driving OR "aerobic training" OR conditioning OR "endurance training" OR exercis* OR exergam* OR jog* OR "resistance training" OR run* OR swim* OR walk* OR weightlift* OR "weight lift*" OR leisure OR camping OR danc* OR gardening OR play OR athlet* OR badminton OR baseball OR basketball OR bicycl* OR boating OR boxing OR canoeing OR climb* OR cycl* OR diving OR football OR golf OR gym* OR hockey OR kayaking OR lacrosse OR "martial art*" OR mountaineering OR netball OR powerlifting OR racketball OR racquetball OR rowing OR rugby OR skat* OR skiing OR sledding OR snowboard* OR soccer OR softball OR sport* OR squash OR surf* OR "track and field" OR tennis OR volleyball OR "water polo" OR wrestling OR "electronic use" OR "screen time" OR "screen use" OR commut* OR transport* OR travel* OR movement OR behavior* OR behaviour* OR inactivit* OR lifestyle* OR "life style*" OR seden*) AND ("action camera*" OR "action image*" OR "action wearable camera*" OR autographer OR "automatic ingestion monitor" OR "body-worn camera*" OR "body-worn image*" OR "body-worn video*" OR brinno OR ebutton OR "egocentric camera*" OR "egocentric image*" OR "egocentric video*" OR "egocentric wearable camera*" OR "first-person camera*" OR "first-person image*" OR "first-person video*" OR "first-person wearable camera*" OR gopro OR "go pro" OR "narrative clip" OR sensecam OR "sense cam" OR "vicon revue" OR "wearable camera*" OR "wearable image*" OR "wearable video*") NOT (memor* OR kinematic* OR kinetic* OR robot* OR crim* OR law* OR officer* OR diet OR drinking OR eating OR fasting OR feeding OR food* OR nutrition OR mastication OR animal OR arthropod OR bird OR cattle OR fish* OR horse*))

Appendix B: Scoping Review Publications Per Year By Record Type



Appendix C: Scoping Review Study Characteristics

Reference	Theme	Record Type	Country	Sample Size	Population Characteristics	% Female	Age (mean years (SD) [range])	BMI (mean kg/m2 (SD) [range])
Abebe et al. 2016 [1]	FAR	Journal Article	United Kingdom	4	-	-	- (-) [-]	- (-) [-]
Aguilar Grajeda 2018 [2]	GRT	Thesis	Singapore	15	Physically able to sit and stand without assistance	0	25.2 (3.0) [21-32]	22.4 (2.0) [-]
Andriyani et al. 2022 [3]	OCM	Journal Article	Indonesia	5	Adolescents	1	13.9 (0.4) [-]	21.9 (4.3) [-]
Bach et al. 2022 [4]	GRT	Journal Article	Norway	22	Healthy Adults	0.36	38.7 (14.4) [25-68]	- (-) [-]
Bokhari & Kitani 2017 [5]	FAR	Conference Paper	United States	-	-	-	- (-) [-]	- (-) [-]
Bourke et al. 2017 [6]	GRT	Journal Article	Norway	20	Healthy Older Adults	0.75	76.4 (5.6) [68-90]	- (-) [-]
Carlson et al. 2015 [7]	GRT	Journal Article	same as	Kerr et al. 2013	-	-	-	-
Cartas et al. 2018 [8]	FAR	Journal Article	Not Applicable	-	-	-	- (-) [-]	- (-) [-]
Cartas et al. 2020 [9]	FAR	Journal Article	Spain	15	Post-Graduate Students	0.2	- (-) [-]	- (-) [-]
Chasen-Taber et al. 2023 [10]	GRT	Journal Article	United States	50	Pregnant - All Trimesters	1	32.9 (4.2) [-]	25.1 (3.6) [-]
Cho et al. 2008 [11]	FAR	Conference Paper	Korea	-	-	-	- (-) [-]	- (-) [-]
Chou et al. 2016 [12]	FAR	Conference Paper	Taiwan	4	-	-	- (-) [-]	- (-) [-]
Davies et al. 2020 [13]	VAL	Journal Article	Australia	53	-	0.51	- (-) [-]	- (-) [-]
Davies et al. 2021 [14]	OCM	Journal Article	Australia	78	-	0.49	- (-) [-]	- (-) [-]

Reference	Theme	Record Type	Country	Sample Size	Population Characteristics	% Female	Age (mean years (SD) [range])	BMI (mean kg/m2 (SD) [range])
Doherty et al. 2012 [15]	VAL	Abstract	-	62	-	-	- (-) [-]	- (-) [-]
Doherty et al. 2013 [16]	VAL	Journal Article	New Zealand & United States	49	- (-) [-]	- (-) [-]	- (-) [-]	- (-) [-]
Ellis et al. 2016 [17]	GRT	Journal Article	United States	40	Overweight or Obese Women	1	55.2 (15.3) [-]	32.0 (3.7) [-]
Femiano et al. 2022 [18]	GRT	Journal Article	Switzerland	22	Cardiac Rehabilitation Patients	-	56.6 (9) [-]	27.8 (4.9) [-]
Freeman et al. 2021 [19]	OCM	Journal Article	New Zealand	74	Healthy Children	0.54	12.6 (-) [-]	- (-) [-]
Fullerton et al. 2017 [20]	GRT	Journal Article	United Kingdom	10	Healthy	0.3	23.1 (1.7) [-]	- (-) [-]
Gao et al. 2022 [21]	FAR	Conference Paper	China	10	-	0.4	- (-) [18-25]	- (-) [-]
Gershuny et al. 2020 [22]	GRT	Journal Article	United Kingdom	131	-	0.6	- (-) [-]	- (-) [-]
Gjoreski et al. 2018 [23]	FAR	Journal Article	United Kingdom	3	-	-	- (-) [-]	- (-) [-]
Hänggi et al. 2020 [24]	OCM	Journal Article	Switzerland	14	Children	0.57	10.3 (0.6) [9-11]	- (-) [-]
Hao et al. 2023 [25]	FAR	Conference Paper	Japan	12	-	0.33	- (-) [-]	- (-) [-]
Hipiny & Mayol-Cuevas 2012 [26]	FAR	Report	United Kingdom	6	Adults	0.33	- (-) [-]	- (-) [-]
Hipiny 2013 [27]	FAR	Thesis	Not Applicable	-	-	-	-	-
Karaman et al. 2011 [28]	FAR	Conference Paper	France	-	Individuals with Dementia	-	- (-) [-]	- (-) [-]

Reference	Theme	Record Type	Country	Sample Size	Population Characteristics	% Female	Age (mean years (SD) [range])	BMI (mean kg/m2 (SD) [range])
Kelly et al. 2011 [29]	OCM	Journal Article	United Kingdom	20	Well-educated volunteers	0.6	- (-) [24-60]	- (-) [-]
Kelly 2013 [30]	VAL	Thesis	United Kingdom	1	-	-	- (-) [-]	- (-) [-]
Kelly et al. 2014 [31]	GRT	Journal Article	New Zealand, United Kingdom, & United States	84	-	0.48	33.3 (12.3) [19-60]	- (-) [-]
Kelly et al. 2015 [32]	VAL	Journal Article	United Kingdom	14	-	0.71	33.5 (10.3) [21-58]	- (-) [-]
Kerr et al. 2013 [33]	GRT	Journal Article	United States	40	Healthy Cyclists	0.3	36 (12) [-]	- (-) [-]
Kerr et al. 2016 [34]	GRT	Journal Article	United States	76	Cyclists (n = 40)			
Overweight Women (n = 36)	0.63	- (-) [-]	- (-) [-]					
Kim et al. 2015 [35]	GRT	Journal Article	United States	11	Convenience Sample	0.27	30.67 (7.24) [-]	25.36 (4.57) [-]
Kim et al. 2019 [36]	GRT	Journal Article	United States	27	No Physical or medical disabilities	0.44	33.3 (11.4) [20-64]	24.9 (4.8) [-]
Kitani et al. 2011 [37]	FAR	Conference Paper	Japan	-	-	-	- (-) [-]	- (-) [-]
Kneiirt et al. 2022 [38]	VAL	Abstract	United States	-	-	-	- (-) [-]	- (-) [-]
Kode et al. 2017 [39]	FAR	Thesis	United States	-	-	-	- (-) [-]	- (-) [-]
Laskaris et al. 2019 [40]	OCM	Journal Article	Ghana	141	e-Waste Workers	0	26.9 (-) [16-50]	- (-) [-]
Leask et a. 2015 [41]	OCM	Journal Article	United Kingdom	36	Community-dwelling , medically stable older adults	0.64	- (-) [65-82]	25.6 (5.2) [-]
Li et al. 2015 [42]	FAR	Journal Article	United States	10	-	-	- (-) [-]	- (-) [-]

Reference	Theme	Record Type	Country	Sample Size	Population Characteristics	% Female	Age (mean years (SD) [range])	BMI (mean kg/m2 (SD) [range])
Li et al. 2022 [43]	OCM	Journal Article	China	4	-	-	39.5 (25.7) [23-84]	- (-) [-]
Liu et al. 2020 [44]	FAR	Conference Paper	Japan	-	-	-	- (-) [-]	- (-) [-]
Liu et al. 2023 [45]	FAR	Journal Article	Not Applicable	-	-	-	- (-) [-]	- (-) [-]
Lynn et al. 2020 [46]	GRT	Journal Article	United States	16	-	-	-	-
Marinac et al. 2013 [47]	VAL	Conference Paper	United States	28	Healthy Cyclists	0.32	37 (3.6) [-]	- (-) [-]
Martinez et al. 2021 [48]	VAL	Journal Article	United States	16	Healthy	0.56	46.7 (23.8) [-]	24.9 (4.1) [-]
Miller et al. 2017 [49]	VAL	Abstract	United States	13	Older Adults	-	- (-) [-]	- (-) [-]
Moghimi et al. 2014 [50]	FAR	Conference Paper	same as	Kerr et al. 2013	-	-	-	-
Nakamura et al. 2017 [51]	FAR	Conference Paper	United States	10	-	-	- (-) [-]	- (-) [-]
Nawab et al. 2021 [52]	GRT	Journal Article	United Kingdom	25	Adults on Maintenance Dialysis	0.24	69.6 (11.2) [-]	- (-) [-]
O'Connor et al. 2016 [53]	GRT	Journal Article	Ireland	30	Collegiate Gaelic football players	0.27	20.6 (2.3) [-]	- (-) [-]
Ohnishi et al. 2016 [54]	FAR	Conference Paper	Japan	20	-	-	- (-) [-]	- (-) [-]
Oliveria-Barra et al. 2017 [55]	FAR	Conference Paper	Not Applicable	3	-	-	- (-) [-]	- (-) [-]
Possas et al. 2018 [56]	FAR	Conference Paper	Australia	-	-	-	- (-) [-]	- (-) [-]
Ragusa et al. 2023 [57]	FAR	Journal Article	Italy & United Kingdom	20	-	0.23	29.2 (10.6) [18-55]	- (-) [-]
Rieken et al. 2015 [58]	OCM	Journal Article	Columbia	15	Students	-	- (-) [18-30]	- (-) [-]

Reference	Theme	Record Type	Country	Sample Size	Population Characteristics	% Female	Age (mean years (SD) [range])	BMI (mean kg/m ² (SD) [range])
Rosenberg et al. 2017 [59]	GRT	Journal Article	United States	39	Older Women	1	69.4 (-) [56-94]	- (-) [19.7-45.6]
Sanal Kumar & Bhavani 2019 [60]	FAR	Journal Article	India	-	-	-	- (-) [-]	- (-) [-]
Song et al. 2016 [61]	FAR	Conference Paper	Singapore	-	-	-	- (-) [-]	- (-) [-]
Steinbrink et al. 2022 [62]	VAL	Abstract	United States	-	Healthy Adults	-	- (-) [-]	- (-) [-]
Sundaram & Mayol Cuevas 2009 [63]	FAR	Conference Paper	United Kingdom	1	-	-	- (-) [-]	- (-) [-]
Toth et al. 2018 [64]	GRT	Journal Article	United States	12	Healthy	0.5	35 (13) [-]	24.3 (4.4) [-]
Tsutsui et al. 2023 [65]	GRT	Journal Article	Japan	20	Factory Managers & Workers	0	47.0 (11.6) [-]	- (-) [-]
Wang et al. 2016 [66]	FAR	Conference Paper	China	4	-	-	- (-) [-]	- (-) [-]
Willets et al. 2018 [67]	GRT	Journal Article	United Kingdom	132	-	-	- (-) [-]	- (-) [-]
Wilson et al. 2018 [68]	OCM	Journal Article	United Kingdom	17	Individuals with persistent pain living in the community; older adults without persistent pain	0.65	67.9 (7.0) [52-78]	- (-) [-]
Xiong et al. 2022 [69]	FAR	Journal Article	Australia	26	Community-dwelling individuals with type 2 diabetes	0.38	- (-) [-]	- (-) [-]
Xu et al. 2023 [70]	FAR	Journal Article	China	2	-	-	- (-) [-]	- (-) [-]
Yin et al. 2012 [71]	FAR	Conference Paper	China	-	-	-	- (-) [-]	- (-) [-]

Reference	Theme	Record Type	Country	Sample Size	Population Characteristics	% Female	Age (mean years (SD) [range])	BMI (mean kg/m2 (SD) [range])
Zhan et al. 2012 [72]	FAR	Conference Paper	China	-	-	-	- (-) [-]	- (-) [-]
Zhao et al. 2015 [73]	GRT	Conference Paper	China	10	Older Adults	-	- (-) [55-80]	- (-) [-]

^aFirst-person Activity Recognition

^bOutcome Measure

^cGround-Truth

^dValidation

Appendix D: Extracted Dimensions of Physical Activity and Sedentary Behavior from Included Sources

Reference	Theme	Frequency	Intensity	Duration	Type
Abebe et al. 2016 [1]	FAR	-	-	-	PA
Aguilar Grajeda 2018 [2]	GRT	-	METS	X	PA
Andriyani et al. 2022 [3]	OCM	-	-	-	PA&SB
Bach et al. 2022 [4]	GRT	-	-	X	PA
Bokhari & Kitani 2017 [5]	FAR	-	-	-	PA
Bourke et al. 2017 [6]	GRT	X	-	X	PA
Carlson et al. 2015 [7]	GRT	-	-	X	PA
Cartas et al. 2018 [8]	FAR	-	-	-	PA&SB
Cartas et al. 2020 [9]	FAR	-	-	-	PA
Chasen-Taber et al. 2023 [10]	GRT	-	-	X	PA&SB
Cho et al. 2008 [11]	FAR	-	-	-	PA
Chou et al. 2016 [12]	FAR	-	-	-	PA
Davies et al. 2020 [13]	VAL	-	METS	X	PA&SB
Davies et al. 2021 [14]	OCM	-	-	-	PA&SB
Doherty et al. 2012 [15]	VAL	-	-	X	SB
Doherty et al. 2013 [16]	VAL	-	-	-	PA&SB
Ellis et al. 2016 [17]	GRT	-	-	-	PA&SB
Femiano et al. 2022 [18]	GRT	X	-	-	Steps
Freeman et al. 2021 [19]	OCM	-	-	X	SB
Fullerton et al. 2017 [20]	GRT	X	-	X	PA&SB
Gao et al. 2022 [21]	FAR	-	-	-	PA
Gershuny et al. 2020 [22]	GRT	-	METS	X	PA&SB
Gjoreski et al. 2018 [23]	FAR	-	-	X	PA
Hänggi et al. 2020 [24]	OCM	-	-	X	SB
Hao et al. 2023 [25]	FAR	-	-	-	PA
Hipiny & Mayol-Cuevas 2012 [26]	FAR	-	-	-	PA

Reference	Theme	Frequency	Intensity	Duration	Type
Hipiny 2013 [27]	FAR	-	-	-	PA
Karaman et al. 2011 [28]	FAR	-	-	-	PA
Kelly et al. 2011 [29]	OCM	X	-	X	PA
Kelly 2013 [30]	VAL	X	-	X	PA
Kelly et al. 2014 [31]	GRT	X	-	X	PA
Kelly et al. 2015 [32]	VAL	-	-	X	PA&SB
Kerr et al. 2013 [33]	GRT	-	-	X	PA&SB
Kerr et al. 2016 [34]	GRT	-	-	X	PA&SB
Kim et al. 2015 [35]	GRT	-	-	X	SB
Kim et al. 2019 [36]	GRT	-	-	-	SB
Kitani et al. 2011 [37]	FAR	-	-	-	PA
Kneiert et al. 2022 [38]	VAL	-	-	X	PA
Kode et al. 2017 [39]	FAR	-	-	-	PA
Laskaris et al. 2019 [40]	OCM	X	-	X	PA&SB
Leask et a. 2015 [41]	OCM	-	-	-	SB
Li et al. 2015 [42]	FAR	X	-	-	PA
Li et al. 2022 [43]	OCM	X	-	-	PA
Liu et al. 2020 [44]	FAR	-	-	-	PA
Liu et al. 2023 [45]	FAR	X	-	-	PA
Lynn et al. 2020 [46]	GRT	X	-	-	Steps
Marinac et al. 2013 [47]	VAL	X	-	X	PA&SB
Martinez et al. 2021 [48]	VAL	-	-	X	PA
Miller et al. 2017 [49]	VAL	-	-	-	PA
Moghimi et al. 2014 [50]	FAR	-	-	-	PA&SB
Nakamura et al. 2017 [51]	FAR	-	METS	-	PA&SB
Nawab et al. 2021 [52]	GRT	-	-	-	PA&SB
O'Connor et al. 2016 [53]	GRT	-	-	X	PA&SB
Ohnishi et al. 2016 [54]	FAR	X	-	X	PA
Oliveria-Barra et al. 2017 [55]	FAR	-	-	-	PA

Reference	Theme	Frequency	Intensity	Duration	Type
Possas et al. 2018 [56]	FAR	-	-	-	PA&SB
Ragusa et al. 2023 [57]	FAR	X	-	-	PA&SB
Rieken et al. 2015 [58]	OCM	-	-	-	PA
Rosenberg et al. 2017 [59]	GRT	-	-	-	PA&SB
Sanal Kumar & Bhavani 2019 [60]	FAR	-	-	-	PA&SB
Song et al. 2016 [61]	FAR	-	-	-	PA&SB
Steinbrink et al. 2022 [62]	VAL	-	Category	-	PA
Sundaram & Mayol Cuevas 2009 [63]	FAR	-	-	-	PA
Toth et al. 2018 [64]	GRT	X	-	-	Steps
Tsutsui et al. 2023 [65]	GRT	-	-	X	PA
Wang et al. 2016 [66]	FAR	-	-	-	PA&SB
Willets et al. 2018 [67]	GRT	-	METS	-	PA&SB
Wilson et al. 2018 [68]	OCM	X	-	-	PA
Xiong et al. 2022 [69]	FAR	X	-	-	PA&SB
Xu et al. 2023 [70]	FAR	-	-	-	PA
Yin et al. 2012 [71]	FAR	-	-	-	PA
Zhan et al. 2012 [72]	FAR	-	-	-	PA
Zhao et al. 2015 [73]	GRT	Bouts	-	-	PA

^aFirst-person Activity Recognition

^bOutcome Measure

^cGround-Truth

^dValidation

Appendix E: Extracted Wearable Camera Characteristics from Included Sources

Reference	Theme	Wearable Camera	Location	Mounting Apparatus	Media
Abebe et al. 2016 [1]	FAR	GoPro Hero3+	Sternum	-	Video
Aguilar Grajeda 2018 [2]	GRT	GoPro HERO Session 4	-	-	Video
Andriyani et al. 2022 [3]	OCM	Brinno TLC120	Sternum	Adjustable Chest Harness	Still-Image
Bach et al. 2022 [4]	GRT	GoPro Hero 3+	Sternum	GoPro Chesty	Video
Bokhari & Kitani 2017 [5]	FAR	-	-	-	Video
Bourke et al. 2017 [6]	GRT	GoPro Hero 3+	Sternum	GoPro Chesty	Video
Carlson et al. 2015 [7]	GRT	same as	Kerr et al. 2013	-	-
Cartas et al. 2018 [8]	FAR	OMG Life Autographer	Sternum	Lanyard Around Neck	Still-Image
Cartas et al. 2020 [9]	FAR	Narrative Clip 2	Sternum	Lanyard Around Neck	Still-Image
Chasen-Taber et al. 2023 [10]	GRT	OMG Life Autographer	Sternum	Lanyard Around Neck or Adjustable Chest Harness	Still-Image
Cho et al. 2008 [11]	FAR	-	-	-	-
Chou et al. 2016 [12]	FAR	Serial Camera	Sternum	-	Still-Image
Davies et al. 2020 [13]	VAL	OMG Life Autographer	Sternum	Lanyard Around Neck	Still-Image
Davies et al. 2021 [14]	OCM	OMG Life Autographer	Sternum	Lanyard Around Neck	Still-Image
Doherty et al. 2012 [15]	VAL	Microsoft/Vicon Revue SenseCam	-	-	Still-Image
Doherty et al. 2013 [16]	VAL	Microsoft/Vicon Revue SenseCam	-	-	Still-Image
Ellis et al. 2016 [17]	GRT	Microsoft/Vicon Revue SenseCam	Sternum	Lanyard Around Neck	Still-Image
Femiano et al. 2022 [18]	GRT	GoPro (Unknown)	Sternum	Adjustable Chest Harness	Video
Freeman et al. 2021 [19]	OCM	OMG Life Autographer	Sternum	Lanyard Around Neck	Still-Image

Reference	Theme	Wearable Camera	Location	Mounting Apparatus	Media
Fullerton et al. 2017 [20]	GRT	iON SnapcamLite	-	-	Still-Image
Gao et al. 2022 [21]	FAR	Ubiquiti Labs FrontRow	-	-	Still-Image
Gershuny et al. 2020 [22]	GRT	OMG Life Autographer	Sternum	Lanyard Around Neck or Clip to Upper Garment	Still-Image
Gjoreski et al. 2018 [23]	FAR	Snapcam Drift Compass	Sternum	Adjustable Chest Harness	Still-Image
Hänggi et al. 2020 [24]	OCM	OMG Life Autographer	Sternum	Lanyard Around Neck	Still-Image
Hao et al. 2023 [25]	FAR	GoPro 5	Forehead	Headband	Video
Hipiny & Mayol-Cuevas 2012 [26]	FAR	Mobile Eye	Eyeline	Glasses	Video
Hipiny 2013 [27]	FAR	Not Applicable	-	-	-
Karaman et al. 2011 [28]	FAR	GoPro (-)	Shoulder	Adjustable Chest Harness	Video
Kelly et al. 2011 [29]	OCM	Microsoft/Vicon Revue SenseCam	Sternum	Lanyard Around Neck	Still-Image
Kelly 2013 [30]	VAL	Microsoft/Vicon Revue SenseCam	Sternum	Lanyard Around Neck	Still-Image
Kelly et al. 2014 [31]	GRT	Microsoft/Vicon Revue SenseCam	Sternum	Lanyard Around Neck	Still-Image
Kelly et al. 2015 [32]	VAL	OMG Life Autographer	Sternum	Lanyard Around Neck	Still-Image
Kerr et al. 2013 [33]	GRT	Microsoft/Vicon Revue SenseCam	Sternum	Lanyard Around Neck	Still-Image
Kerr et al. 2016 [34]	GRT	Microsoft/Vicon Revue SenseCam	Sternum	Lanyard Around Neck	Still-Image
Kim et al. 2015 [35]	GRT	OMG Life Autographer	Sternum	Lanyard Around Neck	Still-Image
Kim et al. 2019 [36]	GRT	OMG Life Autographer	Sternum	Lanyard Around Neck	Still-Image
Kitani et al. 2011 [37]	FAR	-	-	-	-

Reference	Theme	Wearable Camera	Location	Mounting Apparatus	Media
Kneiart et al. 2022 [38]	VAL	-	Sternum	-	Still-Image
Kode et al. 2017 [39]	FAR	GoPro Hero 4	Forehead	-	Video
Laskaris et al. 2019 [40]	OCM	GoPro Hero 4	Shoulder	-	Still-Image
Leask et a. 2015 [41]	OCM	Microsoft/Vicon Revue SenseCam	Sternum	Lanyard Around Neck	Still-Image
Li et al. 2015 [42]	FAR	eButton	Sternum	Clip	Still-Image
Li et al. 2022 [43]	OCM	Narrative Clip 2	-	Clip	Still-Image
Liu et al. 2020 [44]	FAR	-	Sternum	-	-
Liu et al. 2023 [45]	FAR	Not Applicable	-	-	Video
Lynn et al. 2020 [46]	GRT	GoPro (-)	Sternum	Adjustable Chest Harness	Video
Marinac et al. 2013 [47]	VAL	same as	Kerr et al. 2013	-	-
Martinez et al. 2021 [48]	VAL	OMG Life Autographer	Sternum	Lanyard Around Neck	Still-Image
Miller et al. 2017 [49]	VAL	-	Sternum	-	-
Moghimi et al. 2014 [50]	FAR	same as	Kerr et al. 2013	-	-
Nakamura et al. 2017 [51]	FAR	-	Sternum	-	Video
Nawab et al. 2021 [52]	GRT	OMG Life Autographer	-	-	Still-Image
O'Connor et al. 2016 [53]	GRT	Microsoft/Vicon Revue SenseCam	Sternum	Lanyard Around Neck	Still-Image
Ohnishi et al. 2016 [54]	FAR	Panasonic HX-A100	Wrist	-	Video
Oliveria-Barra et al. 2017 [55]	FAR	Not Applicable	-	-	-
Possas et al. 2018 [56]	FAR	Vuzix M300 Smart Glasses	Eyeline	Glasses	Video
Ragusa et al. 2023 [57]	FAR	Intel RealSense SR300	Forehead	Headset	Video
Rieken et al. 2015 [58]	OCM	Microsoft/Vicon Revue SenseCam	Sternum	-	Still-Image
Rosenberg et al. 2017 [59]	GRT	Microsoft/Vicon Revue SenseCam	Sternum	Lanyard Around Neck	Still-Image

Reference	Theme	Wearable Camera	Location	Mounting Apparatus	Media
Sanal Kumar & Bhavani 2019 [60]	FAR	-	-	-	-
Song et al. 2016 [61]	FAR	Google Glass	Eyeline	Glasses	Video
Steinbrink et al. 2022 [62]	VAL	-	Sternum	-	Still-Image
Sundaram & Mayol Cuevas 2009 [63]	FAR	-	Shoulder	-	-
Toth et al. 2018 [64]	GRT	GoPro Hero 3+	Sternum	Adjustable Chest Harness	Video
Tsutsui et al. 2023 [65]	GRT	Brinno TLC120	Waist	Clip to Belt	Still-Image
Wang et al. 2016 [66]	FAR	Microsoft/Vicon Revue SenseCam	-	-	Still-Image
Willets et al. 2018 [67]	GRT	same as	Gershuny et al. 2020	-	-
Wilson et al. 2018 [68]	OCM	Microsoft/Vicon Revue SenseCam	Sternum	Lanyard Around Neck	Still-Image
Xiong et al. 2022 [69]	FAR	Edesix VB-300	Sternum	Lanyard Around Neck	Still-Image
Xu et al. 2023 [70]	FAR	Kuaiyan Vision Smart Glasses	Eyeline	Glasses	Video
Yin et al. 2012 [71]	FAR	eButton	Sternum	-	Video
Zhan et al. 2012 [72]	FAR	-	Eyeline	Glasses	Video
Zhao et al. 2015 [73]	GRT	eButton	Sternum	-	Still-Image

^aFirst-person Activity Recognition

^bOutcome Measure

^cGround-Truth

^dValidation

1. Abebe G, Cavallaro A, Parra X (2016) Robust multi-dimensional motion features for first-person vision activity recognition. *Computer Vision and Image Understanding* 149:229–248
2. Aguilar Grajeda R (2018) Using plantar pressure for free-living posture recognition and sedentary behaviour monitoring. PhD thesis, Loughborough University (United Kingdom)
3. Andriyani FD, Biddle SJH, Priambadha AA, Thomas G, De Cocker K (2022) Physical activity and sedentary behaviour of female adolescents in Indonesia: A multi-method study on duration, pattern and context. *Journal of Exercise Science & Fitness* 20:128–139
4. Bach K, Kongsvold A, Bårdstu H, Bardal EM, Kjærnli HS, Herland S, Logacjov A, Mork PJ (2022) A Machine Learning Classifier for Detection of Physical Activity Types and Postures During Free-Living. *Journal for the Measurement of Physical Behaviour* 5:24–31
5. Bokhari SZ, Kitani KM (2017) Long-Term Activity Forecasting Using First-Person Vision. In: Lai S-H, Lepetit V, Nishino K, Sato Y (eds) *Computer Vision – ACCV 2016*. Springer International Publishing, Cham, pp 346–360
6. Bourke AK, Ihlen EAF, Bergquist R, Wik PB, Vereijken B, Helbostad JL (2017) A Physical Activity Reference Data-Set Recorded from Older Adults Using Body-Worn Inertial Sensors and Video Technology-The ADAPT Study Data-Set. *Sensors (Basel)*. <https://doi.org/10.3390/s17030559>

7. Carlson JA, Jankowska MM, Meseck K, Godbole S, Natarajan L, Raab F, Demchak B, Patrick K, Kerr J (2015) Validity of PALMS GPS Scoring of Active and Passive Travel Compared with SenseCam. *Medicine & Science in Sports & Exercise* 47:662–667
8. Cartas A, Marín J, Radeva P, Dimiccoli M (2018) Batch-based activity recognition from egocentric photo-streams revisited. *PATTERN ANALYSIS AND APPLICATIONS* 21:953–965
9. Cartas A, Radeva P, Dimiccoli M (2020) Activities of Daily Living Monitoring via a Wearable Camera: Toward Real-World Applications. *IEEE Access* 8:77344–77363
10. Chasan-Taber L, Park S, Marcotte RT, Staudenmayer J, Strath S, Freedson P (2023) Update and Novel Validation of a Pregnancy Physical Activity Questionnaire. *Am J Epidemiol* 192:1743–1753
11. Cho Y, Nam Y, Choi Y-J, Cho W-D (2008) SmartBuckle: Human activity recognition using a 3-Axis accelerometer and a wearable camera. In: *Proceedings of the 2nd International Workshop on Systems and Networking Support for Health Care and Assisted Living Environments*. Association for Computing Machinery, New York, NY, USA, pp 1–3
12. Chou C-K, Lin C-C, Chen M-S (2016) Context-aware daily activity summarization with adaptive transmission. In: *Proceedings of the 31st Annual ACM Symposium on Applied Computing*. Association for Computing Machinery, New York, NY, USA, pp 560–565

13. Davies A, Allman-Farinelli M, Owen K, Signal L, Hosking C, Wang L, Bauman A (2020) Feasibility Study Comparing Physical Activity Classifications from Accelerometers with Wearable Camera Data. *INTERNATIONAL JOURNAL OF ENVIRONMENTAL RESEARCH AND PUBLIC HEALTH*. <https://doi.org/10.3390/ijerph17249323>
14. Davies A, Chan V, Bauman A, Signal L, Hosking C, Gemming L, Allman-Farinelli M (2021) Using wearable cameras to monitor eating and drinking behaviours during transport journeys. *Eur J Nutr* 60:1875–1885
15. Doherty A, Marshall S, Kelly P, Hamilton A, Oliver M, Badland H, Kerr J, Foster C (2012) Identifying sedentary behaviour types using SenseCam: A pilot study. *Journal of Science and Medicine in Sport* 15:S296–S297
16. Doherty AR, Kelly P, Kerr J, Marshall S, Oliver M, Badland H, Hamilton A, Foster C (2013) Using wearable cameras to categorise type and context of accelerometer-identified episodes of physical activity. *Int J Behav Nutr Phys Act* 10:22
17. Ellis K, Kerr J, Godbole S, Staudenmayer J, Lanckriet G (2016) Hip and Wrist Accelerometer Algorithms for Free-Living Behavior Classification. *Medicine & Science in Sports & Exercise* 48:933–940
18. Femiano R, Werner C, Wilhelm M, Eser P (2022) Validation of open-source step-counting algorithms for wrist-worn tri-axial accelerometers in cardiovascular patients. *Gait & Posture* 92:206–211
19. Freeman N, Gage R, Chambers T, Blaschke P, Cook H, Stanley J, Pearson A, Smith M, Barr M, Signal L (2021) Where do the children play? An objective analysis of children’s use of green space. *Health Promotion International* 36:846–853

20. Fullerton E, Heller B, Munoz-Organero M (2017) Recognizing Human Activity in Free-Living Using Multiple Body-Worn Accelerometers. *IEEE Sensors Journal* 17:5290–5297
21. Gao Q, Pei M, Shen H (2022) Do You Live a Healthy Life? Analyzing Lifestyle by Visual Life Logging. In: *ICASSP 2022 - 2022 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP)*. pp 1845–1849
22. Gershuny J, Harms T, Doherty A, Thomas E, Milton K, Kelly P, Foster C (2020) Testing Self-Report Time-Use Diaries against Objective Instruments in Real Time. *Sociological Methodology* 50:318–349
23. Gjoreski H, Ciliberto M, Wang L, Ordonez Morales FJ, Mekki S, Valentin S, Roggen D (2018) The University of Sussex-Huawei Locomotion and Transportation Dataset for Multimodal Analytics With Mobile Devices. *IEEE Access* 6:42592–42604
24. Hänggi JM, Spinnler S, Christodoulides E, Gramespacher E, Taube W, Doherty A (2020) Sedentary Behavior in Children by Wearable Cameras: Development of an Annotation Protocol. *Am J Prev Med* 59:880–886
25. Hao Y, Uto K, Kanezaki A, Sato I, Kawakami R, Shinoda K (2023) EvIs-Kitchen: Egocentric Human Activities Recognition with Video and Inertial Sensor Data. In: Dang-Nguyen D-T, Gurrin C, Larson M, Smeaton AF, Rudinac S, Dao M-S, Trattner C, Chen P (eds) *MultiMedia Modeling*. Springer International Publishing, Cham, pp 373–384
26. Hipiny I, Mayol-Cuevas W (2012) Recognising Egocentric Activities from Gaze Regions with Multiple-Voting Bag of Words. CTIT technical reports series
27. Hipiny I (2013) Egocentric activity recognition using gaze. PhD thesis, University of Bristol (United Kingdom)

28. Karaman S, Benois-Pineau J, Mégret R, Pinquier J, Gaëstel Y, Dartigues J-F (2011) Activities of daily living indexing by hierarchical HMM for dementia diagnostics. In: 2011 9th International Workshop on Content-Based Multimedia Indexing (CBMI). pp 79–84
29. Kelly P, Doherty A, Berry E, Hodges S, Batterham AM, Foster C (2011) Can we use digital life-log images to investigate active and sedentary travel behaviour? Results from a pilot study. *Int J Behav Nutr Phys Act* 8:44
30. Kelly P (2013) Assessing the utility of wearable cameras in the measurement of walking and cycling. PhD thesis, University of Oxford (United Kingdom)
31. Kelly P, Doherty A, Mizdrak A, Marshall S, Kerr J, Legge A, Godbole S, Badland H, Oliver M, Foster C (2014) High group level validity but high random error of a self-report travel diary, as assessed by wearable cameras. *Journal of Transport & Health* 1:190–201
32. Kelly P, Thomas E, Doherty A, Harms T, Burke Ó, Gershuny J, Foster C (2015) Developing a Method to Test the Validity of 24 Hour Time Use Diaries Using Wearable Cameras: A Feasibility Pilot. *PLOS ONE* 10:e0142198
33. Kerr J, Marshall S, Godbole S, Chen J, Legge A, Doherty A, Kelly P, Oliver M, Badland H, Foster C (2013) Using the SenseCam to Improve Classifications of Sedentary Behavior in Free-Living Settings. *AMERICAN JOURNAL OF PREVENTIVE MEDICINE* 44:290–296
34. Kerr J, Patterson RE, Ellis K, Godbole S, Johnson E, Lanckriet G, Staudenmayer J (2016) Objective Assessment of Physical Activity: Classifiers for Public Health. *Med Sci Sports Exerc* 48:951–957

35. Kim Y, Barry VW, Kang M (2015) Validation of the ActiGraph GT3X and activPAL Accelerometers for the Assessment of Sedentary Behavior. *Measurement in Physical Education and Exercise Science* 19:125–137
36. Kim H, Kang M (2019) Validation of Sedentary Behavior Record Instrument as a Measure of Contextual Information of Sedentary Behavior. *J Phys Act Health* 16:623–630
37. Kitani KM, Okabe T, Sato Y, Sugimoto A (2011) Fast unsupervised ego-action learning for first-person sports videos. In: *CVPR 2011*. pp 3241–3248
38. Kneiert MF, Martinez J, Steinbrink GM, Strath SJ (2022) Comparison Of Wearable Camera Image Physical Activity Behavior Estimates To Direct Observation. *Medicine & Science in Sports & Exercise* 54:175–176
39. Kode KA (2017) Recognizing Manual Actions from Egocentric Videos. M.S., University of Maryland, Baltimore County
40. Laskaris Z, Milando C, Batterman S, Mukherjee B, Basu N, O’neill MS, Robins TG, Fobil JN (2019) Derivation of Time-Activity Data Using Wearable Cameras and Measures of Personal Inhalation Exposure among Workers at an Informal Electronic-Waste Recovery Site in Ghana. *Annals of Work Exposures and Health* 63:829–841
41. Leask C, Harvey J, Skelton D, Chastin S (2015) Exploring the context of sedentary behaviour in older adults (what, where, why, when and with whom). *European Reviews of Aging & Physical Activity* 12:1–8
42. Li Z, Wei Z, Yue Y, Wang H, Jia W, Burke L, Baranowski T, Sun M (2015) An Adaptive Hidden Markov Model for Activity Recognition Based on a Wearable Multi-Sensor Device. *Journal of Medical Systems* 39:1–10

43. Li W, Long Y, Kwan M-P, Liu N, Li Y, Zhang Y (2022) Measuring individuals' mobility-based exposure to neighborhood physical disorder with wearable cameras. *Applied Geography* 145:102728
44. Liu Z, Chihara T, Tan JK (2020) Ego-Posture Estimation for a Pedestrian Using a Monocular Wearable Camera. In: 2020 5th International Conference on Computer and Communication Systems (ICCCS). pp 409–412
45. Liu X, Zhou S, Lei T, Jiang P, Chen Z, Lu H (2023) First-Person Video Domain Adaptation with Multi-Scene Cross-Site Datasets and Attention-Based Methods. *IEEE Transactions on Circuits and Systems for Video Technology* 1–1
46. Lynn R, Pfitzer R, Rogers RR, Ballmann CG, Williams TD, Marshall MR (2020) Step-Counting Validity of Wrist-Worn Activity Monitors During Activities With Fixed Upper Extremities. *Journal for the Measurement of Physical Behaviour* 3:197–203
47. Marinac C, Merchant G, Godbole S, Chen J, Kerr J, Clark B, Marshall S (2013) The feasibility of using SenseCams to measure the type and context of daily sedentary behaviors. In: *Proceedings of the 4th International SenseCam & Pervasive Imaging Conference*. Association for Computing Machinery, New York, NY, USA, pp 42–49
48. Martinez J, Decker A, Cho CC, Doherty A, Swartz AM, Staudenmayer JW, Strath SJ (2021) Validation of Wearable Camera Still Images to Assess Posture in Free-Living Conditions. *J Meas Phys Behav* 4:47–52
49. Miller N, Welch W, Doherty A, Strath S (2017) Accuracy Of Behavioral Assessment With A Wearable Camera in Semi-structured And Free Living Conditions In Older Adults. *MEDICINE AND SCIENCE IN SPORTS AND EXERCISE* 49:651–651

50. Moghimi M, Wu W, Chen J, Godbole S, Marshall S, Kerr J, Belongie S (2014) Analyzing sedentary behavior in life-logging images. In: 2014 IEEE International Conference on Image Processing (ICIP). IEEE, Paris, France, pp 1011–1015
51. Nakamura K, Yeung S, Alahi A, Fei-Fei L (2017) Jointly Learning Energy Expenditures and Activities Using Egocentric Multimodal Signals. In: 2017 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp 6817–6826
52. Nawab KA, Storey BC, Staplin N, et al (2021) Accelerometer-measured physical activity and functional behaviours among people on dialysis. *Clinical Kidney Journal* 14:950–958
53. O. Connor S, McCaffrey N, Whyte E, Moran K (2016) The novel use of a SenseCam and accelerometer to validate training load and training information in a self-recall training diary. *Journal of Sports Sciences* 34:303–310
54. Ohnishi K, Kanehira A, Kanezaki A, Harada T (2016) Recognizing Activities of Daily Living with a Wrist-Mounted Camera. In: 2016 IEEE Conference on Computer Vision and Pattern Recognition (CVPR). pp 3103–3111
55. Oliveira-Barra G, Dimiccoli M, Radeva P (2017) Leveraging Activity Indexing for Egocentric Image Retrieval. In: Alexandre LA, Salvador Sánchez J, Rodrigues JMF (eds) *Pattern Recognition and Image Analysis*. Springer International Publishing, Cham, pp 295–303
56. Possas R, Caceres SP, Ramos F (2018) Egocentric Activity Recognition on a Budget. In: 2018 IEEE/CVF Conference on Computer Vision and Pattern Recognition. pp 5967–5976

57. Ragusa F, Furnari A, Farinella G (2023) MECCANO: A multimodal egocentric dataset for humans behavior understanding in the industrial-like domain. *COMPUTER VISION AND IMAGE UNDERSTANDING*.
<https://doi.org/10.1016/j.cviu.2023.103764>
58. Rieken J, Garcia-Sanchez E, Trujillo M, Bear D (2015) Digital Ethnography and the Social Dimension of Introspection: An Empirical Study in Two Colombian Schools. *INTEGRATIVE PSYCHOLOGICAL AND BEHAVIORAL SCIENCE* 49:253–274
59. Rosenberg D, Godbole S, Ellis K, Di C, Lacroix A, Natarajan L, Kerr J (2017) Classifiers for Accelerometer-Measured Behaviors in Older Women. *Medicine & Science in Sports & Exercise* 49:610–617
60. Sanal Kumar KP, Bhavani R (2019) Human activity recognition in egocentric video using PNN, SVM, kNN and SVM+kNN classifiers. *Cluster Comput* 22:10577–10586
61. Song S, Cheung N-M, Chandrasekhar V, Mandal B, Liri J (2016) Egocentric activity recognition with multimodal fisher vector. In: 2016 IEEE International Conference on Acoustics, Speech and Signal Processing (ICASSP). pp 2717–2721
62. Steinbrink GM, Martinez J, Kneiort MF, Strath SJ (2022) Assessing Posture And Activity Intensity Agreement Between Wearable Camera Images And Criterion Direct Observation. *Medicine & Science in Sports & Exercise* 54:176–177

63. Sundaram S, Mayol Cuevas WW (2009) High level activity recognition using low resolution wearable vision. In: 2009 IEEE Computer Society Conference on Computer Vision and Pattern Recognition Workshops. pp 25–32
64. Toth LP, Park S, Springer CM, Feyerabend MD, Steeves JA, Bassett DR (2018) Video-Recorded Validation of Wearable Step Counters under Free-living Conditions. *Medicine & Science in Sports & Exercise* 50:1315
65. Tsutsui T, Tsutsui Y, Tsukamoto M, Nakamura E (2023) Validation of foot plantar pressure sensor data used to estimate standing, sitting, and moving durations in one working day. *J Orthop Sci* 28:217–221
66. Wang P (2016) Investigating Factorizations in Everyday Activity Recognition. Tsinghua University. <https://doi.org/10.1117/12.2243847>
67. Willetts M, Hollowell S, Aslett L, Holmes C, Doherty A (2018) Statistical machine learning of sleep and physical activity phenotypes from sensor data in 96,220 UK Biobank participants. *Sci Rep* 8:7961
68. Wilson G, Jones D, Schofield P, Martin DJ (2018) The use of a wearable camera to explore daily functioning of older adults living with persistent pain: Methodological reflections and recommendations. *Journal of Rehabilitation and Assistive Technologies Engineering* 5:2055668318765411
69. Xiong H, Phan HN, Yin K, Berkovsky S, Jung J, Lau AYS (2022) Identifying daily activities of patient work for type 2 diabetes and co-morbidities: A deep learning and wearable camera approach. *J Am Med Inform Assoc* 29:1400–1408

70. Xu L, Wu Q, Pan L, Meng F, Li H, He C, Wang H, Cheng S, Dai Y (2023) Towards Continual Egocentric Activity Recognition: A Multi-Modal Egocentric Activity Dataset for Continual Learning. *IEEE Transactions on Multimedia* 1–15
71. Yin B, Qi W, Wei Z, Nie J (2012) Indirect human activity recognition based on optical flow method. In: 2012 5th International Congress on Image and Signal Processing. pp 99–103
72. Zhan K, Ramos F, Faux S (2012) Activity recognition from a wearable camera. In: 2012 12th International Conference on Control Automation Robotics & Vision (ICARCV). IEEE, Guangzhou, China, pp 365–370
73. Zhao Q, Wang J, Feng W, Jia W, Burke LE, Zgibor JC, Sun M (2015) Assessing physical performance in free-living older adults with a wearable computer. In: 2015 41st Annual Northeast Biomedical Engineering Conference (NEBEC). pp 1–2

Appendix F: Oxford Image Browser Behavior Annotation Codes

Terminology

- **IMG(s)**: Images
- **Code Line**: The line above the images in the Oxford interface.
- **“Put a Break”**: When the coder hovers the mouse pointer over the code line (in between images) and right-clicks it to separate the code line.
- **“Apply Code”**: When the coder right-clicks on a code in the schema and drags it over the code line.
- **Object of Interaction (OI)**: An object that the individual can grasp and then perform an activity with or interacts with in some other way (reference coding manual for what counts as an “interaction”).
 - OI’s will fall under categories that may be dependent on the setting
 - A broom, duster and dustpan would all be OI’s related to CLEANING if the individual is in a DOMESTIC setting. If these OI’s are seen in a NON-DOMESTIC setting, then the EP will most likely be under Occupational – CUSTODIAL WORK.
 - A tablet, computer monitor and phone would all be OI’s related to ELECTRONICS but if a computer is seen in a NON-DOMESTIC setting then the EP may be Occupational – OFFICE WORK.
- **Established Pattern (EP)**: The code that has been determined for the three images after a break in the code line. Keep in mind the code is NOT dragged from the schema to the code line yet.

- **Deviant:** An image that does not follow an established pattern due to:
 - The image does not meet the Pattern Requirements for a given Method
 - The individual moves from a DOMESTIC setting to a NON-DOMESTIC setting

General Notes (Applies to all methods)

- All activities, except for **UNCODED** or **Transition (< 3 IMGs)** must have at least 3 codeable IMGs in a row in order to assign a code. Any fewer than three IMGs must be coded as **UNCODED** or **Transition (< 3 IMGs)**. In addition, if the IMG set for the camera start time or the camera stop time has more than two IMGs for any reason, you will still use those codes.
- Only one activity code is able to be assigned per photo.
- Always go forward in terms of assigning breaks in a sequence of IMGs. Go backwards and forwards in terms of developing a “mental map” of where participant is.
- Make sure not to code blurry/dark IMGs as transitions- they have their own code. If an IMG is obscured/blurred, a code may still be applied if the Pattern Requirements (OIs or Cues are seen) are met but not if the IMG is dark (no way to tell if there is still an OI or in same setting).
- When indoors, keep in mind the room furnishings, décor, and possible OIs.
- When outdoors, create a mental map of the area around the participant (vicinity and environment). Keep in mind OI’s as well.

- Researchers talking towards camera for IMG sets:
 - These IMGs are not considered deviant UNLESS there are 5 consecutive IMGs of this.
 - If there are 5 consecutive images of the researchers talking to the participant, put a break between the last activity image and first “researcher talking” image.
 - The code that should be applied when the researcher is talking to the participant is one of the NO CLEAR ACTIVITY codes.

General Procedure

1. After the IMG set has been selected and the behavior schema is selected, go through the IMGs until a “camera start time” can be applied. When this code cannot be applied anymore, put a break between the last “camera start time” image and the next image.
2. Look at the three IMGs immediately after the break in the code line to determine which Method will be used for the EP:
 - a. Is the individual in a DOMESTIC setting or not?
 - b. If YES, then only Method #1 will be used for an EP.
 - c. If NO, then any Method may be used for an EP. Additional information will need to be determined in this order:
 - i. Is there an OI? – Most likely a Method #1 Code

- ii. Is the individual in a specific NON-DOMESTIC setting? – Most likely a Method #2 code
- iii. Is there movement between the first three images (reference Posture Annotation Rules) – Most likely a Method #3 code.

3. If an EP cannot be determined from using a method or a method cannot be determined, then **No Specific Activity** will be the EP.
4. After an EP has been determined for the three IMGs, go forward in the IMG set until you see a deviant.
5. After an IMG is determined to be a deviant, look at the NEXT IMG in the sequence:
 - a. If the NEXT image follows the EP, do not put a break (EP is maintained)
 - b. If the NEXT image does not follow the EP (meaning there are TWO deviant IMGs in a row), put a break between the last image in the EP and the first deviant IMG.
6. If a break is put, apply the EP code for the code line that has been broken.
7. For the three IMGs after the last break, repeat steps 2-7.
8. Reference any additional steps that are unique to the last method used for the EP.
9. Once “camera stop time” code can be applied, end the coding session and follow the procedure for downloading annotation files.

Method #1 (Rolly Polly)

For Codes:

- INDEPENDENT ; caring/grooming
- INDEPENDENT ; leisure active
- INDEPENDENT ; leisure inactive
- DOMESTIC (all)

Pattern Requirements:

1. OI
 - Reference Coding Manual for OI's that would fall under each code
2. OI Proximity (to camera): Interaction definition for the OI code is met.
 - The OI is within arm's reach (DOMESTIC codes) or meets the code's "interaction" definition (INDEPENDENT codes).
3. ****OI Vicinity****: The immediate environment (a.k.a. vicinity) in which the OI was last seen.
 - A point of reference or setting cues in the image inform you that they are still within the same area.
 - Ask yourself, "Can the individual be still doing [CODE] in this room/area?"

Deviations:

1. No pattern requirements are met.

2. An OI related to another DOMESTIC or INDEPENDENT code appears
3. Individual leaves DOMESTIC setting
4. ****OI is not seen anymore (only in NON-DOMESTIC settings)****

Notes:

- ****Requirement 3 is only applicable in a DOMESTIC setting EXCEPT FOR Leisure Active****
- Steps 1 and 2 are necessary for and EP after a break. After an EP is determined, they are not needed for all IMGs afterwards and meeting requirement #3 is ample enough (Reference DOMESTIC #1)
- An individual moving around their house with no OI does NOT indicate a change to use Method #3. (Reference DOMESTIC #4). Remember, once an individual is in a DOMESTIC setting only Method #1 will be used.

205

Method #2 (Easy Going Flowing)

For Codes:

- NON-DOMESTIC (all)

Pattern Requirements:

1. Two Specific Setting Cues
 - Reference Coding Manual for Cues that are related to a code.

- Cues may not be immediate and appear later when individual is in a setting, requiring you to go back in the image sequence to either change the EP (Reference NON-DOMESTIC #2) OR put a break. (Reference NON-DOMESTIC #3).
- Once the Two Specific Setting Cues are seen and an EP is established, only Requirement #2 is needed to maintain EP barring no deviant cues are given.

2. Remain in Setting

- Individual remains in the setting that the cues arose in. EP is maintained barring no deviant cues are seen.

206

Deviations:

1. Individual enters their DOMESTIC setting.
2. Individual leaves specific NON-DOMESTIC setting.
3. An INDEPENDENT-related OI appears.

Notes:

- Once the Two Specific Setting Cues are seen and an EP is established, only Requirement #2 is needed to maintain EP barring no deviant cues are given.

Method #3 (MoveMint OH NO Cycle-dent)

For Codes:

- INDEPENDENT ; cycling
- INDEPENDENT ; movement

Pattern Requirements:

1. NON-DOMESTIC setting
 - Individual is not at their DOMESTIC setting
2. Movement
 - Use Posture Annotation Rules to determine if there is movement.

Deviations:

1. Individual has reached a new area.
 - Individual is in a DOMESTIC setting or specific NON-DOMESTIC setting for 5 images.
2. Individual is not moving anymore
 - No movement for 5 images
3. A DOMESTIC-related OI appearing MAY be a deviation

Notes:

- If an INDEPENDENT-related OI appears while the Pattern Requirements are met, there are still no deviations
- An individual moving around their house with no OI does NOT indicate a change to use Method #3. Remember, once an individual is in a DOMESTIC setting only Method #1 will be used.

- If an individual stops moving (requiring the coder to put a break) but Method#3 is still used after the break, still use the initial setting from before the break.

Name	Operational Definition	Example	Notes
<i>DOMESTIC</i>			
Cleaning	<p>OI: Broom / mop / sweeper brush / cloth /vacuuming / duster / dishes</p> <p>Individual is using OI to free objects or surfaces of dust, dirt, and scraps.</p>	<p>Dusting</p> <p>Mopping / Sweeping</p> <p>Scrubbing</p> <p>Cleaning dirty dishes / putting them away</p> <p>Vacuuming</p> <p>Washing/ organizing car</p>	<p>OIs are tools used to perform the activities related to cleaning.</p> <p>Cleaning a textile is NOT this code but rather under the LAUNDRY code.</p>
Cooking (meal prep/cleanup)	<p>OI: Groceries / veggies & meat / stove & oven / dishes / kitchen utensils</p> <p>Individual is preparing a meal and cleaning up any utensils used in the process.</p>	<p>Chopping vegetables.</p> <p>Making a meal (sandwich, entrée)</p> <p>Setting dishes on table or using utensils to cook</p> <p>Bringing in groceries from car.</p>	<p>A tool (knife to cut groceries, blender to mix ingredients) may be used to interact with OI.</p>
C/F/R/M (house)	<p>OI: Architecture (floor, roof, windows, wall, door)</p> <p>Individual is Constructing, Fixing, Repairing, or Maintaining an architecture (house, shed, garage) on their property.</p>	<p>Repairing roof tiles.</p> <p>Constructing a wall</p> <p>Repairing kitchen floor tile.</p> <p>Maintaining windows (applying caulk on sides).</p>	<p>A tool (power saw to cut a pipe, screwdriver to install a doorknob) will most likely be used to interact with OI.</p> <p>Fixtures (large household appliances, sink, chandeliers) are NOT considered part of architecture</p>
C/F/R/M (non-house)	<p>OI: Large household appliance (washer/dryer, stove/oven) / sink / various objects not part of an architecture</p> <p>Individual is Constructing, Fixing, Repairing, or Maintaining a fixture or object not part of an architecture in their DOMESTIC setting.</p>	<p>Fixing a leaky faucet on a sink.</p> <p>Constructing playhouse for child.</p> <p>Repairing vacuum.</p> <p>Interacting with cables attached to TV.</p>	<p>A tool (wrench for a pipe, screwdriver or hammer for nails) may be used to interact with the OI.</p>

Laundry	<p>OI: Textiles (clothing, towels, linen)</p> <p>Individual is interacting with a textile to clean or organize.</p>	<p>Washing/Drying textiles (appliance or not)</p> <p>Gathering curtains to wash.</p> <p>Ironing clothes to straighten</p> <p>Loading/unloading washer or dryer.</p> <p>Folding towels and hanging clothes</p>	<p>A tool (iron to straighten clothes, laundry basket to carry clothes, hangers to hang clothes) may be used to interact with OI.</p>
Lawn & Garden	<p>OI: Lawnmower / rake / shovel / (snow)blower / hose / wheelbarrow</p> <p>Individual is improving the appearance of land on their property or clearing land of unwanted green matter.</p>	<p>Clearing snow from the sidewalk.</p> <p>Shoveling dirt away from garden.</p> <p>Mowing the grass.</p> <p>Raking leaves on the waterway.</p> <p>Watering plants and flowers.</p> <p>Pulling out weeds.</p>	<p>OIs are tools are used to perform activities related to landscaping/gardening.</p>
Other	<p>OI: unknown OI</p> <p>Individual is grasping/manipulating an object(s) that has no clear activities related to it or are performing an activity not covered by any DOMESTIC codes.</p>	<p>Individual is grasping objects and moving them around (organizing)</p> <p>Taking out the trash (begins with trash in hand and ends when individual is back inside house).</p> <p>Moving furniture in/out of house</p> <p>Getting the mail.</p> <p>Decorating/setting up decorations around house</p>	<p>Activities related to upkeep of their DOMESTIC setting (ask yourself: can I call this a chore?)</p>
<i>NON-DOMESTIC</i>			
Errands/Social Setting – Gas Station	<p>Cue: Gas Pumps / Cars Parked / Air Compressor</p> <p>Individual is refueling their automobile or using other utilities at a gas station for the purpose of vehicle maintenance.</p>	<p>Refilling gasoline tank of car.</p> <p>Pumping air into tire.</p> <p>Getting car wash (manual or drive-thru)</p>	

Errands/Social Setting – Shopping	<p>Cue: Goods on shelves/ perishables in refrigeration / store fronts / kiosks with goods / counter with cashier and store menu in background / putting goods in automobile / fast-food restaurant</p> <p>Individual is in a setting where an exchange of goods may take place or goods may be taken (food from cafeteria in nursing home)</p>	<p>Inside a grocery store. Inside a mall walking around even if not in a store. At a farmers market looking at goods. *Taking any bought goods and putting them in their vehicle.*</p>	<p>If individual is at a fast-food restaurant, EP is SHOPPING then changes to EATING/DRINKING if they decide to sit down and eat.</p>
Errands/Social Setting – Social Event	<p>Cue: Large gathering of people / sports arena / non-domestic house talking to people / sit-down restaurant / work social / bar / tavern</p> <p>Individual is in a setting for the purpose of socializing or to experience some form of entertainment</p>	<p>Sitting in an arena watching a sports game. At a friend's or relative's house socializing. At a bar / sit-down restaurant waiting for food/drinks or check.</p>	<p>If individual is at a sit-down restaurant, EP is SOCIAL EVENT then changes to EATING/DRINKING once food/drink arrives. EP changes back to SOCIAL EVENT once food/drinks have stopped coming to table.</p>
Errands/Social Setting – Other	<p>Cue: Inside building that provides setting cues but no code fits it.</p> <p>Individual is in a setting that provides cues (can be described) but does not fall under a NON-DOMESTIC code.</p>	<p>At a bank depositing money or using ATM At a clinic receiving medical advice, information, attention. At a shipping/mailling office (UPS, FedEx). In a gym or recreational center.</p>	<p>At an airport terminal. At a park (jungle gym, benches)</p>
Occupation – Blue Collar Work	<p>Cue: CFRM-related OIs & tools / cleaning tools / laundry / gardening tools / heavy machinery (bulldozer, forked lift, tractor, etc.) / construction material (lumbar, metal, cement) / livestock / barns</p> <p>Individual is in a setting where tools are used to perform some kind of manual labor (skilled, technical work)</p>	<p>Construction work (public roads, fixing houses, carpentry) Electrical work (fixing lamplights, installing house electrical system) In a warehouse working with materials. Plumbing (Pipe laying along roads, installing sprinkler system) Technician Work.</p>	<p>If the C/F/R/M, CLEANING, LAUNDRY or LAWN&GARDEN codes could be applied in a NON-DOMESTIC setting and there are no other specific setting cues, EP is most likely in an Occupation – BLUE COLLAR WORK. An individual COOKING/MEAL PREP with food that is from home or food bought for them to eat</p>

		Janitorial work (cleaning bathrooms). Farming (tending livestock/crops).	while at work are not deviants. Continue to role the occupation code.
Occupation – Service Work	Cue: CARING/GROOMING-related OIs / classroom / hospital / library / retail tasks / cashier Individual is providing a specialized service (hospital, classroom) or customer service in a store.	Teaching Nursing/Doctoring Cashier completing customers purchase.	If the CARING/GROOMING code could be applied in a NON-DOMESTIC setting and there are no other specific setting cues, EP is most likely SERVICE WORK. An individual COOKING/MEAL PREP with food that is from home or food bought for them to eat while at work are not deviants. Continue to role the occupation code.
Occupation – White Collar Work	Cue: Multiple computer screens / printers / stacks of books / stacks of papers / professional attire seen on other people / hallways of doors Individual is in an office setting performing some kind of administrative work.	At a desk on an electronic (phone, computer, industrial electronic). Meetings: in a room with a large round table and other individuals are seen with ties / suits / dresses.	Reference “Leisure Inactive” sub-category of INDEPENDENT domain as those activities are commonly done in an office setting, An individual COOKING/MEAL PREP with food that is from home or food bought for them to eat while at work are not deviants. Continue to role the occupation code.
Occupation – Other	Cue: Classroom sitting down (student) / public transportation (bus driver, train operator) Individual is in an occupational setting that does not fit under a code.	Bus Driving / Train Operator Student in classroom (on a college campus, picking up textbooks, filling out enrollment documents). Furniture Mover. Musician playing at bar. Zookeeper. Chef.	If the COOKING(meal pre/cleanup) code could be applied in a NON-DOMESTIC setting and there are no other specific setting cues, EP is most likely OTHER. (this is in reference to the chef occupation). An individual COOKING/MEAL PREP with food that is from home or food bought for them to eat while at work are not deviants.

			Continue to role the occupation code.
Transportation – Driving (Auto)	Cue: Automobile / steering wheel / windshield Individual is operating an automobile.	Driving a car to the store	If the environment from the windshield is EXACTLY the same for 5 consecutive IMGs, these IMGs are considered deviant. EP is then NCA. If the background is DARK then keep code as DRIVING
Transportation – Driving/Riding (Motor)	Cue: Motorcycle / handles Individual is operating a motor vehicle	Driving oneself to a place of destination on either a motor scooter or a motorcycle.	If the vicinity of the motor vehicle is not changing for 5 consecutive IMGs, these IMGs are considered deviant. EP is then NCA
Transportation – Riding (Auto/Public)	Cue: passenger seat of automobile / bus seat / train seat Individual must be a passenger in an automobile or mode of public transportation.	Being driven to the grocery store. Taking the train back home. Riding the bus to a friend's house.	
Transportation – Other	Cue: skateboard / unicycle / airplane seat Individual is using another mode of transportation that does not fit under the codes listed.	Skateboarding to the park. On an airplane. Using a pogo stick.	
<i>INDEPENDENT</i>			
Caring/Grooming – Adult	OI: Adult Taking care of an adult's hygiene or physical needs (to live).	Dressing Showering Massaging Feeding	A tool (spoon for feeding, brush for hair) may be used to interact with OI.

Caring/Grooming – Animal/Pet	<p>OI: Animal/pet</p> <p>Taking care of a pet's hygiene or physical needs (to live). Playing with them or petting them.</p>	<p>Throwing ball to catch</p> <p>Giving medication.</p> <p>Feeding</p> <p>Petting</p>	A tool (toy for playing, brush for brushing) may be used to interact with OI.
Caring/Grooming – Child/Infant	<p>OI: Child/infant</p> <p>Taking care of a child's hygiene or physical needs (to live). Playing with them.</p>	<p>Dressing</p> <p>Bathing</p> <p>Feeding</p> <p>Playing along with toys</p> <p>Placing child/infant into a car seat.</p> <p>Homeschooling.</p>	A tool (spoon for feeding, toy for playing) may be used to interact with OI.
Caring/Grooming – Self	<p>OI: Participant</p> <p>Taking care of personal hygiene.</p>	<p>Washing face</p> <p>Brushing teeth/flossing</p> <p>Putting on makeup</p> <p>Shaving</p> <p>Fixing/drying hair</p>	A tool (toothbrush for brushing teeth, hair iron for straightening hair) may be used to interact with OI.
Cycling – Exercise	<p>Cue: Different between IMGs (Posture Annotation Rules) / bicycle / stationary bike / recumbent ergometer</p> <p>Individual is riding a bicycle from initial setting to the SAME setting or on a stationary bike.</p>	<p>Riding a bicycle from home then returning home</p> <p>In a recreational area on a stationary bike</p>	Setting = DOMESTIC, specific NON-DOMESTIC setting (NON-DOMESTIC code), no movement for 5 IMGs.
Cycling – Transportation	<p>Cue: Different between IMGs (Posture Annotation Rules)</p> <p>Individual is riding a bicycle from initial setting to a NEW setting.</p>	<p>Riding a bicycle from home to office / grocery store</p> <p>Riding a bicycle from school to home</p>	Setting = DOMESTIC, specific NON-DOMESTIC setting (NON-DOMESTIC code), no movement for 5 IMGs.
Leisure Active – Exercise	<p>OI: Dumbbells / weight machines / movement machines / other exercise equipment / none</p> <p>Individual is engaging in activity that improves their fitness</p>	<p>Resistance training</p> <p>Aerobics</p> <p>Core Exercises</p> <p>Yoga</p> <p>Stretching</p>	An OI is not necessary. If in an image you can tell they are stretching or doing yoga (looking at a mirror for example) this code would be applied.

	(cardiorespiratory and musculoskeletal systems)		An individual performing exercises at a physical therapy clinic would still be coded as EXERCISE.
Leisure Active – Gross Sports	<p>OI: Sport-specific ball/tools (object) / none</p> <p>Individual is interacting with a sport-specific OI to accomplish a goal.</p>	<p>Basketball</p> <p>Volleyball</p> <p>Track and Field: Field Event</p> <p>Soccer</p> <p>Golf</p> <p>Darts</p> <p>Pool/Billiards</p> <p>Croquet</p>	
Leisure Inactive – Arts&Crafts(3)	<p>OI: Yarn / cardboard / scrapbook / gift bags / gift wrap / sewing needles(machine) / needles (knitting, crocheting) / art tools / painting</p> <p>Individual is constructing objects that are abstract/imaginative and pleasing to the eye (arts) or constructing objects that have no utility in household-related tasks.</p>	<p>Knitting a scarf / sewing clothes.</p> <p>Crafting a poster or banner.</p> <p>Painting on a canvas / art piece.</p> <p>Wrapping gifts or making gift bags</p> <p>Making a piñata (thanks Emilee - .-)</p>	<p>Although this code has “Constructing” in it which is the same activity under DOMESTIC-CFRM, the main difference is the objects that are being constructed to only be admired and have no utility in DOMESTIC-related codes.</p> <p>If other Leisure Inactive OIs are seen, this code is priority #3.</p>
Leisure Inactive – Drawing/Writing(2)	<p>OI: Writing utensil / paper / canvas</p> <p>Individual is grasping a writing utensil to either draw, write or paint on a paper product.</p>	<p>Writing in journal</p> <p>Drawing in sketchbook</p> <p>Painting a picture.</p>	<p>If this code could be applied in a NON-DOMESTIC setting and there are no other specific setting cues, EP is most likely in an occupation – OFFICE WORK setting.</p> <p>If other Leisure Inactive OIs are seen, this code is priority #2.</p>
Leisure Inactive – Eating/Drinking(1)	<p>OI: Food products / consumables</p> <p>Individual is stationary and food / consumables seen in the images are disappearing or being grasped.</p>	<p>Eating dinner at a kitchen table.</p> <p>A food item is visible and there is no change between pictures</p> <p>No food but a clear cup with liquid slowly disappearing overtime.</p>	<p>Individual MUST be stationary.</p> <p>Use Posture Annotation Rules to determine if individual is stationary. Only code drinking if you can clearly see the contents of the drinkware.</p>

			If other Leisure Inactive OIs are seen, this code is priority #1. [INDEPENDENT #4] – stationary eating + priority
Leisure Inactive – Electronics(5)	<p>OI: Phone, television, video game console, computer monitor</p> <p>Individual is interacting with a consumer electronic by: direct means (hand manipulation) indirect means (screen is changing between images). Electronic makes up vertically makes up 50% of image. (Why #3? - Individuals are typically talking with researchers if electronic does not vertically make up 50%)</p>	<p>Grasping phone, using fingers to text or swipe Grasping controller for video game console Turned on computer monitor. Television turned on and changes between images. Graphing calculator.</p>	<p>If this code could be applied in a NON-DOMESTIC setting and there are no other specific setting cues, EP is most likely in an occupation – OFFICE WORK setting. If other Leisure Inactive OIs are seen, this code is priority #5.</p>
Leisure Inactive – Reading(4)	<p>OI: Book / newspaper / manual / calendar</p> <p>Individual is grasping or has in front of them a paper product with characters (letters & numbers) on it to read.</p>	<p>Reading the morning newspaper or book.</p>	<p>If this code could be applied in a NON-DOMESTIC setting and there are no other specific setting cues, EP is most likely in an occupation – OFFICE WORK setting. If other Leisure Inactive OIs are seen, this code is priority #4.</p>
Leisure Inactive – Other	<p>OI: Variable</p> <p>Individual is interacting with an OI that is typically seen as light intensity and can be seen as hobby or recreational activity</p>	<p>Putting together a puzzle. Playing a board game. Playing an instrument.</p>	<p>Think of hobbies and other pastimes. If an activity is seen that falls under a code, that activity takes priority (seeing a person using the phone and playing a board game will be coded as ELECTRONICS).</p>

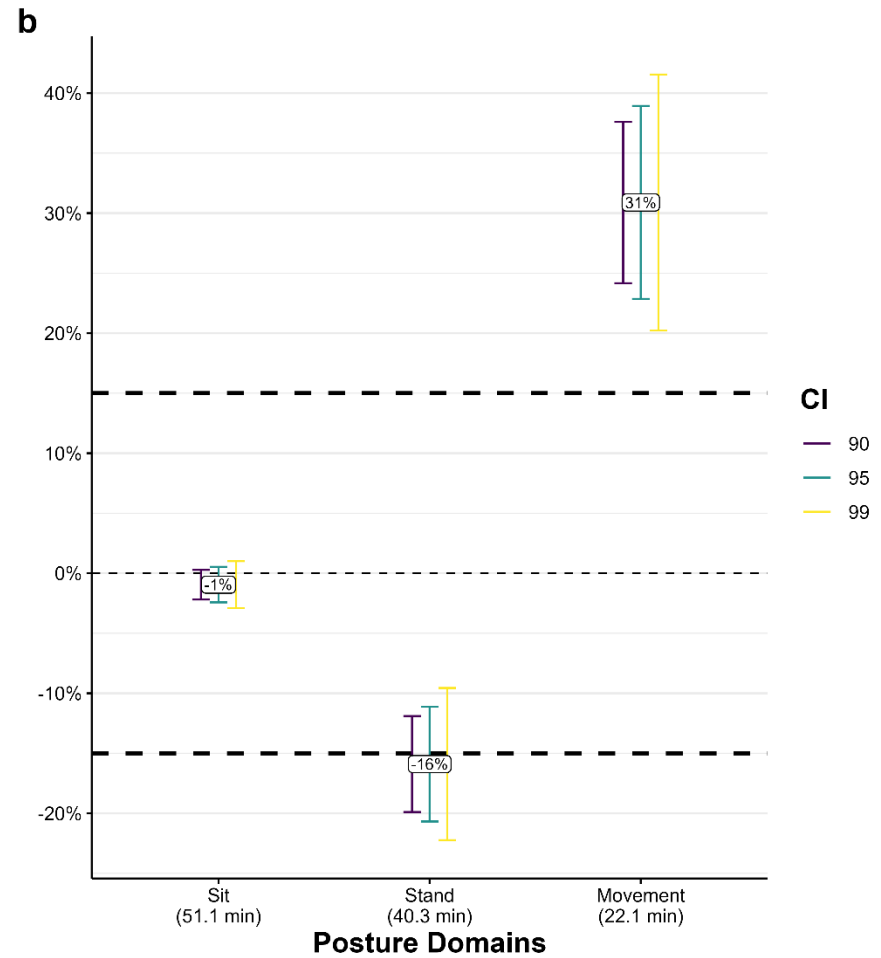
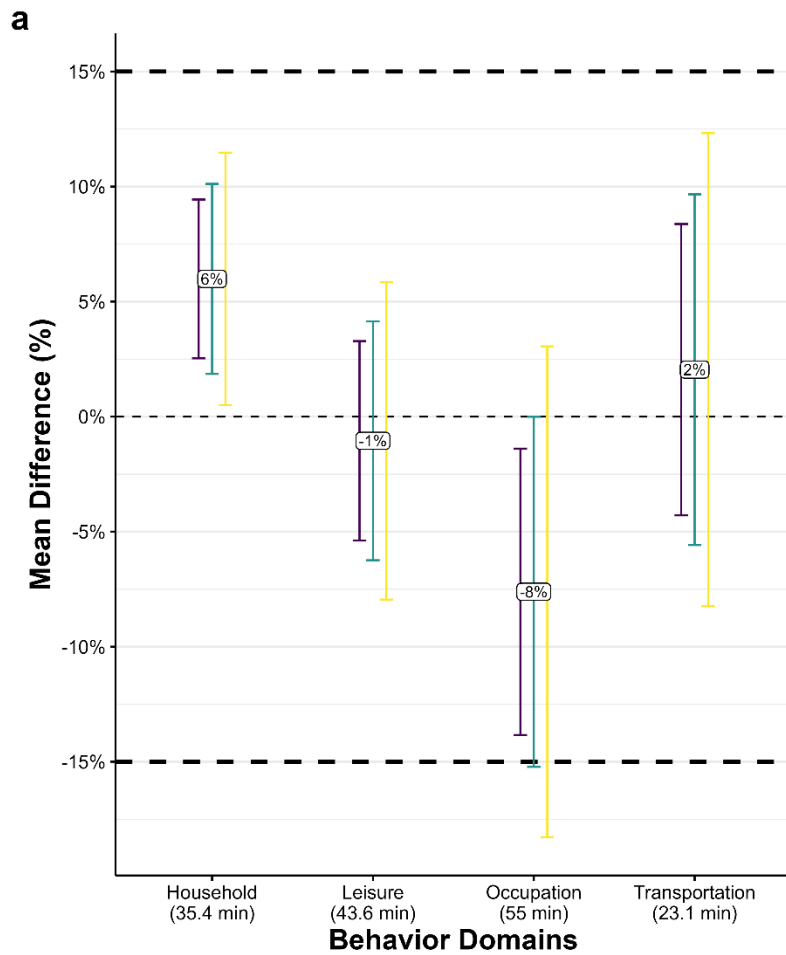
Movement – Exercise	Cue: Different between IMGs (Posture Annotation Rules) / No OI Individual is moving from initial setting to the SAME setting	Walking on the treadmill. Leaving from work to walk and then come back. Walking on a track.	Setting = DOMESTIC, specific NON-DOMESTIC setting (NON-DOMESTIC code) No movement seen for ≥ 5 IMGs = break when non-movement was first seen and NCA becomes EP. [INDEPENDENT #3] -
Movement – Leisure	Cue: Different between IMGs (Posture Annotation Rules) / Pet / stroller Individual is moving with a pet (seen in the images) or a stroller (seen in the images).	Walking the dog. Pushing a stroller	Code does not depend on whether or not the destination setting is the same as the initial setting.
Movement – Transportation	Cue: Different between IMGs (Posture Annotation Rules / No OI Individual is moving from initial setting to a NEW setting.	Walking from the home to work or walking from home to the library or grocery store	Setting = DOMESTIC, specific NON-DOMESTIC setting (NON-DOMESTIC code) No movement seen for ≥ 5 IMGs = break when non-movement was first seen and NCA becomes EP.
<i>TRANSITION/NO SPECIFIC ACTIVITY</i>			
Transition (< 3 IMGs)	Images are seen clearly, but there are fewer than 3 images with the same EP.	This category would apply when a person moves from activity to activity for less than 3 images	If there are 2 activities in a row that are each < 3 IMGs, put a break between each activity.
Domestic – No Specific Activity	Code for when none of the Requirements for Method #1 are met or researchers are talking towards the camera for 5 consecutive images.	Movement around the house where no OI can be seen. On the lawn but no OI's related to gardening or landscaping are seen.	If an individual is urinating or defecating, NSA will be used.
Non-Domestic – No Specific Activity	Code for when a method cannot be determined while following the general procedure or researchers are talking towards the camera for 5 consecutive images.	Individual in NON-DOMESTIC setting but no specific setting cues are seen	If an individual is urinating or defecating, NSA will be used.

UNCODED

Camera start time	Stopwatch and clipboard visible in front of camera indicating start time	A series of images at the start of the observation period denoting the start time	
Camera stop time	Stopwatch and clipboard visible in front of camera indicating stop time	A series of images at the end of the observation period denoting the end time	
Camera taken or turned off	The camera has been turned off	Private time when the participant is going to the restroom A sequence of IMGs looks EXACTLY the same, signifying the camera is taken off.	
Image dark/blurred/obscured	Domain and activity type cannot be determined because the image is obscured, dark, or obstructed	Individual is moving around but the image is blurry and nothing can be made out from the image.	If 1/3 of the image is viewable, this code is not applied. There may still be an EP if an image is only obscured/blurry but not if the image is dark. OIs/Cues may still be seen in obscured/blurred IMGs but not in dark IMGs.

Appendix G: Behavior and Posture Domain Equivalence Plots using 90%, 95% and 99% Confidence Intervals

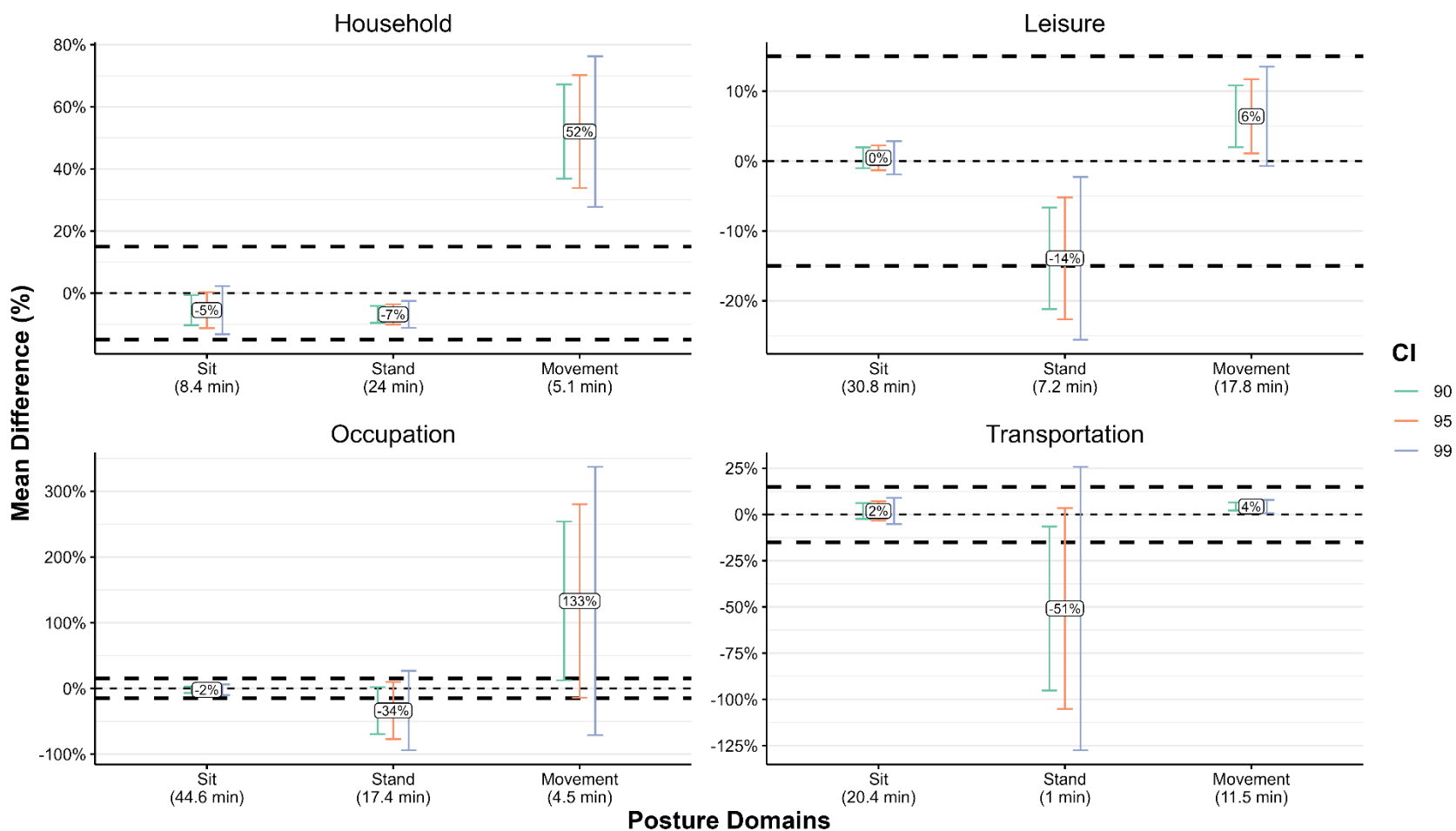
219



CI: Confidence Interval

Appendix H: Posture Domain Equivalence Plots Using 90%, 95% and 99% Confidence Intervals Stratified by Behavior Domain

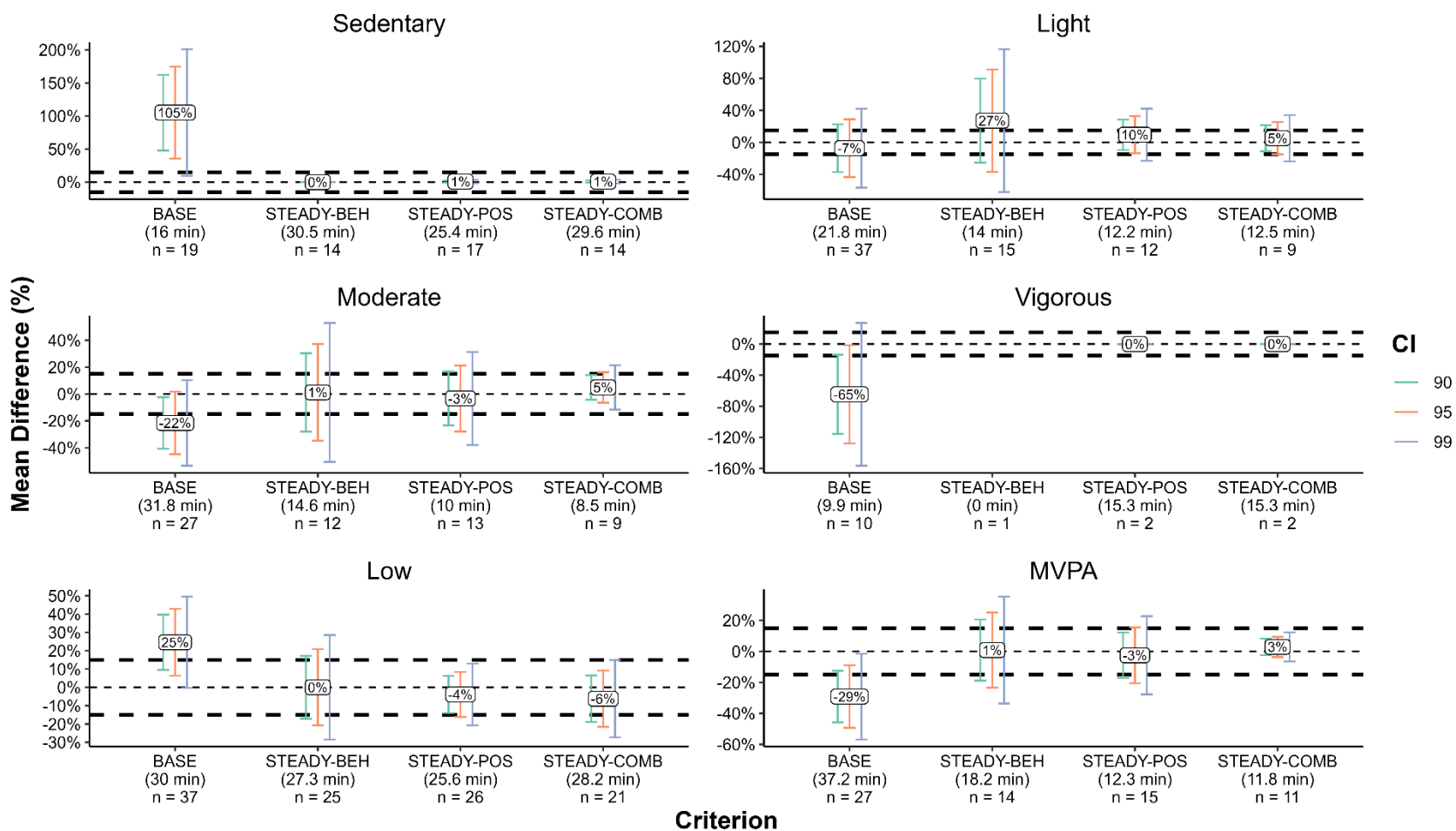
220



CI: Confidence Interval

Appendix I: Intensity Category Equivalence Plots Using 90%, 95% and 99% Confidence Intervals

221



CI: Confidence Interval

Appendix J: Intensity Category Equivalence Testing Using 90%, 95% and 99% Confidence Intervals

Procedure	N Subject	N Visit	Estimate Mean (mins)	Criterion Mean (mins)	Minutes				%				
					Bias	90%	95%	99%	Bias	90%	95%	99%	
Sedentary													
BASE	16	19	30.8	16.0	16.8	(7.6, 26)	(5.7, 27.9)	(1.5, 32.1)	105%	(48%, 163%)	(36%, 175%)	(9%, 201%)	
STEADY-BEH	13	14	30.8	30.5	0.0	(0, 0)	(0, 0)	(0, 0)	0%	(0%, 0%)	(0%, 0%)	(0%, 0%)	
STEADY-POS	17	17	26.6	25.4	0.2	(-0.2, 0.6)	(-0.3, 0.7)	(-0.5, 0.9)	1%	(-1%, 3%)	(-1%, 3%)	(-2%, 4%)	
STEADY-COMB	14	14	31.0	29.6	0.3	(-0.2, 0.7)	(-0.3, 0.8)	(-0.5, 1.1)	1%	(-1%, 2%)	(-1%, 3%)	(-2%, 4%)	
Light													
BASE	19	37	20.2	21.8	-1.6	(-8.1, 4.9)	(-9.5, 6.3)	(-12.3, 9.2)	-7%	(-37%, 22%)	(-43%, 29%)	(-57%, 42%)	
STEADY-BEH	13	15	16.8	14.0	3.8	(-3.5, 11.1)	(-5.2, 12.7)	(-8.7, 16.3)	27%	(-25%, 80%)	(-37%, 91%)	(-62%, 116%)	
STEADY-POS	12	12	13.4	12.2	1.2	(-1.2, 3.5)	(-1.7, 4)	(-2.8, 5.1)	10%	(-10%, 29%)	(-14%, 33%)	(-23%, 42%)	
STEADY-COMB	9	9	13.2	12.5	0.6	(-1.4, 2.7)	(-1.9, 3.2)	(-3, 4.3)	5%	(-11%, 21%)	(-15%, 25%)	(-24%, 34%)	
Moderate													
BASE	18	27	25.6	31.8	-6.9	(-13, -0.7)	(-14.3, 0.5)	(-17, 3.3)	-22%	(-41%, -2%)	(-45%, 2%)	(-53%, 10%)	
STEADY-BEH	9	12	14.7	14.6	0.2	(-4.1, 4.4)	(-5.1, 5.4)	(-7.4, 7.7)	1%	(-28%, 30%)	(-35%, 37%)	(-50%, 53%)	

Procedure	N Subject	N Visit	Estimate Mean (mins)	Criterion Mean (mins)	Minutes				%			
					Bias	90%	95%	99%	Bias	90%	95%	99%
STEADY-POS	11	13	9.8	10.0	-0.3	(-2.3, 1.7)	(-2.8, 2.1)	(-3.8, 3.1)	-3%	(-23%, 17%)	(-28%, 21%)	(-38%, 31%)
STEADY-COMB	8	9	8.9	8.5	0.4	(-0.4, 1.2)	(-0.5, 1.4)	(-1, 1.8)	5%	(-4%, 14%)	(-6%, 16%)	(-12%, 21%)
Vigorous												
BASE	8	10	4.2	9.9	-6.4	(-11.4, -1.4)	(-12.6, -0.2)	(-15.5, -2.7)	-65%	(-116%, -14%)	(-128%, -2%)	(-156%, 27%)
STEADY-BEH	1	1	0.0	0.0		(NA, NA)	(NA, NA)	(NA, NA)		(NA, NA)	(NA, NA)	(NA, NA)
STEADY-POS	2	2	15.3	15.3	0.0	(0, 0)	(0, 0)	(0, 0)	0%	(0%, 0%)	(0%, 0%)	(0%, 0%)
STEADY-COMB	2	2	15.3	15.3	0.0	(0, 0)	(0, 0)	(0, 0)	0%	(0%, 0%)	(0%, 0%)	(0%, 0%)
Low												
BASE	19	37	37.4	30.0	7.4	(2.9, 11.9)	(1.9, 12.9)	(-0.1, 14.9)	25%	(10%, 40%)	(6%, 43%)	(0%, 50%)
STEADY-BEH	18	25	27.4	27.3	0.0	(-4.7, 4.7)	(-5.6, 5.7)	(-7.7, 7.8)	0%	(-17%, 17%)	(-21%, 21%)	(-28%, 29%)
STEADY-POS	18	26	24.6	25.6	-1.0	(-3.6, 1.6)	(-4.1, 2.2)	(-5.3, 3.3)	-4%	(-14%, 6%)	(-16%, 8%)	(-21%, 13%)
STEADY-COMB	17	21	27.0	28.2	-1.7	(-5.3, 1.8)	(-6.1, 2.6)	(-7.7, 4.2)	-6%	(-19%, 6%)	(-22%, 9%)	(-27%, 15%)
MVPA												
BASE	18	27	27.2	37.2	-10.8	(-17, -4.6)	(-18.4, -3.3)	(-21.1, -0.6)	-29%	(-46%, -12%)	(-49%, -9%)	(-57%, -1%)
STEADY-BEH	10	14	18.3	18.2	0.2	(-3.4, 3.7)	(-4.3, 4.6)	(-6.1, 6.4)	1%	(-19%, 21%)	(-23%, 25%)	(-34%, 35%)

Procedure	N Subject	N Visit	Estimate Mean (mins)	Criterion Mean (mins)	Minutes				%			
					Bias	90%	95%	99%	Bias	90%	95%	99%
STEADY-POS	12	15	12.1	12.3	-0.3	(-2.1, 1.5)	(-2.5, 1.9)	(-3.4, 2.8)	-3%	(-17%, 12%)	(-21%, 15%)	(-28%, 23%)
STEADY-COMB	9	11	12.1	11.8	0.3	(-0.3, 1)	(-0.4, 1.1)	(-0.8, 1.4)	3%	(-2%, 8%)	(-4%, 9%)	(-7%, 12%)

CI: Confidence Interval