# Preface

The journey of my PhD has been a fulfilling expedition, layered with explorations, discoveries, struggles, and growth. This endeavor was fueled by my interest in understanding the objective measurements of physical behavior and sleep. During my Masters, I found myself increasingly engrossed in these domains.

My subsequent role as a research assistant at Aarhus University opened another dimension of learning for me. The works of my peers, employing machine learning and advanced statistics on accelerometer data, intrigued me. It was as if I found the nexus of my research interests, a perfect alignment that seamlessly fused my curiosities and passions.

One of the most significant hurdles was my limited experience with programming and machine learning, which proved to be a steep learning curve. However, through persistence, I slowly developed the necessary skills to analyze and interpret my data effectively. Another major setback was the failed data collection for my third paper. I spent months visiting families, mounting an ambulatory PSG device on children before bedtime, and facing the harsh reality of dealing with poor data quality.

This thesis brings together my explorations and findings across three papers that carry a consistent emphasis on improving and validating methods to leverage accelerometer data for studying human behaviors. The common thread across these papers is the application of innovative methods, particularly machine learning techniques, to enhance the utility, reliability, and accuracy of free-living accelerometer data for monitoring human sleep and physical activity. The work presented here constitutes a substantial contribution to the field of sleep and physical activity research, particularly in the context of large-scale studies.

Two of these papers have already found their place in peer-reviewed scientific journals, and the third is under review. All of these works are included as appendices to this thesis, and their content has been weaved into the fabric of this thesis.

As I look back at my journey through the PhD program, I am grateful for this opportunity to delve deep into a subject that I am passionate about and to contribute to a field that is evolving rapidly. This experience has instilled in me a sense of tenacity and patience, qualities that I have come to value deeply. I learned that even the most frustrating problems have solutions, and the path to those solutions often leads to personal growth and novel insights.

As I stand on the precipice of my future, I am filled with a sense of anticipation and excitement for the possibilities that lie ahead. I am eager to explore new horizons, to encounter new challenges, and to continue growing as a researcher and as an individual. However, wherever I go and whatever I do, I will carry with me the memories, experiences, and lessons from this incredible journey.

These years have shaped me in ways I could never have imagined at the outset, and for that, I am profoundly grateful. As I close this chapter of my life, I do so with a sense of accomplishment and a promise of continued exploration and discovery in my field. After all, every ending is but a new beginning, and I look forward to the adventures that await.

# Acknowledgements

Throughout this journey, there have been several people who have influenced, inspired, and supported me. My Main Supervisor, Jan Christian Brønd, deserves special mention for his guidance and patience. His commitment to nurturing my development as a researcher and lecturer has been instrumental. Our collaborative dialogues, be it at the office or during examinations, have been pivotal in my growth. I also extend my sincere gratitude to my co-supervisors [insert name 2] and [insert name 3], and my colleague [insert name 4], who have always provided invaluable insights and perspectives.

Amidst all the academic pursuits, my family remained the cornerstone of my journey. My wife, the bedrock of our family, kept our home running smoothly and offered endless support and curiosity about my work. The joy and love from my four children were my constant sources of motivation and inspiration.

The PhD journey has taught me the importance of rigour and attention to detail. My approach to work has been permanently shaped by my experience as a researcher. The discipline and precision that is required in research has translated into my everyday life, impacting my approach to problem-solving, decision-making, and even communication. It’s impressive how research is not merely a vocation but a lens through which we view the world.

There were also moments of immense joy and satisfaction, like finally solving a complex analytical problem, having my work accepted for publication, or simply receiving positive feedback from a student or a colleague. Those moments fueled my motivation and reminded me of the importance and impact of my work.

One of the most rewarding aspects of this journey was the opportunity to be part of an international recognized and experienced research group. This gave me the chance to work with and learn from some of the most talented people in my field, to discuss ideas and collaborate on projects, and to be part of a collective effort to advance knowledge and understanding in our field.

In retrospect, this PhD journey has been much more than a professional pursuit. It has been a personal voyage of self-discovery and growth. Through the highs and lows, the victories and setbacks, the late nights and early mornings, I’ve discovered a resilience in myself that I hadn’t known before. I found that I could rise to challenges, learn from failures, and continue to strive for excellence, no matter the odds.

In closing, I wish to express my deep gratitude for all those who have supported me throughout this journey - my supervisors, colleagues, friends, and family. Their faith in my abilities and their constant encouragement have been my pillars of strength. I hope that the work presented in this thesis reflects the depth of my dedication and the extent of my learning journey.

# Supervisor

Associate Professor Jan Christian Brønd, PhD

Research Unit for Exercise Epedimiology, Centre of Research in Childhood Health, Department of Sports Science and Clinical Biomechanics, University of Southern Denmark, 5230 Odense, Denmark

# Assessment Committee

## Chair

Associate Professor Anders And, PhD

## Opponents

Professor Andersine And, PhD

Research Unit for Exercise Epedimiology, Centre of Research in Childhood Health, Department of Sports Science and Clinical Biomechanics, University of Southern Denmark, 5230 Odense, Denmark

Associate Professor Fætter Højben, PhD

Research Unit for Exercise Epedimiology, Centre of Research in Childhood Health, Department of Sports Science and Clinical Biomechanics, University of Southern Denmark, 5230 Odense, Denmark

# Funding

The research presented in this thesis was generously funded by TrygFonden, under grant numbers ID 130081 and 115606, and by the European Research Council, under grant number 716657. Additional support was provided by a one-year scholarship from the Faculty of Health Sciences.

# Included Papers

## Paper I

Manual Annotation of Time in Bed Using Free-Living Recordings of Accelerometry Data(Skovgaard et al. 2021)

published in [Sensors](https://doi.org/10.3390/s21248442).

The first paper is focused on evaluating the manual annotation to enrich datasets for use in machine learning of in-bed periods by comparing the manual annotation method with established EEG-based sleep monitoring devices and self-reported sleep diaries.

## Paper II

Generalizability and Performance of Methods to Detect Non‑Wear with Free‑Living Accelerometer Recordings(Skovgaard et al. 2023)

published in [Scientific Reports](https://doi.org/10.1038/s41598-023-29666-x).

The second paper delve into a more specific challenge in physical activity sensor usage - the detection of non-wear. We propose decision tree models that combine raw acceleration and skin temperature data to detect non-wear time and emphasize the importance of external validation in machine-learned models.

## Paper III

Improving Sleep Quality Estimation: A Comparative Study of Machine Learning and Deep Learning Techniques Utilizing Free-Living Accelerometer Data from Thigh-Worn Devices and EEG-Based Sleep Tracking

Submitted to [npj Digital Medicin](https://www.nature.com/npjdigitalmed/).

The third paper focuses on sleep quality estimation using machine learning and deep learning models. We evaluate these models using data from thigh-worn accelerometers, presenting a potential alternative for large-scale sleep studies. We underscore the challenges of classifying awake periods during in-bed time and the need for further precision in assessing sleep quality metrics an individual-basis.

# English Summary

bla

# Danish Summary

bla

# Introduction

## Outline of Introduction Section

### Overview and Background

* The importance of sleep and physical activity tracking in health research.
* The limitations of traditional methods, such as polysomnography and self-reported diaries.
* The emergence and potential of wearable accelerometers and machine learning models in this field.

#### Scope and Relevance

-The need for cost-effective, reliable, and practical alternatives for large-scale studies. - The potential of free-living accelerometers, and why they are a compelling subject of study.

#### Existing Challenges

* Discuss the challenges with existing methods, such as identifying non-wear time, annotating in-bed periods, and classifying awake periods during in-bed time.
* Address the lack of exploration of certain sensor locations, like the thigh.

#### Thesis Goals and Objectives

* Clearly state the aim and objectives of your thesis.
* Explain how your thesis will address the identified challenges, including improving the manual annotation of in-bed periods, enhancing non-wear detection, and estimating sleep quality metrics.

#### Overview of the Papers

* Briefly introduce each paper, highlighting the key research question, methods, and findings.
* Explain how each paper contributes to your thesis goals and objectives.

### Motivation for the Research

#### The Need for Improved Annotation Techniques

* Importance of accurate annotation in accelerometer data analysis.
* A brief discussion of the first paper’s findings and implications.

#### Improving Non-Wear Detection

* Explain the implications of undetected non-wear time on data quality.
* Highlight the findings of your second paper and its relevance.

#### Advancing Sleep Quality Estimation

* Discuss the impact of sleep quality estimation on understanding human sleep behavior.
* Briefly describe the conclusions of your third paper.

### Methodological Approaches

* Give a brief overview of the methods used across all three studies, such as the use of machine learning models, deep learning techniques, manual annotation, and decision tree models.
* Explain how these methods address the research objectives and the challenges identified earlier.

### Thesis Structure

Provide an outline of the subsequent chapters of your thesis.

# Test Header

Utilizing machine learning for sleep and physical activity identification from accelerometry data is a burgeoning field. This approach offers potential to model complex non-linear relationships unattainable with simple statistical methods such as multiple linear or logistic regression (Fiorillo et al. 2019). However, supervised machine learning requires large amounts of accurately annotated data to ensure accuracy and generalizability(Ploeg, Austin, and Steyerberg 2014).

Sleep is considered a vital element for the overall health and development of children(Chaput et al. 2017, 2016; St-Onge et al. 2016). Healthy sleep is characterized by sufficient duration, appropriate timing, quality, and absence of disturbances or disorders(Gruber et al. 2014). Despite its importance, the use of advanced machine learning techniques to assess sleep measures from accelerometer data remains underdeveloped(Haghayegh et al. 2020).

Accelerometry provides an affordable and minimally invasive method to analyze sleep patterns. Objective measurements are crucial for insights into individual and population-wide circadian rhythms. Polysomnography (PSG), the gold standard for objective sleep assessment, records electroencephalographic (EEG), electromyographic (EMG), and electrooculographic (EOG) activity. However, PSG is costly and burdensome due to technician support requirements, intrusive sensor placements, and overnight monitoring(Vaughn and Giallanza 2008).

Recent studies have tried to use machine learning techniques for PSG-assessed sleep-wake classification with wrist acceleration(Haghayegh et al. 2020; Sundararajan et al. 2021; Hees et al. 2015). Sundararajan et al.(Sundararajan et al. 2021) used a random forest machine learning algorithm, achieving an F1 score of 73.9%. However, the high false discovery rate indicates limitations in wrist-worn accelerometers, possibly due to the lack of subject variation and the use of single-night PSG-recordings.

To overcome these limitations, researchers should increase the number of subjects and recording days to capture more variation in movement behavior during sleep. Accelerometry, despite its limitations, is practical for extended recordings outside of the lab (Van De Water, Holmes, and Hurley 2011). The focus should be on developing algorithms for sleep timing rather than sleep staging.

Identifying sleep/wake cycles from accelerometry data requires time in bed annotation, when participants go to bed and wake up. Although this isn’t actual sleep time, accelerometry is still widely used in sleep research due to its practical advantages (Hees et al. 2015; Madsen, Rosenberg, and Gögenur 2013; Schwab et al. 2018; Barouni et al. 2020) This annotation could be based on individual sleep diaries, EEG-based recordings (Younes, Raneri, and Hanly 2016), or systems for recording tracheal sounds (Dafna, Tarasiuk, and Zigel 2015; Montazeri Ghahjaverestan et al. 2020).

This study aims to (1) describe a method for manual annotation of bedtime and wake-up time with raw accelerometry, (2) evaluate the accuracy of manual annotation against a single-channel EEG-based sleep staging system and sleep diary, and (3) assess the inter- and intra-rater reliability of annotations.

The use of body-worn motion sensors, especially accelerometers, to study human physical activity behavior has gained significant popularity over recent years, offering an efficient and cost-effective method for capturing objective movement data (Dowd et al. 2018; Loyen et al. 2017; Montoye et al. 2018; Migueles et al. 2019). These devices can be worn during various activities with some protocols allowing detachment during water-based activities, sleep, or certain sports to prevent injury.

However, such detachment periods, referred to as non-wear time, present researchers with a challenge in the form of missing data. Non-wear time can significantly influence the outcomes derived from the acceleration measurements (J. A. Lee and Gill 2018). While some researchers exclude these periods or attempt to impute the missing data using various methods, such strategies can introduce bias, particularly when non-wear times are longer. This issue underscores the importance of accurately classifying and handling non-wear periods for reliable estimates of subjects’ physical activity behavior during free-living (J. A. Lee and Gill 2018).

The classification of non-wear periods can be acquired by having subjects keep individual log diaries, although this method can be cumbersome and potentially error-prone (Ainsworth et al. 2012). In a bid to reduce subject burden and enhance accuracy, researchers have employed rule-based methods and advanced algorithms to classify non-wear time (Hecht et al. 2009; Ruiz et al. 2011; Troiano et al. 2008). Yet, such methods can yield disparate physical activity and sedentary behavior aggregates depending on non-wear settings, age, and obesity level, limiting their utility and the ability to make comparisons across studies (Aadland et al. 2018; Toftager et al. 2013).

Advancements in accelerometer technology in recent years have enabled researchers to store raw accelerations, enhancing data granularity and potentially improving non-wear period classification (Duncan et al. 2018; Rasmussen et al. 2020; Zhou et al. 2015). However, even with access to higher quantity and quality data, simple duration-based algorithms carry the risk of falsely misclassifying true non-wear as inactivity, restricting the ability to detect non-wear episodes shorter than the designated interval.

Recently, studies have explored the potential of machine learning, including random forests and deep learning techniques, to classify non-wear using raw accelerometer data Syed et al. (2021). Machine learning algorithms aim to learn patterns from the training data and approximate the complex model that best describes the relationship between the predictors and the outcome. The balance between model variance and bias is a critical consideration in this process, with the ultimate goal of optimizing the predictive performance of a machine-learned model on unseen data.

Despite the performance of models utilizing complex machine learning algorithms on testing data, their performance on external unseen data remains largely unknown. This gap in knowledge is often due to a lack of out-of-distribution data sources and the desire to incorporate all available data into model training to maximize information capture. Some studies have utilized surface skin temperature in conjunction with raw acceleration for non-wear classification (Duncan et al. 2018; Zhou et al. 2015), but the performance and generalizability of adding surface skin temperature with advanced machine learning methods have yet to be explored.

Despite technological advancements, there is still room for improvement in accurately classifying non-wear time in raw accelerometer data. It prompts the question: what heuristic algorithm or machine-learned model will perform best on unseen data for classifying non-wear time? To address this, we created three datasets of raw accelerometer data with correctly labeled wear- and non-wear time, including surface skin temperature measurements. Our study aims to (1) train three decision tree models on accelerometer data from thigh and hip-worn accelerometers for non-wear time classification and evaluate the importance of surface skin temperature and minimizing the number of predictors provided to the model, and (2) assess the performance of machine-learned models and simple heuristic algorithms across datasets of varying age ranges for non-wear time classification.

A vast body of research highlights the critical role of sleep in maintaining both mental and physical health(Ma 2017; Meyer et al. 2022; K Pavlova and Latreille 2019; Difrancesco et al. 2019). Consequently, accurate sleep assessment methods are crucial for tracking sleep patterns and improving our understanding of the sleep-health relationship. Furthermore, the ease of use and high acceptability of these methods are essential to facilitate large-scale, longitudinal studies.

The traditional gold standard for objective sleep measurement, laboratory-based polysomnography (PSG), has been found to be impractical in large-scale epidemiological studies due to its high cost, need for professional administration, and susceptibility to rater bias(Van De Water, Holmes, and Hurley 2011; Y. J. Lee et al. 2022). As an alternative, diaries have been used due to their cost-effectiveness and simplicity, although they are subject to recall bias and other limitations(Moore, Schmiege, and Matthews 2015). An innovative approach involves device-based measurement methods. These tools, which estimate sleep duration, are advantageous due to their reduced participant burden and elimination of potential recall biases. A prominent example of such tools is body-worn accelerometers, which offer a practical and affordable means of objectively assessing sleep patterns at home for extended periods. Accelerometers collect continuous, high-resolution data for several weeks without requiring recharging, further minimizing participant burden. Their use in sleep and wake classification began with a wrist movement-based algorithm developed in 1982, and validated using PSG(Webster et al. 1982). This algorithm was refined in 1992(Cole et al. 1992), leading to the widely adopted Cole-Kripke model. With advancements in the field, a variety of techniques, including heuristic algorithms, machine learning models, regression, and deep learning, are now used to analyze data from hip and wrist-worn accelerometers(Palotti et al. 2019; Cole et al. 1992; Sazonov et al. 2004; Sadeh, Sharkey, and Carskadon 1994; Hees et al. 2015; Sundararajan et al. 2021).

While wrist and hip-worn devices have benefited from extensive methodological development, thigh-worn accelerometers have not seen the same level of advancement. Existing studies mainly focus on distinguishing sleep from wakefulness, with emphasis on defining ‘waking time’ and ‘bedtime’ (Carlson et al. 2021; Inan-Eroglu et al. 2021; Berg et al. 2016; Winkler et al. 2016). Recent strides in estimating sleep duration using thigh-worn devices have been made, including the introduction of a promising algorithm and its comparison against PSG(Johansson et al. 2023). Despite these advancements, the application of machine learning techniques in this area is still unexplored. Considering the potential of thigh-worn accelerometers for accurate physical behavior assessment(Skotte et al. 2014; Arvidsson et al. 2019), there is a significant research gap. Therefore, future studies need to develop techniques similar to those used for wrist and hip-worn accelerometers, with the ultimate goal of establishing a more holistic, accurate, and user-friendly method of sleep and physical activity tracking.

The Zmachine®️ Insight+ (ZM) emerges as a valuable tool within this landscape. Favorably validated against PSG(Kaplan et al. 2014; Wang et al. 2015), the ZM provides comparable data without the high costs or the need for professional monitoring typically associated with PSG. Crucially, the ZM facilitates multi-night analysis in free-living conditions due to its ease of use(Pedersen et al. 2021), capturing the natural variations in sleep patterns. This makes it advantageous over single-night PSG, particularly as a gold standard data source in machine learning tasks, as it provides multiple nights of measurements without inter-rater bias. Despite these benefits, the ZM, like PSG, still poses a significant participant burden and cost, reinforcing the need for more accessible alternatives like accelerometers.

Our primary objective in this study was to evaluate a range of machine learning and deep learning models, utilizing the raw data collected from a tri-axial thigh-worn accelerometer to estimate in-bed and sleep time. To ensure the reliability and effectiveness of our models, we compared their outputs with an electroencephalography-based (EEG) sleep tracking device, which we, in this current study, considered as the gold standard for measuring sleep. Furthermore, our secondary goal was to assess the developed models’ performance in evaluating important sleep quality metrics, including sleep period time (SPT), total sleep time (TST), sleep efficiency (SE), latency until persistent sleep (LPS), and wake after sleep onset (WASO).

Aadland, Eivind, Lars Bo Andersen, Sigmund Alfred Anderssen, and Geir Kåre Resaland. 2018. “A Comparison of 10 Accelerometer Non-Wear Time Criteria and Logbooks in Children.” *BMC Public Health* 18 (1): 323. <https://doi.org/10.1186/s12889-018-5212-4>.

Ainsworth, Barbara E., Carl J. Caspersen, Charles E. Matthews, Louise C. Mâsse, Tom Baranowski, and Weimo Zhu. 2012. “Recommendations to Improve the Accuracy of Estimates of Physical Activity Derived from Self Report.” *Journal of Physical Activity & Health* 9 Suppl 1 (0): S76–84. <https://doi.org/10.1123/jpah.9.s1.s76>.

Arvidsson, Daniel, Jonatan Fridolfsson, Mats Börjesson, Lars Bo Andersen, Örjan Ekblom, Magnus Dencker, and Jan Christian Brønd. 2019. “Re-Examination of Accelerometer Data Processing and Calibration for the Assessment of Physical Activity Intensity.” *Scandinavian Journal of Medicine & Science in Sports* 29 (10): 1442–52. <https://doi.org/10.1111/sms.13470>.

Barouni, Amna, Jörg Ottenbacher, Johannes Schneider, Bernd Feige, Dieter Riemann, Anne Herlan, Driss El Hardouz, and Darren McLennan. 2020. “Ambulatory Sleep Scoring Using Accelerometers-Distinguishing Between Nonwear and Sleep/Wake States.” *PeerJ* 8: e8284. <https://doi.org/10.7717/peerj.8284>.

Berg, Julianne D. van der, Paul J. B. Willems, Jeroen H. P. M. van der Velde, Hans H. C. M. Savelberg, Nicolaas C. Schaper, Miranda T. Schram, Simone J. S. Sep, et al. 2016. “Identifying Waking Time in 24-h Accelerometry Data in Adults Using an Automated Algorithm.” *Journal of Sports Sciences* 34 (19): 1867–73. <https://doi.org/10.1080/02640414.2016.1140908>.

Carlson, Jordan A., Fatima Tuz-Zahra, John Bellettiere, Nicola D. Ridgers, Chelsea Steel, Carolina Bejarano, Andrea Z. LaCroix, et al. 2021. “Validity of Two Awake Wear-Time Classification Algorithms for activPAL in Youth, Adults, and Older Adults.” *Journal for the Measurement of Physical Behaviour* 4 (2): 151–62. <https://doi.org/10.1123/jmpb.2020-0045>.

Chaput, Jean-Philippe, Casey E. Gray, Veronica J. Poitras, Valerie Carson, Reut Gruber, Catherine S. Birken, Joanna E. MacLean, Salomé Aubert, Margaret Sampson, and Mark S. Tremblay. 2017. “Systematic Review of the Relationships Between Sleep Duration and Health Indicators in the Early Years (0-4 Years).” *BMC Public Health* 17 (November): 855. <https://doi.org/10.1186/s12889-017-4850-2>.

Chaput, Jean-Philippe, Casey E. Gray, Veronica J. Poitras, Valerie Carson, Reut Gruber, Timothy Olds, Shelly K. Weiss, et al. 2016. “Systematic Review of the Relationships Between Sleep Duration and Health Indicators in School-Aged Children and Youth.” *Applied Physiology, Nutrition, and Metabolism = Physiologie Appliquee, Nutrition Et Metabolisme* 41 (6): S266–282. <https://doi.org/10.1139/apnm-2015-0627>.

Cole, R. J., D. F. Kripke, W. Gruen, D. J. Mullaney, and J. C. Gillin. 1992. “Automatic Sleep/Wake Identification from Wrist Activity.” *Sleep* 15 (5): 461–69. <https://doi.org/10.1093/sleep/15.5.461>.

Dafna, Eliran, Ariel Tarasiuk, and Yaniv Zigel. 2015. “Sleep-Wake Evaluation from Whole-Night Non-Contact Audio Recordings of Breathing Sounds.” *PLOS ONE* 10 (2): e0117382. <https://doi.org/10.1371/journal.pone.0117382>.

Difrancesco, Sonia, Femke Lamers, Harriëtte Riese, Kathleen R. Merikangas, Aartjan T. F. Beekman, Albert M. van Hemert, Robert A. Schoevers, and Brenda W. J. H. Penninx. 2019. “Sleep, Circadian Rhythm, and Physical Activity Patterns in Depressive and Anxiety Disorders: A 2-Week Ambulatory Assessment Study.” *Depression and Anxiety* 36 (10): 975–86. <https://doi.org/10.1002/da.22949>.

Dowd, Kieran P., Robert Szeklicki, Marco Alessandro Minetto, Marie H. Murphy, Angela Polito, Ezio Ghigo, Hidde van der Ploeg, et al. 2018. “A Systematic Literature Review of Reviews on Techniques for Physical Activity Measurement in Adults: A DEDIPAC Study.” *International Journal of Behavioral Nutrition and Physical Activity* 15 (1): 15. <https://doi.org/10.1186/s12966-017-0636-2>.

Duncan, Scott, Tom Stewart, Lisa Mackay, Jono Neville, Anantha Narayanan, Caroline Walker, Sarah Berry, and Susan Morton. 2018. “Wear-Time Compliance with a Dual-Accelerometer System for Capturing 24-h Behavioural Profiles in Children and Adults.” *International Journal of Environmental Research and Public Health* 15 (7): 1296. <https://doi.org/10.3390/ijerph15071296>.

Fiorillo, Luigi, Alessandro Puiatti, Michela Papandrea, Pietro-Luca Ratti, Paolo Favaro, Corinne Roth, Panagiotis Bargiotas, Claudio L. Bassetti, and Francesca D. Faraci. 2019. “Automated Sleep Scoring: A Review of the Latest Approaches.” *Sleep Medicine Reviews* 48 (December): 101204. <https://doi.org/10.1016/j.smrv.2019.07.007>.

Gruber, Reut, Normand Carrey, Shelly K. Weiss, Jean Yves Frappier, Leslie Rourke, Robert T. Brouillette, and Merrill S. Wise. 2014. “[Position Statement on Pediatric Sleep for Psychiatrists](https://www.ncbi.nlm.nih.gov/pmc/articles/PMC4197518).” *Journal of the Canadian Academy of Child and Adolescent Psychiatry = Journal De l’Academie Canadienne De Psychiatrie De L’enfant Et De L’adolescent* 23 (3): 174–95.

Haghayegh, Shahab, Sepideh Khoshnevis, Michael H. Smolensky, and Kenneth R. Diller. 2020. “Application of Deep Learning to Improve Sleep Scoring of Wrist Actigraphy.” *Sleep Medicine* 74 (October): 235–41. <https://doi.org/10.1016/j.sleep.2020.05.008>.

Hecht, Ariel, Shuyi Ma, Janos Porszasz, Richard Casaburi, and COPD Clinical Research Network. 2009. “Methodology for Using Long-Term Accelerometry Monitoring to Describe Daily Activity Patterns in COPD.” *COPD* 6 (2): 121–29. <https://doi.org/10.1080/15412550902755044>.

Hees, Vincent T. van, Séverine Sabia, Kirstie N. Anderson, Sarah J. Denton, James Oliver, Michael Catt, Jessica G. Abell, Mika Kivimäki, Michael I. Trenell, and Archana Singh-Manoux. 2015. “A Novel, Open Access Method to Assess Sleep Duration Using a Wrist-Worn Accelerometer.” *PLOS ONE* 10 (11): e0142533. <https://doi.org/10.1371/journal.pone.0142533>.

Inan-Eroglu, Elif, Bo-Huei Huang, Leah Shepherd, Natalie Pearson, Annemarie Koster, Peter Palm, Peter A. Cistulli, Mark Hamer, and Emmanuel Stamatakis. 2021. “Comparison of a Thigh-Worn Accelerometer Algorithm with Diary Estimates of Time in Bed and Time Asleep: The 1970 British Cohort Study.” *Journal for the Measurement of Physical Behaviour* 4 (1): 60–67. <https://doi.org/10.1123/jmpb.2020-0033>.

Johansson, Peter J., Patrick Crowley, John Axelsson, Karl Franklin, Anne Helene Garde, Pasan Hettiarachchi, Andreas Holtermann, et al. 2023. “Development and Performance of a Sleep Estimation Algorithm Using a Single Accelerometer Placed on the Thigh: An Evaluation Against Polysomnography.” *Journal of Sleep Research* 32 (2): e13725. <https://doi.org/10.1111/jsr.13725>.

K Pavlova, Milena, and Véronique Latreille. 2019. “Sleep Disorders.” *The American Journal of Medicine* 132 (3): 292–99. <https://doi.org/10.1016/j.amjmed.2018.09.021>.

Kaplan, Richard F, Ying Wang, Kenneth A Loparo, Monica R Kelly, and Richard R Bootzin. 2014. “Performance Evaluation of an Automated Single-Channel Sleep–Wake Detection Algorithm.” *Nature and Science of Sleep* 6 (October): 113–22. <https://doi.org/10.2147/NSS.S71159>.

Lee, Jung Ae, and Jeff Gill. 2018. “Missing Value Imputation for Physical Activity Data Measured by Accelerometer.” *Statistical Methods in Medical Research* 27 (2): 490–506. <https://doi.org/10.1177/0962280216633248>.

Lee, Yun Ji, Jae Yong Lee, Jae Hoon Cho, and Ji Ho Choi. 2022. “Interrater Reliability of Sleep Stage Scoring: A Meta-Analysis.” *Journal of Clinical Sleep Medicine: JCSM: Official Publication of the American Academy of Sleep Medicine* 18 (1): 193–202. <https://doi.org/10.5664/jcsm.9538>.

Loyen, Anne, Alexandra M. Clarke-Cornwell, Sigmund A. Anderssen, Maria Hagströmer, Luís B. Sardinha, Kristina Sundquist, Ulf Ekelund, et al. 2017. “Sedentary Time and Physical Activity Surveillance Through Accelerometer Pooling in Four European Countries.” *Sports Medicine (Auckland, N.Z.)* 47 (7): 1421–35. <https://doi.org/10.1007/s40279-016-0658-y>.

Ma, Grandner. 2017. “Sleep, Health, and Society.” *Sleep Medicine Clinics* 12 (1). <https://doi.org/10.1016/j.jsmc.2016.10.012>.

Madsen, Michael T., Jacob Rosenberg, and Ismail Gögenur. 2013. “Actigraphy for Measurement of Sleep and Sleep-Wake Rhythms in Relation to Surgery.” *Journal of Clinical Sleep Medicine: JCSM: Official Publication of the American Academy of Sleep Medicine* 9 (4): 387–94. <https://doi.org/10.5664/jcsm.2598>.

Meyer, Nicholas, Allison G. Harvey, Steven W. Lockley, and Derk-Jan Dijk. 2022. “Circadian Rhythms and Disorders of the Timing of Sleep.” *The Lancet* 400 (10357): 1061–78. <https://doi.org/10.1016/S0140-6736(22)00877-7>.

Migueles, Jairo H., Cristina Cadenas-Sanchez, Alex V. Rowlands, Pontus Henriksson, Eric J. Shiroma, Francisco M. Acosta, Maria Rodriguez-Ayllon, et al. 2019. “Comparability of Accelerometer Signal Aggregation Metrics Across Placements and Dominant Wrist Cut Points for the Assessment of Physical Activity in Adults.” *Scientific Reports* 9 (1): 18235. <https://doi.org/10.1038/s41598-019-54267-y>.

Montazeri Ghahjaverestan, Nasim, Sina Akbarian, Maziar Hafezi, Shumit Saha, Kaiyin Zhu, Bojan Gavrilovic, Babak Taati, and Azadeh Yadollahi. 2020. “Sleep/Wakefulness Detection Using Tracheal Sounds and Movements.” *Nature and Science of Sleep* 12: 1009–21. <https://doi.org/10.2147/NSS.S276107>.

Montoye, Alexander H. K., M. Benjamin Nelson, Joshua M. Bock, Mary T. Imboden, Leonard A. Kaminsky, Kelly A. Mackintosh, Melitta A. McNarry, and Karin A. Pfeiffer. 2018. “Raw and Count Data Comparability of Hip-Worn ActiGraph GT3X+ and Link Accelerometers.” *Medicine and Science in Sports and Exercise* 50 (5): 1103–12. <https://doi.org/10.1249/MSS.0000000000001534>.

Moore, Camille M., Sarah J. Schmiege, and Ellyn E. Matthews. 2015. “Actigraphy and Sleep Diary Measurements in Breast Cancer Survivors: Discrepancy in Selected Sleep Parameters.” *Behavioral Sleep Medicine* 13 (6): 472–90. <https://doi.org/10.1080/15402002.2014.940108>.

Palotti, Joao, Raghvendra Mall, Michael Aupetit, Michael Rueschman, Meghna Singh, Aarti Sathyanarayana, Shahrad Taheri, and Luis Fernandez-Luque. 2019. “Benchmark on a Large Cohort for Sleep-Wake Classification with Machine Learning Techniques.” *Npj Digital Medicine* 2 (1): 1–9. <https://doi.org/10.1038/s41746-019-0126-9>.

Pedersen, Jesper, Martin Gillies Banke Rasmussen, Line Grønholt Olesen, Peter Lund Kristensen, and Anders Grøntved. 2021. “Self-Administered Electroencephalography-Based Sleep Assessment: Compliance and Perceived Feasibility in Children and Adults.” *Sleep Science and Practice* 5 (1): 8. <https://doi.org/10.1186/s41606-021-00059-1>.

Ploeg, Tjeerd van der, Peter C. Austin, and Ewout W. Steyerberg. 2014. “Modern Modelling Techniques Are Data Hungry: A Simulation Study for Predicting Dichotomous Endpoints.” *BMC Medical Research Methodology* 14 (December): 137. <https://doi.org/10.1186/1471-2288-14-137>.

Rasmussen, Martin Gillies Banke, Jesper Pedersen, Line Grønholt Olesen, Søren Brage, Heidi Klakk, Peter Lund Kristensen, Jan Christian Brønd, and Anders Grøntved. 2020. “Short-Term Efficacy of Reducing Screen Media Use on Physical Activity, Sleep, and Physiological Stress in Families with Children Aged 4–14: Study Protocol for the SCREENS Randomized Controlled Trial.” *BMC Public Health* 20 (1): 380. <https://doi.org/10.1186/s12889-020-8458-6>.

Ruiz, Jonatan R., Francisco B. Ortega, David Martínez-Gómez, Idoia Labayen, Luis A. Moreno, Ilse De Bourdeaudhuij, Yannis Manios, et al. 2011. “Objectively Measured Physical Activity and Sedentary Time in European Adolescents: The HELENA Study.” *American Journal of Epidemiology* 174 (2): 173–84. <https://doi.org/10.1093/aje/kwr068>.

Sadeh, A., K. M. Sharkey, and M. A. Carskadon. 1994. “Activity-Based Sleep-Wake Identification: An Empirical Test of Methodological Issues.” *Sleep* 17 (3): 201–7. <https://doi.org/10.1093/sleep/17.3.201>.

Sazonov, Edward, Nadezhda Sazonova, Stephanie Schuckers, Michael Neuman, and CHIME Study Group. 2004. “Activity-Based Sleep-Wake Identification in Infants.” *Physiological Measurement* 25 (5): 1291–1304. <https://doi.org/10.1088/0967-3334/25/5/018>.

Schwab, Kristin E., Bonnie Ronish, Dale M. Needham, An Q. To, Jennifer L. Martin, and Biren B. Kamdar. 2018. “Actigraphy to Evaluate Sleep in the Intensive Care Unit. A Systematic Review.” *Annals of the American Thoracic Society* 15 (9): 1075–82. <https://doi.org/10.1513/AnnalsATS.201801-004OC>.

Skotte, Jørgen, Mette Korshøj, Jesper Kristiansen, Christiana Hanisch, and Andreas Holtermann. 2014. “Detection of Physical Activity Types Using Triaxial Accelerometers.” *Journal of Physical Activity and Health* 11 (1): 76–84. <https://doi.org/10.1123/jpah.2011-0347>.

Skovgaard, Esben Lykke, Jesper Pedersen, Niels Christian Møller, Anders Grøntved, and Jan Christian Brønd. 2021. “Manual Annotation of Time in Bed Using Free-Living Recordings of Accelerometry Data.” *Sensors (Basel, Switzerland)* 21 (24): 8442. <https://doi.org/10.3390/s21248442>.

Skovgaard, Esben Lykke, Malthe Andreas Roswall, Natascha Holbæk Pedersen, Kristian Traberg Larsen, Anders Grøntved, and Jan Christian Brønd. 2023. “Generalizability and Performance of Methods to Detect Non-Wear with Free-Living Accelerometer Recordings.” *Scientific Reports* 13 (1): 2496. <https://doi.org/10.1038/s41598-023-29666-x>.

St-Onge, Marie-Pierre, Michael A. Grandner, Devin Brown, Molly B. Conroy, Girardin Jean-Louis, Michael Coons, Deepak L. Bhatt, and American Heart Association Obesity, Behavior Change, Diabetes, and Nutrition Committees of the Council on Lifestyle and Cardiometabolic Health; Council on Cardiovascular Disease in the Young; Council on Clinical Cardiology; and Stroke Council. 2016. “Sleep Duration and Quality: Impact on Lifestyle Behaviors and Cardiometabolic Health: A Scientific Statement from the American Heart Association.” *Circulation* 134 (18): e367–86. <https://doi.org/10.1161/CIR.0000000000000444>.

Sundararajan, Kalaivani, Sonja Georgievska, Bart H. W. te Lindert, Philip R. Gehrman, Jennifer Ramautar, Diego R. Mazzotti, Séverine Sabia, et al. 2021. “Sleep Classification from Wrist-Worn Accelerometer Data Using Random Forests.” *Scientific Reports* 11 (1): 24. <https://doi.org/10.1038/s41598-020-79217-x>.

Syed, Shaheen, Bente Morseth, Laila A. Hopstock, and Alexander Horsch. 2021. “A Novel Algorithm to Detect Non-Wear Time from Raw Accelerometer Data Using Deep Convolutional Neural Networks.” *Scientific Reports* 11 (1): 8832. <https://doi.org/10.1038/s41598-021-87757-z>.

Toftager, Mette, Peter Lund Kristensen, Melody Oliver, Scott Duncan, Lars Breum Christiansen, Eleanor Boyle, Jan Christian Brønd, and Jens Troelsen. 2013. “Accelerometer Data Reduction in Adolescents: Effects on Sample Retention and Bias.” *International Journal of Behavioral Nutrition and Physical Activity* 10 (1): 140. <https://doi.org/10.1186/1479-5868-10-140>.

Troiano, Richard P., David Berrigan, Kevin W. Dodd, Louise C. Mâsse, Timothy Tilert, and Margaret McDowell. 2008. “Physical Activity in the United States Measured by Accelerometer.” *Medicine and Science in Sports and Exercise* 40 (1): 181–88. <https://doi.org/10.1249/mss.0b013e31815a51b3>.

Van De Water, Alexander T. M., Alison Holmes, and Deirdre A. Hurley. 2011. “Objective Measurements of Sleep for Non-Laboratory Settings as Alternatives to Polysomnography – a Systematic Review.” *Journal of Sleep Research* 20 (1): 183–200. <https://doi.org/10.1111/j.1365-2869.2009.00814.x>.

Vaughn, Bradley V., and Peterson Giallanza. 2008. “Technical Review of Polysomnography.” *Chest* 134 (6): 1310–19. <https://doi.org/10.1378/chest.08-0812>.

Wang, Ying, Kenneth A Loparo, Monica R Kelly, and Richard F Kaplan. 2015. “Evaluation of an Automated Single-Channel Sleep Staging Algorithm.” *Nature and Science of Sleep* 7 (September): 101–11. <https://doi.org/10.2147/NSS.S77888>.

Webster, J. B., D. F. Kripke, S. Messin, D. J. Mullaney, and G. Wyborney. 1982. “An Activity-Based Sleep Monitor System for Ambulatory Use.” *Sleep* 5 (4): 389–99. <https://doi.org/10.1093/sleep/5.4.389>.

Winkler, Elisabeth A. H., Danielle H. Bodicoat, Genevieve N. Healy, Kishan Bakrania, Thomas Yates, Neville Owen, David W. Dunstan, and Charlotte L. Edwardson. 2016. “Identifying Adults’ Valid Waking Wear Time by Automated Estimation in activPAL Data Collected with a 24 h Wear Protocol.” *Physiological Measurement* 37 (10): 1653. <https://doi.org/10.1088/0967-3334/37/10/1653>.

Younes, Magdy, Jill Raneri, and Patrick Hanly. 2016. “Staging Sleep in Polysomnograms: Analysis of Inter-Scorer Variability.” *Journal of Clinical Sleep Medicine: JCSM: Official Publication of the American Academy of Sleep Medicine* 12 (6): 885–94. <https://doi.org/10.5664/jcsm.5894>.

Zhou, Shang-Ming, Rebecca A. Hill, Kelly Morgan, Gareth Stratton, Mike B. Gravenor, Gunnar Bijlsma, and Sinead Brophy. 2015. “Classification of Accelerometer Wear and Non-Wear Events in Seconds for Monitoring Free-Living Physical Activity.” *BMJ Open* 5 (5): e007447. <https://doi.org/10.1136/bmjopen-2014-007447>.