Estimating Sleep Quality Metrics Using Free-Living Accelerometer Data From Thigh-Worn Devices in Comparison to an EEG-Based Sleep Tracking Device

Esben Høegholm Lykke

Jan Christian Brønd

2023-06-22

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# 1. Introduction

Understanding the intricate relationship between sleep, physical activities, sedentary behaviors, and health is crucial for investigating human health. However, our current knowledge in this area heavily relies on self-reported data, which can introduce biases and inaccuracies when estimating sleep duration, physical activity levels, and sedentary behavior (Bull et al. 2020; Cespedes et al. 2016; Ekblom et al. 2015; Troiano, Stamatakis, and Bull 2020; Shephard 2003). This reliance on subjective data limits our depth of understanding and the accuracy of our findings.

While laboratory-based polysomnography is considered the gold standard for objectively measuring sleep, its practicality in large-scale epidemiological studies is limited due to its high cost, the need for professional administration, and the substantial resources required for specialized equipment (Van De Water, Holmes, and Hurley 2011). As an alternative, diaries is commonly used as low-cost and low-tech methods for sleep assessment in population research. However, relying solely on diary-based methods can place a burden on participants and may introduce recall bias and other limitations(Moore, Schmiege, and Matthews 2015). A more feasible approach in large-scale epidemiological studies is the use of device-based measurement methods that can estimate sleep duration. This method offers the advantage of being less burdensome for participants and avoids potential biases associated with recall.

In this context, the Zmachine®️ Insight+ (ZM) has emerges as a valuable tool. Validated against polysomnography with favorable results(Kaplan et al. 2014; Wang et al. 2015), the ZM provides comparable data without the high costs or need for professional monitoring associated with polysomnography. Furthermore, the ease of use of the ZM device makes it compliant for free-living use(Pedersen et al. 2021). This allows for the analysis of multiple consecutive nights, as compared to single-night recordings from PSG, thereby capturing the important variations in sleep across multiple nights.

The emergence of body-worn accelerometers has provided an effective and affordable alternative for objectively assessing sleep patterns in a home environment over extended periods. These accelerometers collect continuous, high-resolution data for several weeks without requiring recharging, thus minimizing participant burden. Initial applications of accelerometry for sleep and wake stage classification were based on wrist movements. The original algorithm, developed in 1982 using simple linear regression and validated with PSG (Webster et al. 1982), was later refined in 1992 (Cole et al. 1992), leading to the widely used Cole-Kripke model. Subsequent research on wrist-worn accelerometer data has employed heuristic algorithms, advanced machine learning models, as well as regression and deep learning techniques(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).

Despite the well-developed field of accelerometer data analysis for sleep detection from wrist and hip-worn devices, the same level of advancement is not mirrored in studies utilizing thigh-worn accelerometers. Methods for assessing sleep using wrist and hip-worn accelerometers have greatly evolved over the years, employing an extensive range of techniques. These include heuristic algorithms, machine learning models, regression and deep learning techniques, all tailored to the specific signal characteristics of wrist and hip-worn devices (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; Patterson et al. 2023).

However, for thigh-worn accelerometers, the landscape appears less mature, with only a handful of studies investigating sleep detection algorithms. The majority of the efforts are focused on delineating wakefulness from sleep, with particular emphasis on the definition of ‘waking time’ and ‘bedtime’ (Carlson et al. 2021; Inan-Eroglu et al. 2021; Berg et al. 2016; Winkler et al. 2016). Furthermore, while strides have been made recently in estimating sleep duration with these devices, with the introduction of a promising algorithm and its comparison against PSG(Johansson et al. 2023), the field is still in its infancy when it comes to employing machine learning techniques. Given the potential for accurate physical behavior assessment that thigh-worn accelerometers provide, a significant research gap exists. Therefore, there is a pressing need for future studies 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.

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 EEG-based sleep tracking device, which we considered 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). By analyzing these additional metrics, we aimed to provide a comprehensive evaluation of the model’s capability in assessing various aspects of sleep quality, allowing us to determine the overall effectiveness of our models in accurately estimating different parameters related to sleep duration and quality.

# 2. Methods

## 2.1 Dataset and participants

The current study leverages data from the SCREENS project(Rasmussen et al. 2020), a study conducted from October 2018 to March 2019 in Middelfart, Southern Denmark, that evaluated the impact of screen media usage on Danish families. Specifically, it focused on children between the ages of 6 to 10 years. For our analysis, we isolated data from child participants within the SCREENS cohort. Our main sources of data were accelerometer readings from Axivity AX3 devices attached to the children’s thighs, and electroencephalography (EEG) data derived from the ZM device. The Axivity AX3, an unobtrusive 3-axis accelerometer, was positioned midway between the hip and knee on the right anterior thigh, recording participant movement data.

Sleep state information was extracted using the ZM, a product of General Sleep Corporation. The ZM, utilizes advanced EEG hardware and signal processing algorithms, employs three self-adhesive, disposable sensors placed outside the hairline for reliable EEG signal acquisition. The ZM uses two proprietary algorithms: Z-ALG and Z-PLUS. The Z-ALG is utilized for accurate sleep detection, showcasing its aptness for in-home monitoring(Kaplan et al. 2014), while the Z-PLUS effectively differentiates sleep stages, as evidenced by its alignment with expert evaluations using PSG data(Wang et al. 2015).

Finally, we affirm that the SCREENS study received approval from the Regional Scientific Committee of Southern Denmark, and all data handling processes complied with the General Data Protection Regulation (GDPR), guaranteeing the ethical and secure management of participant information.

## 2.2 Data Preprocessing and Feature Extraction

In this study, raw data processing began with a low-pass filtration step using a 4th order Butterworth filter with a 5 Hz cut-off frequency to eliminate high-frequency noise. Following filtration, data were partitioned into overlapping 2-second intervals, each successive interval sharing a 50% overlap with the previous one. Subsequently, we performed a feature extraction process that yielded a set of 88 features, providing a robust characterization of the data. Extracted from accelerometer and temperature signals, these features include temporal elements that use both lag and lead values, capturing dynamic data trends by incorporating measurements from preceding and upcoming intervals. Furthermore, inspired by Walch et al.(Walch et al. 2019), we developed sensor-independent features to encapsulate circadian rhythms. These features offer unique insights not directly discernible from sensor outputs and are meant to approximate the changing drive of the circadian clock to sleep over the course of the night (see [Figure 1](#fig-sensor-independent)).

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| Figure 1: Sensor-independent features of circadian rhythms across two consecutive nights. A) cosinus feature, B) linear feature. |

Furthermore, the feature set was enriched by including signal characteristics, which encompass vector magnitude, mean crossing rate, skewness, and kurtosis for each of the x, y, and z dimensions. These features provide a comprehensive understanding of the signal’s attributes, facilitating a more nuanced analysis of the underlying patterns. All features are summarized in table ???. (is it necessary to create a table of features???)

In addition to the engineered features, we made the decision to incorporate the median-filtered raw predictions from the ZM device into our modeling process. This choice was driven by the recognition that children typically undergo approximately five to eight sleep cycles per night, with awakenings commonly occurring at the conclusion of each cycle(Galland et al. 2012). Upon examining the raw predictions from the ZM device, we observed a significant overestimation in the number of awakenings per night among our child participants, surpassing what would typically align with established sleep cycle patterns. As a result, we opted to train and evaluate our models using both the raw ZM output and a 10-minute median-filtered version. This approach yielded a more appropriate and anticipated count of awakenings per night, offering a more realistic representation of children’s sleep patterns (see [Figure 2](#fig-zm-median)).

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| Figure 2: The difference in number of awakenings between the ZM predictions vs. 10-minute median filtered predictions for a random night. Grey line is the raw predictions, black line is the median filtered predictions. |

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## 2.3 Models in Sequence

To predict in-bed time and sleep time accurately, we employed an ensemble learning strategy based on sequential binary classification models. This approach involved constructing a sequence of models using multiple machine learning algorithms to improve predictive accuracy. The process starts with an initial model predicting in-bed time, followed by a second model that utilized the output of the initial model to predict sleep time. This sequential approach was applied across all four algorithms detailed below, with each subsequent model leveraging the outputs of the previous models for improved predictions.

1. **Logistic Regression (LREG):** Logistic regression served as a simple and fast baseline model. However, due to its linear nature, it may struggle with capturing complex relationships and non-linear patterns present in the accelerometer data.
2. **Decision Tree (TREE):** Decision trees are capable of handling non-linear patterns and are easily interpretable. However, they are prone to overfitting, particularly when dealing with complex patterns that require simultaneous consideration of multiple features.
3. **Single-layer Feed-forward Neural Network (SNN):** Single-layer feed-forward neural networks can effectively capture non-linear relationships, even with their relatively simple structure. However, they tend to be more challenging to interpret compared to simpler models. Additionally, careful tuning of the network’s architecture and training process is required to mitigate the risk of overfitting.
4. **XGBoost (XGB):** XGBoost is a powerful algorithm known for its ability to provide highly accurate predictions and handle complex, non-linear patterns in the data. It also incorporates built-in methods to prevent overfitting. However, training XGBoost models can be computationally intensive, and interpreting the predictions it generates can pose challenges.

## 2.4 Multiclass Model

In addition to the sequential models, we also employed a bi-directional LSTM network(Hochreiter and Schmidhuber 1997) (biLSTM) to construct a multiclass classifier capable of predicting the classes of out-bed-awake, in-bed-awake, and in-bed-asleep. The architecture of the biLSTM consisted of four layers, each with 128 hidden units. The bidirectional nature of the LSTM effectively doubled the number of hidden units at each time step by combining the hidden states from both directions.

The biLSTM model was chosen as it offers several advantages in the context of sleep classification using accelerometer data from a thigh-mounted device. This model type excels in the following areas: (1) modeling temporal context, (2) handling a large temporal scope, (3) not relying on absolute time in bed to model class probabilities, and (4) enabling temporal inference over any feature without being restricted to hand-designed temporal features.

Prior studies have explored the use of accelerometer data for sleep detection, often employing LSTM models to capture complex temporal patterns. Notably, Sano et al. (Sano et al. 2019) achieved significant improvements in sleep and wake classification by combining actigraphy, skin conductance, and skin temperature data using an LSTM method. Similarly, Chen et al. (Chen et al. 2021) employed a combination of convolutional neural networks (CNN) and LSTM structures. These studies suggest the potential of LSTM models in improving sleep detection based on accelerometer data by effectively capturing complex temporal patterns. However, further research is needed to fully understand the advantages and limitations of this approach.

## 2.5 Model Training

For the models in sequence, we trained four pairs of classification models, each pair distinguishing between in-bed/out-of-bed and asleep/awake states. The dataset was randomly split into a training set (approximately 50% of the subjects) and a testing set (also approximately 50%), ensuring that samples from the same subject were never simultaneously used in both sets. Hyper-parameter optimization was performed using 10-fold Monte Carlo cross-validation, with the F1 score as the performance metric. The best-performing set of hyperparameters was then used to fit the models to the full training dataset, maximizing accuracy by leveraging all available data.

The biLSTM were… blablablabla…

## 2.6 Imbalanced data

Imbalanced datasets can pose challenges when training machine learning models, as models may favor predicting the majority class. To address this issue, we employed oversampling techniques to ensure that each class had a roughly equal number of training samples. Specifically, we utilized the Synthetic Minority Over-sampling Technique (SMOTE)(Chawla et al. 2002), which generates new samples by interpolating random samples with their nearest neighbors. In our study, we implemented SMOTE using the themis R package(Hvitfeldt 2023), resampling all classes to achieve a balanced distribution of training samples.

## 2.7 Validation

In our study, we employed standard evaluation metrics to assess the epoch-to-epoch performance of each model. These metrics include accuracy as , sensitivity as , specificity as , precision as , F1 score as , and area under the precision-recall curves were also calculated. The Average Precision, represented by the area under the precision-recall curve, provides a quantitative measure of performance. A value of 1 for Average Precision indicates the best performance. For the multiclass biLSTM model, we calculated performance metrics as macroaverages, to treat all classes equally.

Consistent with previous studies in the field(Hjorth et al. 2012; Kushida et al. 2001), we treated the in-bed/out-of-bed and awake/asleep scoring tasks as a binary classification problems, where in-bed and asleep was considered the positive label and out-of-bed and awake the negative label. Furthermore, Bland-Altman and Pearson correlations were used to assess sleep quality summaries of sleep period time (SPT), total sleep time (TST), sleep efficiency (SE), latency until persistent sleep (LPS), and wake after sleep onset (WASO) calculated from the models against the EEG-based ZM sleep quality summaries.

R version 4.3.0 (2023-04-21)(R Core Team 2023) and the Tidymodels(Kuhn and Wickham 2020) and Tidyverse(Wickham et al. 2019) suite of packages were used as the core tools for model development and analyses. Python version 3.10.6(Van Rossum and Drake 2009) and PyTorch(Paszke et al. 2019) were used to implement the biLSTM model. All code used to perform the analysis and generate the figures in this paper are available in [this repository](https://github.com/esbenlykke/sleep_study).

# 3. Results

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| Flowchart of eligible nights included in the study - revise text boxes! |

[table: age and summary sleep quality statistics, both filtered and raw ZM predictions]

# 4. References

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>.

Bull, Fiona C., Salih S. Al-Ansari, Stuart Biddle, Katja Borodulin, Matthew P. Buman, Greet Cardon, Catherine Carty, et al. 2020. “World Health Organization 2020 Guidelines on Physical Activity and Sedentary Behaviour.” *British Journal of Sports Medicine* 54 (24): 1451–62. <https://doi.org/10.1136/bjsports-2020-102955>.

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>.

Cespedes, Elizabeth M., Frank B. Hu, Susan Redline, Bernard Rosner, Carmela Alcantara, Jianwen Cai, Martica H. Hall, et al. 2016. “Comparison of Self-Reported Sleep Duration With Actigraphy: Results From the Hispanic Community Health Study/Study of Latinos Sueño Ancillary Study.” *American Journal of Epidemiology* 183 (6): 561–73. <https://doi.org/10.1093/aje/kwv251>.

Chawla, N. V., K. W. Bowyer, L. O. Hall, and W. P. Kegelmeyer. 2002. “SMOTE: Synthetic Minority Over-Sampling Technique.” *Journal of Artificial Intelligence Research* 16 (June): 321–57. <https://doi.org/10.1613/jair.953>.

Chen, Zhenghua, Min Wu, Wei Cui, Chengyu Liu, and Xiaoli Li. 2021. “An Attention Based CNN-LSTM Approach for Sleep-Wake Detection With Heterogeneous Sensors.” *IEEE journal of biomedical and health informatics* 25 (9): 3270–77. <https://doi.org/10.1109/JBHI.2020.3006145>.

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>.

Ekblom, Örjan, Elin Ekblom-Bak, Kate A. Bolam, Björn Ekblom, Caroline Schmidt, Stefan Söderberg, Göran Bergström, and Mats Börjesson. 2015. “Concurrent and Predictive Validity of Physical Activity Measurement Items Commonly Used in Clinical Settings– Data from SCAPIS Pilot Study.” *BMC Public Health* 15 (1): 978. <https://doi.org/10.1186/s12889-015-2316-y>.

Galland, Barbara C., Barry J. Taylor, Dawn E. Elder, and Peter Herbison. 2012. “Normal Sleep Patterns in Infants and Children: A Systematic Review of Observational Studies.” *Sleep Medicine Reviews* 16 (3): 213–22. <https://doi.org/10.1016/j.smrv.2011.06.001>.

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>.

Hjorth, Mads F., Jean-Philippe Chaput, Camilla T. Damsgaard, Stine-Mathilde Dalskov, Kim F. Michaelsen, Inge Tetens, and Anders Sjödin. 2012. “Measure of Sleep and Physical Activity by a Single Accelerometer: Can a Waist-Worn Actigraph Adequately Measure Sleep in Children?” *Sleep and Biological Rhythms* 10 (4): 328–35. <https://doi.org/10.1111/j.1479-8425.2012.00578.x>.

Hochreiter, Sepp, and Jürgen Schmidhuber. 1997. “Long Short-Term Memory.” *Neural Computation* 9 (8): 1735–80. <https://doi.org/10.1162/neco.1997.9.8.1735>.

Hvitfeldt, Emil. 2023. *Themis: Extra Recipes Steps for Dealing with Unbalanced Data*. <https://CRAN.R-project.org/package=themis>.

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>.

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

Kuhn, Max, and Hadley Wickham. 2020. *Tidymodels: A Collection of Packages for Modeling and Machine Learning Using Tidyverse Principles.* <https://www.tidymodels.org>.

Kushida, C. A., A. Chang, C. Gadkary, C. Guilleminault, O. Carrillo, and W. C. Dement. 2001. “Comparison of actigraphic, polysomnographic, and subjective assessment of sleep parameters in sleep-disordered patients.” *Sleep Medicine* 2 (5): 389–96. <https://doi.org/10.1016/s1389-9457(00)00098-8>.

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>.

Paszke, Adam, Sam Gross, Francisco Massa, Adam Lerer, James Bradbury, Gregory Chanan, Trevor Killeen, et al. 2019. “PyTorch: An Imperative Style, High-Performance Deep Learning Library.” In *Advances in Neural Information Processing Systems 32*, 8024–35. Curran Associates, Inc. <http://papers.neurips.cc/paper/9015-pytorch-an-imperative-style-high-performance-deep-learning-library.pdf>.

Patterson, Matthew R., Adonay A. S. Nunes, Dawid Gerstel, Rakesh Pilkar, Tyler Guthrie, Ali Neishabouri, and Christine C. Guo. 2023. “40 Years of Actigraphy in Sleep Medicine and Current State of the Art Algorithms.” *Npj Digital Medicine* 6 (1): 1–7. <https://doi.org/10.1038/s41746-023-00802-1>.

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>.

R Core Team. 2023. *R: A Language and Environment for Statistical Computing*. Vienna, Austria: R Foundation for Statistical Computing. <https://www.R-project.org/>.

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 414: Study Protocol for the SCREENS Randomized Controlled Trial.” *BMC Public Health* 20 (1): 380. <https://doi.org/10.1186/s12889-020-8458-6>.

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>.

Sano, Akane, Weixuan Chen, Daniel Lopez-Martinez, Sara Taylor, and Rosalind W. Picard. 2019. “Multimodal Ambulatory Sleep Detection Using LSTM Recurrent Neural Networks.” *IEEE journal of biomedical and health informatics* 23 (4): 1607–17. <https://doi.org/10.1109/JBHI.2018.2867619>.

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>.

Shephard, R. J. 2003. “Limits to the Measurement of Habitual Physical Activity by Questionnaires.” *British Journal of Sports Medicine* 37 (3): 197–206. <https://doi.org/10.1136/bjsm.37.3.197>.

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>.

Troiano, Richard P., Emmanuel Stamatakis, and Fiona C. Bull. 2020. “How Can Global Physical Activity Surveillance Adapt to Evolving Physical Activity Guidelines? Needs, Challenges and Future Directions.” *British Journal of Sports Medicine* 54 (24): 1468–73. <https://doi.org/10.1136/bjsports-2020-102621>.

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 (1pt2): 183–200. <https://doi.org/10.1111/j.1365-2869.2009.00814.x>.

Van Rossum, Guido, and Fred L. Drake. 2009. *Python 3 Reference Manual*. Scotts Valley, CA: CreateSpace.

Walch, Olivia, Yitong Huang, Daniel Forger, and Cathy Goldstein. 2019. “Sleep Stage Prediction with Raw Acceleration and Photoplethysmography Heart Rate Data Derived from a Consumer Wearable Device.” *Sleep* 42 (12): zsz180. <https://doi.org/10.1093/sleep/zsz180>.

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>.

Wickham, Hadley, Mara Averick, Jennifer Bryan, Winston Chang, Lucy D’Agostino McGowan, Romain François, Garrett Grolemund, et al. 2019. “Welcome to the tidyverse.” *Journal of Open Source Software* 4 (43): 1686. <https://doi.org/10.21105/joss.01686>.

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>.