

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

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## Abstract

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**Keywords:** Sleep, Accelerometry, EEG, Machine learning, Sleep quality metrics

## 1. Introduction

An extensive array of research underlines the importance of sleep for both mental and physical health<sup>1,2,3,4</sup>. Consequently, accurate sleep assessment methods are essential for tracking sleep patterns, thereby enhancing our comprehension of the sleep-health relationship. Furthermore, ensuring high user-acceptability for these methods is essential in order to conduct large-scale studies over prolonged periods.

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<sup>5</sup>. 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 may introduce recall bias and other limitations<sup>6</sup>. 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) emerges as a valuable tool. Validated against polysomnography with favorable results<sup>7,8</sup>, 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<sup>9</sup>. 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.

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The introduction 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<sup>10</sup>, was later refined in 1992<sup>11</sup>, 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<sup>12,11,13,14,15,16</sup>.

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<sup>12,11,13,14,15,16,17</sup>. 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’<sup>18,19,20,21</sup>. 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<sup>22</sup>, 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<sup>23,24</sup>, 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<sup>25</sup>, a study conducted from October 2018 to March 2019 in Middelfart, Southern Denmark, that evaluated the impact of screen media usage on Danish families. For our analysis, we isolated data from child participants between the ages of 6 to 10 years 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<sup>7</sup>, while the Z-PLUS effectively differentiates sleep stages, as evidenced by its alignment with expert evaluations using PSG data<sup>8</sup>.

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 similar to methods described by Skotte et al.<sup>23</sup>. Any non-wear data was removed using previously described methods<sup>26</sup> and data was resampled to 30-second epochs so every sample classified by the algorithms corresponds to a 30-second epoch scored during the ZM recordings. 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.<sup>27</sup>, 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). 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 ??? (overvej tabel til supp. material)

In addition to the engineered features, we chose to incorporate the median-filtered raw predictions from the ZM device into our modeling process. This decision stemmed from the understanding that children typically undergo around five to eight sleep cycles per night, with awakenings commonly occurring at the end of each cycle<sup>28</sup>. Examining the raw ZM predictions, we noted a significant overestimation in the number of awakenings per night for the children in our study, exceeding what would be expected based on typical sleep cycle patterns. Consequently, we elected to train and evaluate our models using not only the raw ZM output, but also versions that were subjected to 5-minute and 10-minute median filters. This approach resulted in an anticipated, more age-appropriate count of awakenings per night, providing a more accurate depiction of children’s sleep patterns (see Figure 2).

## 2.3. Algorithms, Training and Validation

In our study, we utilize two distinct modeling strategies to predict sleep patterns derived from thigh-mounted accelerometer data: a sequential ensemble and a multiclass bidirectional Long Short-Term Memory (biLSTM)<sup>29</sup> neural network. The sequential ensemble involves using four pairs of models, each pair consisting of the same algorithm, that predict in-bed and sleep time successively. Conversely, the biLSTM is a comprehensive model that predicts multiple classes simultaneously, effectively handling complex temporal patterns. By applying and comparing both, we aim to evaluate their relative effectiveness.

### 2.3.1. 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 began 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.

### 2.3.2. Multiclass Model

The biLSTM is 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 choice of four layers and 128 hidden units in our model balanced complexity and efficiency: it was deep enough to learn intricate patterns yet feasible to train timely. Additionally, the bidirectional nature of the LSTM, doubling the hidden units at each time step, improved data comprehension and avoided overfitting.

The biLSTM model was chosen for sleep classification using accelerometer data from a thigh-mounted device due to its advantages in modeling temporal context, handling a large temporal scope, and enabling temporal inference over any feature without the need for hand-designed temporal features.

Previous studies have explored the use of LSTM models for sleep detection, showing promising results in capturing complex temporal patterns. Notable works by Sano et al.<sup>30</sup> and Chen et al.<sup>31</sup> have demonstrated the potential of LSTM models in improving sleep detection based on accelerometer data. However, further research is necessary to fully comprehend the strengths and limitations of this approach.

### 2.3.3. 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. Furthermore, the dataset for predicting sleep was highly imbalanced which 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)<sup>32</sup>, which generates new samples by interpolating random samples with their nearest neighbors. In our study, we implemented SMOTE using the themis R package<sup>33</sup>, resampling all classes to achieve a balanced distribution of training samples.

The biLSTM model was trained using the Adam optimizer, which is computationally efficient and adapts the learning rate during training. Cross-entropy loss function was employed for its suitability in multiclass classification with mutually exclusive classes. The softmax activation function was selected for the output layer to obtain a probability distribution over the classes. Data for training the biLSTM were randomly divided into a training, validation, and test tensors based on a 50/25/25 split. The model was evaluated using the F1 score on both the training and validation sets. Early stopping was implemented with a patience of 3 epochs, meaning training would stop if there was no improvement in the validation loss for 3 consecutive epochs.

#### 2.3.4. Model Validation [evt bare “statistics”]

In our study, we employed standard evaluation metrics to assess the epoch-to-epoch performance of each model. These metrics include accuracy as  $accuracy = \frac{TP+TN}{TP+TN+FP+FN}$ , sensitivity as  $sensitivity = \frac{TP}{TP+FN}$ , specificity as  $specificity = \frac{TN}{TN+FP}$ , precision as  $precision = \frac{TP}{TP+FP}$ , F1 score as  $F_1 = 2 * \frac{precision * sensitivity}{precision + sensitivity}$ , 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 macro-averages, to treat all classes equally. Consistent with previous studies in the field<sup>34,35</sup>, 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.

To evaluate our developed models’ performance in assessing sleep quality metrics, we employed Bland-Altman plots and Pearson correlations. These methods were used to compare the sleep quality summaries calculated by our models with those obtained from EEG-based ZM sleep quality summaries. The sleep quality summaries included several metrics:

1. Sleep Period Time (SPT) - This refers to the total duration of the sleep period, which is defined as the time from the start to the end of the ZM recording.
2. Total Sleep Time (TST) - This is the time spent asleep within the SPT.
3. Sleep Efficiency (SE) - This is the ratio between TST and SPT, representing the proportion of the sleep period that was actually spent asleep.
4. Latency Until Persistent Sleep (LPS) - This metric represents the time it takes to transition from wakefulness to sustained sleep. It is calculated as the time from the beginning of the ZM recording until a period when 10 out of 12 minutes are scored as sleep.
5. Wake After Sleep Onset (WASO) - This refers to the time spent awake after initially falling asleep and before the final awakening. In our analysis, a period is counted as ‘awake’ only if it consists of 3 or more contiguous 30-second epochs.

R version 4.3.0 (2023-04-21)<sup>36</sup> and the Tidymodels<sup>37</sup> and Tidyverse<sup>38</sup> suite of packages were used as the core tools for model development and analyses. Python version 3.10.6<sup>39</sup> and PyTorch<sup>40</sup> 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](#).

### 3. Results

The children children included in the analyses were 9.4 years old (SD = 2.1).

As reported in Table 1 the sleep quality metrics derived from ZMachine predictions were modified by the implementation of 5-minute and 10-minute median filters. The Sleep Period Time (SPT) remained consistent across raw and filtered datasets (mean:  $9.2 \pm 2.1$  hours). Total Sleep Time (TST) and Sleep Efficiency (SE) increased in the filtered data, implying the filters categorize some wakefulness as sleep. Specifically, TST increased from a raw mean of  $7.7 \pm 1.9$  hours to  $8.1 \pm 2.0$  hours (5-minute filter) and  $8.2 \pm 2.1$  hours (10-minute filter), while SE rose from  $82.6 \pm 12.0\%$  to  $86.4 \pm 12.7\%$  and  $87.5 \pm 12.9\%$  respectively. Latency to Persistent Sleep (LPS) also elevated, suggesting the filter smooths out brief awakenings at sleep onset, leading to a prolonged time to persistent sleep. The most significant change was seen in Wake After Sleep Onset (WASO), which dropped from  $39.0 \pm 33.6$  minutes in raw data to  $30.6 \pm 46.8$  minutes and  $22.3 \pm 55.4$  minutes in the 5-minute and 10-minute filtered data, respectively. The results underscore the influential role of median filters on sleep metrics.

Table 1: Summary of Sleep Quality Metrics based on Raw ZM Predictions and Median Filtering.

	SPT	TST	SE	LPS	WASO
Raw	9.2 (2.1)	7.7 (1.9)	82.6 (12.0)	34.5 (27.9)	39.0 (33.6)
5-Min Median	9.2 (2.1)	8.1 (2.0)	86.4 (12.7)	36.3 (39.8)	30.6 (46.8)
10-Min Median	9.2 (2.1)	8.2 (2.1)	87.5 (12.9)	38.0 (48.7)	22.3 (55.4)

### 3.1. Performance on Epoch-To-Epoch Basis

The results from the epoch-to-epoch evaluation of in-bed performance metrics for our included models are presented in Table 2. The epoch-to-epoch evaluation of in-bed performance metrics, outlined in @tbl-in\_bed\_performance, demonstrates practically equivalent performance across all model types. While the Decision Tree model posted an F1 score of 94.4% and accuracy of 95.3%, the Logistic Regression and Feed-Forward Neural Network models each exhibited an F1 score of 95.0% and similar accuracies of 95.7% and 95.8%, respectively. The XGBoost model, despite recording the highest metrics with an F1 score of 95.4% and accuracy of 96.1%, outpaced the others only marginally. This underscores the consistency of performance among these models in monitoring in-bed conditions.

Table 2: In-Bed Performance Metrics

model	F1 Score (%)	Accuracy (%)	Sensitivity (%)	Precision (%)	Specificity (%)
Decision Tree	9,436.3%	9,527.2%	9,312.3%	9,563.6%	9,686.0%
Logistic Regression	9,498.9%	9,573.9%	9,503.5%	9,494.3%	9,626.0%
Feed-Forward Neural Network	9,502.9%	9,577.4%	9,507.1%	9,498.7%	9,629.2%
XGBoost	9,538.4%	9,605.8%	9,582.7%	9,494.4%	9,622.9%

Table 3 details the performance metrics of the four machine learning models—Decision Tree, Logistic Regression, Neural Network, and XGBoost—applied to raw ZM predictions and 5- and 10-minute median filtered predictions. For raw ZM predictions, all models demonstrated comparable performance, with F1 Scores between 93.27% and 93.58%. The XGBoost model performed marginally better. However, it’s crucial to highlight that Specificity was notably low across models, with the Neural Network model achieving the highest at 48.31%. Performance improved on 5-minute median data. XGBoost again outperformed other models in F1 Score and Accuracy, yet Specificity remained a concern, with scores ranging from 37.47% to 50.90%. On 10-minute median data, all models showed further improvement, and XGBoost continued to lead in F1 Score and Accuracy. It is significant that both Neural Network and XGBoost models achieved a Sensitivity of 99.10%. However, low Specificity scores persisted, with the highest only at 50.98% for the XGBoost model.

Table 3: Sleep Performance Metrics

	F1 Score (%)	Accuracy (%)	Sensitivity (%)	Precision (%)	Specificity (%)
Raw ZM Predictions					
Decision Tree	93.27	88.25	96.92	89.88	42.73
Logistic Regression	93.30	88.14	98.33	88.76	34.65
Neural Network	93.54	88.80	96.52	90.74	48.31
XGBoost	93.58	88.84	96.92	90.47	46.41
5-Min Median					
Decision Tree	95.48	91.87	98.02	93.07	48.01
Logistic Regression	95.37	91.55	99.14	91.87	37.47

Neural Network	95.75	92.33	98.39	93.24	49.14
XGBoost	95.78	92.41	98.23	93.45	50.90
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10-Min Median					
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Decision Tree	96.02	92.75	98.30	93.84	47.95
Logistic Regression	96.04	92.73	99.20	93.09	40.56
Neural Network	96.18	93.06	98.29	94.17	50.90
XGBoost	96.60	93.79	99.10	94.22	50.98
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Analyzing the area under the curve for precision-recall (AUC-PR) for all models across raw ZM predictions and 5- and 10-minute median filtered predictions yielded distinct results. Across all types of ZM predictions, the decision tree consistently yielded the highest AUC-PR, whereas the Neural Network generally performed least effectively. This highlights the superior predictive accuracy of the decision tree model in this context (see Figure 4). The Area Under the Receiver Operating Characteristics Curve (ROC-AUC) results indicate a varying performance of the four models across the ZM predictions types. The XGBoost model consistently outperforms the other models across all data types, suggesting its superior capacity for distinguishing between classes. In contrast, the Neural Network model consistently exhibits the lowest ROC-AUC values, suggesting a weaker performance in this specific context (see Figure 5).



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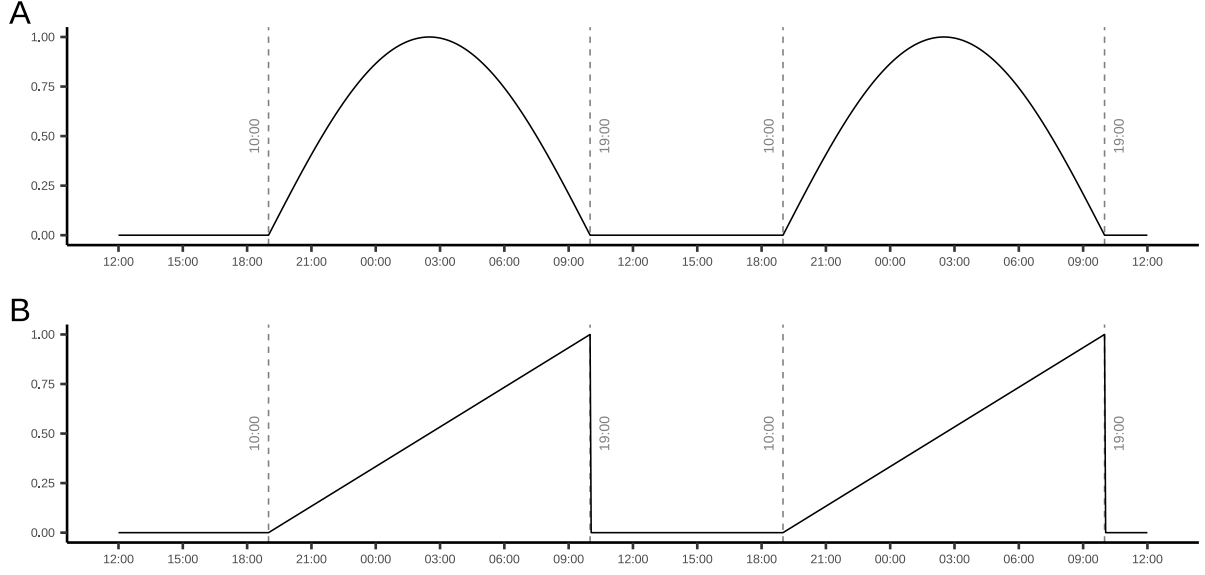


Figure 1: Sensor-independent features of circadian rhythms across two consecutive nights. A) cosine feature, B) linear feature.

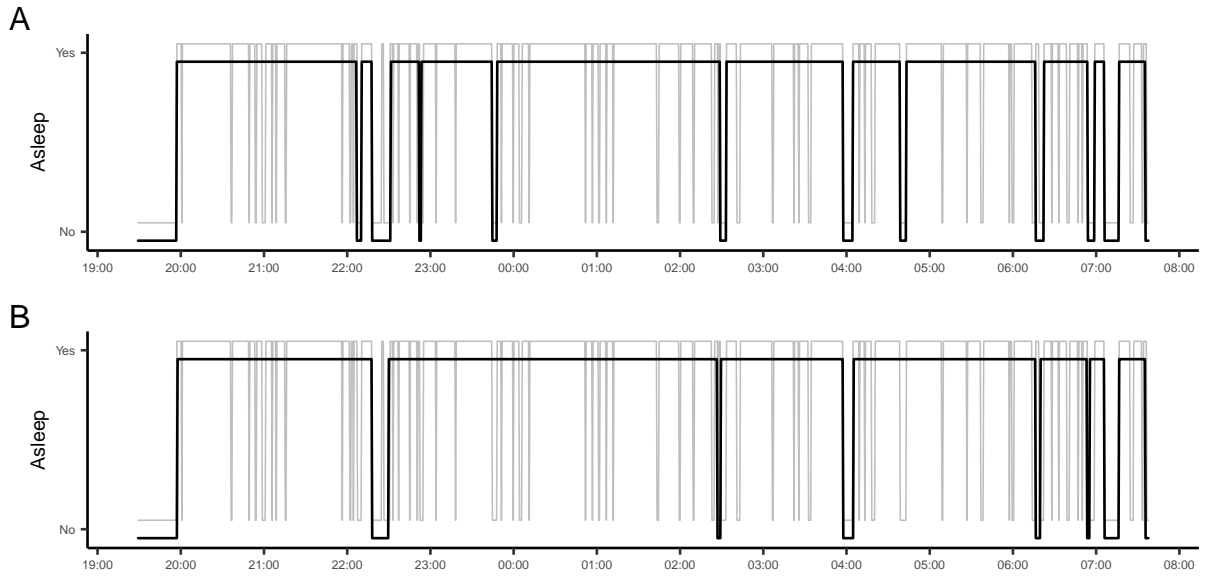


Figure 2: The difference in number of awakenings between the raw ZM predictions vs. 5-minute, and 10-minute median filtered predictions for a random night. Grey line is the raw predictions, black line is the median filtered predictions. A: 5-minute median filter on raw ZM predictions, B: 10-minute median filter on raw ZM predictions.

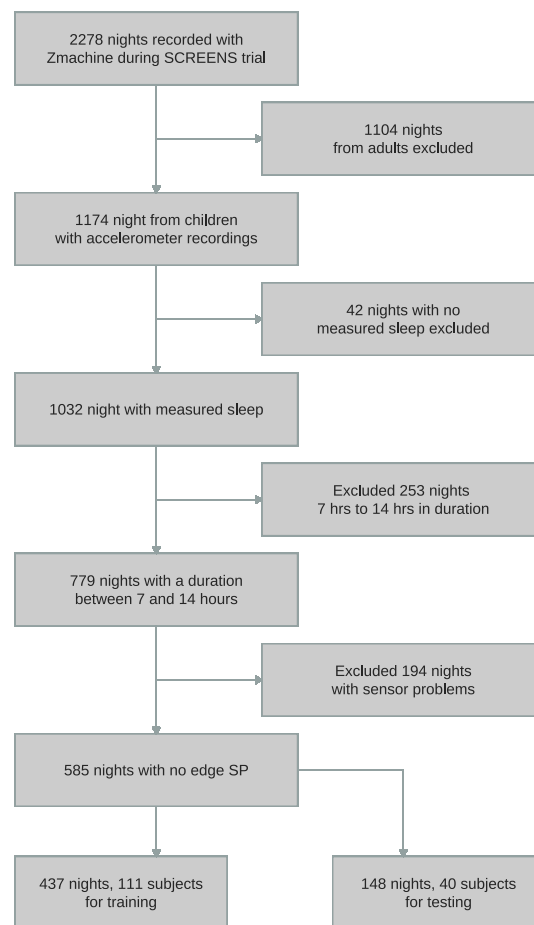


Figure 3: Flowchart of eligible nights included in the study - revise text boxes!

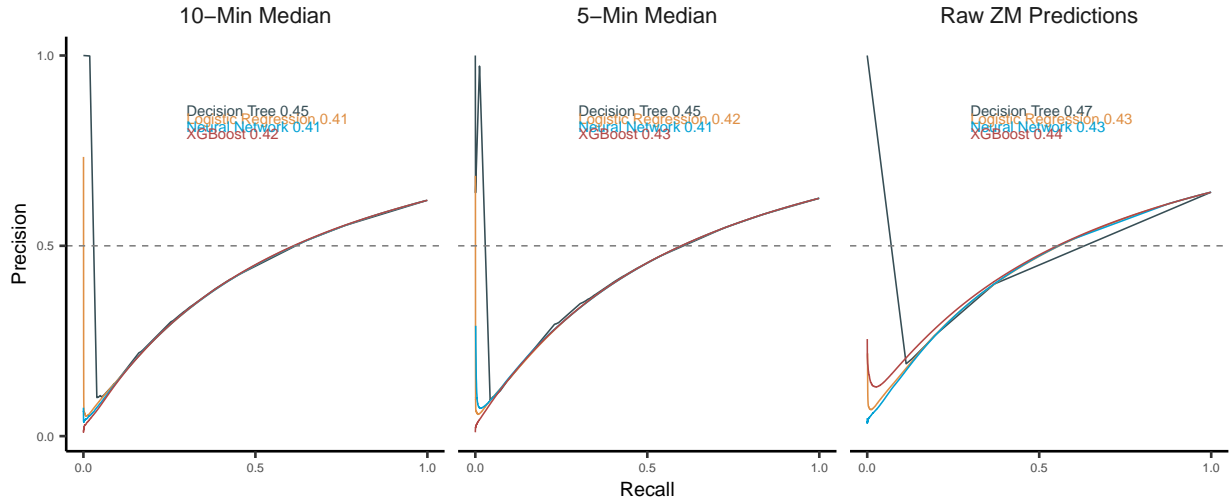


Figure 4: Precision-Recall curves of the models evaluated across the different ZM predictions, including raw ZM predictions, as well as 5-minute and 10-minute median smoothing of the ZM raw predictions. The x-axis of the plot represents the proportion of true wake epochs that were correctly classified as wake, while the y-axis represents the proportion of all epochs labeled as wake by the classifier that were classified correctly. The AUC values displayed in the plot indicate the area under the Precision-Recall curve for each model and condition.

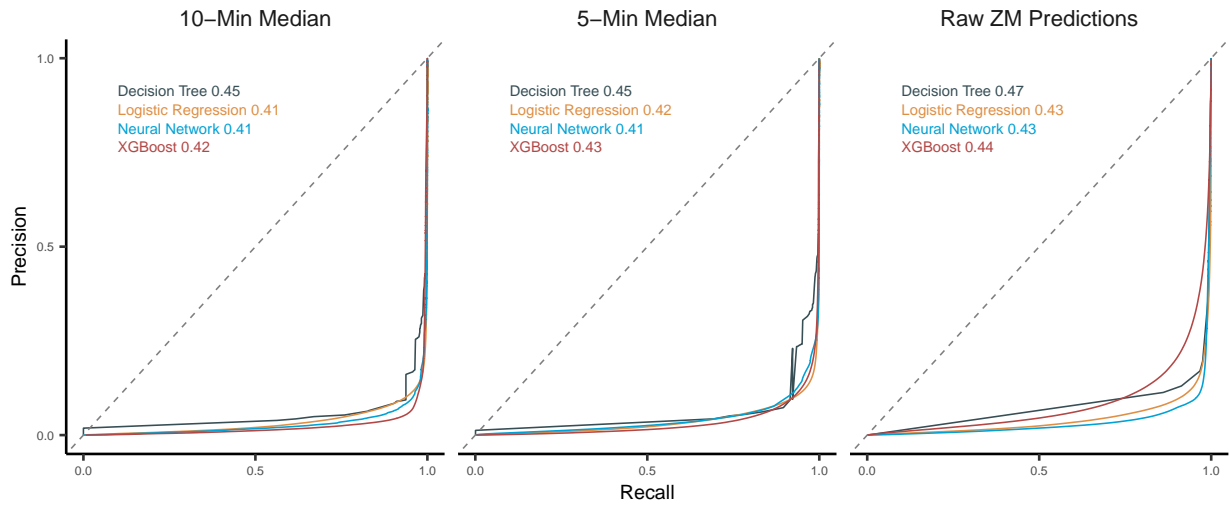


Figure 5: Text bla bla