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Objective prediction of siesta based on machine learning and association with obesity

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ABSTRACT

Objectives: To predict siesta behavior using machine learning models trained on self-reported and objective data—temperature (T), activity (A), position (P), and the integrated TAP variable—and to explore its associations with obesity-related traits.
Methods: From ONTIME-MT, 889 adults wore wrist sensors for 7 days to continuously record temperature, activity, and position, and self-reported daily siesta. Machine learning models were developed to classify 30-second epoch siesta data, to reconstruct weekly siesta behavior. Anthropometric and metabolic parameters were assessed. Associations were analyzed using linear and logistic regression. Model generalizability was evaluated in an independent Mediterranean cohort (n = 70).
Results: The machine learning model allowed to obtain 83% of success in siesta patterns prediction. Among the input variables, activity was the most discriminative by the decision tree (threshold: 27 Δ°/min), followed by TAP (0.51 AU) and position (4.7°). In an independent external validation cohort, success in prediction reached 77%, indicating strong alignment between algorithm-based and self-reported siesta patterns detection. Predicted siesta—but not self-reported alone—was significantly associated with obesity-related traits. Later siesta timing was linked to increased waist circumference in women (β = 0.769 cm per hour; P = 0.026). Longer siesta duration was associated with increased obesity risk (OR=2.081; P=0.002), BMI (β=0.013 kg/m²/h; P = 0.034), and systolic blood pressure (β = 3.540 mmHg/h; P = 0.049). Greater siesta frequency was associated with lower corrected insulin response (β = −0.037 AU/day; P = 0.012).
Conclusion: Objective data from temperature, activity, position, and TAP, combined with ML models, accurately predict siesta behavior and its metabolic relevance. These findings support the use of machine learning approaches based on temperature, activity, position, and the integrated TAP, to assess siesta under free-living conditions.
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Introduction

Obesity is a growing multifactorial condition associated with altered metabolic health. The World Atlas of Obesity 2023 reports that by 2035, 51% of the world's population will have obesity.[1] Since different lifestyle factors may enhance obesity, one of the prevention approaches is the promotion of healthy behaviors, including sleep hygiene.[2]

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What was known

Previous studies suggested a link between siesta and obesity, mostly relying on self-reported data. Objective evidence on how siesta characteristics relate to obesity was limited, and although temperature, activity, and position data are widely used to assess nighttime sleep, their application—together with machine learning—to objectively characterize siesta in free-living conditions remained scarce.

What this study adds

This study is the first to use machine learning to predict siesta behavior by using temperature, activity, position and TAP variable together with self-reported data, achieving high success in reconstructing daily siesta patterns. Predicted siesta timing, duration, and frequency were associated with obesity traits, highlighting the value of integrating objective and self-reported measures to better understand the health impact of siesta.

Prior observational studies have suggested a link between daytime napping or "siesta" and obesity. Our previous study in a Mediterranean population (ONTIME) showed an association between a long duration of siesta (> 30 minutes), obesity and metabolic risk.[3] In a large UK population, we also demonstrated potential causal links between more frequent daytime napping, greater blood pressure and larger waist circumference.[4] However, objective data on the association between siesta characteristics such as timing, duration and frequency and obesity are lacking.

When trying to evaluate siesta in the long-term, most studies about the association between siesta duration and obesity have used self-reported siesta diaries or questionnaires.[3,5,6] Nevertheless, studies have shown that most individuals tend to misjudge their sleep duration (both night and daytime) when self-reported.[7–9] Because of this, it is important to evaluate siesta patterns objectively, and to compare both objective and self-reported siesta determinations to achieve a better characterization of siesta.

To assess nighttime sleep characteristics, a commonly used objective measure is polysomnography, which is primarily performed in a hospital setting.[10] While it is useful for evaluating certain siesta characteristics, such as the depth of sleep reached,[11] polysomnography is not effective for assessing the long-term habitual siesta behavior of individuals in free-living conditions.

Daily records of temperature, motor activity, and body position offer valuable options for measuring nighttime sleep in everyday life.[12,13] The "TAP" variable, which simultaneously integrates wrist temperature (T), activity (A), and position (P), has proven effective in distinguishing between sleep and rest states.[14] However, the application of TAP for objective siesta determination is still not widely adopted. Previously, we used TAP to objectively assess siesta in a twin study aimed at evaluating the heritability of siesta.[15]

In order to predict sleep disorders such as insufficient sleep or sleep apnea,[16,17] previous studies have used Machine Learning (from now on, ML) in the field of human chronobiology and sleep behavior.[18,19] Nevertheless, to the best of our knowledge, no studies have used ML methods based on TAP to capture daytime napping or siesta patterns, yet.

In a Mediterranean population from Spain, where siesta is deeply embedded in the culture, our primary aims were: 1) To develop a ML model for predicting siesta patterns and characteristics (i.e., timing, duration and frequency) by using T, A, P measurements and the integrative variable TAP; and 2) to test potential associations between these predicted siesta patterns characteristics and obesity traits.

We hypothesize that T, A, P, and TAP in combination with self-reported records are effective tools for accurately capturing siesta behavior. Furthermore, we expect that predicted siesta will reveal the association between siesta and obesity more effectively than self-reported assessments alone.

Methods

Participants

Machine learning (ML) analyses were performed in an original cohort from the ONTIME-MT study (n = 889; ClinicalTrials.gov identifier: NCT03036592).

The results were subsequently validated in an independent Mediterranean cohort derived from the ONTIME population (NCT02829619), which was re-contacted after a mean of 12 years (SD = 3) following completion of the weight-loss intervention (ONTIME follow-up, n = 982). Only participants who took siestas with complete, high-quality, and temporally aligned objective wrist sensor data and real-time self-reported siesta diaries were eligible for validation analyses. After applying these criteria, 70 individuals from the validation cohort presented comparable siesta data to ONTIME-MT study and were therefore included.

Baseline obesity-related and metabolic traits, including biochemical markers, were assessed in both cohorts (see **Extended Methods**). In the ONTIME-MT cohort, 2 evening oral glucose tolerance tests (OGTTs) were conducted as previously described.[20] General characteristics of both populations are shown in Table 1.

The study was approved by the University of Murcia Ethics Committee (ID-1188/2015 for ONTIME-MT and ACTA4/2024/CEI for ONTIME follow-up), and all participants provided written informed consent in accordance with the Declaration of Helsinki.

Siesta data collection (both cohorts)

Objective measurements: temperature, activity, position, and TAP

Participants wore a wrist device on their non-dominant hand for 7 consecutive days. The device included a temperature sensor (Thermochron iButton DS1921H) [13] and an accelerometer (G Acceleration Data Logger UA-004–64) to record wrist temperature (°C), physical activity (Δ°/min), and body position (°).[14] Data were recorded in 30-second epochs. To minimize the influence of environmental temperature, data collection was conducted between October and May. Temperature values exceeding 40 °C were considered erroneous and excluded (Supplementary Fig. 1). More than 90% of the 829 participants had complete 7-day data of all 3 objective variables (Temperature (T), Activity (A), and Position (P)). The composite TAP variable was calculated using normalized values according to the formula: **TAP = [(1 − T) + A + P] / 3**, with values ranging from 0 (rest) to 1 (maximum arousal).[14]

Self-reported siesta assessment

Participants completed real-time siesta diaries for 1 week, reporting siesta onset and offset times. These data were used to calculate siesta duration and siesta frequency (days per week). More than 90% of the 829 participants had complete 7-day data of self-reported siesta.

Data pre-processing (both cohorts)

All data pre-processing steps were conducted in R and are summarized in Fig. 1.

Dataset construction

For each participant, 7-day temperature, activity, and position recordings were compiled into an individual dataset that also

Table 1
Descriptive data of the population studied (ONTIME-MT) and validation cohort (ONTIME follow-up)

	ONTIME-MT (n = 889)			ONTIME follow-up validation cohort (n = 70)		
	n	Mean	SD	n	Mean	SD
General characteristics						
Age	887	38.01	14.02	70	53.07	10.4
Sex (% women)	624	70.2		64	91.4	
Siesta characteristics						
Self-reported						
Siesta (% yes)	502	59.3		70	100	
Siesta duration (hh:mm)	502	0:59	0:37	70	0:47	0:27
Siesta frequency (days per week)	502	2.58	1.66	70	2.64	1.55
Siesta start time (hh:mm)	502	15:59	0:55	70	15:46	0:52
Siesta finish time (hh:mm)	502	16:59	1:03	70	16:32	0:55
Predicted						
Siesta (% yes)	369	41.5		66	94.3	
Siesta duration (hh:mm)	382	0:50	0:37	66	0:40	0:25
Siesta frequency (days per week)	369	2.34	1.54	66	2.15	1.32
Siesta start time (hh:mm)	369	16:17	1:07	66	15:48	0:55
Siesta finish time (hh:mm)	369	17:09	1:11	66	16:29	0:59
Obesity traits						
BMI (kg/m^2)	887	25.9	4.95	65	30.68	5.86
Obesity (% yes)	170	19.2		31	47.7	
Waist circumference (cm)	884	86.61	13.58	63	100.32	17.62
Waist-hip ratio	883	0.84	0.08	63	0.89	0.1
Body fat (%)	883	29.15	9.9	65	36.72	6.57
Total cholesterol (mg/dL)	870	171.3	46.94	48	213.15	43.11
Triglycerides (mg/dL)	870	96.15	58.91	48	102.76	44.59
LDL-c	870	92.74	38.48	48	126.39	39.79
HDL-c	870	67.33	16.63	48	66.20	16.71
SBP (mmHg)	479	121.2	16.41	63	119.32	17.11
DBP (mmHg)	479	74.5	11.2	63	77.79	10.32
Glucose tolerance measures						
Glucose AUC (mg × h/dL)	887	299.7	56.62	-	-	-
Insulin AUC (µU × h/ML)	884	96.04	59.37	-	-	-
HOMA-IR (log)	888	0.05	0.33	-	-	-
ISI (log)	874	0.79	0.26	-	-	-
CIR (log)	880	-0.46	0.41	-	-	-

Mean and standard deviation (SD) of each variable studied. BMI, Body Mass Index; LDL-c, Low-Density Lipoprotein cholesterol; HDL-c, High-Density Lipoprotein cholesterol; SBP, Systolic Blood Pressure; DBP, Diastolic Blood Pressure; HOMA-IR, Homeostatic Model Assessment for Insulin Resistance; AUC, Area Under the Curve; ISI, Insulin Sensitivity Index; CIR, Corrected Insulin Response.

included TAP values and temporal information (time of day and day of the week). Each 30-second epoch was labeled as siesta ("1") or no siesta ("0") based on self-reported siesta onset and offset times (Supplementary Fig. 2).

Self-reported real-time siesta diaries were used as the ground truth to generate the target variable for the ML classification task. Although self-reported siesta is subject to reporting bias, real-time diaries represent the current standard reference for assessing daytime sleep behavior under free-living conditions.[3,5,6]

In the original ONTIME-MT dataset, 10.12% of data points were missing, whereas no missing values were observed in the ONTIME follow-up validation cohort.

Moving average

To reduce rapid fluctuations in temperature, activity, and position signals, a 10-minute moving average was applied.[21] This time window was selected to preserve variations typical of siesta episodes, which usually last 20 minutes or longer.

Time-slot filtering for ML analyses

For ML model construction, siesta data points (label = 1) were defined as temperature, activity, and position values occurring within the exact time window between the self-reported siesta start and end times, as previously used.[3,5,6]

To define no siesta data points (label = 0) and clearly differentiate them from siesta periods, data selection started 1 hour after the self-reported siesta end time and extended for a duration equal to that of the corresponding siesta. This approach minimized transitional periods and reduced label ambiguity between post-siesta inactivity and true siesta states. This procedure ensured an equal number of siesta (1) and no siesta (0) data points for ML model training.

Imputation methods

To impute missing values in temperature, activity, and position data in the original ONTIME-MT cohort, several methods were evaluated, including K-nearest neighbors (KNN), cubic spline interpolation, and linear regression. Performance was assessed by artificially removing existing data points and comparing imputed values with the original measurements.[22] KNN was the method that most accurately reconstructed the original data while minimizing residual missingness, whereas linear regression and cubic splines were unable to interpolate values across long gaps (data not shown). Following imputation, the TAP variable was recalculated. No data imputation was required for the ONTIME follow-up cohort.

Machine learning model

ML algorithms and validation pipeline in ONTIME-MT

Several ML classifiers were evaluated using R, and the best-performing model was selected for subsequent analyses (see Extended Methods). All R libraries used are listed in Supplementary Table 1.

The original ONTIME-MT dataset was stratified into a training set (70%) and an independent hold-out test set (30%), preserving class balance. Hyperparameter tuning was conducted within the training set using repeated leave-group-out cross-validation (75% fitting, 25%

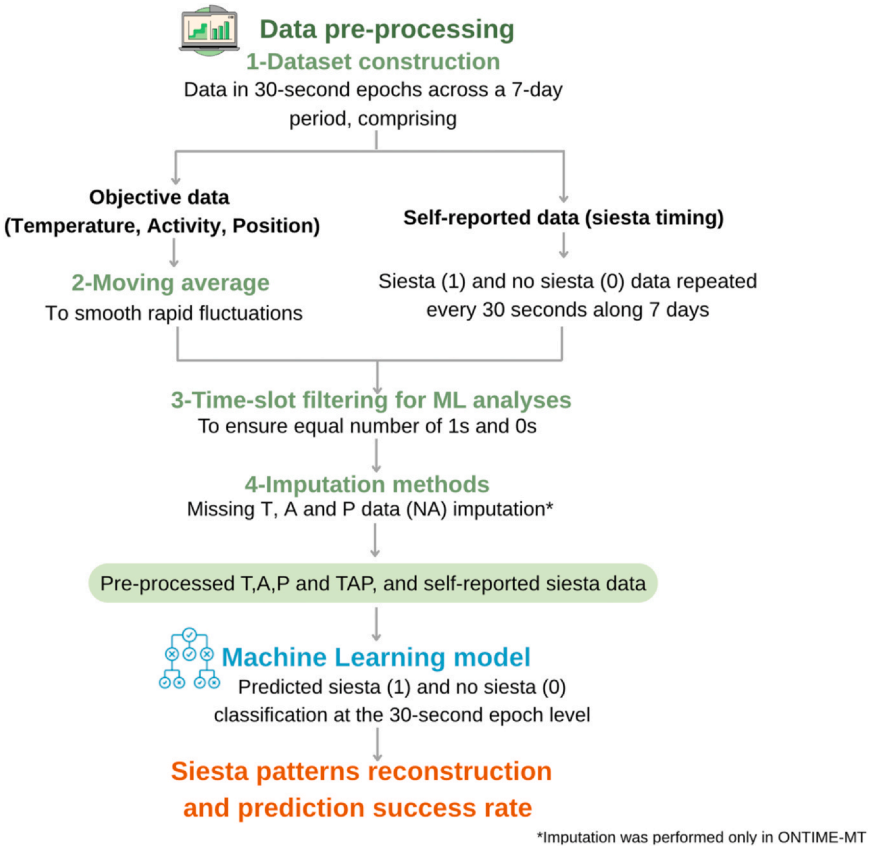

Fig. 1. Data pre-processing for prediction of siesta patterns using machine learning

internal validation, 10 repetitions), following the guidelines of the *caret* package.[23,24]

Model performance was evaluated using standard classification metrics, including accuracy, sensitivity, specificity, and positive/negative prediction values. The final tuned model was evaluated on the untouched 30% hold-out set, ensuring methodological rigor, consistency, and reproducibility (Supplementary Fig. 3, Extended Methods).

Predicted siesta classification at the 30-second epoch level

For each participant, siesta detection was formulated as a binary classification task, assigning each 30-second epoch a predicted label of siesta ("yes" = 1, positive class) or no siesta ("no" = 0, negative class) across the 7-day recording period.

The predicted siesta labels were appended as a new column to the dataset, maintaining alignment with the self-reported siesta data. An illustrative fragment of the reconstructed dataset for 1 participant is shown in Supplementary Fig. 4.

Siesta patterns reconstruction and prediction success rate (both cohorts)

Following epoch-level ML classification, predicted daily siesta patterns were reconstructed by identifying objective siesta blocks. A siesta block was defined as a time window in which at least 75% of predicted epochs were classified as siesta ("1"). For example, within a 10-minute window (20 epochs), at least 15 epochs had to be labeled as siesta for the window to qualify as a siesta block (Supplementary Fig. 5a).

Consecutive siesta blocks were merged if, within a 30-minute interval, at least 50% of epochs (including those within and between blocks) were classified as siesta (Supplementary Fig. 5b). These thresholds were empirically optimized to maximize agreement with self-reported siesta diaries while preserving clinically meaningful siesta duration.[3]

Prediction success rate was calculated by comparing the number of predicted siesta blocks with the number of self-reported siestas. We considered this pattern-based success rate to be more useful for understanding siesta behavior than epoch-level classification alone. In addition, it allows us to better characterize individual siesta patterns (i.e., timing, duration, and frequency).

Association between predicted siesta patterns and obesity traits in ONTIME-MT

Using the reconstructed siesta patterns, we derived objective siesta characteristics, including timing, duration (from reconstructed siesta block onset to offset) and weekly frequency (days per week with a siesta).

Statistical analyses examined associations between predicted siesta characteristics and obesity-related traits in the ONTIME-MT cohort. Exploratory analyses were additionally conducted using self-reported siesta data. Model assumptions, including residual symmetry and goodness-of-fit, were assessed for all analyses. Statistical analyses were performed using R and SPSS.

External validation of the ML siesta classification model in ONTIME follow-up

To evaluate the generalizability and robustness of the ML siesta classification model, the final trained model developed in the ONTIME-MT cohort was directly applied to an independent ONTIME follow-up cohort (n = 70, only individuals who take siesta) to classify siesta at the 30-second epoch level. The ONTIME follow-up cohort was assessed using the same objective and self-reported siesta protocol and underwent identical data pre-processing and feature extraction procedures as those applied in ONTIME-MT.

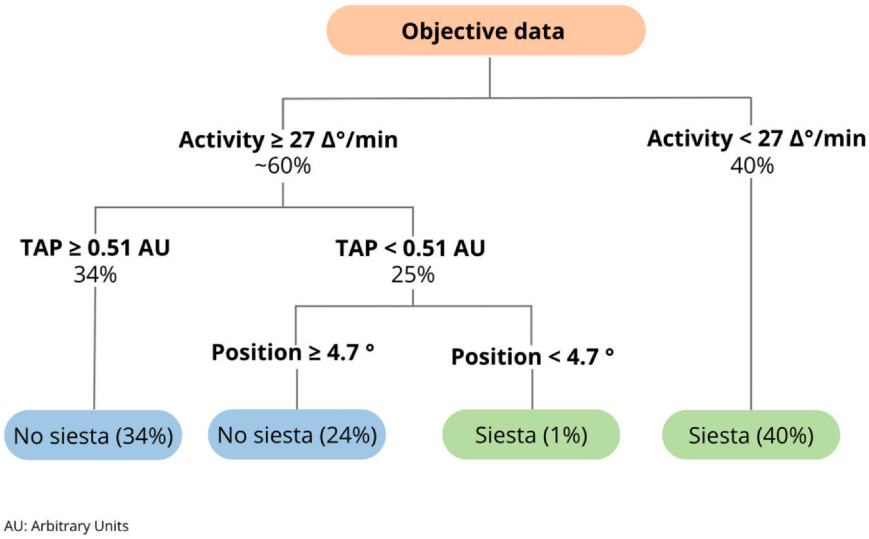

Fig. 2. Decision tree of the machine learning model (using Temperature, Activity, Position and TAP) generated by R

The ONTIME follow-up dataset was never used for model development, retraining, hyperparameter tuning, or internal validation. External validation was focused on pattern-level performance rather than solely on 30-second epoch-level classification. Therefore, following epoch-level classification, siesta pattern reconstruction was performed. Prediction success rate was calculated using the same criteria as in the original cohort.

Results

General characteristics (both cohorts)

Descriptive data are shown in Table 1. In the ONTIME-MT cohort, 70% of participants were women, mean age of 38 years and average BMI of 26 kg/m². Nineteen percent of the population had obesity (BMI ≥ 30 kg/m²), and 59.3% self-reported siesta "yes". The self-reported average siesta frequency was 2.6 days per week, with an average duration of ≈1 hour. The average reported siesta start time was around 4:00 p.m.

In the external validation cohort (ONTIME follow-up), 91% of participants were women, with a mean age of 53 years, and 48% had obesity. The self-reported siesta frequency was similar (2.6 days/week), with an average duration of 47 minutes and a start time of 3:46 p.m.

Machine learning model performance and predicted siesta classification at the 30-second epoch level in ONTIME-MT

Detailed confusion matrices for the algorithms evaluated are shown in Supplementary Table 2. All models achieved a comparable balanced accuracy. Among them, the Decision Tree (RPART) achieved the most favorable combination of performance and interpretability. RPART [25] recursively splits data to best separate siesta *vs*. no siesta based on predictor variables (Temperature, Activity, Position, TAP), testing all possible thresholds. The results of our ML model using RPART are represented in Fig. 2. The model classified siesta data points at 30-second epochs from T, A, P and TAP data.

The ML model began partitioning the 30-second epoch-level dataset at the root node using activity level as the first criterion. Data with activity < 27 Δ°/min (40%) were classified as "siesta" (1). For data with activity ≥27 Δ°/min (60%), the model applied TAP as the next split. Those with TAP > 0.51 AU (34%) were classified as "no siesta" (0), while those with TAP ≤0.51 AU (25%) underwent a final split based on position. Within this group, data with position ≥4.7° (24%) were labeled "no siesta" (0), and the remaining 1% with position < 4.7° were classified as "siesta" (1).

In summary, 41% of the 30-second epochs were classified as "siesta" (1) (by the sum of 40% only considering activity and 1% also considering TAP and position data) and the rest ~59% were predicted as "no siesta" (0) (by the sum of 34% considering activity and TAP and 24% also considering position data) (Fig. 2).

Table 2 represents the confusion matrix of the decision tree model (Table 2a) and the model´s summary statistics (Table 2b). The results show that the model's balanced accuracy was of 68%. The performance of the classification models, or how well the ML model predicts the correct siesta values adjusting for chance agreement (i.e., Kappa value) was 0.4, suggesting a moderate agreement between the model's predictions and self-reported siesta at the 30-second epoch level.

Siesta patterns reconstruction and prediction success rate

In order to reconstruct the siesta pattern and obtain the different characteristics of siesta (i.e, timing, duration, and frequency), we used the siesta datapoints obtained by the ML model, defined a siesta block, and reconstructed siesta patterns.

To define the siesta block in ONTIME-MT

In ONTIME-MT, we tested different time windows to define a siesta block. We finally selected a 10-minute window instead of a longer window, to avoid missing short siestas. Indeed, the prediction accuracy was higher using these 10-minute windows than the 30-minute windows. In addition, the 10-minute chosen window aligns with standard clinical definitions of short siestas.[3] Table 3 compares prediction of siesta using 10- and 30-minute windows in terms of the total number of predicted siestas (for all ONTIME-MT individuals over a 7-day period) relative to the total number of self-reported siestas. Afterwards, we reconstructed siesta patterns (as explained in the Methods section). The same block criteria would be then used to reconstruct siesta patterns in ONTIME follow-up.

Prediction success rate and siesta characteristics in ONTIME-MT

After the reconstruction of siesta patterns in ONTIME-MT, the success in siesta patterns prediction was of 83% (Table 3). The siesta reconstruction method is summarized in Supplementary Fig. 6. In total, the 41.5% of the population was predicted to take siesta, as

Table 2
Confusion matrix and performance metrics of the decision tree model for 30-second epoch siesta prediction using Temperature, Activity, Position and TAP

a. Confusion matrix of the decision tree model for 30-second epoch siesta prediction using temperature, activity, position and TAP

	Self-reported "no siesta" (0)	Prediction value	Self-reported "siesta" (1)	Prediction value	Total
Predicted "no siesta" data point (0)	28,651	64%	15,821	36%	44,472
Predicted "siesta" data point (1)	7688	27%	20,518	73%	28,206
Total	36,339		36,339		72,678

b. Summary of the decision tree model performance for 30-second epoch siesta prediction using Temperature, Activity, Position and TAP

Metric	Value
Accuracy (95%CI)	0.6765 (0.6731, 0.6799)
Kappa	0.3531
Sensitivity	0.5646
Specificity	0.7884
Positive prediction value	0.7274
Negative prediction value	0.6442
Balanced accuracy	0.6765

Table 3
Comparison of success rate in siesta prediction using 10- and 30-minutes time-window for merging of blocks in prediction of siesta

Time-window (min)	Total self-reported siestas	Total predicted siestas	Percentage of success
10	1039	863	83.06
30	1039	760	73.15

compared to the 59.3% that self-reported siesta. The average predicted siesta start time was at 4:17 (1:07) p.m., while the average predicted frequency was 2.34 (1.54) days with siesta per week and the average duration was 50 (37) minutes (Table 1).

An exploratory model using only activity yielded worse success rate in siesta prediction (81.5%, Supplementary Table 3; Supplementary Fig. 7). Furthermore, when checking TAP alone, the success rate was even lower (78%).

Association between predicted siesta patterns and obesity traits in ONTIME-MT

Later siesta timing and waist circumference

Linear regression analyses between predicted siesta pattern characteristics and obesity traits showed that 1-hour delayed siesta start time was significantly associated with an increase of 0.769 cm in waist circumference (Beta (95% CI) = 0.769 (0.092, 1.447); P = 0.026) in women (Table 4), while this association was not significant in men.

Longer siesta duration and obesity

An increase in siesta duration of 1 hour was significantly associated with an increase of 0.013 units in BMI log-transformed (Beta (95% CI) = 0.013 (0.001, 0.025); P = 0.034) (Table 4), which means an increase of 3.02% in BMI (kg/m^2).

Logistic regression results revealed a significant association between longer predicted siesta duration and greater likelihood of obesity. An increase in siesta duration of 1 hour was significantly associated with 2.08 greater odds of having obesity (OR (95% CI) = 2.081(1.313; 3.297); P = 0.002) (Table 4). With ANCOVA analyses, we identified significant longer siesta duration in individuals with obesity (P = 0.003) (Fig. 3). Furthermore, an increase in siesta duration of 1 hour, was significantly associated with an increase of 3.54 mmHg in Systolic Blood Pressure (SBP) (Beta (95% CI) = 3.540 (0.012; 7.068); P = 0.049) (Table 4).

Greater siesta frequency and insulin response

One-day increase in siesta frequency was associated with a decrease of 0.023 units in insulin area under the curve (AUC, log) (Beta (95% CI) = −0.023(−0.040;−0.006); P = 0.008) and a decrease of 0.037 units in corrected insulin response (CIR, log) (Beta (95% CI) = −0.037(−0.066;−0.008); P = 0.012), when simulating a late eating condition (i.e., an evening OGTT 1 hour prior to habitual bedtime).

Overall, these associations highlight the clinical and epidemiological importance of the predicted siesta patterns.

In addition, no significant associations were found between "self-reported" siesta characteristics and different obesity traits (all P > 0.05) (Table 4).

External validation of the ML siesta classification model and prediction of siesta patterns in ONTIME follow-up

Among the 70 independent ONTIME follow-up participants, 185 siestas were self-reported. The same decision tree model from the original ONTIME-MT cohort was applied to this validation cohort

Table 4
Association of predicted and self-reported siesta with obesity traits

Obesity traits	Predicted siesta characteristic	Predicted siesta Beta/ OR (95%CI)	Predicted siesta *P*	Self-reported siesta Beta/ OR (95%CI)	Self-reported siesta *P*
Waist circumference in women (cm)	Siesta start time (hh:mm)	0.769 (0.092, 1.447)	0.026	−0.030 (−0.759; −0.699)	0.935
Obesity	Siesta duration (h)	2.081 (1.313; 3.297)	0.002	0.679 (0.455; 1.014)	0.058
BMI (log)	Siesta duration (h)	0.013 (0.001; 0.025)	0.034	0.006 (−0.005; 0.017)	0.273
Systolic blood pressure (mmHg)	Siesta duration (h)	3.540 (0.012; 7.068)	0.049	2.671 (−0.733; 6.074)	0.124
Insulin AUC (late eating) (log)	Siesta frequency (days per week)	−0.023(−0.040; −0.006)	0.008	0.0001 (−0.009; 0.010)	0.970
CIR (late eating) (log)	Siesta frequency (days per week)	−0.037(−0.066; −0.008)	0.012	−0.00002 (−0.015; 0.015)	0.998

Linear/logistic regression results between predicted siesta and self-reported siesta characteristics and obesity-related traits. All analyses used linear regression, except for obesity, which was analyzed using logistic regression. All analyses were adjusted by sex and age. Residual were approximately symmetrical for all the models. We did not correct for multiple testing since it is an exploratory study adjusted by Body Mass Index (BMI)

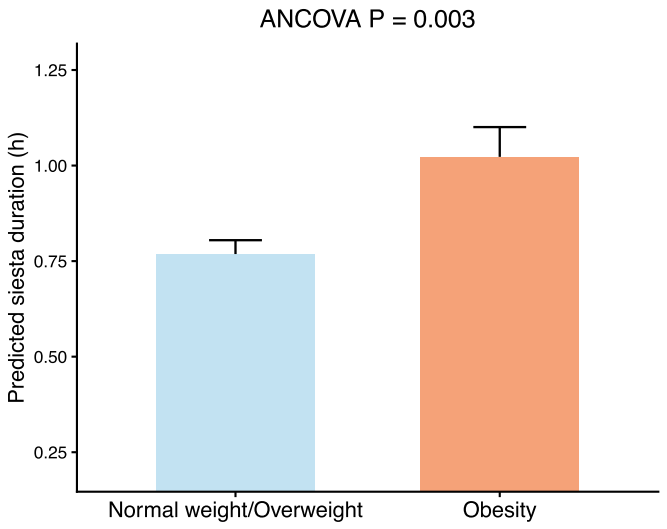

Fig. 3. Predicted siesta duration in individuals with Obesity as compared to those with Normal weight/Overweight. P-value from ANCOVA analysis adjusted by sex and age. Bars represent the adjusted mean siesta duration estimated from the ANCOVA, and error bars indicate the standard deviation (SD)

(Fig. 2). At the 30-second epoch-level siesta prediction, the model achieved moderate classification performance (Supplementary Table 4).

However, after blocks reconstruction, the success rate in siesta patterns prediction was of 77.2% (143/185), showing strong agreement between self-reports and algorithm detection.

Notably, 66 participants (94.3%) had at least 1 siesta accurately detected, while 4 (5.7%) individuals that self-reported taking siesta, had none detected. Non-detection occurred when activity levels during the reported siesta exceeded the model's threshold of 27 Δ°/min (see Supplementary Fig. 8).

Discussion

We developed an ML algorithm to objectively classify 30-second siesta epochs to predict siesta daily patterns using measures of body temperature, activity, position, and TAP, achieving an 83% success rate in siesta daily patterns compared to self-reports alone. Validation in an independent cohort showed a 77% success rate, demonstrating strong agreement between self-reported diaries and algorithm-based siesta patterns detection.

For the first time, we found that later siesta timing is positively associated with obesity. Additionally, the predicted siesta duration confirmed previously reported links between longer siestas and obesity.[3,5]

Previous studies have applied ML to predict nighttime sleep disorders (e.g., apnea) [16] or insufficient sleep using clinical data (e.g., blood metabolomics).[17] A recent study used ML with actigraphy to identify long, frequent nappers linked to higher cardiovascular risk.[26] However, this is the first study to predict daytime sleep using ML based on combined activity, temperature, position, and TAP data.

While activity data is commonly used for predicting both nighttime [27] and daytime sleep/siesta,[26,28] including the TAP variable improved siesta prediction accuracy by about 2% (from 81.5% to 83%). These findings underscore the importance of considering TAP in the objective assessment of sleep, particularly of siesta.

Activity data primarily captures movement and rest periods. However, activity alone may not fully account for identifying sleep onset and wake time, especially during siesta, when an individual might be resting but still engaging in activities such as reading or watching TV. Additionally, temperature alone may not be useful for distinguishing between sleep and inactivity. By adding position and integrating TAP, we achieve a more comprehensive view of physiological changes.[14,15] These factors contribute to a more accurate characterization of sleep, particularly during siestas, where confusion may be more frequent than at night, even after accounting for activity levels.

Novel results indicate a significant association between the timing of siesta and obesity-related traits. Our results show that a 1-hour delay in siesta start time is significantly associated with an increase of 0.77 cm in waist circumference in women. While longer siesta duration and frequency have been previously associated with obesity and metabolic traits,[3,4,26] to the best of our knowledge, no studies have reported an association between later siesta timing and this outcome yet.

Individuals tend to underestimate or overestimate nighttime sleep duration depending on whether they experience short or long nighttime sleep.[7] In the current population, ONTIME-MT participants seem to overestimate siesta duration by about 10 minutes (see Table 1). These results could be attributed to the earlier siesta start times reported by the participants as compared to predicted siesta. Nevertheless, in the ONTIME follow-up validation cohort, predicted siesta timing and duration closely matched self-reported values. A previous study of a middle-aged population where self-reported nighttime sleep was correlated with actigraphy-measured sleep, showed similar bias due to over-reporting.[8] However, no studies have explored the over- or underestimation of self-reported siesta.

The average duration of siesta in the current population is of 50 minutes. Our results showed that a longer predicted siesta duration was associated with increased BMI, obesity, and with other metabolic traits, confirming our previous results using self-reported siesta data from an independent population (ONTIME) in the same Mediterranean area.[3] Indeed, an increase in siesta duration of 1 hour was significantly associated with an increase of 0.013 units in BMI log-transformed and with an increase of 3.54 mmHg in Systolic Blood Pressure (SBP), similar effect size to the previous results in ONTIME.[3] Also, a positive association between siesta (more frequent) and greater BMI and SBP was previously found in the UK Biobank.[4]

Since self-reported siesta variables were not significantly associated with obesity in the current ONTIME-MT study, this suggests that objectively predicted siesta may better capture the association between siesta and obesity than self-reported siesta. In the previous literature, both objective (using actigraphy) and self-reported siesta were associated with obesity in a large population of older women, indicating that objective siesta measurement is also valid to capture this association.[29] In addition, older men who took long and frequent naps, objectively measured using actigraphy, and who had normal nighttime sleep and good sleep quality, tended to have an increased risk of cardiovascular events compared with men with healthy sleep patterns (which included normal nighttime sleep and either short or no siestas).[26]

Among the strengths of this study is our development of an algorithm for predicting and reconstructing siesta using temperature, activity, position and TAP as objective variables. Our results suggest that objective siesta measurement, in addition to self-reported, may better capture the association between siesta and obesity traits than self-reported data alone. Importantly, the validation of success rate in prediction of siesta patterns in an independent population further strengthens the robustness and generalizability of our findings.

Our study has some limitations. A higher sampling frequency could have captured more nuanced physiological data. Nevertheless, the high predictive accuracy of our models indicates that a 30-second epoch was sufficient to capture discriminative patterns in temperature, activity, position, and TAP for siesta classification, supporting the device's feasibility for multi-day monitoring.

The use of moving averages and missing-value imputation may have reduced short-term variability, attenuating fine-grained fluctuations. Future studies minimizing missing data or using alternative imputation strategies would be beneficial. The selection of the RPART model—based on a balance between predictive performance and interpretability—may be considered subjective; however, differences in predictive accuracy between models were minimal in this study. In cases with larger performance differences, future studies should prioritize the top-performing model over interpretability.

Due to the observational design, causal inferences cannot be made. Additionally, there is no gold standard for assessing long-term habitual siesta behavior, leading to reliance on self-reported siesta timing as the ground truth, as used in prior studies. However, current self-report methods for daytime sleep vary widely,[30] causing inconsistencies in data collection and interpretation. This variability hinders cross-study comparisons, highlighting the need for a standardized, objective, and feasible method to evaluate siesta and improve research validity. We recommend combining self-reported and objective measures for more reliable siesta assessment.

Based on the current analysis, the model achieves high accuracy and a high success rate in predicting siesta patterns. We selected a time slot which takes as reference the self-reported siesta timing. Future studies could apply our reconstruction method to a larger range. The analysis of the objectively reconstructed data reveals a link with metabolic outcomes that is not observed with self-reported data. Future studies are needed to determine the sensitivity and specificity when only using objective data without considering self-reported. Also, we want to underline the importance for further studies to validate the use of Temperature, Activity, Position and TAP measurements for sleep assessments in individuals with various health conditions, to explore the broader clinical utility of this method beyond obesity.

Conclusion

This study is the first to use machine learning techniques to objectively predict siesta behavior by combining temperature, activity and position data with the TAP variable. Our findings show that objectively predicted siesta timing, frequency and duration are associated with obesity traits, supporting the link between long siestas and obesity. Further research on objectively determined siesta in other populations is needed to generalize these findings.

Author contributions

M.G.: conceptualized and designed the study, acquired funding, designed the research, managed the project, and helped to write and critically review the final version of the paper. J.T.F.B.: contributed to data analysis and interpretation and reviewed the final manuscript. M.R.M.: wrote and reviewed the final version of the manuscript, performed data analyses and literature research, and figures and tables design. F.M.C.: contributed to perform bioinformatics and statistical data analysis. H.S.D., R.S. and F.A.J.L.S. contributed to ONTIME-MT population recruitment, conceived and designed the study, and contributed to review the final version of the manuscript. All authors approved the final manuscript as submitted and agreed to be accountable for all aspects of the work.

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Declaration of Generative AI and AI-assisted technologies in the writing process

No generative AI tools were used in the writing or preparation of this work.

Declaration of conflicts of interest

Prof. FAJLS served on the Board of Directors for the Sleep Research Society and has received consulting fees from the University of Alabama at Birmingham. Prof. FAJLS interests were reviewed and managed by Brigham and Women's Hospital and Partners HealthCare following their conflict-of-interest policies. Prof. FAJLS consultancies are not related to the current work. Prof. RS is a cofounder of Magnet Biomedicine, which is unrelated to the current work. Prof. HSD is a consultant for Eli Lilly & Company, which is unrelated to the current work. The remaining authors declare they have no competing interests. Given their role as Sleep Health Associate Editor, Dr. Dashti had no involvement in the peer review of this article and has no access to information regarding its peer-review. Full responsibility for the editorial process for this article was delegated to another journal editor.

Data availability

The data underlying this article will be shared on reasonable request to the corresponding authors.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.sleh.2026.02.007.

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