

Review

Unsupervised machine learning in sleep research: a scoping review

Luka Biedebach ^{1,2,*}, Daniela Ferreira-Santos^{3,4}, Marie-Ange Stefanos ⁵, Alva Lindhagen⁶, Gabriel Natan Pires ^{7,8,9},
Erna Sif Arnardóttir^{1,2} and Anna Sigridur Islind¹

¹Department of Computer Science, Reykjavik University, Reykjavik, Iceland, ²Reykjavik University Sleep Institute, Reykjavik University, Reykjavik, Iceland,

³Department of Medical Physics, University of Eastern Finland, Kuopio, Finland, ⁴INESC TEC, Universidade do Porto, Porto, Portugal, ⁵Computer Science

Department, Université Paris-Cité, Paris, France, ⁶Department of Computer Science, Umeå University, Umeå, Sweden, ⁷Departamento de Psicobiologia, Universidade Federal de São Paulo, São Paulo, Brazil, ⁸Hospital Israelita Albert Einstein - Sao Paulo, SP, Brazil and ⁹Faculdade Israelita de Ciencias da Saude Albert Einstein - Sao Paulo, SP, Brazil

*Corresponding author. Luka Biedebach, Department of Computer Science, Reykjavik University, Menntavegur 1, 102 Reykjavik, Iceland. Email: lukab@ru.is.

Abstract

Study Objectives: Unsupervised machine learning—an approach that identifies patterns and structures within data without relying on labels—has demonstrated remarkable success in various domains of sleep research. This underscores the broader utility of machine learning, suggesting that its capabilities extend beyond current applications and warrant further exploration for novel insights in sleep studies, focusing specifically on unsupervised machine learning.

Methods: This paper outlines a scoping review conducted according to the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) guidelines for scoping reviews. A comprehensive search covering various search terms focusing on the intersection between unsupervised machine learning and sleep led to 3960 publications. After screening all titles and abstracts with two independent reviewers, ultimately, 356 publications were included in the full-text review. The data extracted from the full texts included information about the machine learning methods and types of sleep data, as well as the study population.

Results: There has been a steep increase in the number of publications in this research area in the past 10 years. Clustering is the most commonly used method, but other methods are gaining popularity. Apart from classical polysomnography, data from wearable devices, nearables, video, audio, and medical imaging techniques have been used as input to unsupervised machine learning. The broad search allowed us to explore various applications within sleep research, ranging from the general population to populations with various sleep disorders.

Conclusion: The review mapped existing research on unsupervised learning in sleep research, identified gaps in the literature, and derived directions for future research.

Key words: unsupervised machine learning; sleep; scoping review

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Machine learning is a field of study that allows computers to learn from data. Learning in this context means creating an internal model of the data, which can be used to identify patterns or make predictions about new data. There are two main

approaches to achieve this: supervised and unsupervised machine learning. Supervised machine learning relies on labeled data, e.g. polysomnography (PSGs) with manual sleep scoring, for training a model and making predictions. Unsupervised machine learning, on the other hand, uses unlabeled data, e.g. PSGs that have not been scored. Therefore, unsupervised machine learning can infer patterns within data without reference to known or labeled outcomes [11]. Summarizing from multiple resources [11, 12], we derive the following definition:

Definition of unsupervised machine learning:

Every machine learning method that does not rely on labeled data.

Another form of machine learning, which is closely related to unsupervised machine learning, is self-supervised machine learning [13]. This method trains on input–output pairs similar to supervised learning but generates the labels automatically based on the input data [14]. The last form of machine learning included in this review is semi-supervised learning [15], which can be seen as a mix of supervised and unsupervised learning [16]. This learning approach uses a small amount of labeled data to guide the unsupervised learning process. To cover all the different ways of training a machine learning model without labels, we also included publications that apply self-supervised learning and semi-supervised learning in the review.

Core methods of unsupervised machine learning are clustering, dimensionality reduction, anomaly detection, and association rules [17]. Furthermore, different generative models can be considered as unsupervised machine learning [18]. [Appendix 1](#) provides explanations of each method type with examples from sleep research. Many of these methods are inherently different from supervised models, as their strength is in exploring new patterns, clusters, or associations instead of recognizing predefined classes. Metrics such as reconstruction error, silhouette scores, or measures of cluster cohesion can quantify a model but may not fully capture the practical utility of the model. Therefore, when applying unsupervised machine learning methods, it can be difficult to validate and compare the performance of different models.

One strength of unsupervised methods is their independence from labelled data. Especially in sleep research, refraining from using the manual scoring of polysomnography data is desirable for three reasons: (1) manual labels require time-intensive work from a highly skilled professional, (2) manual labels can have high inter-scorer variability [19–21], and (3) training on these manual labels will not find new insights but replicate the rules developed by Rechtschaffen and Kales [22] they are based on. Even though these rules are the accepted standard in sleep scoring [23], they are limited by oversimplification as described by Himanen and Hasan [24]. Therefore, it would be desirable to use methods in sleep research that are not dependent on these labels. Although unsupervised machine learning shows immense potential for sleep research, there is a gap in the literature concerning a review providing a comprehensive overview of the literature published to date, outlining the intersection between unsupervised machine learning and sleep research. For this reason, we aimed to review the entire body of literature existing on unsupervised machine learning in sleep research. This scoping review has the following objectives:

- 1) To investigate and map the current application of unsupervised machine learning in sleep research, both by learning method and data type.
- 2) To identify potential for future research based on gaps in the literature and the temporal progression of research trends

The following section will show the process of conducting the scoping review, including the search strategy, the inclusion and exclusion criteria, the study selection, and data extraction.

Materials & methods

Scoping review

A scoping review is a type of systematic review used to map and analyze a field of research [25]. We did a qualitative assessment of the research output in an emerging field by describing its main characteristics and publication trends. This protocol was elaborated according to the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) and its extensions to protocols and scoping reviews [26]. The protocol is available at Open Science Frameworks [27].

Search strategy

The literature search was performed in four databases: PubMed, Web of Science, Scopus, and ACM Digital Library. The search strings were initially developed for PubMed and then adapted to the other databases' syntax and search engines. The search strategy was composed by combining two components: unsupervised machine learning (methods) and sleep (application domain). To increase the search sensitivity, no restrictions on the type of sleep study, outcomes, or population were set. A combination of Medical Subject Headings (MeSH) terms and free terms was used for each of the search components. The search string for the sleep domain consisted of the search filter proposed by Pires et al. [28] Gray literature and secondary data sources were not screened. An overview of the included search strings and the general search query logic is shown in [Figure 1](#).

Inclusion and exclusion criteria

The eligibility analysis was based on the following inclusion criteria:

- Language: Only papers published in English were considered eligible. Papers in any other languages were excluded.
- Type of paper: Reviews, philosophical or conceptual research, editorials, opinion papers, letters to the editor, and non-peer-reviewed papers, e.g. posters and book chapters, were excluded.
- Population: Only papers studying humans were considered eligible. Animal studies were excluded.
- Sleep: Only papers primarily related to sleep were considered eligible. A paper was considered to be sleep-related if the study population, intervention, exposition factor, or main outcome was related to sleep.
- Unsupervised machine learning: Only papers presenting an application of an unsupervised machine learning method on sleep-related data were considered eligible. The abstract should either mention the term unsupervised, unlabeled data, or unsupervised training or mention an unsupervised machine learning method.

Study selection

Our screening process was done according to the PRISMA guidelines. The number of publications at each step of the process can be seen in [Figure 2](#). The records retrieved from the literature search in the four databases were imported into Rayyan [29], where de-duplication and eligibility analyses were performed. Duplicate records with a similarity above 95% were

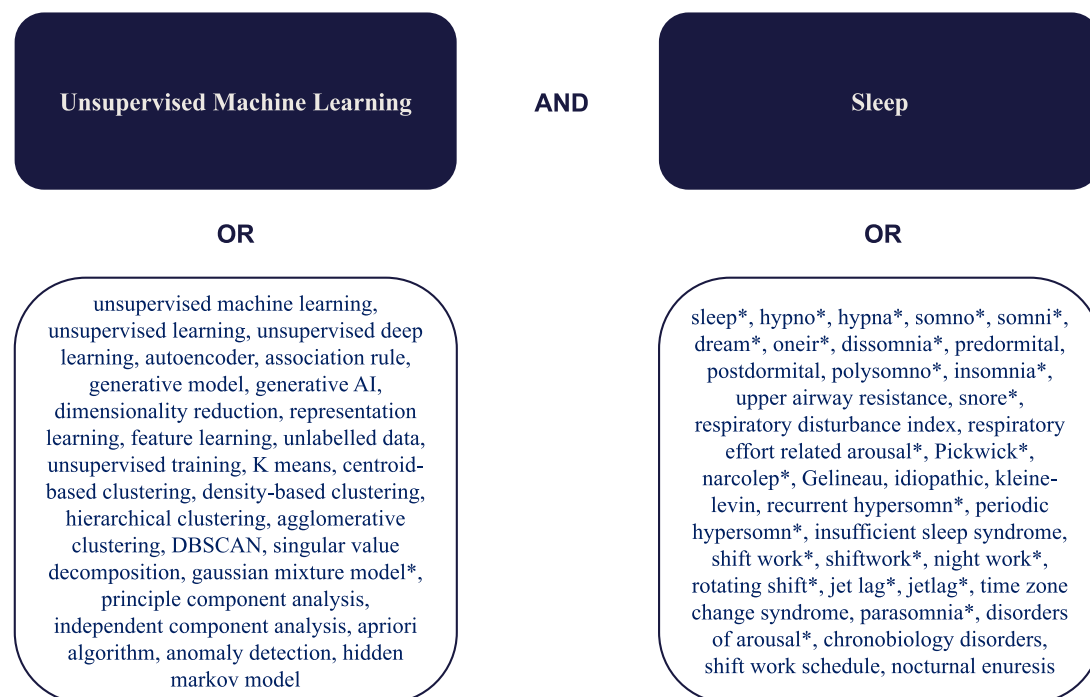


Figure 1. Search terms for unsupervised machine learning and sleep.

excluded automatically, and all remaining identified duplicates were checked manually by the first author. From initially 7043 records, 5004 possible duplicates were identified. Three thousand eighty-three of these duplicate records were removed. Hence, the screening was performed on the remaining 3960 records. All non-duplicated papers were evaluated in a two-step process. The abstracts were screened by the first author and three independent reviewers. Before the start of the screening, each reviewer screened 100 records to ensure that the screening instructions were clear enough to provide a sufficient agreement. All publications that were not in agreement in the pilot screening phase were discussed, and the screening instructions were updated accordingly. This pilot screening resulted in a Cohen's Kappa of 0.54 with reviewer 1, 0.69 with reviewer 2, and 0.62 with reviewer 3. Then, the full set of publications was screened.

All of the abstracts were screened by the first author. Furthermore, reviewer 1 screened 50% of the records, while reviewers 2 and 3 screened 25% of the records each. This way, each record was screened by two independent reviewers to limit individual bias. The screening resulted in an agreement of 0.67 across all three reviewers, which is considered a substantial agreement. The conflicts were resolved by discussing each conflict between the first author and the respective reviewer. All of the 856 included abstracts in this screening round used unsupervised machine learning methods, although they did not focus on the method; instead, they focused on the sleep-related contribution. Therefore, another abstract screening round conducted by the first author, selecting only publications where unsupervised machine learning was the main contribution, resulted in 440 papers, which were then included in the full-text retrieval.

Data extraction and analysis

The data extraction was done in multiple steps. In the first step, we coded all 856 included publications based on their abstract. We coded them by the unsupervised machine learning method and the type of sleep data. This step allowed us to get an overview

of methods and data types across all related publications. We furthermore coded the abstracts by focusing on the purpose of unsupervised machine learning. This includes whether unsupervised machine learning was the main contribution of the paper and whether it was a novel usage of unsupervised machine learning or a known methodology. We continued the in-depth data extraction process only with publications that focused on unsupervised learning and had a methodological contribution. This way, we got a broad overview of unsupervised machine learning in sleep and were then able to further narrow down the most relevant applications for the full-text review.

In the second step, the full text of the 440 included publications was reviewed. The majority of these publications were retrieved using the automatic retrieval of open-access papers with Endnote. The remaining 156 papers, which could not be retrieved this way, were manually downloaded. Fourteen publications, which were not open access and were not provided by the authors within 2 weeks after contacting them, were excluded from the sample. Once the final sample of eligible studies was reached, data extraction was performed. In 67 of the studies, only the full-text review revealed that they were not eligible in terms of language, method, or data type. For each of the 356 included publications, the information listed below was extracted:

- Study description: papers metadata (first author, publication year, source title, and full reference string).
- Source country: The country of the first affiliation of the first author.
- Unsupervised machine learning: The method of unsupervised machine learning was the main focus of the paper.
- Role of unsupervised machine learning: The purpose or role of using unsupervised machine learning in the publication.
- Data type: The type of sleep data used by the unsupervised machine learning method.
- Clinical outcome: The application of the unsupervised machine learning method within sleep research.

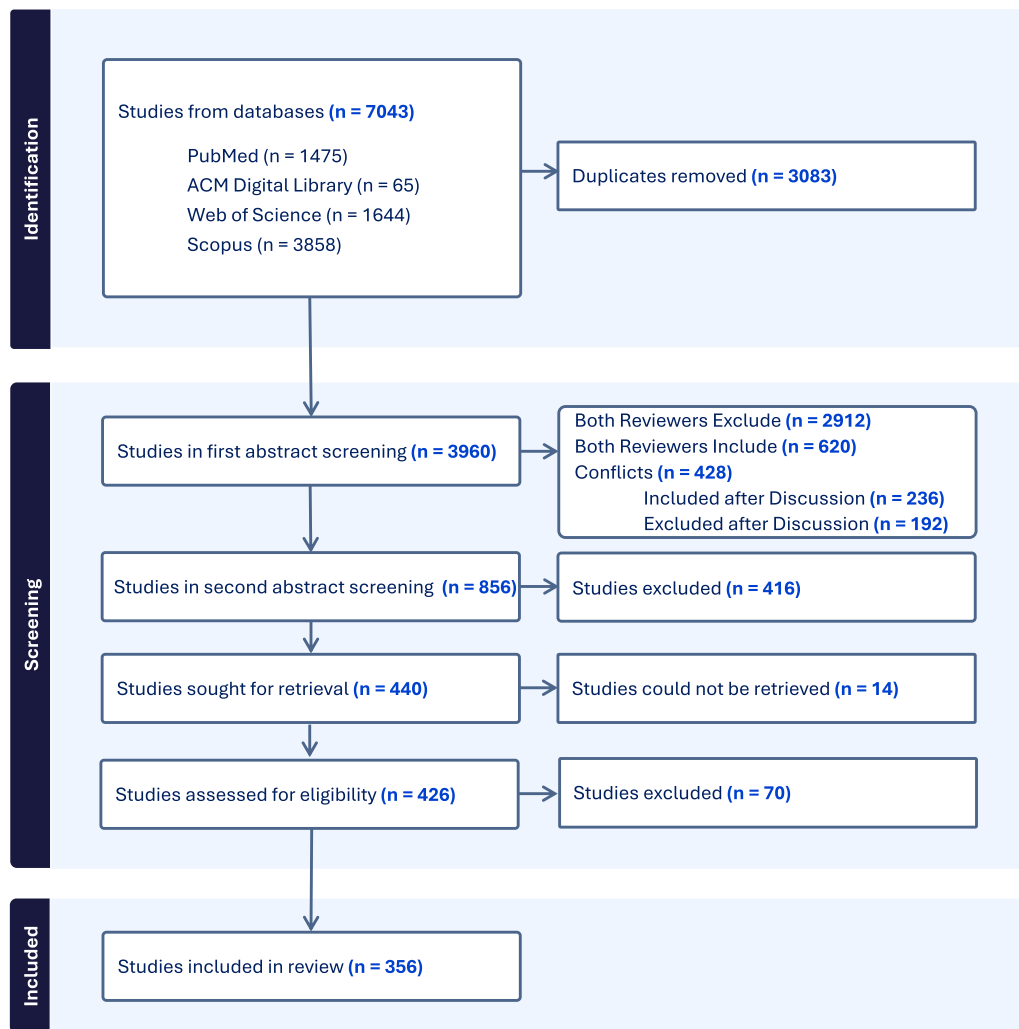


Figure 2. Flow chart according to the PRISMA guidelines.

- **Data set:** The data set used, population characteristics, and overall number of individuals in the study.
- **Results:** The evaluation metric and performance of the machine learning model. Furthermore, whether the author concluded their research as successful or not.
- **Outlook:** The limitations or future research directions the paper mentions.

There were no mandatory or conditional items, and missing items were filled as “non-available/not applicable.” We used both predefined categorical labels as well as free text fields for extracting the information. This way, both a quantitative analysis and a qualitative analysis of the reviewed papers were possible.

Results

The first part of the results is dedicated to providing a comprehensive overview of all the papers included in this review. The second part of the [Results](#) section is structured according to the various application areas within sleep research.

Countries

Most publications on unsupervised machine learning in sleep research stem from the United States, China, and Australia with

57, 54, and 17 publications, respectively. Figure 3 shows a map colored by the number of publications from the respective country. All blue countries have at least one publication, and all dark-blue countries have >10 publications.

Timeline

The research on unsupervised machine learning in sleep research gained increasing popularity in recent years. Figure 4 shows a steep ascent in publications since 2016. This can be explained by the generally increased research interest in machine learning across all application areas and disciplines over the last decades [30]. More than 40 publications on unsupervised machine learning in sleep research were published in 2023 alone. However, the timeline also shows that the theoretical foundations for applying these methods date back to the 1970s.

Multiple of these early publications used fuzzy clustering for sleep staging [31–36]. Other research used X2-based clustering [37], hierarchical clustering [38], self-organizing maps [39], and ISODATA clustering, an iterative self-organizing clustering method [40] to classify sleep stages. Apart from sleep staging, unsupervised machine learning has been used for modeling the process of drifting into sleep [41] and extracting features from sleep data to classify spindles [42, 43] in the 1990s. Early applications of K-Means in sleep research have been

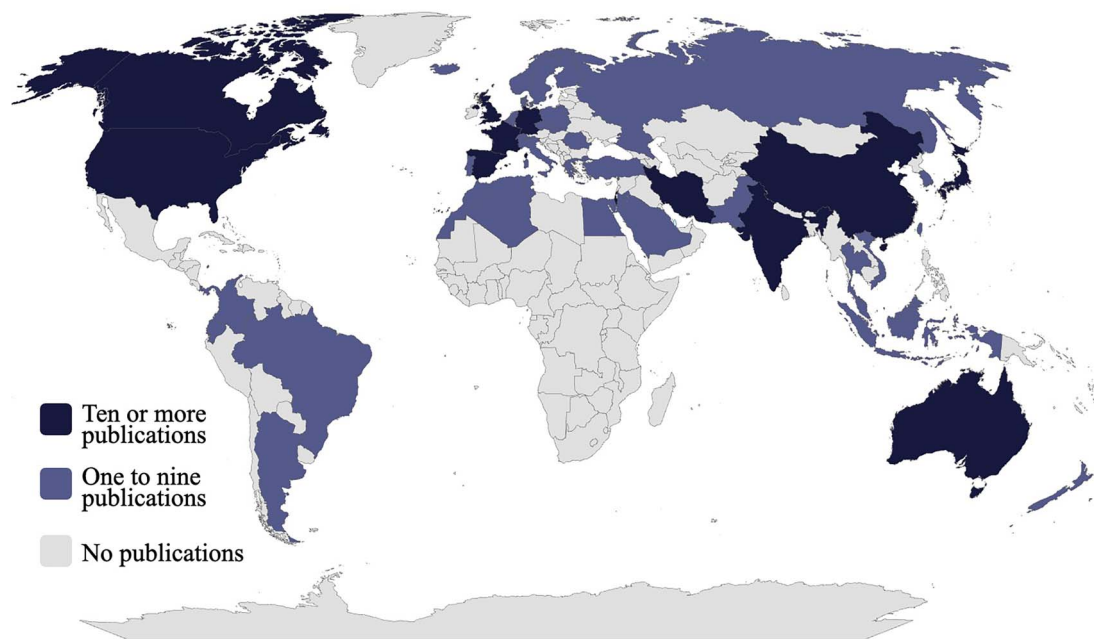


Figure 3. Publication countries based on first author affiliation.

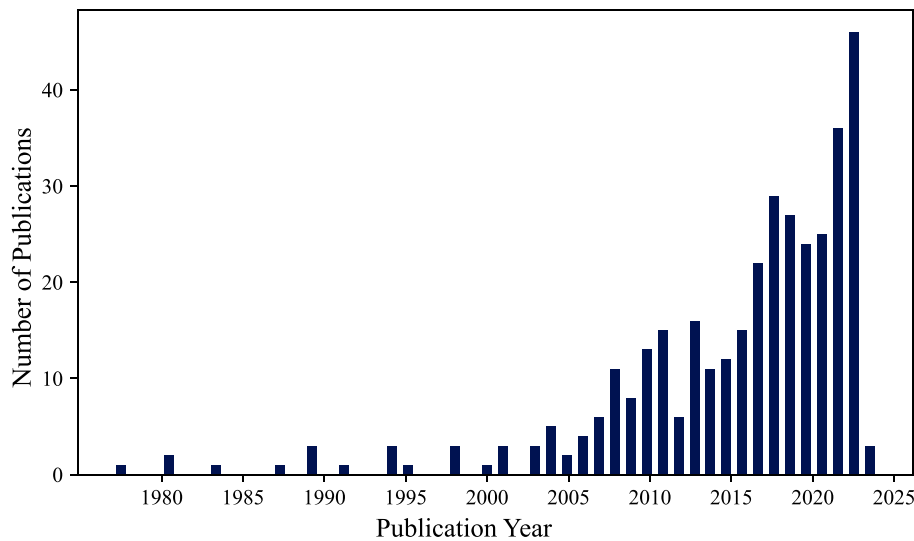


Figure 4. Number of publications by year.

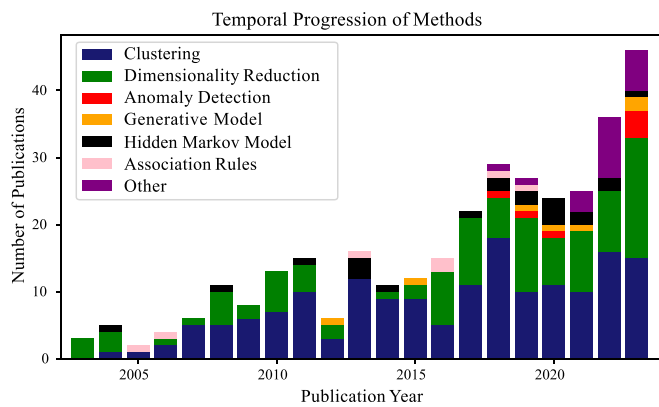


Figure 5. Methods used in publications between 2003 and 2023.

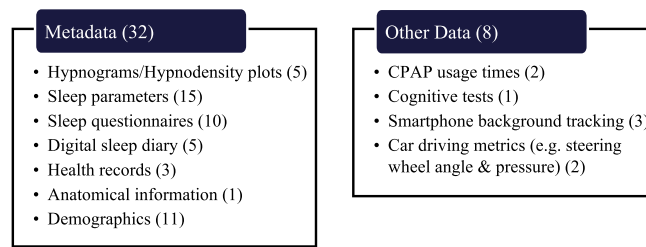


Figure 6. Overview of data from wearables and nearables.

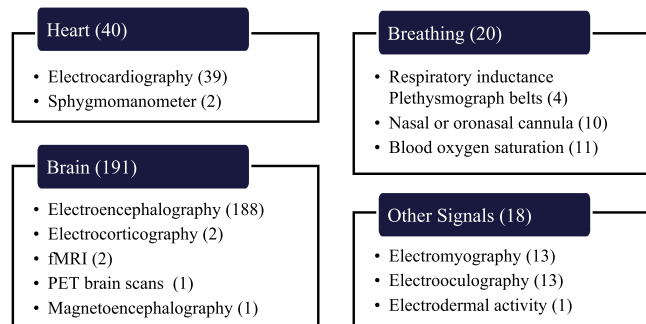


Figure 7. Overview of physiological data.

removing artifacts [44] and detecting micro-arousals [45] in sleep electroencephalography (EEG). Figure 5 shows which unsupervised machine learning methods have been used in the publications since 2003. Clustering is clearly the most widely used unsupervised learning method in sleep research. When zooming in on the publications from the last 20 years, a trend toward other unsupervised machine learning methods becomes visible. The number of publications using dimensionality reduction methods has been rising since 2016. In the past 3 years, we can see that other methods are gaining popularity, which include methods such as unsupervised domain adaptation or contrastive learning.

Data types

The included papers varied strongly in the way data were collected. We mapped the different data types into the categories (1) wearables and nearables, (2) physiological data, and (3) metadata and other data. We logically divided the data types into measurement devices that can be used for long-time monitoring in a home setting, such as wearables, nearables, audio, video, and other types of sensors on the one hand, as seen in Figure 6, and medical devices, which are typically used for one-night studies and require the assistance of a professional, seen in Figure 7, on the other hand. The last category includes different forms of metadata and other data types, as can be seen in Figure 8. The figures show how many publications used each data type, where publications using multiple data types are counted multiple times in this visualization.

Wearables and nearables

Smartwatches have been used for sleep staging [46–48], detect respiratory events [49], and analyze sleep patterns [50]. Actigraphy has been used for sleep–wake monitoring [51, 52], OSA screening [53], and identifying anomalous sleep patterns [54]. Furthermore, a smart ring has been used to collect longitudinal sleep data [55]. There have been eight publications using different types of mattress sensors [56–59] to assess sleep.

There were publications using sensors in the four corners of the bed [60], in the pillow [61], or woven into the bed sheet [62].

Video has been used to identify sleep postures [63], monitor breathing [64–66] during sleep and monitor vigilance when driving a car [67, 68]. While most papers used simple cameras, some research experimented with different types of cameras, including an infrared camera [65, 69] and a three-dimensional camera [70]. There are two major ways that audio data were used: (1) monitoring during sleep and (2) extracting information about sleep from speech during wake. When monitoring sleep, a microphone is typically placed on the body or close to the bed and sounds like coughs [71] or snoring [72, 73] were identified. In most cases, the microphone is the one native to smartphones, but it may also be used as part of other wearable and wearable devices. Audio was used to detect respiratory events [74–76] or predict the age of a sleeping person [77]. When extracting information from speech—and therefore in wake state—the publications used the audio from interviews or experimental settings. Many papers succeeded in predicting OSA severity from speech recordings during wake [78–80].

There are various types of sensors that collect information about sleep. Shahid et al. [81] made use of recent developments in the smart home industry. They drew data from the motion sensors of elderly individuals living in smart homes. They showed that these sensors, primarily designed to control the light, could also be used to gather information about sleep in the form of bed and rise times, as well as awakenings during the night. A different publication used a mattress sensor for sleep monitoring and then communicated with the smart home devices to adjust light and temperature for optimal sleeping conditions [82]. Gu et al. [83] showed that Wi-Fi sensors, typically used to provide internet access, can be reused for sleep monitoring [83]. Based on the channel state information and received signal strength, they can detect movement in sleep with an accuracy of 98.2%. Non-commercial products such as Doppler radar have been used to decompose the respiration signal of two people in one bed [84]. Other forms of data include ultra-wideband radar, which was used to identify anomalous sleep patterns [85], a piezoelectric

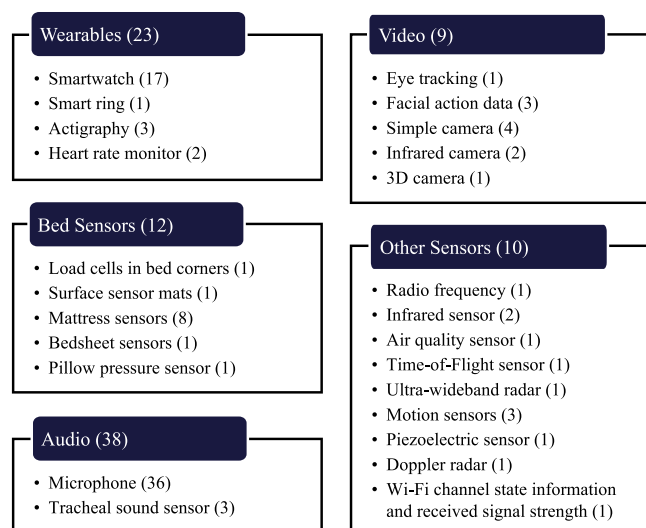


Figure 8. Overview of meta data and other data.

sensor attached to the neck, which tracks snoring vibrations [86], or an infrared sensor, which is used to classify movements in bed [87]. In drowsiness detection, an air quality sensor has been used to predict changes in driver alertness [88].

Clinical physiological signals

The most common way to capture sleep is PSG, which allows measuring several physiological signals during sleep. We categorize signals by the part of the body they measure, such as the brain, the heart, and the breathing. The most common way to measure the brain in sleep research is EEG. A total of 191 of the 356 publications used EEG as an input to unsupervised machine learning. There are different forms of EEG offering varying levels of invasiveness. Wireless EEG [89] is a minimally invasive measurement for monitoring brainwaves with fewer attachments. In contrast, intracranial EEG is a more invasive method, where electrodes are placed directly inside the skull. This technique is primarily used in clinical or research settings, e.g. for conditions like epilepsy, where precise localization of brain signals is crucial [90, 91]. Functional magnetic resonance imaging (fMRI) offers more detailed representations of brain structure and activity compared to EEG, providing high-resolution images that can capture subtle brain changes during sleep. The two included publications used fMRI to remove ballistocardiographic artifacts [92] and modeling brain states from sleep to wake [93].

In the study of cardiovascular function during sleep, different methods offer varying levels of precision. There were 40 publications using cardiovascular measurements as an input for unsupervised learning. Wearable devices, such as smartwatches, commonly measure heart rate through optical sensors, providing a general but less detailed view of heart activity [50, 94–96]. Electrocardiography (ECG) electrodes on the chest offer a more precise measurement of heart function during sleep. The ECG signal has been used in unsupervised machine learning for sleep–wake monitoring [97], drowsiness detection [98], and sleep staging [99]. Blood pressure measurements can also be relevant in research on the morning surge [100] or analyze the relationship between blood pressure and OSA [53].

Twenty reviewed publications included respiration, which can be captured using a nasal or oronasal cannula [101–104]. Another

way to capture respiration is through respiratory movements, using Respiratory Inductance Plethysmograph (RIP) belts around the thorax and abdomen [105–107]. Reimer et al. [108] use a skin conductive electrode belt that captures both the respiratory rate and the heart rate. Another physiological process is blood oxygen saturation, which is influenced by breathing, which is why many OSA-related publications use pulse oximeters to detect respiratory events [109–112]. Thirteen publications used electromyography (EMG) and electrooculography (EOG), which are essential for detecting rapid eye movement (REM) sleep. Electrodermal activity (EDA) is used to measure skin conductance as an indicator of sweating, offering insights into the autonomic nervous system's activity during sleep. Daley et al. [113] use EDA to analyze the body in prolonged wakefulness.

Metadata and other data

The term metadata describes data that provide information about other data. In this category, we summarized data sources that provide information about a person and their sleep but are not direct, continuous measurements of sleep. Figure 8 shows different types of metadata. This includes, for example, hypnograms or sleep parameters derived from a PSG recording. Self-reported sleep data such as sleep questionnaires and sleep diaries also count into this metadata category. There are publications that include general health information in their analysis, such as demographics [114–116], anatomical information [117], lifestyle information [104, 118], co-morbidity [119], or medical history [120]. Examples of publications using only the metadata of sleep staging are Mirth et al. [121] or Jouan et al. [122], who analyze the sleep stage scoring provided by multiple sleep experts instead of analyzing the raw data itself.

Some data types do not fit in any of these categories. Baddam et al. [123] and Kang et al. [124] tracked the adherence to Continuous Positive Airway Pressure (CPAP) usage of OSA patients. Based on current usage hours, they categorized OSA patients and predicted future adherence. Boyraz et al. [125] extract driving metrics such as steering wheel angle or brake behavior to identify drowsy drivers. Massar et al. [55] use the background tracking information from smartphones, such as tapping or usage hours, to analyze sleep patterns. Rošćáková and Rosipal [126] used objective cognitive tests to identify sleep types.



Figure 9. Sankey diagram showing the flow between method types and data types (HMM = hidden Markov model, PSG = polysomnography).

Unsupervised machine learning methods

The most commonly used unsupervised methods are clustering and dimensionality reduction. To cover the entire field of unsupervised machine learning, we also included other methods, such as unsupervised anomaly detection, association rules, generative models, and HMMs. The Sankey diagram in Figure 9 shows how the number of publications of the different method types and data types is distributed. Additionally, we can see the flow, showing how many publications from each method category are used with which data type.

We identified 181 publications using clustering. The most common clustering methods used are K-means clustering, Gaussian Mixture Models (GMMs), Fuzzy C-means clustering, and hierarchical clustering. We reviewed 113 publications that focused on dimensionality reduction. It is important to mention here that dimensionality reduction techniques are already a commonly used method for preprocessing in medical research. The most common forms of dimensionality reduction in sleep research were Principal Component Analysis (PCA), Independent Component Analysis (ICA), Autoencoders, Singular Value Decomposition, Self-Organizing Maps, and Deep Belief Networks. They were most often used for classification, preprocessing, feature extraction [127], pretraining of a supervised model [128, 129], and data compression [105, 130].

There were 22 publications using HMMs with different purposes, such as modeling the process of drifting into sleep [41], modeling sleep transitions [131], and cycling alternating pattern (CAP) analysis [132]. The review includes eight publications that used unsupervised anomaly detection [54, 56, 85, 88, 133–136] in the context of sleep research. Some of them aimed to identify risks based on sleep patterns, such as risk during pregnancy [56] or behavioral risk for the elderly [136]. Other publications used anomaly detection methods for drowsiness detection [88, 135] or identifying mouth breathing during the night [134]. There are seven publications included in the review that create association rules based on sleep data [137–143]. Most of them were used for explorative analysis of clinical data sets. We identified seven publications using generative models in sleep research [72, 144–149]. Most of these publications aimed to generate artificial sleep data as a method to improve the classification performance for spindle detection [144, 147], snore detection [72], and sleep staging

[148]. Other research aimed to explore the sleep data through these generative models [149] or create art [145]. There are 11 publications with other methods that could not be included in any of the aforementioned categories. One of these methods is unsupervised domain adaptation [150–158], where a model trained on a labeled source domain can adapt to a different but related target domain that lacks labeled data. Other methods are a competition convolutional neural network [159], a hierarchical multi-agent system [160], and a Bayesian switch-point model [161].

While the majority of studies employed unsupervised machine learning, 14 studies applied semi-supervised machine learning. Additionally, 16 publications focused on self-supervised methods. Most of these publications used contrastive learning, which compares positive pairs of similar data (e.g. different representations of the same sleep cycle) against negative pairs (e.g. different individuals' sleep data), helping the model learn distinguishing features. For example, Xiao et al. [162] used contrastive learning to predict sleep stages.

Research on sleep monitoring

An overview of different areas of sleep research and the number of publications in each category can be seen in Figure 10. The term sleep monitoring in this context aims to describe any type of measuring physical attributes during sleep or tracking sleep patterns over a period of time.

Sleep staging. Sleep staging is the most common classification task in sleep research. One hundred twenty-seven of the 356 included publications focus on sleep staging. We review the machine learning methods, data types, and data sets, population size (labeled as #) and characteristics, and evaluation metrics in these publications in Appendix 2. Different unsupervised machine learning methods have been applied for sleep staging. The most common methods are various variations of K-Means clustering with 25 publications and different variations of autoencoders with 19 publications. The most common roles of unsupervised machine learning in sleep staging besides classification are domain adaptation and feature extraction. Some publications use unsupervised machine learning in unique ways, such as weighting features [163] and clustering the training set [164, 165]. Tian et al. [166] use unsupervised machine learning to refine the accuracy

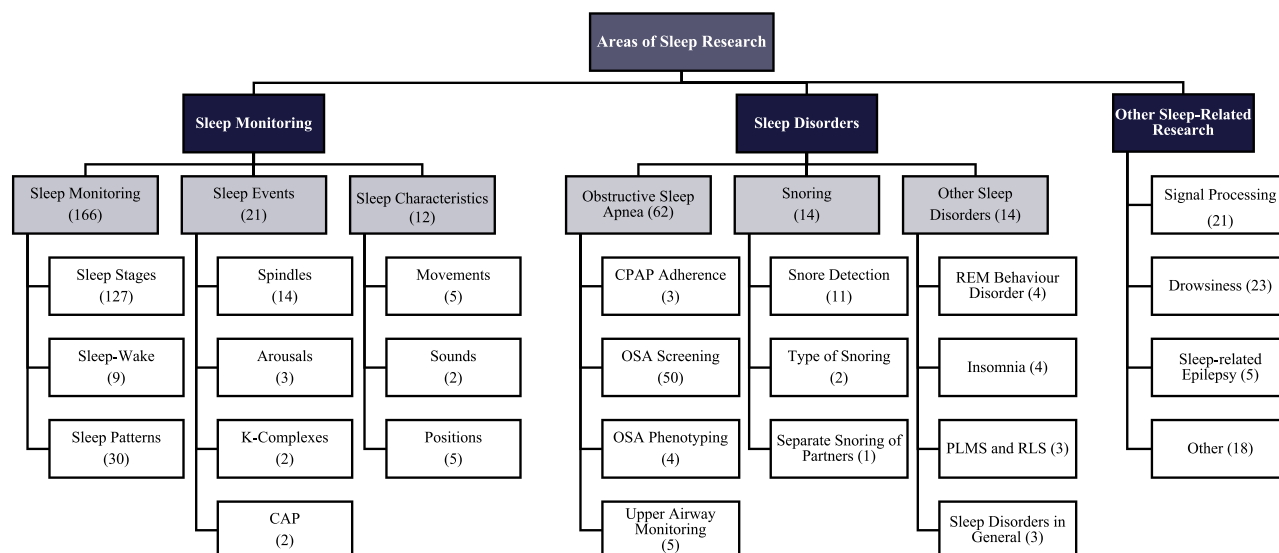


Figure 10. Categorization of publications in different areas of sleep research.

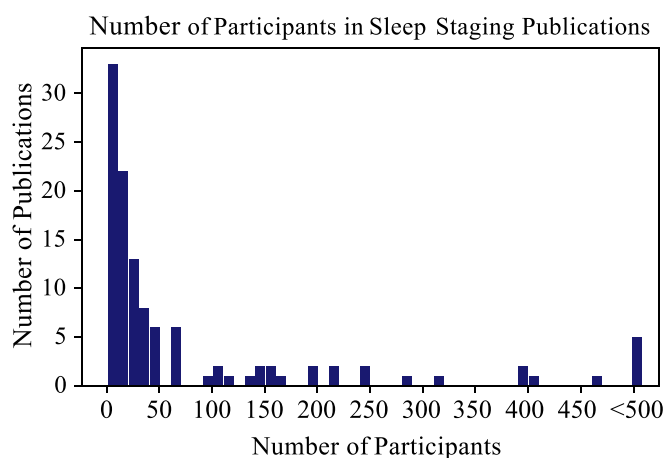


Figure 11. Number of participants in sleep staging publications.

of a supervised model. They use clustering to classify only the epochs that the supervised classifier is not sure about.

Most publications use EEG for sleep staging. Some of the reviewed publications on sleep staging used other measurement channels, such as ECG [148, 167], Photoplethysmography [46, 168], accelerometer [47, 108, 169], and video [69, 70]. Vanbuis et al. [107] predict the sleep stages of participants with sleep-disordered breathing using only respiratory signals and the heart rate and achieve an accuracy of 0.79. Reviewing the data sets used for training and testing the automated sleep staging models showed that 49 of 127 publications on sleep staging rely on the publicly available Sleep-EDF data set. This data set is available through physionet.org and consists of PSG recordings of healthy adults. An extended version with healthy and sleep-disordered adults is available as well. The recordings took place between 1989 and 1994. Other common public data sets are the Montreal Archive of Sleep Studies (MASS) data set, St. Vincent’s University Hospital/University College Dublin Sleep Apnea Database (UCD), the ISRUC data set [170], and the Sleep Heart Health Study (SHHS) data set [171]. Even though the goal of using public data sets is often comparability, the reviewed publications often use subsets of the public data sets or combine multiple public data sets.

Specifically, 69 of 112 sleep staging papers, which provide information about their population, train and validate their models on a healthy population only. Most of the publications use the data

of adults or don't specify the age range. There are seven publications doing sleep staging with the data of elderly citizens, six publications with the data of children, and seven with the data of newborns. The size of the data sets used in sleep staging publications can be seen in [Figure 11](#). Most publications train and validate their models on the data of one to ten participants. There are five publications that use data sets with 500 participants or more.

Sleep-wake monitoring. Sleep-wake monitoring can be used to calculate sleep parameters, such as the sleep duration, sleep efficiency, sleep onset latency, and wake after sleep onset. It can be used to track sleep longitudinally and monitor, for example, regularity of sleep and wake times. An overview of all publications using unsupervised machine learning for sleep-wake detection can be found in [Table 2](#). While the publications on automatic sleep staging were usually based on EEG, the publications on sleep-wake monitoring mostly use wearables or nearables. This allows a longitudinal tracking of sleep-wake rhythms. Some of the included publications use the longitudinal sleep-wake patterns for an early diagnosis of neurological disorders or to detect other anomalies.

Sleep patterns. With the technological enhancements in wearable and nearable technologies, we can observe a growing interest in longitudinal analysis of sleep patterns across multiple nights.

Table 2. Publications on Sleep–Wake Monitoring

Reference	Method	Data type	Population	#	Duration	Metric	Value
El-Khadiri et al., 2018 [161]	Bayesian Switch Point Model	Motion sensors	Healthy adults	1	219 nights	Accuracy	0.94
Geng et al., 2022 [97]	Shapelets and K-Means	ECG	Healthy adults, suspected SDB	30	1 night	Accuracy	0.78–0.88
Rai et al., 2015 [172]	Fuzzy C-Means	EEG	Healthy adults	8	1 night	Accuracy	0.95
Liu et al., 2020 [96]	HMM	Smartwatch heart rate and accelerometer	Elderly	14	3 months	Agreement	0.87
Muns et al., 2017 [51]	K-Means	Actigraphy	Healthy adults	10	80 days	—	—
Fung et al., 2023 [95]	K-Means	Smartwatch heart rate	Healthy adults	1	1 night	Accuracy	0.97
Shahid et al., 2022 [81]	K-Means	Motion sensors	Elderly	6	3 years	Silhouette core	0.4
Subramanian and Coleman, 2022 [173]	K-Means and HMM	Smartwatch accelerometer	Healthy adults	7	1 day	Accuracy	0.93
El-Manzalawy et al., 2017 [52]	K-Means, Fuzzy C-Means, and GMM	Actigraphy	Insomnia patients and healthy adults	37	3–11 nights	Accuracy	0.85

Table 3. Continued.

Reference	Method	Role	Data type	Population	#	Duration
Rošťáková et al., 2019 [126]	K Medoids with Dynamic Time Warping	Identifying sleep types	EEG, self-reported sleep, vigilance test, and blood pressure	Healthy adults	146	2 nights
Khasawneh et al., 2011 [186]	Gaussian Mixture Model	Identifying sleep types	Sleep parameter	Suspected sleep disorders	244	1 night
Alfeo et al., 2018 [50]	Fuzzy Clustering	Identifying sleep types	Heart Rate, accelerometer, and sleep quality reporting	Healthy adults	7	20 nights
Biedebach et al., 2023 [187]	K-Means	Identifying sleep types	Smartwatch and digital sleep diary	Healthy adults	45	3 months
Wallace et al., 2018 [188]	Mixture Model based on Multivariate Skew Normal Distribution	Identifying sleep types	PSG, smartwatch, and self-reported sleep data	Older adults with and without insomnia	216	1 week

Long-term monitoring can identify irregular sleep behaviors or deviations from normal sleep patterns, which may be indicative of underlying health issues [54, 85]. The duration of sleep monitoring also varies, from one-night studies to longitudinal studies spanning up to a year. An overview of all publications on sleep patterns can be found in Table 3. Other publications use unsupervised learning to analyze [187] and predict [118] sleep quality. Clustering has been applied to identify groups of individuals with similar sleep patterns based on demographics or sleep parameters. The sample sizes vary significantly across the literature, ranging from small cohorts of seven participants [50] to large-scale studies with up to 2579 individuals [116]. There are five publications using the a priori algorithm to derive association rules. These rules aim, for example, to discover factors relevant to sleep quality [137, 140] or find associations between sleep-related variables and health status [139].

Sleep events. Apart from sleep stages, there are other events visible in EEG, such as sleep spindles, K-complexes, and arousal. Table 4 provides an overview of all publications using unsupervised machine learning methods to detect sleep spindles. Of the 14 papers detecting spindles, all used EEG. Piza et al. [189] used kernelized K-Means clustering to sample the training set before

using a supervised model for classification. Loza et al. [147] uses hierarchical clustering to create a structure of patterns from vector spaces of different dimensions. Chen et al. [190] classify spindles using K-Means with an accuracy of 0.927. There are two publications that use unsupervised machine learning to classify K-Complexes. Ranjan et al. [191] use fuzzy C Means clustering, and Zacharaki et al. [192] use spectral clustering to detect K-Complexes with an accuracy of 0.912 and 0.84.

Arousals are another event in sleep EEG and can be defined as a sudden shift in EEG frequency that indicates a brief disruption in sleep. They are difficult to identify with supervised machine learning since the agreement of manual scoring is low [20]. Identifying arousals with unsupervised machine learning was first approached by Pacheco and Vaz in 1998 by using K-Means clustering [45]. In recent years, Safont et al. have attempted to classify arousals with Sequential Independent Analysis Mixture Models [193, 194]. They tested their model on three participants with OSA and reported a classification accuracy of 0.8. There are two publications on cyclic alternating pattern, which are both by Mendonça et al. [132, 195]. Their first publication is based on a single-lead ECG signal. They use a deep stacked autoencoder to predict sleep quality based on the Cycling Alternating Pattern

Table 3. Publications on sleep patterns

Reference	Method	Role	Data type	Population	#	Duration
Caroppo et al., 2018 [85]	Incremental Clustering	Detect anomalous sleep patterns	Accelerometer, Time-of-Flight sensor, and ultra-wideband radar	Healthy adults	18	3–5 months
Huijben et al., 2022 [174]	Contrastive Predictive Coding and Self-organizing Maps	Exploratory analysis of sleep patterns	EEG, EOG, and EMG	Healthy adults	96	1 night
Massar et al., 2021 [55]	K-Means	Explore sleep behavior	Smart ring, smartphone background tracking app, and digital sleep diary	Healthy adults	198	8 weeks
Liang et al., 2016 [137]	Apriori Algorithm	Derive association rules	Smartwatch	Healthy adults	2	30 days
Laxminarayan et al., 2005 [139]	Apriori Algorithm	Derive association rules	Sleep questionnaire, demographics, and sleep parameters	Suspected sleep disorders	81	1 night
Kim et al., 2019 [140]	Apriori Algorithm	Derive association rules	Sleep questionnaire, demographics, and sleep parameters	Suspected sleep disorders	81	1 night
Liang et al., 2016 [141]	Apriori Algorithm	Derive association rules	Smartwatch	Healthy adults	5	180 days
Laxminarayan et al., 2006 [142]	Apriori Algorithm	Derive association rules	Sleep questionnaire, demographics, and sleep parameters	Suspected sleep disorders	81	1 night
Gasmi et al., 2023 [54]	Mean Shift Algorithm and Autoencoder	Identify anomalous nights	Actigraphy	Elderly	1	1 year
Jansen et al., 1987 [37]	X2-based Clustering	Sleep patterns	EEG and EOG	OSA patients and healthy adults	25	1–2 nights
Li et al., 2023 [175]	K-Means	Predict sleep health indicators	Mobile application (audio and usage activity)	Healthy adults	1	4 years
Alabdan et al., 2023 [176]	Stacked Sparse Autoencoder	Predict sleep quality	Mobile application	Healthy adults	1	1.5 years
Khumngoen et al., 2023 [177]	Principal Component Analysis and K-Means	Predict sleep quality	—	—	—	7 weeks
Zhang et al., 2017 [178]	Transfer Learning using Deep Autoencoder	Sleep quality prediction	EEG and smartwatch	Healthy adults	10	1 night
Hong et al., 2017 [118]	Deep Belief Network	Sleep quality prediction	IoT devices, demographics, daily lifestyle reports	Healthy adults	333	2 weeks
Wu et al., 2017 [179]	Self-organizing Maps, Hierarchical Clustering, and Hidden Markov Model	Sleep quality prediction	Microphone and questionnaire	Healthy adults	36	1 night
Park et al., 2023 [180]	K-Means and Collaborative Filtering	Sleep recommendations	Smart bed	—	—	—
Wang et al., 2013 [181]	Expectation Maximization Clustering	Identify sleep patterns	EEG, demographics, and sleep questionnaire	Suspected sleep disorders	244	1 night
Lee et al., 2022 [116]	Autoencoder and K-Means	Identify sleep patterns	Demographics and sleep questionnaires	Soldiers with sleep disturbances	2579	—
Usher et al., 2012 [182]	Expectation Maximization Clustering	Identify sleep patterns	Hypnogram	Healthy adults	244	1 night
Wang et al., 2017 [183]	Combined Dynamical Modeling Clustering	Identify sleep patterns	Hypnogram	Healthy adults	244	1 night
Bajkowski et al., 2023 [184]	Fuzzy Evidence Accumulation Clustering	Identifying sleep types	Respiration, activity, and heart rate	Elderly	19	One year on average
Usami, 2014 [114]	Constrained K-Means	Identifying sleep types	Sleep parameters and demographics	Junior high school children	100	3 years (annually)
Khasawneh et al., 2010 [185]	Gaussian Mixture Model	Identifying sleep types	Sleep parameters, demographics, and health factors	Healthy adults	244	1 night
Mirth et al., 2023 [121]	K-Means, K Modes, and Principal Component Analysis	Identifying sleep types	Hypnogram and hypnodensity plot	Healthy adults	98	1 night

(continued)

Table 4. Publications on sleep spindles

Reference	Method	Population	#	Duration	Metric	Value
Patti, Penzel, and Cvetkovic, 2015 [196]	Gaussian Mixture Model	Healthy adults	6	1 night	Sensitivity	0.57
Patti, Chaparro-Vargas, and Cvetkovic, 2014 [197]	Gaussian Mixture Model	Healthy adults	6	1 night	Sensitivity	0.75
He et al., 2022 [198]	Variational Switching State-Space Model	Healthy adults	1	2 nights	—	—
Chen et al., 2021 [199]	K-Means	Sleep-disordered adults	6	1 night	Accuracy	0.93
Rosipal et al., 1998 [42]	ICA	—	1	7 min	—	—
O'Reilly et al., 2015 [200]	Hierarchical clustering	Healthy adults	9	1 night	Sensitivity	0.85
Loza et al., 2021 [144]	Deep Neural Dynamic Bayesian Network	Healthy adults	55	30 min	Accuracy	0.42
Piza et al., 2017 [189]	Kernelized K-Means	Healthy adults	27	1 night	Sensitivity	0.86
Caspary et al., 1994 [43]	Singular Value Decomposition	—	—	—	—	—
Chen et al., 2023 [201]	K-Means	Sleep-disordered adults	20	1 night	Accuracy	0.90
Ventouras et al., 2010 [202]	ICA	Healthy adults	1	1 night	—	—
Patti et al., 2018 [203]	Multivariate Gaussian mixture model	Healthy adults	25	1 night	Sensitivity	0.74
Ventouras et al., 2008 [204]	ICA	Healthy adults	1	1 night	—	—
Loza et al., 2019 [147]	Hierarchical Clustering	—	8	30 min	Sensitivity	0.68

Table 5. Publications on sleep movements

Reference	Method	Data type	Movement	#	Duration	Acc.
Gu et al., 2019 [295]	Gaussian Mixture Model	Radio frequency-based monitoring	General movement	11	Short time	0.97
Adami et al., 2011 [60]	Gaussian Mixture Model	Load cells in bed corners	Major posture shifts, smaller movements in upper body or legs	15	Short time	0.85
Bagci et al., 2023 [87]	K-Means	Infrared sensor	Respiration, twitches and limb movements, tossing and turning	1	Short time	0.88
Heinrich et al., 2013 [206]	K-Means	Video	Turning, stretching legs, moving arms and head	1	Short time	0.67
Gu et al., 2020 [83]	Gaussian Mixture Model	Wi-Fi	Roll-overs	7	1 hour	0.98

[195]. The second publication extracts features from EEG signals and uses an HMM, a GMM, and self-organizing maps to estimate the cycling alternating pattern [132].

Sleep characteristics.

SLEEP MOVEMENTS. Detecting movements during sleep has been approached with various measurement devices. Table 5 provides an overview of the different methods and data types used to classify movement during sleep. Wi-Fi [83], radio frequency [205], infrared sensors [87], and video [206] have been used to monitor sleep movements from a distance. These different publications defined different classes of movement. While two publications only differentiate between movement and no movement, or roll-over or no rollover, others identify more specific movements. Adami et al. [60] used load cells in the corners of the bed to classify a movement as a major posture shift, a smaller movement in the upper body, or leg movement. Bagci Nguyen and Ozturk [87] differentiate between respiration, twitches, limb movements, and tossing and turning. All of the mentioned publications use clustering either in the form of K-Means or GMMs.

SLEEP SOUNDS. Sounds can reveal information about sleep. Sounds related to sleep-disordered breathing will be treated in the sections on OSA and snoring. In this section, we review publications that aim to detect sounds during sleep in general. Barata et al. [71] aim to detect coughs during sleep. They use a

GMM to cluster audio segments. They even take one step further, to differentiate between the coughs of partners sleeping in one bed. Their work was tested on 94 participants with asthma over 28 nights each and resulted in a Matthews correlation coefficient of 0.92. Another work on sound classification during sleep is by Wu et al. [207]. They classify sounds during the night as tooth grinding, snoring, movement, or environmental noise. They use self-organizing maps and test the performance of this unsupervised method on seven healthy adults for one night of audio recording. Their model classifies the event with a pairwise F Measure of 0.58.

Sleep postures. During sleep, we switch between different sleeping postures or positions. Evaluating sleeping positions might be relevant in the evaluation of sleep disorders, such as postural obstructive sleep apnea (i.e. sleep apneas occurring only in the supine position) [208] or restless sleep disorder (a sleep-related movement disorder characterized by frequent and large movements during sleep) [209]. Research has aimed to automatically identify these postures with unsupervised machine learning, as can be seen in Table 6. The papers either differentiate between supine, i.e. lying on the back, left side, and right side [58, 59, 63], or additionally classify prone, i.e. lying on the stomach or on the side [62]. The overarching goal of the sleep posture classification can be relevant to monitoring the health status of the elderly [63] or assessing the risk of pressure ulceration in bed-bound patients [58].

Table 6. Publications on sleep postures

Reference	Method	Role	Data type	Positions	#	Metric	Value
Baran Pouyan et al., 2015 [59]	Fuzzy C-Means	Classification	Surface sensor mats	Supine, left, right	10	Accuracy	0.93
Ostadabbas et al., 2014 [58]	GMM with EM Algorithm	Classification	Mattress sensor	Supine, left, right	9	Accuracy	0.98
Bhatlawande et al., 2022 [63]	K-Means	Feature extraction	Images	Supine, left, right	109	F1 score	0.92
Hsiao et al., 2018 [62]	Fuzzy C-Means	Feature extraction	Bedsheet sensor, infrared sensor	Supine, prone, left lateral, right lateral, left side, right side	—	Accuracy	0.88

Research on sleep disorders

There are multiple publications that analyze sleep disorders in general [210, 211]. For example, Bruce [212] uses K-Means to cluster EEG sequences by participants with insomnia, nocturnal frontal lobe epilepsy, periodic leg movements, and REM behavior disorder. This research showed that the clustering was useful in identifying oscillatory patterns in the EEG of these sleep disorders and neurological disorders.

Obstructive sleep apnea. The review shows that most publications on obstructive sleep apnea (OSA) focus on automatically scoring respiratory events, including apneas and hypopneas, during the night. There are multiple publications using GMMs to predict OSA from speech [78–80, 236–241]. The choice of data type varies significantly across studies. For instance, 18 publications rely on audio recordings to capture respiratory patterns, 6 use SpO2 data, and 17 utilize ECG signals. A full overview of publications using unsupervised machine learning to detect respiratory events is shown in Table 7.

Other publications use clustering to identify phenotypes of OSA. They use metadata such as sleep parameters, health records, lifestyle information, and self-reported sleep information as a basis for the clustering [104, 115, 120, 242]. Some publications monitor the upper airway using audio [243, 244] or a static-charge-sensitive bed and a nasal cannula [103]. There are publications that specifically aim to identify the side of upper airway collapse [48, 245]. Three publications analyze [123, 246] the CPAP usage times of OSA patients and predict their future adherence [124].

Snoring. We identified 14 publications using unsupervised machine learning to classify snoring. An overview of the used machine learning methods, data sets, and performance metrics can be found in Table 8. All of these publications use audio data from microphones except Romero et al. [247], who use a piezoelectric sensor. Most of the research aims to detect snoring events, while others more specifically try to classify the type of snoring [73, 248] or separate the snoring of partners [249].

Insomnia. There are four publications using unsupervised machine learning focusing on insomnia. Park et al. [258] cluster people with insomnia based on sleep patterns collected with a smartwatch. They aim to detect different types of insomnia and run their model on 6 weeks of longitudinal data from 42 adults with insomnia. There are two publications aiming to detect insomnia based on EEG recordings [154, 259]. Frederic et al. [260] use ICA for EEG signal preprocessing, specifically for people with insomnia.

REM sleep behavior disorder. There are multiple applications of unsupervised machine learning methods in the context of REM sleep behavior disorder (RBD). Tripathi and Rajendra [261] use PET brain scans to predict whether a person with idiopathic RBD is likely to develop Parkinson’s or Lewy body dementia. Koch et al. [262] aim to classify people with RBD using EEG-based sleep staging. There are two publications that analyze the sleep of people with RBD based on PPG and accelerometer data from wearables [168] and EMG [263].

Restless legs syndrome and periodic limb movement disorder. Restless legs syndrome (RLS) is characterized by an uncomfortable urge to move the legs [264], often worsening at night, while periodic limb movement disorder (PLMD) involves repetitive, involuntary leg movements in the daytime and during sleep [265]. There are two publications that use clustering to identify movements based on mattress sensor data [266] and EMG [267]. Fairly et al. [268] use PCA to extract features from EMG data, to detect phasic EMG activity.

Research on other sleep-related topics

Drowsiness. Vigilance analysis aims to detect sleepiness or microsleep during wake time, often in the context of driving. A full overview of publications using unsupervised machine learning to assess drowsiness can be found in Table 9. A substantial number of studies in this field concentrate on physiological signals. Some employ EEG to monitor brain activity, while others utilize ECG to analyze heart rate variability. Furthermore, researchers have attempted to derive levels of sleepiness from speech patterns [269, 270]. More recent advancements involve the real-time collection of data within the vehicle itself, including the tracking of facial expressions [67, 68], eye movements [113], and steering behavior [125], as well as the monitoring of environmental factors such as air quality [88].

Signal processing. Unsupervised learning has been used to extract and decompose signals. ICA and PCA have been used to extract the respiratory rate from video [64, 66]. Additionally, both the respiratory rate and the heart rate have been extracted from infrared video [65], piezoelectric sensors [57], and pillow pressure sensors [61]. Signal decomposition can also be applied to separate the respiration of two people in one bed [84]. Poreé et al. [271] applied ICA to extract EEG, EMG, and EOG from a simplified EEG set-up. ICA is not only useful for decomposition but also for data compression. Crainiceanu et al. [272] developed a dimensionality reduction method they call population value decomposition, which they use to compress EEG signals. They work with the data

Table 7. Publications on OSA

Reference	Method	Role	Data type	Population	#	Duration	Metric	Value
Haidar et al., 2019 [105]	Autoencoder	Classify respiratory events	RIP belts and cannula	—	2056	Subset of a night	Accuracy	0.81
Moeynoi et al., 2017 [213]	Canonical Correlation Analysis	Classify respiratory events	ECG	OSA patients	25	1 night	Accuracy	0.90
Biedebach et al., 2024 [134]	Convolutional Autoencoder	Classify respiratory events	Different respiration signals	Children with and without OSA	20	1 night	F1 Score	0.51
Hu et al., 2023 [214]	Convolutional Autoencoder	Classify respiratory events	ECG	OSA patients and healthy adults	95	1 night	Accuracy	0.90
Almarshad et al., 2023 [112]	Convolutional Autoencoder and Transformer Neural Network	Classify respiratory events	SPO2	Middle-aged adults	30	1 night	Accuracy	0.80
Mostafa et al., 2017 [109]	Deep Belief Network	Classify respiratory events	SpO2	OSA patients	33	1 night	Accuracy	0.85–0.98
Li et al., 2020 [111]	Dirichlet Process Mixture Model	Classify respiratory events	SpO2	—	33	1 night	Accuracy	0.85–0.97
Le et al., 2013 [94]	Dirichlet Process–based Mixture Gaussian Process Model	Classify respiratory events	ECG and wearables	OSA patients and healthy adults	26	1–2 nights	Accuracy	0.77–0.88
Feng et al., 2021 [215]	Frequential stacked sparse auto-encoder and Hidden Markov Model	Classify respiratory events	ECG	OSA patients	32	2–4 nights	Accuracy	0.851
Ravelo-García et al., 2004 [216]	Gaussian Mixture Model	Classify respiratory events	ECG and SpO2	OSA patients and healthy adults	66	1 night	Accuracy	1
Goldshtein et al., 2011 [76]	Gaussian Mixture Model	Classify respiratory events	Speech audio	OSA patients and healthy adults	83	1 night	Specificity, Sensitivity	0.79, 0.83
Elmoaqet et al., 2020 [102]	Gaussian Mixture Modeling	Classify respiratory events	Oronasal airflow	OSA patients	96	1 night	Accuracy	0.80
Ben-Israel et al., 2010 [74]	Gaussian Mixture Modeling	Classify respiratory events	Sleep audio	Healthy adults	60	1 night	Sensitivity	0.92
Sim et al., 2022 [217]	Greedy Pre-pruned Tree-based Clustering	Classify respiratory events	—	—	—	—	Accuracy	0.92–0.99
Al-Ani et al., 2008 [218]	Hidden Markov Model	Classify respiratory events	ECG	OSA patients	70	1 night	Accuracy	0.7
Novák et al., 2004 [219]	Hidden Markov Model	Classify respiratory events	EEG	—	—	—	—	—
Feng et al., 2019 [220]	Hidden Markov Model and Sparse Autoencoder	Classify respiratory events	ECG	—	70	1 night	Accuracy	0.85
Ostadieh et al., 2020 [221]	Hybrid Radial Basis Function using K-Means	Classify respiratory events	ECG	OSA patients and healthy adults	70	1 night	Accuracy	0.96
Zhao et al., 2011 [75]	K-Means	Classify respiratory events	Sleep audio	Snorers and OSA patients	42	1 night	Sensitivity, Specificity	0.90, 0.92
Boudaoud et al., 2005 [222]	K-Means	Classify respiratory events	ECG	OSA patients	5	30 min	Sensitivity	0.84
Boppana et al., 2019 [223]	K-Means combined with KNN	Classify respiratory events	ECG	—	—	1 night	Accuracy	0.97
Marcos et al., 2008 [110]	K-Means with RBF	Classify respiratory events	SpO2	Suspected OSA	187	1 night	Accuracy	0.86
Alvarez et al., 2007 [224]	K-Means, Hierarchical Clustering, and Fuzzy C-Means	Classify respiratory events	Pulse oximetry	Suspected OSA	74	1 night	Accuracy	0.91
Robertson et al., 2007 [225]	Principal Component Analysis, Empirical Mode Decomposition	Classify respiratory events	Airflow	OSA patients	3	1 night	Sensitivity	0.81
Ostadieh et al., 2020 [226]	Hybrid RBF network with K-Means	Classify respiratory events	ECG	OSA patients and healthy adults	70	1 night	Accuracy	0.96

(continued)

Table 7. Continued.

Reference	Method	Role	Data type	Population	#	Duration	Metric	Value
Kumar Tyagi et al., 2023 [227]	Restricted Boltzmann Machine in Deep Belief Networks	Classify respiratory events	Single-lead ECG	OSA patients	70	1 night	Accuracy	0.89
Kumar et al., 2023 [228]	Self-supervised representation learning	Classify respiratory events	ECG	OSA patients	95	1 night	Accuracy	0.85
Takao et al., 2019 [49]	Stacked Autoencoder	Classify respiratory events	Mattress sensor	Healthy adults	5	2.5 min	Accuracy	0.90
Li et al., 2018 [229]	Stacked Sparse Autoencoder and Hidden Markov Model	Classify respiratory events	Single-lead ECG	OSA patients	70	1 night	Accuracy	0.847
Zubair et al., 2023 [230]	Sub-pattern-based PCA	Classify respiratory events	ECG	OSA patients	70	1 night	Accuracy	0.87–1
Sepúlveda-Cano et al., 2011 [231]	Time-adapted Principal Component Analysis	Classify respiratory events	PPG	Children with suspected SDB	21	1 night	Accuracy	0.83
Sepúlveda-Cano et al., 2011 [127]	Time-adapted Principal Component Analysis	Classify respiratory events	PPG	Children with suspected SDB	21	1 night	Accuracy	0.83
Sharma et al., 2020 [232]	Variational Mode Decomposition	Classify respiratory events	ECG	OSA patients	70	1 night	Accuracy	0.88
Alshaer et al., 2009 [233]	K-Means	Creating segments of Breath	Sleep audio	OSA patients	—	—	—	—
Joergensen et al., 2021 [101]	Agglomerative Hierarchical Clustering	Identify patterns in breathing	Airflow, SpO2, and heart rate	Healthy adults	10	1 night	Accuracy	0.64
Álvarez et al., 2013 [131]	Apriori Simple Temporal Problem Miner	Identify patterns in breathing	Scoring of respiratory events	OSA patients	50	1 night	—	—
Boudaoud et al., 2007 [234]	K-Means	Identify patterns in breathing	ECG		7	2 min	Sensitivity, Specificity	0.81, 0.84
Holm et al., 2023 [106]	Variational Autoencoder and K-Means	Identify patterns in breathing	Airflow and RIP belts	OSA patients and snorers	100	1 night	—	—
Temrat et al., 2018 [235]	Fuzzy C-Means	Predict OSA from audio	Tracheal sound	OSA patients	49	1 night	Accuracy	0.88
Ren et al., 2020 [53]	Multivariate Dirichlet Process Mixture	Analyze OSA and blood pressure	Blood pressure monitoring cuff and actigraphy	Children with and without OSA	97	1 night	—	—
Wong et al., 2023 [119]	Principal Component Analysis	Predict OSA from metadata	Sleep parameters, demographics, and comorbidities	Cancer patients	249	1 night	F1 Score	0.91
Zigel, Tarasiuk and Goldshtein, 2008 [236]	Gaussian Mixture Model	Predict OSA from speech	Speech audio	OSA patients and healthy adults	26	1 night	Accuracy	0.92
Blanco et al., 2009 [237]	Gaussian Mixture Model	Predict OSA from speech	Speech audio	OSA patients and healthy adults	26	Short time measurement	Error Rate	0.078
Blanco et al., 2011 [238]	Gaussian Mixture Model	Predict OSA from speech	Speech audio	OSA patients and healthy adults	-	Short time measurement	Relative Reduction in EER	0.25
Pozo et al., 2009 [239]	Gaussian Mixture Model	Predict OSA from speech	Speech audio	OSA patients and healthy adults	80	Short time measurement	Accuracy	0.81
Elisha et al., 2011 [240]	Gaussian Mixture Model	Predict OSA from speech	Speech audio	Suspected OSA	92	1 min	Sensitivity, Specificity	0.92, 0.92
Blanco et al., 2013 [78]	Gaussian Mixture Model	Predict OSA from speech	Speech audio	OSA patients and healthy adults	80	Short time measurement	Accuracy	0.89
Fernández et al., 2009 [80]	Gaussian Mixture Model	Predict OSA from speech	Speech audio	OSA patients and healthy adults	80	Short time measurement	Accuracy	0.81
Gómez-García et al., 2013 [79]	Gaussian Mixture Model Variations	Predict OSA from speech	Speech audio	OSA patients and healthy adults	520	Short time measurement	Accuracy	0.65
Fernández et al., 2010 [241]	Gaussian Mixture Model	Predict OSA from speech	Speech audio	OSA patients and healthy adults	80	Short time measurement	Accuracy	0.81

(continued)

Table 8. Publications on snoring

Reference	Method	Role	Data type	Population	#	Duration	Metric	Value
Schmitt et al., 2016 [250]	Deep autoencoder and HMM-GMM	Snore detection	Microphone	Healthy adults	44	1 night	F1 score	0.95
Wongsirichot et al., 2016 [249]	Degenerate unmixing estimation technique	Separate snoring from partners	Microphone	Adults with suspected sleep disorders	110	Short time measurement	Mean source-to-interference ratio	12.83
Mordoh and Zigel, 2021 [248]	Fuzzy 2-Means	Classify type of snoring	Microphone	Adults with suspected OSA or snoring	15	1 night	—	—
Azarbarzin and Moussavi, 2011 [251]	Gaussian Mixture Model	Snore detection	Directional microphone	Adults with OSA	33	1 night	Detection rate	0.97
Dafna et al., 2011 [252]	GMM with EM Algorithm	Snore detection	Smartphone microphone	Healthy adults	6	1 night	Accuracy	0.91–0.8
Romero et al., 2019 [247]	Hierarchical Clustering	Snore detection	Piezoelectric sensor	Healthy adults	156	2 nights	F1 Score	0.93
Yadollahi et al., 2009 [253]	ICA	Snore detection	Microphone	—	1	Short time measurement	—	—
Vrins et al., 2004 [254]	K-Means	Snore detection	Smartphone microphone	Healthy adults	5	1 night	Accuracy	0.75
Goh et al., 2018 [86]	K-Means	Snore detection	Microphone	Healthy adults	15	1 night	—	—
Beeton et al., 2007 [73]	K-Means “random++” variant	Classify type of snoring	Nasopharyngo-scope and headset microphone	Adults with OSA and snoring	24	1 night	Unweighted Average Recall	0.80
Zhang et al., 2020 [72]	K-Harmonic-Means Clustering	Snore detection	Microphone	Adults with OSA	1	1 night	Accuracy	0.96
Azarbarzin et al., 2010 [255]	PCA and Fuzzy C-Means	Snore detection	Ambient microphone and tracheal microphone	Adults with suspected OSA	30	1 night	Accuracy	0.99
Bublitz et al., 2017 [256]	PCA and K-Means	Snore detection	Microphone	Adults with suspected OSA	20	1 night	Accuracy	0.956
Ma et al., 2015 [257]	Semi-supervised Conditional GAN	Snore detection	Microphone	—	—	—	Unweighted Average Recall	0.52

of the SHHS data set, including 3201 recordings. This compression is desirable for storing the data and for subsequent data analysis.

Back in 1989, Lima, Leitao, and Paiva [44] used K-Means to remove artifacts from EEG. Today, most publications use ICA [273–275]. More specifically, ICA has been used to clean EEG data by removing muscle artifacts [276, 277], cardiac artifacts [278–280], and eye movement artifacts [281]. Somervail et al. [282] use Artifact Subspace Reconstruction to clean the EEG signal. These methods can also be used to create new data for signals with faulty [283] or missing [284] data.

Sleep-related epilepsy. Five of the reviewed papers focus on epilepsy patients. Lee et al. [92] use ICA to remove ballistocardiographic and ocular artifacts from EEG and model the hemodynamic response functions. The overall goal of the research is to use simultaneous EEG and fMRI recording to analyze brain areas generating interictal epileptic discharge spikes during sleep onset. Zacharaki et al. [285] classify spikes as well but use only EEG. Other publications aim to detect epileptic seizures during sleep based on EEG [286] and use intracranial EEG to detect sleep stages [90] and sleep–wake states [287].

Other. Several studies have employed sleep measurements to assess risk in specific population groups, such as pregnant women

[56] and elderly [136]. Wang et al. [56] utilized sleep data from smartwatches and sleep diaries collected throughout pregnancy to predict high-risk pregnancies and reported a Spearman correlation of 1.125 between sleep metrics and high-risk pregnancy outcomes. Notably, Abeyasinghe and Cui [143] applied association rule mining to large-scale clinical datasets, combining data from multiple cohorts with a total of 24 515 clinical records.

Other publications have applied unsupervised learning techniques to gain deeper insights into physiological processes during sleep, such as cardiac activity [288] or the transition process from wakefulness to sleep [41]. Houdin et al. [93] employed ICA to compare resting-state networks in wakefulness and sleep using fMRI data. Another interesting work using EEG signals called the *Dream Catcher experiment* aimed to detect markers of dreaming consciousness with evidence accumulation clustering [289]. Other publications aim to adjust light and room temperature to sleep [82], detect blood pressure transition during sleep [100], or estimate the age of a sleeping person based on audio [77].

Several publications have analyzed sleep on a meta-level through the examination of hypnograms, such as Jouan et al. [122], who applied a multinomial mixture model to analyze sleep stage decisions made by multiple experts, allowing them to estimate the uncertainty in manual scoring for each epoch, highlighting “gray areas” in sleep staging. Similarly, Bentrup [290]

Table 9. Publications on drowsiness

Reference	Method	Data type	#	Duration	Metric	Value
Shi and Lu, 2008 [292]	Dynamic Clustering	EEG	17	Daytime experiment	—	—
Shi et al., 2007 [293]	Extended Graph	EEG	16	Daytime experiment	—	—
Staroniewicz, 2021 [269]	Factorization Clustering	Audio of speech	6	Overnight	Equal error rate	0.03–0.11
	Gaussian Mixture Model				Accuracy	
Rajini et al., 2018 [294]	K-Means	EEG	—	—	—	1
Yin et al., 2011 [295]	K-Means	EEG	1	Daytime experiment	—	—
Gurudath et al., 2014 [296]	K-Means	EEG	12	Overnight	—	—
Rezaee et al., 2013 [67]	K-Means	Facial expressions	4	Daytime experiment	Accuracy	0.93
Fujiwara et al., 2019 [135]	Multivariate Statistical Process Control using PCA	ECG and EEG	34	Daytime experiment	Sensitivity	0.92
Li et al., 2008 [297]	Probabilistic Principal Component Analysis	EEG	10	Daytime experiment	Accuracy	0.96
Fujiwara et al., 2023 [98]	Self-attention Autoencoder	ECG	20	Daytime experiment	Sensitivity	0.88
Sommer et al., 2001 [298]	Self-organizing Map Network	EEG	11	Daytime experiment	None	—
Noori et al., 2016 [299]	Self-organizing Map Network	EEG	7	Daytime experiment	Accuracy	0.77
Wali et al., 2013 [89]	Subtractive Fuzzy Clustering	Wireless EEG	50	Daytime experiment	Accuracy	0.84
Chung and Kim 2020 [88]	VAE and skip-GAN	Air quality sensor	95	Longitudinal tracking	—	—
Ayyagari et al., 2021 [130]	PCA	EEG	8	Daytime experiment	AUC	0.91
Boyras et al., 2008 [125]	Fuzzy Subtractive Clustering	Video and car metrics	30	Daytime experiment	Accuracy	0.89
Dutta, Kour and Taran, 2020 [300]	Clustering Variational Mode Decomposition	EEG	16	Overnight	Accuracy	0.97
Schwarz et al., 2023 [68]	HMM, PCA, K-Means, Hierarchical Clustering	Facial expressions and car metrics	40	Daytime experiment	AUC	0.85–0.87
Amiriparian et al., 2020 [270]	Recurrent Autoencoder	Audio of speech	915	Daytime experiment	Spearman's correlation coefficients	0.367
Maftukhaturrizqoh et al., 2019 [301]	K-Means as Part of a Radial Basis Function Neural Network	ECG	14	Daytime experiment	Accuracy	0.82
Daley et al., 2022 [113]	Gaussian Mixture Model	Eye and face tracking, ECG, and EDA	20	Overnight	—	—
Hsu et al., 2017 [302]	ICA	EEG	10	Daytime experiment	AUC	0.75
Leong and Mandic, 2008 [303]	Noisy Component Extraction Algorithm	EEG and EOG	—	—	—	—

utilized single linkage clustering to identify gray areas in the predictions from automated sleep staging systems. This approach was proposed as a quality assurance method to enhance the reliability of automated sleep staging outcomes. Alvarez and Ruiz [131] developed an HMM based on hypnograms to model the transitions between different sleep stages and provide a probabilistic framework to better understand the dynamics of sleep stage progression.

Generative machine learning methods have been applied in sleep research to improve the representation of EEG signals [291] or generate artificial sleep EEG [149]. Kumi et al. [146] applied a Gaussian copula model to generate synthetic sleep data that mimic longitudinal smartwatch measurements, capturing realistic sleep patterns. Shahid et al. [117] use PCA to generate interactive visualizations of respiratory signals. Fernandes et al. [145] took a more conceptual approach, using the KANTS clustering algorithm to create art from sleep EEG signals,

demonstrating a novel intersection between sleep research and creative data representation.

Discussion

Contribution of unsupervised machine learning

The review showed that unsupervised machine learning has a significant contribution to sleep research. The 356 publications on unsupervised machine learning in the field of sleep research cover a wide range of sleep-related research areas. This showed that sleep research can gain a lot more from unsupervised machine learning than only sleep staging. The current state and aim of unsupervised machine learning is, in most applications, to improve and simplify the work of the human expert but not fully replace them. The review showed the most common ways of simplifying the process of sleep staging, for example, with clustering algorithms to group similar patterns in sleep

data automatically, reducing the need for manual annotations. Additionally, dimensionality reduction techniques were employed to condense high-dimensional data into interpretable formats, facilitating quicker insights without significant loss of information. Unsupervised learning can support supervised machine learning methods to improve their accuracy, for example, with feature extraction [210, 230, 304] or clustering of the training set beforehand [164, 165, 189, 305].

Limitations in existing research

Bridging the gap between sleep expertise and machine learning expertise is necessary to create meaningful applications. The expertise of a sleep researcher is needed to fully understand the data, ensuring the application has a meaningful contribution for them. The expertise of the machine learning engineer is needed to decide which methods can be considered and how to implement them. We aimed to bring both parties on the same page and start a discourse about unsupervised machine learning in sleep research.

Public data sets. The review revealed a clear trend of many publications relying on the same datasets, with the Sleep-EDF dataset being the most commonly used [306]. While the Sleep-EDF dataset has been widely used to train and test machine learning models, it is important to critically assess its limitations. Collected in the 1980s, this dataset consists predominantly of healthy, young Caucasian individuals, which raises concerns about its representativeness and applicability to broader, more diverse populations. Especially in clinical applications, where classification performance can have direct consequences on the diagnosis, it is important to consider a diverse population in the training set to create a machine learning model that is equally reliable for patients of all ages, genders, and races [307]. Therefore, although it is used as a benchmarking standard for comparing sleep staging performance, this reliance on a single, outdated dataset limits the generalizability of findings. Additionally, the focus on incremental performance gains, often in the form of small percentage improvements in sleep staging accuracy, suggests that sleep staging may already be a solved problem from a machine learning perspective. These marginal improvements lack significant clinical relevance, as they may not be meaningful for real-world sleep health outcomes. Another common flaw is training the models on 80% of the recordings of all participants and then testing the models on the remaining 20% of their recordings. This form of evaluation includes data from each participant in the training, which do not reflect the generalizability to completely new participants.

Population characteristics. The same diversity issue arises for people with sleep disorders. The review showed that the majority of sleep staging models are validated primarily on healthy participants, despite the fact that individuals with sleep disorders are the population most in need of accurate and reliable sleep staging. More than half of the publications on automatic sleep staging rely on data from healthy participants only, limiting their clinical applicability to the general population. This focus on healthy populations may be due to the availability of clean, easily accessible datasets and the inherent challenges in working with disordered sleep data, which can be more variable and difficult to model. However, this practice leaves a critical gap in sleep research, as models that perform well on healthy individuals may not generalize effectively to those with conditions like insomnia, sleep apnea, or other disorders. For future advancements in sleep staging to have a clinical impact, models must be validated

on diverse populations, including those with sleep disorders, to ensure their effectiveness in real-world clinical settings.

Limitations of the review. One limitation of the review is the lack of comparability between studies. However, we intentionally sacrificed this comparability to widen the scope of included studies. Therefore, our review provides a broad analysis of how unsupervised machine learning has been used in sleep research but does not allow any conclusion regarding their accuracy, efficacy, or practical implementation. A traditional review with meta-analysis would be feasible if we had focused on one type of study. However, we aimed to create an overview of all the different forms of research publications within this field. For this reason, we did not analyze any effects and did not do a bias assessment. In any case, the exploratory nature of our review may serve as an initial step for future meta-analyses of unsupervised machine learning in sleep research, both by our groups and by others.

New pathways for sleep research

Sleep applications. By mapping out the entire body of literature on unsupervised learning in sleep research, gaps in the sleep research areas became visible. Comparing the number of publications by the sleep disorders they aim to analyze, diagnose, or treat showed a high imbalance. Eighty publications were working on topics related to sleep-disordered breathing, including OSA and snoring. Only 19 papers in total considered other sleep disorders and related neurological conditions, including sleep-related epilepsy, insomnia, RBD, PLMS, and RLS. Even though sleep apnea is a highly prevalent and serious sleep disorder, this imbalance does not seem proportional. Furthermore, other sleep disorders such as narcolepsy, circadian rhythm disorders, sleep terrors, somnambulism, or bruxism have not been approached with unsupervised machine learning at all.

This may stem from varying knowledge about these disorders, diagnostic methods, and treatment options. For this reason, some of these disorders might have lower demands or no demand for technological support in either of these steps, leading to an imbalance in research. The lack of machine learning-based research on these disorders may also be lower availability of sleep data from affected individuals. Lastly, this imbalance might also stem from a bias toward disorders with greater commercial potential, such as sleep apnea, which is widely recognized and has a clear market for diagnostic tools and treatments like CPAP machines. The lack of attention to a broader range of sleep disorders points to a need for more balanced research efforts that address a wider spectrum of sleep conditions, particularly those that remain under-represented despite their prevalence and impact on sleep health. We suggest filling these gaps by exploring applications of unsupervised machine learning targeting specifically underrepresented sleep disorders.

Unsupervised methods. Considering the temporal progression of publications, generative machine learning models, association rules, and unsupervised domain adaptation are methods with little research thus far and an increasing number of publications in recent years. Generative machine learning models experienced large technological advancements, which led to an increased interest in these methods in the general population. Existing publications used generative models to visualize [106] and generate artificial sleep data [149]. Even though the low reliability of generative models is problematic for their usage in the medical domain, other medical fields have ongoing research on integrating them into diagnosis, medical education, and treatment strategies [308].

We therefore identify these applications of generative models as a research gap and propose, for example, text generation for the training of sleep technologists or personalized content for digital sleep tracking as potential research directions. Regarding association rules, noticeably, six out of seven publications using this method did explorative analysis of clinical data sets. In other medical fields, this method has been used to detect risk factors contributing to a specific condition [309, 310] or analyze EEG [311, 312]. Therefore, we encourage future sleep research to apply them to different data types, similar to how it has been done with respiratory event scoring [138]. Unsupervised domain adaptation could be particularly valuable in sleep research, where access to fully labeled data is limited and varies significantly between research areas. This method has, for example, been used for combining wake MRI data from different centers [313] and could be suitable for increasing the amount of available sleep MRI data. We suggest exploring these methods further, which could ultimately reveal new pathways for sleep research.

Future directions for clinical usefulness

In order to steer machine learning in sleep research toward more clinical usefulness, a public data set that covers a broad population range is needed. This data set should be complemented by an open-access and peer-reviewed data descriptor that clearly describes the data set and the characteristics of the population, as well as guiding the evaluation procedure to ensure comparability between publications. Standards for a common evaluation procedure should be designed in a way that shows that the application of unsupervised machine learning makes sense in a clinical context. It should be given that publications aiming to contribute to sleep monitoring should also test their methods on a whole-night sleep recording. Still, multiple publications tested their applications only on short-time recordings during the day. Surprisingly, many applications evaluated their model only on the data of a single subject. Therefore, we suggest that future research use a test set including participants of different ages, genders, and pathologies for a comparable and generalizable evaluation.

Conclusion

This scoping review illustrated the diversity of research related to the use of unsupervised machine learning for analyzing sleep and sleep disorders. The various forms of data collection efforts and machine learning methods identified in this scoping review showed that unsupervised machine learning is already an important and embedded part of modern sleep research. Furthermore, our findings show the potential for novel applications in the future by outlining particular pathways that could be promising research directions for sleep. When analyzing the chronological rise in the number of publications that utilize unsupervised machine learning in sleep research, we can see that the interest is growing rapidly, especially in less-known unsupervised learning methods. This clearly illustrates that unsupervised machine learning research is on the rise, and although its uptake has not yet reached the same heights as supervised machine learning, the tables are turning. This confirms LeCun, Bengio, and Hinton's [314], p.7 prediction that unsupervised machine learning may gain greater impact and importance in the long term. Their words, "We discover the structure of the world by observing it, not by being told the name of every object," apply to sleep research as well since unsupervised machine learning allows for the direct discovery of sleep by observing it.

Supplementary material

Supplementary material is available at SLEEP online.

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Data availability

All relevant data are contained within the article and in the supplementary material. Further inquiries can be directed to the corresponding author/s.

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