**Abstract**

The causes of musculoskeletal conditions are partially understood, with several risk factors, one of which is often overlooked: sleep. On average, one spends one-third of their lifetime asleep. Clinical studies showed that such a prolonged sedentary state can initiate or exacerbate various sleep-related musculoskeletal conditions and musculoskeletal-related sleep disorders. Sustained provocative sleep postures adversely impact musculoskeletal health causing, for example, joint inflammation, while musculoskeletal disorders are detrimental to sleep hygiene and quality, developing into a vicious cycle. In clinical practice, a multitude of sleep assessments is available to assess sleep physiology. As much as these assessments aid in diagnosing various disorders, they have limitations, particularly in regard to sleep posture analysis. Postural analysis in clinical assessments is premature, physically intrusive, privacy-invading, and requires trained personnel. These limitations together with condition management and treatment challenges render it difficult to devise optimal treatments and make accurate prognoses. Clinicians welcome the uprising of sensor technologies to automate sleep posture analysis and democratise it beyond in-the-clinic environments. The chapter presents a systematic review of sleep posture sensor technologies and critically discusses their usability in light of clinical needs and challenges. It is argued that wearable devices are best suited for this purpose. The review then extends to wearable sensor data processing techniques underpinning sleep posture analysis, whilst embarking on the latest intelligent perception trends, such as hierarchical sensor information fusion. The chapter entails a deep critical style throughout as it acknowledges the limitations of sensor technologies, including wearable devices, and outlines future recommendations from sensing and intelligent perception standpoints. Overall, the chapter offers a comprehensive and up-to-date review of the clinical practices and research efforts towards sensor-enabled sleep posture perception. It is a valuable resource for researchers, clinicians, and practitioners interested in the overlap between sleep disorders and human motion analysis.

**CHAPTER**

**4**

# Sleep Posture Analysis: State-of-the-art and Opportunities of Wearable Technologies from Clinical, Sensing and Intelligent Perception Perspectives

Omar, Elnaggar, The University of Liverpool, School of Engineering, Liverpool, United Kingdom

Paolo, Paoletti

Andrew, Hopkinson, BSc, PhD, University of Liverpool, Honorary Fellow, Psychological Sciences, WIRRAL, United Kingdom

Frans, Coenen

## 1. Introduction

Musculoskeletal conditions are a significant challenge for a large portion of the global population, causing individual health issues and imposing economic and social burdens (Bevan, 2015) (Rosenfeld et al., 2018). Although various factors play a role in the onset and progression of these conditions, their risk factors remain partially understood. Sleep is one key risk factor that has gained recognition for its potential adverse impact on musculoskeletal health. Understanding the relationship between sleep and musculoskeletal conditions can yield valuable insights that benefit both areas, paving the way for targeted interventions and therapeutic approaches. This chapter provides a comprehensive review from two perspectives. Firstly, the chapter discusses the clinical literature at the intersection between human sleep behavior and musculoskeletal health complications, encompassing the implications of sleep and the clinical practices for the assessment, management and treatment of sleep-related musculoskeletal conditions and sleep disorders. Secondly, the chapter then provides a review of the technical literature within the domain of sleep posture analysis from two complementary angles: sensor technologies and data processing algorithms. Across both perspectives, the chapter highlights the unmet clinical needs and the most critical opportunities for technological improvement in responding to these needs.

## 2. Health Complications: A Sleep Behaviour Perspective

This section presents a clinical background and introduces terminology and concepts related to sleep and musculoskeletal health. It focuses on the relationship between sleep and various health complications, with a particular emphasis on musculoskeletal pathology. It will elucidate how certain sleep patterns indicate musculoskeletal pathologies and how musculoskeletal patterns and habits can impact sleep and drive other health problems. The discussion extends to clinical practices for assessing sleep disorders and sleep-related musculoskeletal pathologies, as well as the options clinicians have for condition management and treatment. As recommended by the National Sleep Foundation, adults should aim for seven to nine hours of sleep per night for optimal health (Hirshkowitz et al., 2015). Contrary to the widespread belief that sleep solely aids in recovery and restoration after daytime fatigue, there is empirical evidence suggesting broader implications (Vyazovskiy, 2015). While sleep is not intrinsically harmful or unhealthy, it is nonetheless a complex phenomenon with interrelated processes that may lead to risk factors. Therefore, it is important to study human sleep behavior from a biomarker perspective to trace the development of sleep-related morbidities and identify underlying health conditions. *Human sleep behaviour* refers to the patterns and habits individuals exhibit while sleeping, including aspects like sleep staging, sleep episodes and duration, physiological processes, biomotor behavioral patterns, and psychosocial changes (Mahowald & Schenck, 2005) (Dahl & Lewin, 2002). The bidirectional relationship between sleep disorders and musculoskeletal conditions will be revealed, with examples showing how sleep disorders manifest in physical sleep behaviour and how certain musculoskeletal habits can lead to sleep-related pathologies.

**The Musculoskeletal System: A Biomarker of and Risk Factor for Sleep-related Pathologies**

The abnormalities in the human sleep behavior are indicators of sleep disorders. These disorders can be symptomatic or sign of developing morbidity. The aetiology of sleep disorders is influenced by the physical behaviour that involves the musculoskeletal system, which is viewed as a biomarker of underlying sleep disorders and a risk factor for sleep-related health complications (Ibáñez et al., 2018a). According to the International Classification of Sleep Disorders (Sateia, 2014), sleep disorders follow a six-level taxonomy, including insomnia, sleep-related breathing disorders, central disorders of hypersomnolence, circadian rhythm sleep-wake disorders, parasomnias, and sleep-related movement disorders. The aetiology of sleep disorders can be internal or external (Karna et al., 2022) (Sletten et al., 2013) (Fadhel, 2020) (Potter et al., 2016), with internal causes including physical pain, genetic predisposition, psychological factors, and abnormalities with the central nervous system. External causes include environmental factors, pharmacological effects of medications, and substance abuse.

The musculoskeletal system supports the body's posture and movement through a unique integration of bones, joints, muscles, tendons, and ligaments (Paz & West, 2013). It is a vital system that has direct interactions with various other body systems, including cardiovascular, respiratory, and neurologic systems. Understanding the associations between sleep disorders and the musculoskeletal system is crucial for understanding and treating sleep-related musculoskeletal pathologies.

The term "*risk factor*" refers to a characteristic or hazard that increases an individual's chance of developing a disorder (Werner & Smith, 1992). Sleep habits and patterns, such as posture and in-bed body movement, can be considered risk factors for health complications. Similarly, musculoskeletal conditions can also be risk factors for sleep disorders. The bidirectional relationship between sleep disorders and musculoskeletal conditions is illustrated in Figure 4.1. There are two types of sleep behavior: *movement* and *stable state behaviours* (Fallmann & Chen, 2019).

**Fig. 4.1 The bidirectional relationship between sleep disorders and musculoskeletal conditions.** *No Permission Required*

Movement behaviour comprises a pattern or sequence of movement states spanning the duration of sleep, which can be useful for different purposes, such as differentiation between sleep and wake episodes, evaluating sleep quality and duration, and diagnosing circadian rhythm disorders (Kuo et al., 2017). Abnormal movements during sleep vary in complexity. Simple behaviours include single, repetitive, or rhythmic movements affecting specific body parts or larger muscle groups (Bergmann et al., 2019). Complex behaviours, such as parasomnias, can involve bizarre actions during various sleep states and may pose risks to the sleeper or those around them (Vaughn et al., 2018).

Stable state sleep behaviour corresponds to periods of no movement (Bilston & Gandevia, 2014), which are independent of the sleep stage and provide insights into sleep postures, such as the supine and lateral positions. The sleep posture behaviour has significant implications for the health (Haex, 2004) (Gordon et al., 2004), and can exacerbate conditions, such as *obstructive sleep apnoea* due to the gravitational pull on the upper airway (Menon & Kumar, 2013) (Bidarian-Moniri et al., 2015). Moreover, prolonged pressure on certain body parts during sleep can cause pressure ulcers, leading to severe consequences in some cases (Jaul, 2010). Over the past decade, specialised studies have linked postural cues to musculoskeletal morbidities, for example, spinal health. Poor spinal posture during sleep increases biomechanical stresses along the spine, which triggers neck pain episodes and stiffness (Cary et al., 2019) (Cary et al., 2021). Studies on patients with neck pain investigated factors such as pillow type, neck muscle activity, and asymmetrical lateral sleep postures (Lee &

Ko, 2017). Additionally, stable state sleep behaviours can provide sensible explanations for musculoskeletal joint pain, which cannot be understood through the conventional joint overuse theory. For example, unilateral shoulder pain, which often affects the right shoulder (dominant side), is a strong example of this (Zenian, 2010). Sleep posture is not the sole cause of musculoskeletal pain. The prolonged duration in certain provocative sleep postures can aggravate musculoskeletal pain, potentially causing pressure sores, tissue damage, and inflammation (Cary et al., 2021) (Zenian, 2010). Prolonged joint immobilisation can lead to muscular contractions, which can develop into chronic pain episodes (Parisi et al., 2003). Thus, changes in sleep posture overnight play a crucial role in preventing these complications.

**Clinical Assessment of Sleep Disorders**

The understanding of sleep disorders and their associated health complications is crucial. Equally important is the grasp of the methods healthcare professionals utilise to diagnose these disorders. This review delves into the various clinical practices adopted for sleep disorder assessment, highlighting their benefits and challenges.

Sleep assessment methods can be broadly categorised based on their focus. Some methods, for instance, are tailored to scrutinise sleep at the behavioural level, which encompasses aspects such as movements and responsiveness. Others delve deeper, examining the quality, duration, and brain activity patterns of sleep (Sadeh, 2015). Moreover, specialised diagnostic tools target specific disorders like respiratory sleep disorders (Riha & L., 2015). The choice of the most suitable method depends on factors such as the clinical need being addressed and the availability of specialised equipment or trained personnel.

The hierarchy of clinical sleep assessments typically starts with patient-reported sleep diaries and questionnaires, which offer a rapid and inexpensive preliminary evaluation of a patient's sleep (Carney et al., 2012). Sleep diaries offer an advantage over questionnaires due to the extended period of self-monitoring, which helps capture the variability in sleep behavior across different days (Ibáñez et al., 2018b). However, both methods lack the capability to precisely gauge certain aspects of human sleep behavior, such as movement and posture states and their duration due to the absence of direct behavioural observation.

When further diagnosis is deemed necessary, the clinical gold standard for sleep disorder diagnosis is *polysomnography*, an in-clinic medical procedure that involves simultaneous recording of several parameters linked to sleep staging and physiology. Polysomnography uses electrodes in contact with the skin to record a wide range of measurements (Markun & Sampat, 2020), including electroencephalograms to measure brain activity and distinguish sleep stages, electrocardiograms to assess cardiovascular health, and electromyography to monitor electrical muscle activity of muscles. Some polysomnography systems integrate further measurements for specific analyses, such as a thoracic sensor for sleep posture tracking to study posture-dependent breathing disorders (Tiotiu et al., 2011). While polysomnongraphy offers comprehensive insights on sleep, it faces challenges such as costly overnight hospitalisation, discomfort from electrodes and sensors attached to the body, and rudimentary insights in relation to, for example, sleep posture analysis. Not to mention, its operation demands the expertise of a trained sleep technologist (Mendonça et al., 2019).

An alternative method, *videosomnography*, involves video recordings, capturing the patient's behaviour in their natural sleep setting (Ipsiroglu et al., 2015). It is particularly effective for disorders like sleepwalking, not adequately addressed by polysomnography. Yet, videosomnography is not without downsides. The ethical and privacy implications associated with video surveillance often act as a deterrent to its widespread adoption (Sadeh, 2015) (Schwichtenberg et al., 2018).

A relatively recent entrant in the sleep assessment landscape is *actigraphy*. This non-invasive method employs a wearable sensor, drawing the attention of sleep specialists due to its convenience and lesser privacy concerns. Actigraphy has shown promise in assessing a range of sleep disorders and in monitoring the efficacy of medical interventions (Allen et al., 2010) (Natale et al., 2009). Actigraphy has shown strong correlations with polysomnography in some clinical studies, but its validity remains questionable in other settings (Sadeh, 2011). However, despite advances in sensor precision and algorithm accuracy, the clinical use of actigraphic devices remains limited, with further validation and standardisation of proprietary algorithms required before a smooth integration into healthcare can be realised (D. J. Miller et al., 2020) (Boyne et al., 2013). Regulation concerns include potential harmful consequences from device misuse, measurement inaccuracy, algorithm uncertainty, failure modes, and misinterpretation of device-generated results (Bonafide et al., 2017) (Piwek et al., 2016). These risks may necessitate specialised training of healthcare professionals on wearable sleep technologies to increase their awareness of the effective use and limitations of these devices.

In summary, while numerous methods for sleep disorder assessment exist, each comes with its unique set of advantages and challenges. As technology progresses, the hope is for the development of more accurate, convenient, and patient-friendly tools to improve sleep disorder diagnosis and management.

**Management and Treatment Practices for Sleep Disorders**

Understanding sleep disorders, and their subsequent management and treatment, is paramount for optimal patient care. Once a healthcare practitioner diagnoses a sleep-related disorder, various strategies, encompassing management and treatment, are employed to address it effectively.

Management of sleep disorders is a comprehensive process enabling patients to actively cope with an underlying sleep disorder, with the aim of managing symptoms and mitigating its impact on their quality of life (W. R. Miller et al., 2015). Clinicians recommend several management techniques for sleep disorders, one of which is improving sleep hygiene. Sleep hygiene encompasses daily routines, behaviours, and environmental factors that promote healthy sleep (Stepanski & Wyatt, 2003). Research indicates that improved sleep hygiene can alleviate symptoms in patients with sleep-related behavioural disorders, such as restless leg syndrome and periodic limb movement disorder (Sönmez & Aksoy Derya, 2018) (Pigeon & Yurcheshen, 2009).

The treatment of sleep disorders comprises a multitude of pharmacological and non-pharmacological clinical interventions aimed at addressing the underlying cause of a sleep disorder and potentially reversing its progression. For instance, medications can target specific biochemical pathways, such as increasing dopamine levels to alleviate restless leg syndrome (Suzuki et al., 2017). Others relax muscles to reduce the characteristic twitches of the periodic limb movement disorder (Hoxha et al., 2022). However, it is worth noting that while many of these medications are effective, they often come with side effects that can further disrupt sleep or pose other health risks (Suzuki et al., 2017).

Beyond medications, non-pharmacological treatments are also available. A common example is continuous positive airway pressure, which is effective for obstructive sleep apnea by keeping the airway open during sleep (Basner, 2007). However, this treatment does not cure apnea, as breathing difficulties may return if treatment is halted. Additionally, there is an emphasis on addressing psychiatric disturbances, which, if marginalised and left untreated, can aggravate sleep disorders. One prominent option is cognitive-behavioural therapy, which combines cognitive and behavioural components to treat sleep disorders like insomnia, restless leg syndrome, and periodic limb movement disorder (Babson et al., 2010). However, this therapy has limitations, such as the need for patient commitment and its unsuitability for patients with complex mental health needs (Holmes, 2002).

Physical therapy, or physiotherapy, is another effective non-pharmacological treatment for sleep-related musculoskeletal pathologies, such as sleep pain and nocturnal leg cramps (Andrews & Pine, 2019) (Eadie et al., 2013). Physiotherapy methods typically involve self- or clinician-administered exercises or passive massage of affected muscles. However, like other treatments, physiotherapy has its challenges, such as high costs or the need for further clinical validation (Tramontano et al., 2021).

In cases where the aforementioned treatments fail to achieve the desired outcomes, surgical interventions might be considered. Examples include gastrocnemius release surgery, which aims to relieve tension in the calf muscle, causing pain episodes during sleep and early morning (Arshad et al., 2022). Other surgeries target conditions like obstructive sleep apnoea by focusing on weight loss or tissue removal (Ashrafian et al., 2015). However, while surgical intervention can be justified for some conditions, it should be approached with caution due to potential risks during and after the surgery.

**Clinical Needs and Challenges in Sleep Posture Analysis**

The pursuit of understanding sleep-related behavioural and musculoskeletal pathologies has indeed advanced, yet a distinct gap persists between clinical needs and challenges. This section discusses these challenges in relation to the clinical assessment, management, and treatment of sleep-related conditions, while highlighting areas where improvements in clinical practices and patient outcomes can be further enhanced.

Medical screening for sleep disorders faces several inefficiencies. Patient-reported tools, such as diaries and questionnaires, are subjective and sensitive to factors such as bias and forgetfulness (Cary et al., 2019). These tools often overlook crucial information, like the duration spent in each sleep posture or the intensity of abnormal movements during sleep. Observation-based assessments, such as polysomnography and videosomnography, provide a more objective and evidence-based evaluation of sleep-related disorders, but they still have major limitations. These limitations include the need for overnight hospitalisation, sleeping in unfamiliar environments, heavy use of intrusive electrodes, trained personnel, and laborious manual assessments (Hossain & Shapiro, 2002). Even wearable actigraphic devices are far from being reliable clinical tools in sleep medicine due to several challenges. Notably, the *American Academy of Sleep Medicine*'s recommendations on the use of actigraphy in clinical practice do not exceed the "conditional" strength category (Dijkers, 2013), citing limited confidence in the outcomes of actigraphy-based diagnosis (Smith et al., 2018). Additionally, there are challenges tied to the lack of accuracy and reliability of actigraphy-generated results, difficulty in interpreting device outcomes, and potential misuse of these devices.

The management and treatment of sleep-related pathologies also face hurdles. Many individuals remain unaware of their sleep disorders, and this lack of awareness leads to delayed treatments, which can be exacerbated by the shortage of sleep specialists. Post-diagnosis, the multifactorial nature of sleep pathologies can make treatment selection challenging. Clinicians are increasingly questioning the cost-to-benefit ratio of current treatments (Cary et al., 2019) (Zenian, 2010) and are constantly looking for new, cheaper medical interventions, such as postural modifications, wearable night splints, and vibrational devices (W. C. Chen et al., 2015) (Van Maanen & De Vries, 2014). Furthermore, evaluating the effectiveness of these treatments becomes problematic due to the reliance on subjective measures, such as patient-reported outcomes. This can result in patients switching between different therapies that did not work for them, leading to a lack of patient commitment to the treatment protocol.

Further technological advancement would be essential to address the aforementioned unmet needs and challenges. More broadly, these advancements could also support clinicians in understanding the causes of sleep-related conditions, facilitating the early detection of their risk factors, and devising optimal treatments. While current clinical assessments are effective in diagnosing certain sleep-related conditions, they fall short in sleep posture sensing as they typically consider only four standard sleep postures (supine, prone, left and right lateral positions). This lack of information about the position of the upper or lower limbs relative to the trunk makes it difficult to provide insight into the underlying aetiology. Therefore, the posture sensing capability still needs refinement to provide clinicians with access to more granular measurements that would, in turn, contribute to a better understanding of how postural cues correlate with sleep-related musculoskeletal conditions.

Moreover, sleep technologists manually assess postural immobility and duration to avoid errors inherent to automatic algorithms in sleep medicine (Tripathi, 2008). This leads to inefficiency loops in providing care to patients, leaving many without diagnosis. It is, therefore, important to develop advanced algorithms, such as automatic posture recognition and posture duration estimation, to automate this laborious task while maintaining satisfactory reliability of automatic determination of sleep posture duration.

There are methodological considerations fundamental to technological interventions in sleep medicine. At the top of these considerations is the human interpretability of device-reported outcomes, which is important to reassure the clinicians about the technology and gain their trust in using it. Moreover, the safety and usability are crucial factors to ensure the device is reliable and easy to use. The major drawbacks of existing clinical assessments in sleep medicine also qualify as considerations for improvement. Examples of these drawbacks include the sensor intrusiveness of polysomnography and the privacy violations of videosomnography.

## 3. Sleep Posture Analysis: Current State of Research

Sleep posture analysis is a vital area of research with significant implications for sleep-related musculoskeletal conditions. The field encompasses various subtopics, including human motion analysis, sensor technologies, algorithmic trends, and intelligent perception.

The human body undergoes various movements and postural adjustments during sleep, which can be analysed digitally as a sequence of body postures (Park et al., 2022). This analysis involves two main research directions: motion quantification and classification (Lopez-Nava & Angelica, 2016). Motion quantification is concerned with the estimation of body- or motion-specific parameters, whereas classification focuses on obtaining high-level interpretations or descriptions of the recorded human motion. Sleep posture analysis can be a quantification problem, a classification problem, or both, depending on the output definition. Clinical practice typically involves classification, examining four standard sleep postures.

After gaining an understanding of sleep posture analysis through the lens of human motion analysis, the following section embarks on an exploration of the sensor technology options available for capturing and assessing human sleep postures. The discussion will encompass the distinctive sensor categories, their sensing principles, and the general advantages and disadvantages associated with each option.

**Human Sleep Posture Sensing Technologies**

Sleep posture analysis is crucial for understanding and managing sleep-related disorders. Various sensor technologies have been developed for this purpose, broadly categorised into contact-based and contactless sensors (X. Li et al., 2023).

**Contactless Sensor Technologies**

Contactless sensor technologies represent a category of devices that can capture and analyse data without the need for direct contact with the human body. In the context of sleep posture analysis, contactless sensor technologies offer a non-intrusive way to monitor a person's sleep posture throughout the night. These technologies can be broadly categorized into two groups: wireless sensors and vision sensors.

Wireless sensors operate at different frequencies and include Radio Frequency Identification (RFID), WiFi, Ultra-Wideband (UWB), and millimeter wave (mmWave) technologies. RFID technology involves passive tag devices attached to the beddings or mattress that communicate with an RFID reader device (X. Hu et al., 2018) (P.-J. Chen et al., 2022). This communication helps in identifying the posture of the person sleeping. WiFi-based sleep posture sensing takes advantage of the reflection of radiofrequency signals upon striking objects and obstacles, producing a unique reflected signal signature indicative of the posture (Yue et al., 2020) (J. Liu et al., 2018). UWB technology provides higher spatial scanning resolution compared to WiFi systems, capturing finer-grain postural variations (Lai et al., 2023). mmWave technology shares the same working principle as UWB and WiFi signals but has a much wider bandwidth, allowing for higher data transfer rates, although it has relatively weaker penetrability (Sitar & Sur, 2023). Wireless sensors are non-intrusive and can be deployed in the bedroom without the need for a dedicated sleep laboratory, but they have limited angular and/or spatial resolution (Yue et al., 2020) and are susceptible to noise from environmental changes and radio signal interference (J. Liu et al., 2018).

Vision sensors, on the other hand, are popular for sleep posture monitoring in both academic and clinical settings and can be classified into marker-based and markerless vision systems. Marker-based systems track the positions of on-body retroreflective markers but are not suitable for sleep posture monitoring due to several reasons, including severe marker occlusion, high costs, and lack of portability. Markerless vision sensors do not require the placement of markers on the human body and include visible light imaging, depth imaging, infrared imaging, and thermal imaging. Visible light imaging captures full-colour images of the sleeping person and their surroundings (S. Liu & Ostadabbas, 2017). Depth imaging constructs a depth map of the camera's surroundings (Tam et al., 2021) (Ren et al., 2020). Infrared imaging detects the infrared spectrum present in the naturally emitted thermal radiation in the scene (S. Liu et al., 2019). Thermal imaging captures the thermal state of different objects in the scene (Z. Chen & Wang, 2021). Vision sensors have a large field of view and no physical intrusiveness, but they raise ethical concerns surrounding personal privacy and data usage, and their reliability degrades under occlusion by blankets and certain environmental factors.

**Contact-based Sensor Technologies**

Contact-based sleep posture sensors require physical contact with the body or bed and are divided into bed-embedded and wearable sensors.

Bed-embedded sensors are further classified based on their location, either in the mattress or attached to the bed frame. Various types of pressure-sensitive mattresses exist, such as piezoresistive, piezoelectric, and triboelectric mattresses (Tang et al., 2021) (Q. Hu et al., 2021) (Hsiao et al., 2018) (Viriyavit & Sornlertlamvanich, 2020) (Zhou et al., 2020) (Chao et al., 2023). These mattresses gauge spatial weight distribution, equilibrium air pressures, or cardiac activity to infer sleep postures (Hoque et al., 2010) (Khare & Chawala, 2016) (Peng et al., 2022) (M. Liu & Ye, 2018). Load cells attached to bed frames measure vertical reaction forces acting on the bed legs to classify sleep postures (Beattie et al., 2011) (Wong et al., 2020). Although bed-embedded sensors are non-invasive and convenient, they have limitations such as indirect pose inference methods, high fabrication costs, and potential failure to capture slight posture variations.

Wearable sensors, specifically magneto-inertial sensors, measure physical quantities correlated with sleep postures. These sensors include accelerometers, gyroscopes, and magnetometers (Jussi et al., 2019) (El-Sheimy & Youssef, 2020). Actigraphy, using accelerometers, measures Earth's gravitational acceleration in sensor space to discriminate between different sleep postures (Jeng et al., 2021) (Razjouyan et al., 2017). Integrating accelerometers with gyroscopes forms an inertial measurement unit (IMU) that provides information on both tilt and rotational movements of body parts (Bernal Monroy et al., 2020). The magneto-inertial measurement unit (M-IMU) adds a magnetometer to the IMU, providing a richer pool of information for sleep posture classification (Kwasnicki et al., 2018). Smartphones, with built-in magneto-inertial sensors, have also been used for sleep posture classification (Behar et al., 2015) (Ferrer-Lluis et al., 2021a, 2021b) (Ramanujam et al., 2021) (Lima et al., 2019). Sensor placement on the human body is crucial for collecting accurate information about sleep postures (Zhang & Yang, 2015) (Eyobu et al., 2018) (Alinia et al., 2020). While wearable inertial sensors offer direct observability of the body, low computational cost, social acceptability, and cost-effectiveness, they also have downsides such as physical intrusiveness, placement inconsistency, and susceptibility to environmental factors (Fan et al., 2022) (Fallmann & Chen, 2019) (Qureshi & Golnaraghi, 2017).

**The Sensor Technology Debate: Which One Tops The List?**

The suitability of sensor technologies for sleep posture analysis is a critical consideration in sleep medicine research. The selection of appropriate sensor technology is influenced by several criteria, including research needs and constraints, data privacy, usability, affordability, and clinical relevance of the sensor technology. These criteria play a crucial role in determining the sensor technology most appropriate for fulfilling the needs of clinical practice.

The central need is the advanced sensing of sleep postures, moving beyond the four standard postures - supine, prone, left and right lateral positions - to a higher granularity that includes limb positions relative to the trunk. This is essential for diagnosing orthopaedic conditions related to limb position or contracture, which cannot be concluded from the trunk position alone.

Besides, there are additional criteria critically related to the implemetability of the sensor technology. Data privacy is a paramount consideration due to the sensitive nature of sleep data. The protection of privacy and confidentiality of patients with sleep disorders influences the adoption of sensor technology. Usability is another vital factor, affecting user satisfaction and adoption. It encompasses the level of physical intrusiveness of the device and the ease of setup and use. Affordability is a key selection criterion as it determines the accessibility of healthcare devices to a larger portion of the patient population, including low-income individuals and marginalised communities. Lastly, the meaningfulness of quantitative measurements is crucial for developing trust in the sensor technology among healthcare professionals and supporting clinicians in the diagnosis and monitoring of medical conditions.

In light of the aforementioned criteria, several studies have underscored the impracticality of using vision sensors due to the associated privacy concerns and computational challenges (Cabitza et al., 2017) (Z. Chen & Wang, 2021) (S. Liu & Ostadabbas, 2017). Similarly, contactless wireless sensor technologies also score poorly against these criteria as they are generally capable of classifying no more than four standard postures, a limitation primarily attributed to the effective reflectance area of the body (Lai et al., 2023) (Yue et al., 2020). This major limitation hinders the ability to capture slight variations in body posture, such as limb positions. The approach of utilising contact-based bed-embedded sensors is also compromised due to the ambiguity in sleep posture recognition and the indirect means of sensing sleep posture (Tang et al., 2021) (Viriyavit & Sornlertlamvanich, 2020) (Hsiao et al., 2018). It has been observed that similar data patterns can emerge from different positions, and the spatial distribution of body weight can be influenced by variations in body sizes and weights. Additionally, the fabrication and installation of bed-embedded sensors can be costly, and the deployment of these systems in patient homes is challenging.

Among the considered options, wearable inertial sensors perhaps hold the most promise for sleep posture analysis, albeit with some limitations that need to be addressed. These sensors offer several advantages, including the direct measurement of body posture, high resolution and bandwidth, and cost-effectiveness. Wearable inertial sensors are affixed onto body parts, such as limbs, allowing them to capture slight variations in quasistatic sleep posture as well as in-bed dynamic movements. The MEMS technology driving these sensors is well-established, rendering them significantly cost-effective for utilisation in the healthcare sector. Moreover, many lay individuals have grown accustomed to employing wearable devices, making their adoption and operation feasible without the presence of specialist technical staff.

However, there are challenges associated with wearable inertial sensors, such as potential discomfort and physical intrusiveness (Kwasnicki et al., 2018), measurement errors (Qureshi & Golnaraghi, 2017) (Woodman, 2007), sensor misalignment (Fan et al., 2022) (Z. Wang et al., 2017), and soft tissue artefacts (Forner-Cordero et al., 2008) (Leardini et al., 2005). These challenges can affect the comfort of the user, the accuracy of the data, and the performance of the employed algorithms. For example, sensor misalignment, which is the orientation offset between the sensor and the attached body part, can alter the inertial data distribution each time the sensor is worn. Soft tissue artefacts, which arise due to motion, vibration, or deformation of the underlying soft tissues, can cause the sensors to record data that is not reflective of the actual physical movement or posture of the body.

Despite these challenges, wearable inertial sensors present opportunities for improvement and innovation in the development of wearable sleep technology. Their advantageous position compared to other sleep sensor technologies makes them a promising choice for sleep posture monitoring in sleep medicine.

**Algorithmic Trends in Wearable Sensor-based Sleep Posture Analysis**

Sleep posture analysis is procedurally similar to human motion analysis, involving two main research directions: motion quantification and classification. Posture quantification involves measuring and quantifying parameters related to sleep posture, such as joint angles, duration spent in different postures, and in-bed activity level. Understanding these characteristics and patterns can help medical consultants draw important conclusions about the severity of abnormal body movements during sleep (Zampogna et al., 2020). Posture classification involves categorising sleep posture-related parameters into discrete states or classes, such as classifying sleep postures and detecting temporal postural changes. This is particularly useful in studying specific sleep disorders, as it enables clinicians to identify the role of provocative sleep postures and their durations in developing spinal pain (Cary et al., 2021).

Most literature on sleep posture analysis using wearable sensors focuses on classification-based approaches. No prior research has attempted to quantify sleep posture as a continuous variable via wearable sensors, although vision sensors have been employed for this purpose (Achilles et al., 2016). Even in the less common works that involved quantifying parameters like the torso's inclination angle (Ferrer-Lluis et al., 2021a) or extremity joint angles (Elnaggar et al., 2020; Elnaggar, Coenen, et al., 2023), some classification was still necessary to categorise sleep posture.

**Sensor Data Classification Pipeline**

In the context of wearable sensors for sleep posture analysis, the classification of sensor data is a critical task that involves several stages to transform raw sensor data into a trained model that can be used for labelling the data. The classification pipeline typically involves data preprocessing, feature extraction, model selection, model training, model evaluation, and model deployment (Paleyes et al., 2022). Understanding each stage of the classification pipeline is crucial for comprehending and gaining insights into published works on wearable sensor data processing for sleep posture analysis.

**Data Preprocessing:** This stage involves cleaning up the data, handling missing data, converting it to a standard or normalised format, removing outliers, or encoding categorical variables (Abedjan et al., 2016).

**Feature Extraction:** This involves extracting the most relevant features from the preprocessed data, which can then be passed as inputs to a learning algorithm (Bennett et al., 2016). There are four main types of extractable features: time-domain features, frequency-domain features, time-frequency features, and pseudo features (Krishnan & Athavale, 2018) (Bennett et al., 2016).

**Model Selection:** This stage involves selecting the most appropriate machine learning model for the task. There are generally two known pipelines to building a machine learning system: modular learning approach and end-to-end learning approach (Janiesch et al., 2021). There are five common categories of classifiers used in sleep posture analysis: rule-based classifiers, decision tree classifiers, neural network classifiers, nearest neighbour classifiers, and statistical classifiers (Bennett et al., 2016) (Bishop & Nasrabadi, 2006).

**Model Training:** This involves adjusting the internal model parameters so it can more accurately classify the data. The training procedure varies depending on the underlying algorithm and model architecture (Q. Wang et al., 2022) (Bishop & Nasrabadi, 2006).

**Model Evaluation:** This involves assessing the performance of the trained model on a testing dataset to determine how well the model generalises to unseen data (Goodfellow et al., 2016). Several metrics can be used for this purpose, such as accuracy, precision, recall, and F1 score (Mohammad & M.N, 2015).

**Model Deployment:** This involves making the model available for use in production, either through web services, mobile applications or otherwise. In research settings, there is typically less emphasis on this stage, but it is crucial for the usability and scalability of the model in the real world.

**Hierarchical Sensor Information Fusion**

Magneto-inertial sensors provide valuable insights into sleep posture and movements, such as torso tilt angle and in-bed body rollovers, despite their limitations and caveats. To compensate for individual sensor weaknesses, obtain more accurate and reliable measurements, and compute more advanced features, it is common practice to package these sensors together in multi-sensor devices like IMUs and M-IMUs, and perform multi-sensor information fusion (Nakamura et al., 2007). This approach is also extended to the deployment of multiple wearable sensors forming a body sensor network (BSN) that clinicians often welcome, as it enables low-cost and non-invasive monitoring of vital signs and physiology, overcoming many shortcomings of single-sensor systems or systems with multiple standalone sensors (Elnaggar, Coenen, et al., 2023) (Markun & Sampat, 2020) (Gravina et al., 2017).

Sensor data can either be *uni-modal* or *multi-modal*. Uni-modal data refers to data originating from a single type of sensor or data source, whereas multi-modal data refers to data collected from multiple different types of sensors or data sources. Information fusion can occur at different stages of the classification pipeline, namely at the data, feature, or decision levels (Q. Li et al., 2020) (Gravina et al., 2017) (Nakamura et al., 2007).

Data-level fusion strategies combine data from multiple sources at the data level, producing a single stream of data or features for further processing or direct input into the classification model. This can involve concatenating raw or preprocessed sensor data into a single data vector, data compression to speed up transmission and reduce computational burden, or feature extraction techniques based on statistical measures, biomechanical, and behavioural features (Pesenti et al., 2023) (Fallmann et al., 2017) (Kwasnicki et al., 2018) (Chang et al., 2018) (Behar et al., 2015).

Feature-level fusion strategies combine multiple features extracted from one or more data sources at the feature level, producing a new feature set for the classification model. This can involve simple concatenation of extracted features into an extended feature vector, feature selection algorithms to obtain a subset of features that improve classification accuracy, or a two-stage feature extraction process where basic features are used to compute more advanced features (Elnaggar et al., 2020) (Jeon et al., 2019) (Muthukrishnan & Rohini, 2017) (Leone et al., 2023) (Nakazaki et al., 2014).

Decision-level fusion involves selecting or generating a single hypothesis from a set of hypotheses generated by individual decisions from multiple independent sensor data streams or decision-making nodes like classifiers (Bulling et al., 2014). Inference methods, such as Bayesian inference, fuzzy logic, and the mixture of experts framework, are commonly used in decision fusion to draw conclusions from partially abstracted information from preliminary data- or feature-level processing (Kwasnicki et al., 2018) (Reyes-García & Torres-García, 2021) (Elnaggar, Coenen, et al., 2023) (Airaksinen et al., 2020) (Bernal Monroy et al., 2020).

## 4. Monitoring Sleep Postures Using Wearable Sensors

Monitoring sleep postures is fundamental for comprehending the effects of various sleeping postures on overall health and well-being. This is one of the two clinical risk factors underpinning the stable state sleep behaviour. The review presented here provides a thorough examination of the significant works that have aimed to address the challenge of sleep posture monitoring. It covers a broad spectrum of study elements, including the study's objectives, the types of wearable sensors used, their placement on the body, the number of participants, the duration of the sensor data collected, the features extracted from the sensor data, the algorithms used for posture classification, the performance metrics reported, and any notable findings.

The existing literature on sleep posture classification can be organised in several ways. This review categorises the works based on the number of sleep postures considered. Organizing the literature in this fashion aids in clarifying how the complexity of the sleep posture classification problem increases with the number of postures included. Moreover, this categorisation helps in comprehending the effectiveness of algorithms at varying levels of complexity, thereby providing crucial insights into the challenges that need addressing.

### The Standard Four Sleep Postures

The literature predominantly considers four standard sleep postures: supine, prone, and right and left lateral positions. These postures are prevalent in both technical research and clinical studies. The literature on this topic can be classified into three distinct subcategories based on the posture learning methodology underpinning the classification process.

The first subcategory comprises early attempts at classifying sleep postures using either raw or lightly preprocessed sensor data. For instance, (Kishimoto et al., 2006) used a single accelerometer attached to the chest and employed a three-stage classification method, achieving 100% accuracy for all participants. Similarly, (Zhang & Yang, 2015) used a single accelerometer and a Linear Discriminant Analysis (LDA) classifier, achieving 99% posture recognition accuracy.

The second subcategory of studies involves extracting features from the sensor data to describe the patterns. (Sun et al., 2017) used a smartwatch-based system and compared four classifiers, achieving the highest accuracy of 91.8% with the random forest classifier. (Chang et al., 2018) proposed a two-stage approach using actigraphy-based orientation and respiratory information and achieved an average accuracy of 98%. (Jeng et al., 2021) used two accelerometers for intelligent sleep posture monitoring and achieved an accuracy of 72% to 84% using an ensemble of SVM binary classifiers and the random forest classifier. (Jeon et al., 2019) used three wearable sensors and a two-stage dynamic state transition framework, achieving an F1 score of 87% in a pilot experiment but only 79% in a more realistic on-site experiment. (Abdulsadig et al., 2022) used a neck-located accelerometer sensor and two classifiers, achieving 99% accuracy and F1 score with the Extra Trees classifier. (Eyobu et al., 2018) used a single device equipped with an accelerometer and gyroscope and a deep long short-term memory (LSTM) neural network classifier, achieving 99% classification accuracy.

The third subcategory leverages human expert knowledge of sleep posture definitions. Behar et al. (Behar et al., 2015) used a smartphone with a built-in accelerometer, a microphone, and an oximeter to classify users as either *obstructive sleep apnoea* (OSA) patients or non-OSA users. Ferrer- Lluis et al. (Ferrer-Lluis et al., 2021a) used a smartphone accelerometer sensor and an oximeter to explore the relationship between sleep postures and oxygen desaturation events. They found that smartphone vibrations helped participants reduce the average time spent in the supine posture from 45.6% to only 2%. In a separate study, Ferrer- Lluis et al. (Ferrer-Lluis et al., 2021b) used a video-based polysomnography system for ground-truth sleep posture monitoring and achieved an average accuracy of up to 95.9% when compared to reference polysomnography data.

The literature demonstrates the feasibility of learning a few sleep postures using sensor data, extracted features and expert knowledge. Several studies have achieved high classification accuracies using various sensor placements, classifiers, and methodologies. However, some limitations include the lack of interpretability of extracted features in deeper network layers, computationally expensive training, and the requirement of large datasets for reliable performance. Additionally, some studies (Jeng et al., 2021) found that certain postures, such as the prone posture, were harder to correctly classify, and the reliability of some systems remained questionable. Therefore, further research is needed to address these limitations and develop more reliable and efficient systems for sleep posture classification.

**Beyond the Standard Four Sleep Postures**

While most research focuses on the standard four sleep postures—supine, prone, right lateral, and left lateral—some studies have attempted to increase the granularity of sleep posture classification by considering minor variations of the standard postures, such as Fowler's position and torso postures with varying arm and leg positions. This increased granularity has the potential to provide clinicians with more valuable insights into sleep behaviour.

Bernal Monroy et al. (Bernal Monroy et al., 2020) integrated three wearable devices into two socks and a T-shirt to classify six sleep postures and automatically determine the priority of in-bed postural changes to prevent pressure ulcers in care homes. The study employed the k-nearest neighbor, decision tree, and SVM classifiers, with the SVM classifier performing the best during pilot experiments, achieving an average F1 score exceeding 99%.

Fallmann et al. (Fallmann et al., 2017) used three accelerometers attached to the ankles and chest to classify two sets of sleep postures consisting of six and eight postures, respectively. The authors employed a distance-based sleep posture classification algorithm called the generalized matrix learning vector quantization. The personalized classifier achieved an average classification accuracy of 99.8% on the set of eight postures in the pilot study, while the multi-subject classifier achieved 83.6% accuracy. However, fusing variations of the left and right lateral postures improved the multi-subject classifier's performance, resulting in 98.3% accuracy on the reduced set of six postures. In the real sleep study, the multi-subject classifier achieved an average accuracy of 98% for the two participants, while the personalized classifier had a lower accuracy, scoring 58% for one participant.

Kwansicki et al. (Kwasnicki et al., 2018) used three wearable devices equipped with accelerometers, gyroscopes, and magnetometers to monitor sleep posture and quality. The study included two sets of sleep postures: the four standard postures and eight minor variations of the standard postures. The k-nearest neighbor classifier achieved an overall classification accuracy of 99.5% for the set of four postures and 92.5% for the set of eight postures. The lowest participant accuracy was reported to be 84.3%. The study also investigated the estimation of sleep stages based on the activity level present in the actigraphy data. However, the authors identified short battery life and bulky sensor size as limitations of their work.

While the aforementioned studies have achieved remarkable accuracies in sleep posture classification, it is important to note that these results were obtained using a significant amount of training data, which is a practical barrier to the widespread application of wearable sensors for sleep posture monitoring. The requirement for large datasets not only increases the time and cost associated with data collection but also raises privacy concerns. Therefore, there has been a pressing need for novel approaches that can achieve high classification accuracies with a minimal amount of training data.

Recently proposed was a novel approach to augmenting human sleep postures using a one-shot learning method (Elnaggar, Coenen, et al., 2023), which significantly boosted the classification of twelve sleep postures by up to 50% even with single-observations of each posture. The authors utilised four bespoke miniature wearable sensor modules to measure four extremity joints' orientations that formed a unique posture representation that is more comprehensible to non-technical end users, such as clinicians. Additionally, new metric-based and data visualisation approaches were utilised to extract insights on postural analysis, the added value of data augmentation, and the interpretation of the classification performance. The proposed framework attained promising overall accuracy as high as 100% on synthetic data and 92.7% on real data, on par with state-of-the-art data-hungry algorithms available in the literature.

**5. Temporal Analysis of in-Bed Postural Activity Using Wearable Sensors**

The use of wearable sensors for sleep posture analysis offers the potential to understand the relationship between physical sleep behaviour and musculoskeletal health. While in-bed postures themselves do not pose potential risks, it is the extended periods spent in "*provocative postures*" that can exert strain on various body regions and physiological systems, adversely affecting overall well-being. Despite its significance, there has been limited research focused on the estimation of posture-wise durations, necessitating the consideration of related studies on active-idle state classification, sleep-wake state classification, and sleep stage classification. The review herein categorises literature according to the classification approach underpinning the research methodology, rule-based classification, linear regression-based classification, supervised classification, and hybrid approaches.

Rule-based classification approaches involve applying rules or conditions to specific sensor measurements or features. For example, (Sun et al., 2017) reported a rule-based classification approach for respiratory rate estimation using smartwatch actigraphy. Another study investigated sleep stage classification using three accelerometers attached to the wrists and chest (Kwasnicki et al., 2018). However, these approaches have limitations, such as the need for participant-specific calibration and the potential for overestimation of sleep time. Other studies, such as (Borazio et al., 2014) (Chang et al., 2018), adopted two consecutive rules for classification to distinguish between different micromovements, achieving improved classification performance near 80% in accuracy.

Linear regression-based classification methods prominently relied conditioning an extracted feature called the 'activity count' to make classifications. (Palotti et al., 2019) compared several methods within this category in the domain of wake-sleep state classification. Despite achieving a category-wide average F1 score of 80.4%, these methods tended to overestimate the "sleep" state. The use of rescoring rules, as proposed by (Webster et al., 1982), can enhance the specificity and accuracy of the classification.

Supervised classification approaches involved training machine learning models on labeled examples to classify new and unseen data. (Khademi et al., 2019) found that personalized models performed significantly better than generalized models in estimating sleep quality parameters. (Banfi et al., 2021) proposed a lightweight CNN architecture, lightCCNA, which outperformed baseline models with an average F1 score of 90.9%. While deep learning models have relatively higher performance, (Palotti et al., 2019) discouraged augmenting them with rescoring rules as they resulted in decreased accuracy and F1 score.

Hybrid approaches combine rule-based classification and supervised classification and aim at harnessing the interpretability of rule-based classifiers and the predictive power of supervised classifiers. (Domingues et al., 2014) demonstrated the efficacy of an advanced hierarchical synergistic approach in addressing the challenge of overestimating sleep in wake-sleep state classification. The proposed approach achieved an average geometric mean of 78.5% in distinguishing between wake and sleep states, outperforming traditional methods reported in clinical research. (Chang et al., 2018) proposed a hybrid approach for detecting body rollovers, achieving an average accuracy of 92%.  More recently, (Elnaggar, Arelhi, et al., 2023) proposed a novel hybrid framework for the temporal segmentation of sleep posture. The framework combines a Bayesian inference method with a rule-based changepoint detection logic in its decision-making core. The method achieved superior performance compared to other related approached within the literature, yielding consistently over 96% in the correlation between predicted and ground-truth posture durations.

**6. Conclusion**

The role of sleep in musculoskeletal health is an area of critical importance, given the substantial burden that musculoskeletal conditions impose on both individual and societal levels. As the chapter has highlighted, sustained provocative sleep postures can initiate or exacerbate musculoskeletal conditions, contributing to a vicious cycle that also detrimentally impacts sleep hygiene and quality. Although current clinical assessments provide some insight into sleep physiology and its related disorders, they present considerable limitations, particularly in the area of sleep posture analysis. These limitations include being physically intrusive, privacy-invading, and requiring trained personnel, all of which hinder the development of optimal treatments and accurate prognoses. In light of these challenges, the rise of sensor technologies, and particularly wearable devices, presents a promising avenue for automating and democratising sleep posture analysis beyond in-the-clinic environments. The potential of wearable sensors to measure or classify sleep postures has been proven by several groups, but further research and innovation to overcome or work around the difficulty of obtaining training data for sleep postures is required before their wider adoption by the healthcare sector is possible. Overall, the chapter has provided a systematic and critical review of the state-of-the-art in sleep posture sensor technologies and data processing algorithms, arguing that wearable devices are best suited to address the unmet clinical needs identified. Despite the limitations of current sensor technologies, including wearable devices, the chapter has highlighted key limitations that could merit opportunities of future research and development from both sensing and intelligent perception standpoints. These opportunities encompass the need for further research into hierarchical sensor information fusion, among other intelligent perception trends, to enhance the accuracy and usability of sleep posture analysis. Furthermore, the chapter has emphasised the limitations of existing sensor technologies and approaches, and in guiding the development of more effective solutions.

**REFERENCES**

Abdulsadig, R. S., Singh, S., Patel, Z., & Rodriguez-Villegas, E. (2022). Sleep Posture Detection Using an Accelerometer Placed on the Neck. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS* (Vols. 2022-July). https://doi.org/10.1109/EMBC48229.2022.9871300

Abedjan, Z., Chu, X., Deng, D., Fernandez, R. C., Ilyas, I. F., Ouzzani, M., Papotti, P., Stonebraker, M., & Tang, N. (2016). Detecting data errors: Where are we and what needs to be done? In *Proceedings of the VLDB Endowment* (Vol. 9, Issue 12). https://doi.org/10.14778/2994509.2994518

Achilles, F., Ichim, A. E., Coskun, H., Tombari, F., Noachtar, S., & Navab, N. (2016). Patient MoCap: Human pose estimation under blanket occlusion for hospital monitoring applications. In *Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics): Vol. 9900 LNCS.* https://doi.org/10.1007/978-3-319-46720-7_57

Airaksinen, M., Räsänen, O., Ilén, E., Häyrinen, T., Kivi, A., Marchi, V., Gallen, A., Blom, S., Varhe, A., Kaartinen, N., Haataja, L., & Vanhatalo, S. (2020). Automatic Posture and Movement Tracking of Infants with Wearable Movement Sensors. *Scientific Reports*, *10*(169), 1–12. https://doi.org/10.1038/s41598-019-56862-5

Alinia, P., Samadani, A., Milosevic, M., Ghasemzadeh, H., & Parvaneh, S. (2020). Pervasive lying posture tracking. *Sensors (Switzerland)*, *20*(20), 1–22. https://doi.org/10.3390/s20205953

Allen, R., Chen, C., Soaita, A., Wohlberg, C., Knapp, L., Peterson, B. T., García-Borreguero, D., & Miceli, J. (2010). A randomized, double-blind, 6-week, dose-ranging study of pregabalin in patients with restless legs syndrome. *Sleep Medicine*, *11*(6). https://doi.org/10.1016/j.sleep.2010.03.003

Andrews, A. W., & Pine, R. (2019). Physical therapy for nocturnal lower limb cramping: A case report. *Physiotherapy Theory and Practice*, *35*(2). https://doi.org/10.1080/09593985.2018.1441932

Arshad, Z., Aslam, A., Razzaq, M. A., & Bhatia, M. (2022). Gastrocnemius Release in the Management of Chronic Plantar Fasciitis: A Systematic Review. *Foot and Ankle International*, *43*(4). https://doi.org/10.1177/10711007211052290

Ashrafian, H., Toma, T., Rowland, S. P., Harling, L., Tan, A., Efthimiou, E., Darzi, A., & Athanasiou, T. (2015). Bariatric Surgery or Non-Surgical Weight Loss for Obstructive Sleep Apnoea? A Systematic Review and Comparison of Meta-analyses. *Obesity Surgery*, *25*(7). https://doi.org/10.1007/s11695-014-1533-2

Babson, K. A., Feldner, M. T., & Badour, C. L. (2010). Cognitive behavioral therapy for sleep disorders. *Psychiatric Clinics*, *33*(3), 629–640.

Banfi, T., Valigi, N., di Galante, M., d'Ascanio, P., Ciuti, G., & Faraguna, U. (2021). Efficient embedded sleep wake classification for open-source actigraphy. *Scientific Reports*, *11*(345). https://doi.org/10.1038/s41598-020-79294-y

Basner, R. C. (2007). Continuous positive airway pressure for obstructive sleep apnea. *New England Journal of Medicine*, *356*(17), 1751–1758.

Beattie, Z. T., Hagen, C. C., & Hayes, T. L. (2011). Classification of lying position using load cells under the bed. In *Proceedings of the Annual International Conference of the IEEE Engineering in Medicine and Biology Society, EMBS.* https://doi.org/10.1109/IEMBS.2011.6090068

Behar, J., Roebuck, A., Shahid, M., Daly, J., Hallack, A., Palmius, N., Stradling, J., & Clifford, G. D. (2015). SleepAp: An automated obstructive sleep apnoea screening application for smartphones. *IEEE Journal of Biomedical and Health Informatics*, *19*(1). https://doi.org/10.1109/JBHI.2014.2307913

Bennett, T. R., Wu, J., Kehtarnavaz, N., & Jafari, R. (2016). Inertial measurement unit-based wearable computers for assisted living applications: A signal processing perspective. *IEEE Signal Processing Magazine*, *33*(2). https://doi.org/10.1109/MSP.2015.2499314

Bergmann, M., Stefani, A., Brandauer, E., Holzknecht, E., Hackner, H., & Högl, B. (2019). Hypnagogic Foot Tremor, Alternating Leg Muscle Activation or High Frequency Leg Movements: clinical and phenomenological considerations in two cousins. *Sleep Medicine*, *54*. https://doi.org/10.1016/j.sleep.2018.10.024

Bernal Monroy, E., Polo Rodríguez, A., Espinilla Estevez, M., & Medina Quero, J. (2020). Fuzzy monitoring of in-bed postural changes for the prevention of pressure ulcers using inertial sensors attached to clothing. *Journal of Biomedical Informatics*, *107*(103476), 1–12. https://doi.org/10.1016/j.jbi.2020.103476

Bevan, S. (2015). Economic impact of musculoskeletal disorders (MSDs) on work in Europe. *Best Practice and Research: Clinical Rheumatology*, *29*(3). https://doi.org/10.1016/j.berh.2015.08.002

Bidarian-Moniri, A., Nilsson, M., Rasmusson, L., Attia, J., & Ejnell, H. (2015). The effect of the prone sleeping position on obstructive sleep apnoea. *Acta Oto-Laryngologica*, *135*(1). https://doi.org/10.3109/00016489.2014.962183

Bilston, L. E., & Gandevia, S. C. (2014). Biomechanical properties of the human upper airway and their effect on its behavior during breathing and in obstructive sleep apnea. *Journal of Applied Physiology*, *116*(3). https://doi.org/10.1152/japplphysiol.00539.2013

Bishop, C. M., & Nasrabadi, N. M. (2006). *Pattern recognition and machine learning* (Vol. 4, Issue 4). Springer.

Bonafide, C. P., Jamison, D. T., & Foglia, E. E. (2017). The emerging market of smartphone-integrated infant physiologic monitors. *Jama*, *317*(4), 353–354.

Borazio, M., Berlin, E., Kucukyildiz, N., Scholl, P., & Van Laerhoven, K. (2014). Towards benchmarked sleep detection with wrist-worn sensing units. In *Proceedings - 2014 IEEE International Conference on Healthcare Informatics, ICHI 2014* (pp. 125–134). https://doi.org/10.1109/ICHI.2014.24

Boyne, K., Sherry, D. D., Gallagher, P. R., Olsen, M., & Brooks, L. J. (2013). Accuracy of computer algorithms and the human eye in scoring actigraphy. *Sleep and Breathing*, *17*(1). https://doi.org/10.1007/s11325-012-0709-z

Bulling, A., Blanke, U., & Schiele, B. (2014). A tutorial on human activity recognition using body-worn inertial sensors. *ACM Computing Surveys*, *46*(3). https://doi.org/10.1145/2499621

Cabitza, F., Rasoini, R., & Gensini, G. F. (2017). Unintended consequences of machine learning in medicine. *JAMA - Journal of the American Medical Association*, *318*(6). https://doi.org/10.1001/jama.2017.7797

Carney, C. E., Buysse, D. J., Ancoli-Israel, S., Edinger, J. D., Krystal, A. D., Lichstein, K. L., & Morin, C. M. (2012). The consensus sleep diary: Standardizing prospective sleep self-monitoring. *Sleep*, *35*(2). https://doi.org/10.5665/sleep.1642

Cary, D., Briffa, K., & McKenna, L. (2019). Identifying relationships between sleep posture and non-specific spinal symptoms in adults: A scoping review. *BMJ Open*, *9*(6), 1–10. https://doi.org/10.1136/bmjopen-2018-027633

Cary, D., Jacques, A., & Briffa, K. (2021). Examining relationships between sleep posture, waking spinal symptoms and quality of sleep: A cross sectional study. *PLoS ONE*, *16*(11). https://doi.org/10.1371/journal.pone.0260582

Chang, L., Lu, J., Wang, J., Chen, X., Fang, D., Tang, Z., Nurmi, P., & Wang, Z. (2018). SLEEPGUARD: Capturing Rich Sleep Information using Smartwatch Sensing Data. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *2*(3), 1–34. https://doi.org/10.1145/3264908

Chao, Y., Liu, T., & Shen, L.-M. (2023). Method of recognizing sleep postures based on air pressure sensor and convolutional neural network: For an air spring mattress. *Engineering Applications of Artificial Intelligence*, *121*, 106009–106009. https://doi.org/10.1016/j.engappai.2023.106009

Chen, P.-J., Hu, T.-H., & Wang, M.-S. (2022). Raspberry Pi-Based Sleep Posture Recognition System Using AIoT Technique. *Healthcare*, *10*(3). https://doi.org/10.3390/healthcare10030513

Chen, W. C., Lee, L. A., Chen, N. H., Fang, T. J., Huang, C. G., Cheng, W. N., & Li, H. Y. (2015). Treatment of snoring with positional therapy in patients with positional obstructive sleep apnea syndrome. *Scientific Reports*, *5*. https://doi.org/10.1038/srep18188

Chen, Z., & Wang, Y. (2021). Remote Recognition of In-Bed Postures Using a Thermopile Array Sensor with Machine Learning. *IEEE Sensors Journal*, *21*(9). https://doi.org/10.1109/JSEN.2021.3059681

Dahl, R. E., & Lewin, D. S. (2002). Pathways to adolescent health: Sleep regulation and behavior. *Journal of Adolescent Health*, *31*(6 SUPPL.). https://doi.org/10.1016/S1054-139X(02)00506-2

Dijkers, M. (2013). Introducing GRADE: a systematic approach to rating evidence in systematic reviews and to guideline development. *E-Newsletter: Center on Knowledge Translation for Disability and Rehabilitation Research*, *1*(5).

Domingues, A., Paiva, T., & Sanches, J. M. (2014). Sleep and wakefulness state detection in nocturnal actigraphy based on movement information. *IEEE Transactions on Biomedical Engineering*, *61*(2), 426–434. https://doi.org/10.1109/TBME.2013.2280538

Eadie, J., Van De Water, A. T., Lonsdale, C., Tully, M. A., Van Mechelen, W., Boreham, C. A., Daly, L., McDonough, S. M., & Hurley, D. A. (2013). Physiotherapy for sleep disturbance in people with chronic low back pain: Results of a feasibility randomized controlled trial. *Archives of Physical Medicine and Rehabilitation*, *94*(11). https://doi.org/10.1016/j.apmr.2013.04.017

Elnaggar, O., Arelhi, R., Coenen, F., Hopkinson, A., Mason, L., & Paoletti, P. (2023). *arXiv Preprint arXiv:2301.03469*.

Elnaggar, O., Coenen, F., Hopkinson, A., Mason, L., & Paoletti, P. (2023). *Information Fusion*, *95*, 215–236. https://doi.org/10.1016/j.inffus.2023.02.003

Elnaggar, O., Coenen, F., & Paoletti, P. (2020). *In-Bed Human Pose Classification Using Sparse Inertial Signals* (pp. 331–344). Springer International Publishing.

El-Sheimy, N., & Youssef, A. (2020). Inertial sensors technologies for navigation applications: state of the art and future trends. *Satellite Navigation*, *1*(1), 2–2. https://doi.org/10.1186/s43020-019-0001-5

Eyobu, O. S., Kim, Y. W., Cha, D., & Han, D. S. (2018). A real-time sleeping position recognition system using IMU sensor motion data. In *IEEE International Conference on Consumer Electronics (ICCE)* (Vols. 2018-Janua, pp. 1–2). https://doi.org/10.1109/ICCE.2018.8326209

Fadhel, F. H. (2020). Exploring the relationship of sleep quality with drug use and substance abuse among university students: a cross-cultural study. *Middle East Current Psychiatry*, *27*(1). https://doi.org/10.1186/s43045-020-00072-7

Fallmann, S., & Chen, L. (2019). Computational sleep behavior analysis: A survey. *IEEE Access*, *7*, 142421–142440. https://doi.org/10.1109/ACCESS.2019.2944801

Fallmann, S., Van Veen, R., Chen, L., Walker, D., Chen, F., & Pan, C. (2017). Wearable accelerometer based extended sleep position recognition. In *IEEE 19th International Conference on e-Health Networking, Applications and Services (Healthcom)* (pp. 1–6). https://doi.org/10.1109/HealthCom.2017.8210806

Fan, B., Li, Q., Tan, T., Kang, P., & Shull, P. B. (2022). Effects of IMU Sensor-to-Segment Misalignment and Orientation Error on 3-D Knee Joint Angle Estimation. *IEEE Sensors Journal*, *22*(3), 2543–2552. https://doi.org/10.1109/JSEN.2021.3137305

Ferrer-Lluis, I., Castillo-Escario, Y., Montserrat, J. M., & Jané, R. (2021a). Enhanced monitoring of sleep position in sleep apnea patients: Smartphone triaxial accelerometry compared with video-validated position from polysomnography. *Sensors*, *21*(11). https://doi.org/10.3390/s21113689

Ferrer-Lluis, I., Castillo-Escario, Y., Montserrat, J. M., & Jané, R. (2021b). Sleeppos app: An automated smartphone application for angle based high resolution sleep position monitoring and treatment. *Sensors*, *21*(13). https://doi.org/10.3390/s21134531

Forner-Cordero, A., Mateu-Arce, M., Forner-Cordero, I., Alcántara, E., Moreno, J. C., & Pons, J. L. (2008). Study of the motion artefacts of skin-mounted inertial sensors under different attachment conditions. *Physiological Measurement*, *29*(4). https://doi.org/10.1088/0967-3334/29/4/N01

Goodfellow, I., Bengio, Y., & Courville, A. (2016). *Deep Learning*. MIT Press.

Gordon, S., Grimmer, K., & Trott, P. (2004). Self-Reported Versus Recorded Sleep Position: An Observational Study. *Internet Journal of Allied Health Sciences and Practice*. https://doi.org/10.46743/1540-580x/2004.1034

Gravina, R., Alinia, P., Ghasemzadeh, H., & Fortino, G. (2017). Multi-sensor fusion in body sensor networks: State-of-the-art and research challenges. *Information Fusion*, *35*, 68–80. https://doi.org/10.1016/j.inffus.2016.09.005

Haex, B. (2004). Bed and Back: Ergonomic Aspects of Sleeping. In *Back and Bed: Ergonomic Aspects of Sleeping* (Vol. 1, Issue 1).

Hirshkowitz, M., Whiton, K., Albert, S. M., Alessi, C., Bruni, O., DonCarlos, L., Hazen, N., Herman, J., Adams Hillard, P. J., Katz, E. S., Kheirandish-Gozal, L., Neubauer, D. N., O'Donnell, A. E., Ohayon, M., Peever, J., Rawding, R., Sachdeva, R. C., Setters, B., Vitiello, M. V., & Ware, J. C. (2015). National Sleep Foundation's updated sleep duration recommendations: Final report. *Sleep Health*, *1*(4). https://doi.org/10.1016/j.sleh.2015.10.004

Holmes, J. (2002). All you need is cognitive behaviour therapy? *British Medical Journal*, *324*(7332). https://doi.org/10.1136/bmj.324.7352.1522

Hoque, E., Dickerson, R. F., & Stankovic, J. A. (2010). Monitoring Body Positions and Movements during Sleep Using WISPs. In *Wireless Health 2010* (pp. 44–53). Association for Computing Machinery. https://doi.org/10.1145/1921081.1921088

Hossain, J. L., & Shapiro, C. M. (2002). The prevalence, cost implications, and management of sleep disorders: An overview. *Sleep and Breathing*, *6*(2). https://doi.org/10.1007/s11325-002-0085-1

Hoxha, O., Jairam, T., Kendzerska, T., Rajendram, P., Zhou, R., Ravindran, P., Osman, S., Banayoty, M., Qian, Y., Murray, B. J., & Boulos, M. I. (2022). Association of Periodic Limb Movements With Medication Classes. *Neurology*, *98*(15), e1585–e1585. https://doi.org/10.1212/WNL.0000000000200012

Hsiao, R. S., Chen, T. X., Bitew, M. A., Kao, C. H., & Li, T. Y. (2018). Sleeping posture recognition using fuzzy c-means algorithm. *BioMedical Engineering Online*, *17*. https://doi.org/10.1186/s12938-018-0584-3

Hu, Q., Tang, X., & Tang, W. (2021). A Real-Time Patient-Specific Sleeping Posture Recognition System Using Pressure Sensitive Conductive Sheet and Transfer Learning. *IEEE Sensors Journal*, *21*(5). https://doi.org/10.1109/JSEN.2020.3043416

Hu, X., Naya, K., Li, P., Miyazaki, T., Wang, K., & Sun, Y. (2018). Non-Invasive Sleeping Posture Recognition and Body Movement Detection Based on RFID. In *2018 IEEE International Conference on Internet of Things (iThings) and IEEE Green Computing and Communications (GreenCom) and IEEE Cyber, Physical and Social Computing (CPSCom) and IEEE Smart Data (SmartData)* (pp. 1817–1820). https://doi.org/10.1109/Cybermatics_2018.2018.00302

Ibáñez, V., Silva, J., & Cauli, O. (2018a). A survey on sleep assessment methods. *PeerJ*, *2018*(5). https://doi.org/10.7717/peerj.4849

Ibáñez, V., Silva, J., & Cauli, O. (2018b). A survey on sleep questionnaires and diaries. *Sleep Medicine*, *42*, 90–96. https://doi.org/10.1016/j.sleep.2017.08.026

Ipsiroglu, O. S., Hung, Y. H. A., Chan, F., Ross, M. L., Veer, D., Soo, S., Ho, G., Berger, M., McAllister, G., Garn, H., Kloesch, G., Barbosa, A. V., Stockler, S., McKellin, W., & Vatikiotis-Bateson, E. (2015). Diagnosis by behavioral observation" home-videosomnography - a rigorous ethnographic approach to sleep of children with neurodevelopmental conditions. *Frontiers in Psychiatry*, *6*(MAR). https://doi.org/10.3389/fpsyt.2015.00039

Janiesch, C., Zschech, P., & Heinrich, K. (2021). Machine learning and deep learning. *Electronic Markets*, *31*(3). https://doi.org/10.1007/s12525-021-00475-2

Jaul, E. (2010). Assessment and management of pressure ulcers in the elderly. *Drugs & Aging*, *27*(4), 311–325.

Jeng, P.-Y., Wang, L.-C., Hu, C.-J., & Wu, D. (2021). A Wrist Sensor Sleep Posture Monitoring System: An Automatic Labeling Approach. *Sensors*, *21*(1). https://doi.org/10.3390/s21010258

Jeon, S., Park, T., Paul, A., Lee, Y. S., & Son, S. H. (2019). A wearable sleep position tracking system based on dynamic state transition framework. *IEEE Access*, *7*, 135742–135756. https://doi.org/10.1109/ACCESS.2019.2942608

Jussi, C., Davidson, P., Martti, K.-J., & Helena, L. (2019). Inertial Sensors and Their Applications. In *Handbook of Signal Processing Systems* (pp. 51–85). Springer International Publishing. https://doi.org/10.1007/978-3-319-91734-4_2

Karna, B., Sankari, A., & Tatikonda, G. (2022). Sleep Disorder. In *StatPearls [Internet]*. Treasure Island (FL): StatPearls Publishing. https://www.ncbi.nlm.nih.gov/books/NBK560720/

Khademi, A., El-Manzalawy, Y., Master, L., Buxton, O. M., & Honavar, V. G. (2019). Personalized sleep parameters estimation from actigraphy: A machine learning approach. *Nature and Science of Sleep*, *11*. https://doi.org/10.2147/NSS.S220716

Khare, S., & Chawala, A. (2016). Effect of change in body position on resting electrocardiogram in young healthy adults. *Nigerian Journal of Cardiology*, *13*(2). https://doi.org/10.4103/0189-7969.187711

Kishimoto, Y., Akahori, A., & Oguri, K. (2006). Estimation of sleeping posture for M-Health by a wearable tri-axis accelerometer. In *Proceedings of the 3rd IEEE-EMBS International Summer School and Symposium on Medical Devices and Biosensors, ISSS-MDBS 2006* (pp. 45–48). https://doi.org/10.1109/ISSMDBS.2006.360093

Krishnan, S., & Athavale, Y. (2018). Trends in biomedical signal feature extraction. In *Biomedical Signal Processing and Control* (Vol. 43). https://doi.org/10.1016/j.bspc.2018.02.008

Kuo, C. E., Liu, Y. C., Chang, D. W., Young, C. P., Shaw, F. Z., & Liang, S. F. (2017). Development and Evaluation of a Wearable Device for Sleep Quality Assessment. *IEEE Transactions on Biomedical Engineering*, *64*(7). https://doi.org/10.1109/TBME.2016.2612938

Kwasnicki, R. M., Cross, G. W. V., Geoghegan, L., Zhang, Z., Reilly, P., Darzi, A., Yang, G. Z., & Emery, R. (2018). A lightweight sensing platform for monitoring sleep quality and posture: A simulated validation study. *European Journal of Medical Research*, *23*(28), 1–9. https://doi.org/10.1186/s40001-018-0326-9

Lai, D. K.-H., Zha, L.-W., Leung, T. Y.-N., Tam, A. Y.-C., So, B. P.-H., Lim, H.-J., Cheung, D. S. K., Wong, D. W.-C., & Cheung, J. C.-W. (2023). Dual ultra-wideband (UWB) radar-based sleep posture recognition system: Towards ubiquitous sleep monitoring. *Engineered Regeneration*, *4*(1), 36–43. https://doi.org/10.1016/j.engreg.2022.11.003

Leardini, A., Chiari, A., Della Croce, U., & Cappozzo, A. (2005). Human movement analysis using stereophotogrammetry Part 3. Soft tissue artifact assessment and compensation. *Gait and Posture*, *21*(2), 212–225. https://doi.org/10.1016/j.gaitpost.2004.05.002

Lee, W. H., & Ko, M. S. (2017). Effect of sleep posture on neck muscle activity. *Journal of Physical Therapy Science*, *29*(6). https://doi.org/10.1589/jpts.29.1021

Leone, A., Rescio, G., Caroppo, A., Siciliano, P., & Manni, A. (2023). Human Postures Recognition by Accelerometer Sensor and ML Architecture Integrated in Embedded Platforms: Benchmarking and Performance Evaluation. *Sensors*, *23*(2). https://doi.org/10.3390/s23021039

Li, Q., Gravina, R., Li, Y., Alsamhi, S. H., Sun, F., & Fortino, G. (2020). Multi-user activity recognition: Challenges and opportunities. *Information Fusion*, *63*, 121–135. https://doi.org/10.1016/j.inffus.2020.06.004

Li, X., Gong, Y., Jin, X., & Shang, P. (2023). Sleep posture recognition based on machine learning: A systematic review. *Pervasive and Mobile Computing*, *90*(101752). https://doi.org/10.1016/j.pmcj.2023.101752

Lima, W. S., Souto, E., El-Khatib, K., Jalali, R., & Gama, J. (2019). Human activity recognition using inertial sensors in a smartphone: An overview. *Sensors (Switzerland)*, *19*(14). https://doi.org/10.3390/s19143213

Liu, J., Chen, Y., Wang, Y., Chen, X., Cheng, J., & Yang, J. (2018). Monitoring Vital Signs and Postures During Sleep Using WiFi Signals. *IEEE Internet of Things Journal*, *5*(3), 2071–2084. https://doi.org/10.1109/JIOT.2018.2822818

Liu, M., & Ye, S. (2018). A Novel Body Posture Recognition System on Bed. In *2018 IEEE 3rd International Conference on Signal and Image Processing (ICSIP)* (pp. 38–42). https://doi.org/10.1109/SIPROCESS.2018.8600465

Liu, S., & Ostadabbas, S. (2017). A Vision-Based System for In-Bed Posture Tracking. In *Proceedings - 2017 IEEE International Conference on Computer Vision Workshops, ICCVW 2017* (Vols. 2018-Janua). https://doi.org/10.1109/ICCVW.2017.163

Liu, S., Yin, Y., & Ostadabbas, S. (2019). In-Bed Pose Estimation: Deep Learning with Shallow Dataset. *IEEE Journal of Translational Engineering in Health and Medicine*, *7*. https://doi.org/10.1109/JTEHM.2019.2892970

Lopez-Nava, I. H., & Angelica, M. M. (2016). Wearable Inertial Sensors for Human Motion Analysis: A review. *IEEE Sensors Journal*, *16*(22), 7821–7834. https://doi.org/10.1109/JSEN.2016.2609392

Mahowald, M. W., & Schenck, C. H. (2005). Insights from studying human sleep disorders. *Nature*, *437*(7063). https://doi.org/10.1038/nature04287

Markun, L. C., & Sampat, A. (2020). Clinician-Focused Overview and Developments in Polysomnography. *Current Sleep Medicine Reports*, *6*(4), 309–321. https://doi.org/10.1007/s40675-020-00197-5

Mendonça, F., Mostafa, S. S., Morgado-Dias, F., Ravelo-Garcia, A. G., & Penzel, T. (2019). A Review of Approaches for Sleep Quality Analysis. *IEEE Access*, *7*, 24527–24546. https://doi.org/10.1109/ACCESS.2019.2900345

Menon, A., & Kumar, M. (2013). Influence of Body Position on Severity of Obstructive Sleep Apnea: A Systematic Review. *ISRN Otolaryngology*, *2013*. https://doi.org/10.1155/2013/670381

Miller, D. J., Lastella, M., Scanlan, A. T., Bellenger, C., Halson, S. L., Roach, G. D., & Sargent, C. (2020). A validation study of the WHOOP strap against polysomnography to assess sleep. *Journal of Sports Sciences*, *38*(22). https://doi.org/10.1080/02640414.2020.1797448

Miller, W. R., Lasiter, S., Ellis, R. B., & Buelow, J. M. (2015). Chronic disease self-management: a hybrid concept analysis. *Nursing Outlook*, *63*(2), 154–161.

Mohammad, H., & M.N, S. (2015). A Review on Evaluation Metrics for Data Classification Evaluations. *International Journal of Data Mining & Knowledge Management Process*, *5*(2). https://doi.org/10.5121/ijdkp.2015.5201

Muthukrishnan, R., & Rohini, R. (2017). LASSO: A feature selection technique in predictive modeling for machine learning. In *2016 IEEE International Conference on Advances in Computer Applications, ICACA 2016*. https://doi.org/10.1109/ICACA.2016.7887916

Nakamura, E. F., Loureiro, A. A. F., & Frery, A. C. (2007). Information fusion for wireless sensor networks: Methods, models, and classifications. *ACM Computing Surveys*, *39*(3). https://doi.org/10.1145/1267070.1267073

Nakazaki, K., Kitamura, S., Motomura, Y., Hida, A., Kamei, Y., Miura, N., & Mishima, K. (2014). Validity of an algorithm for determining sleep/wake states using a new actigraph. *Journal of Physiological Anthropology*, *33*(31). https://doi.org/10.1186/1880-6805-33-31

Natale, V., Plazzi, G., & Martoni, M. (2009). Actigraphy in the assessment of insomnia: A quantitative approach. *Sleep*, *32*(6). https://doi.org/10.1093/sleep/32.6.767

Paleyes, A., Urma, R. G., & Lawrence, N. D. (2022). Challenges in Deploying Machine Learning: A Survey of Case Studies. *ACM Computing Surveys*, *55*(6). https://doi.org/10.1145/3533378

Palotti, J., Mall, R., Aupetit, M., Rueschman, M., Singh, M., Sathyanarayana, A., Taheri, S., & Fernandez-Luque, L. (2019). Benchmark on a large cohort for sleep-wake classification with machine learning techniques. *Npj Digital Medicine*, *2*(50). https://doi.org/10.1038/s41746-019-0126-9

Parisi, L., Pierelli, F., Amabile, G., Valente, G., Calandriello, E., Fattapposta, F., Rossi, P., & Serrao, M. (2003). Muscular cramps: Proposals for a new classification. *Acta Neurologica Scandinavica*, *107*(3), 176–186. https://doi.org/10.1034/j.1600-0404.2003.01289.x

Park, C., Noh, S. D., & Srivastava, A. (2022). Data Science for Motion and Time Analysis with Modern Motion Sensor Data. *Operations Research*, *70*(6). https://doi.org/10.1287/opre.2021.2216

Paz, J. C., & West, M. P. (2013). Acute Care Handbook for Physical Therapists: Fourth Edition. In *Acute Care Handbook for Physical Therapists: Fourth Edition*. https://doi.org/10.1016/C2011-0-05707-1

Peng, S., Li, Y., Cui, R., Xu, K., Wu, Y., Huang, M., Dai, C., Tamur, T., Mukhopadhyay, S., Chen, C., & Chen, W. (2022). Sleep postures monitoring based on capacitively coupled electrodes and deep recurrent neural networks. *BioMedical Engineering OnLine*, *21*(1), 75–75. https://doi.org/10.1186/s12938-022-01031-5

Pesenti, M., Invernizzi, G., Mazzella, J., Bocciolone, M., Pedrocchi, A., & Gandolla, M. (2023). IMU-based human activity recognition and payload classification for low-back exoskeletons. *Scientific Reports*, *13*(1). https://doi.org/10.1038/s41598-023-28195-x

Pigeon, W. R., & Yurcheshen, M. (2009). Behavioral Sleep Medicine Interventions for Restless Legs Syndrome and Periodic Limb Movement Disorder. *Sleep Medicine Clinics*, *4*(4). https://doi.org/10.1016/j.jsmc.2009.07.008

Piwek, L., Ellis, D. A., Andrews, S., & Joinson, A. (2016). The Rise of Consumer Health Wearables: Promises and Barriers. *PLoS Medicine*, *13*(2). https://doi.org/10.1371/journal.pmed.1001953

Potter, G. D. M., Skene, D. J., Arendt, J., Cade, J. E., Grant, P. J., & Hardie, L. J. (2016). Circadian rhythm and sleep disruption: Causes, metabolic consequences, and countermeasures. *Endocrine Reviews*, *37*(6). https://doi.org/10.1210/er.2016-1083

Qureshi, U., & Golnaraghi, F. (2017). An Algorithm for the In-Field Calibration of a MEMS IMU. *IEEE Sensors Journal*, *17*(22), 7479–7486. https://doi.org/10.1109/JSEN.2017.2751572

Ramanujam, E., Perumal, T., & Padmavathi, S. (2021). Human Activity Recognition with Smartphone and Wearable Sensors Using Deep Learning Techniques: A Review. *IEEE Sensors Journal*, *21*(12). https://doi.org/10.1109/JSEN.2021.3069927

Razjouyan, J., Lee, H., Parthasarathy, S., Mohler, J., Sharafkhaneh, A., & Najafi, B. (2017). Improving Sleep Quality Assessment Using Wearable Sensors by Including Information From Postural/Sleep Position Changes and Body Acceleration: A Comparison of Chest-Worn Sensors, Wrist Actigraphy, and Polysomnography. *Journal of Clinical Sleep Medicine*, *13*(11). https://doi.org/10.5664/jcsm.6802

Ren, W., Ma, O., Ji, H., & Liu, X. (2020). Human Posture Recognition Using a Hybrid of Fuzzy Logic and Machine Learning Approaches. *IEEE Access*, *8*. https://doi.org/10.1109/ACCESS.2020.3011697

Reyes-García, C. A., & Torres-García, A. A. (2021). Fuzzy logic and fuzzy systems. In *Biosignal Processing and Classification Using Computational Learning and Intelligence: Principles, Algorithms, and Applications*. https://doi.org/10.1016/B978-0-12-820125-1.00020-8

Riha, & L., R. (2015). Diagnostic approaches to respiratory sleep disorders. *Journal of Thoracic Disease*, *7*(8).

Rosenfeld, S. B., Schroeder, K., & Watkins-Castillo, S. I. (2018). The Economic Burden of Musculoskeletal Disease in Children and Adolescents in the United States. *Journal of Pediatric Orthopaedics*, *38*(4). https://doi.org/10.1097/BPO.0000000000001131

Sadeh, A. (2015). III. SLEEP ASSESSMENT METHODS. *Monographs of the Society for Research in Child Development*, *80*(1), 33–48. https://doi.org/10.1111/mono.12143

Sadeh, A. (2011). The role and validity of actigraphy in sleep medicine: An update. *Sleep Medicine Reviews*, *15*(4). https://doi.org/10.1016/j.smrv.2010.10.001

Sateia, M. J. (2014). International classification of sleep disorders-third edition highlights and modifications. *Chest*, *146*(5). https://doi.org/10.1378/chest.14-0970

Schwichtenberg, A. J., Choe, J., Kellerman, A., Abel, E. A., & Delp, E. J. (2018). Pediatric videosomnography: Can signal/video processing distinguish sleep and wake states? *Frontiers in Pediatrics*, *6*. https://doi.org/10.3389/fped.2018.00158

Sitar, E. M., & Sur, S. (2023). A Millimeter-Wave Wireless Sensing Approach for Sleep Posture Classification. In *Proceedings of the 20th ACM Conference on Embedded Networked Sensor Systems* (pp. 794–796). Association for Computing Machinery. https://doi.org/10.1145/3560905.3568088

Sletten, T. L., Rajaratnam, S. M. W., Wright, M. J., Zhu, G., Naismith, S., Martin, N. G., & Hickie, I. (2013). Genetic and environmental contributions to sleep-wake behavior in 12-year-old twins. *Sleep*, *36*(11). https://doi.org/10.5665/sleep.3136

Smith, M. T., McCrae, C. S., Cheung, J., Martin, J. L., Harrod, C. G., Heald, J. L., & Carden, K. A. (2018). Use of Actigraphy for the Evaluation of Sleep Disorders and Circadian Rhythm Sleep-Wake Disorders: An American Academy of Sleep Medicine Clinical Practice Guideline. *Journal of Clinical Sleep Medicine*, *14*(7). https://doi.org/10.5664/jcsm.7230

Sönmez, A., & Aksoy Derya, Y. (2018). Effects of sleep hygiene training given to pregnant women with restless leg syndrome on their sleep quality. *Sleep and Breathing*, *22*(2), 527–535. https://doi.org/10.1007/s11325-018-1619-5

Stepanski, E. J., & Wyatt, J. K. (2003). Use of sleep hygiene in the treatment of insomnia. *Sleep Medicine Reviews*, *7*(3). https://doi.org/10.1053/smrv.2001.0246

Sun, X., Qiu, L., Wu, Y., Tang, Y., & Cao, G. (2017). SleepMonitor: Monitoring Respiratory Rate and Body Position During Sleep Using Smartwatch. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, *1*(3), 1–22. https://doi.org/10.1145/3130969

Suzuki, K., Miyamoto, M., & Hirata, K. (2017). Sleep disorders in the elderly: Diagnosis and management. *Journal of General and Family Medicine*, *18*(2). https://doi.org/10.1002/jgf2.27

Tam, A. Y. C., So, B. P. H., Chan, T. T. C., Cheung, A. K. Y., Wong, D. W. C., & Cheung, J. C. W. (2021). A blanket accommodative sleep posture classification system using an infrared depth camera: A deep learning approach with synthetic augmentation of blanket conditions. *Sensors*, *21*(16). https://doi.org/10.3390/s21165553

Tang, K., Kumar, A., Nadeem, M., & Maaz, I. (2021). CNN-Based Smart Sleep Posture Recognition System. *IoT*, *2*(1). https://doi.org/10.3390/iot2010007

Tiotiu, A., Mairesse, O., Hoffmann, G., Todea, D., & Noseda, A. (2011). Body position and breathing abnormalities during sleep: A systematic study. *Pneumologia*, *60*(4), 216–221. https://europepmc.org/article/med/22420172

Tramontano, M., De Angelis, S., Galeoto, G., Cucinotta, M. C., Lisi, D., Botta, R. M., D'ippolito, M., Morone, G., & Buzzi, M. G. (2021). Physical therapy exercises for sleep disorders in a rehabilitation setting for neurological patients: A systematic review and meta-analysis. *Brain Sciences*, *11*(9). https://doi.org/10.3390/brainsci11091176

Tripathi, M. (2008). Technical notes for digital polysomnography recording in sleep medicine practice. *Annals of Indian Academy of Neurology*, *11*(2). https://doi.org/10.4103/0972-2327.41887

Van Maanen, J. P., & De Vries, N. (2014). Long-term effectiveness and compliance of positional therapy with the sleep position trainer in the treatment of positional obstructive sleep apnea syndrome. *Sleep*, *37*(7). https://doi.org/10.5665/sleep.3840

Vaughn, B. V., Avidan, A. Y., & Eichler, A. F. (2018). Approach to abnormal movements and behaviors during sleep. *UpToDate. Updated June 6*.

Viriyavit, W., & Sornlertlamvanich, V. (2020). Bed Position Classification by a Neural Network and Bayesian Network Using Noninvasive Sensors for Fall Prevention. *Journal of Sensors*, *2020*. https://doi.org/10.1155/2020/5689860

Vyazovskiy, V. V. (2015). Sleep, recovery, and metaregulation: Explaining the benefits of sleep. In *Nature and Science of Sleep* (Vol. 7). https://doi.org/10.2147/NSS.S54036

Wang, Q., Ma, Y., Zhao, K., & Tian, Y. (2022). A Comprehensive Survey of Loss Functions in Machine Learning. *Annals of Data Science*, *9*(2). https://doi.org/10.1007/s40745-020-00253-5

Wang, Z., Wu, D., Gravina, R., Fortino, G., Jiang, Y., & Tang, K. (2017). Kernel fusion based extreme learning machine for cross-location activity recognition. *Information Fusion*, *37*, 1–9. https://doi.org/10.1016/j.inffus.2017.01.004

Webster, J. B., Kripke, D. F., Messin, S., Mullaney, D. J., & Wyborney, G. (1982). An activity-based sleep monitor system for ambulatory use. *Sleep*, *5*(4), 389–399. https://doi.org/10.1093/sleep/5.4.389

Werner, E. E., & Smith, R. S. (1992). Overcoming the odds: High risk children from birth to adulthood. *Overcoming the Odds: High Risk Children from Birth to Adulthood*.

Wong, G., Gabison, S., Dolatabadi, E., Evans, G., Kajaks, T., Holliday, P., Alshaer, H., Fernie, G., & Dutta, T. (2020). Toward mitigating pressure injuries: Detecting patient orientation from vertical bed reaction forces. *Journal of Rehabilitation and Assistive Technologies Engineering*, *7*. https://doi.org/10.1177/2055668320912168

Woodman, O. J. (2007). An Introduction to Inertial Navigation (Report No. UCAM-CL-TR-696). In *University of Cambridge*. https://www.cl.cam.ac.uk/techreports/UCAM-CL-TR-696.pdf

Yue, S., Yang, Y., Wang, H., Rahul, H., & Katabi, D. (2020). BodyCompass: Monitoring Sleep Posture with Wireless Signals. *Proc. ACM Interact. Mob. Wearable Ubiquitous Technol.*, *4*(2). https://doi.org/10.1145/3397311

Zampogna, A., Manoni, A., Asci, F., Liguori, C., Irrera, F., & Suppa, A. (2020). Shedding light on nocturnal movements in parkinson's disease: Evidence from wearable technologies. *Sensors (Switzerland)*, *20*(18). https://doi.org/10.3390/s20185171

Zenian, J. (2010). Sleep position and shoulder pain. *Medical Hypotheses*, *74*(4). https://doi.org/10.1016/j.mehy.2009.11.013

Zhang, Z., & Yang, G. Z. (2015). Monitoring cardio-respiratory and posture movements during sleep: What can be achieved by a single motion sensor. In *IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks (BSN)* (pp. 1–6). https://doi.org/10.1109/BSN.2015.7299409

Zhou, Z., Padgett, S., Cai, Z., Conta, G., Wu, Y., He, Q., Zhang, S., Sun, C., Liu, J., Fan, E., Meng, K., Lin, Z., Uy, C., Yang, J., & Chen, J. (2020). Single-layered ultra-soft washable smart textiles for all-around ballistocardiograph, respiration, and posture monitoring during sleep. *Biosensors and Bioelectronics*, *155*. https://doi.org/10.1016/j.bios.2020.112064