Module 1. Introduction to Wearable Technology – Non-Feedback and Feedback

Wearable technologies are becoming increasingly popular for use in professional sports, research, in behavioural sleep medicine clinics, and in the population at large. They are gaining acceptance as a reliable and valid way to prospectively, objectively approximate activity and sleep patterns, including time spent in sleep versus wake, as well as different sleep stages and, even more general, the 24-hour activity cycle (24 HAC). For the general consumer, sleep measures are often combined with additional fitness, health, and performance tracking parameters that maximise performance and reduce risk of injury.

While the industry continues to gain momentum, adoption of these devices is still relatively limited, and many individuals lack an understanding of the history, mechanics, technology, and appropriate applications of these devices. It can be challenging to incorporate wearable technologies into research, clinical practice, or health and wellness routines without knowing where to begin. The purpose of this module is to explain how and why these devices were developed, how they function, and what their realistic limitations are. In particular, we will emphasize sleep wearables and how to track them appropriately, as currently they are one of the most popular KPIs in sports performance today in professional sports. By the end, **you** should be able to make informed decisions about how to effectively incorporate wearable technologies into professional athletes' routines.

History

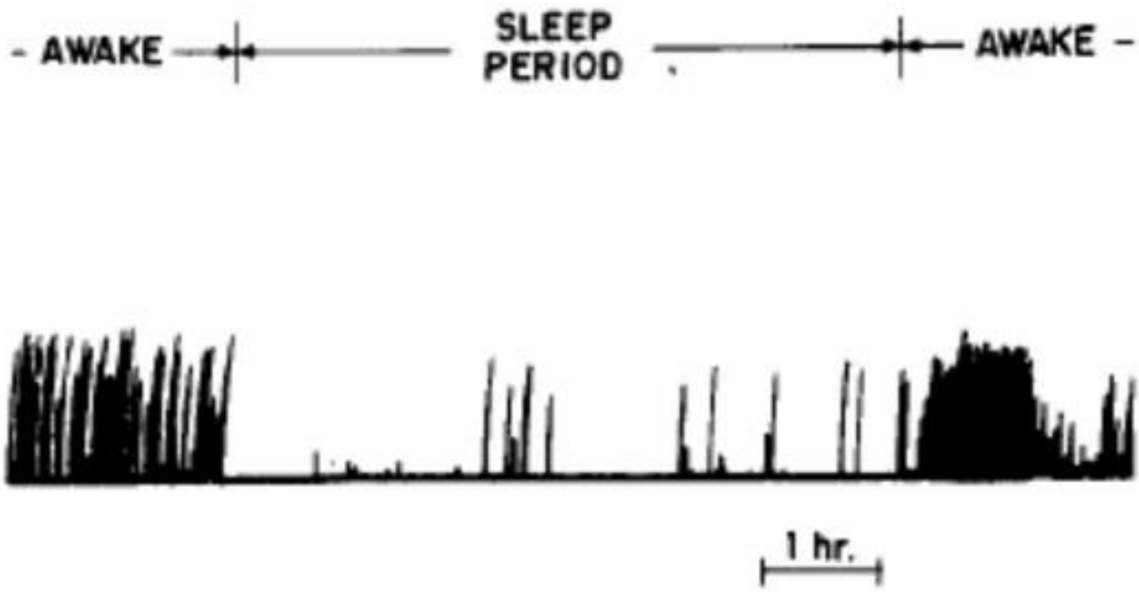
The first wearable technology included analog transducers, which measured movement as it happened. Typically, these devices consisted of a metallic object contained within a magnetic field. As the wearer moved, the metal object moved, altering the voltage in the magnetic field. This change in voltage was recorded externally.

The first documented study of actigraphy in humans was in 1972. David J. Kupfer, a graduate student at Yale University School of Medicine, conducted continuous telemetric recording of eight psychiatric inpatients and compared the data to overnight EEG recordings over two consecutive nights (Kupfer *et al.*, 1972). The actigraphy recordings were found to be comparable to EEG, thus opening the door for a new study technique to discern between sleep and wake via motor activity.

The device that Kupfer *et al*. (1972) utilised had first been designed for use in animals by Jose Delgado, a professor of neurophysiology also at Yale University. By adding a wristband, the device could easily be worn by the human participants in Kupfer's study. The simple design consisted of a ball held within a metal tube. As the participant moved, the ball also moved and this changed the voltage output.

The next iteration was the MediLog system, a more stable movement transducer created by Daniel F. Kripke and colleagues at the University of California, San Diego, in 1978 (Kripke *et al*., 1978). This system worked by soldering an off-centre nut attached to one end of an EEG pen wire, with the other end attached to a piezo-ceramic element. As the device moved, the nut moved, and the change in voltage was documented on an external tape recorder that was worn at the waist. The tracings were similar to those produced today (figure 1).

Figure 1. Trace produced by analog recorder



Source: Kripke *et al*., 1978, p. 675.

These devices were also designed to be waterproof. This meant they could be worn over a continuous 24-hour period – an important feature considering the time-consuming nature of these devices to take on and off.

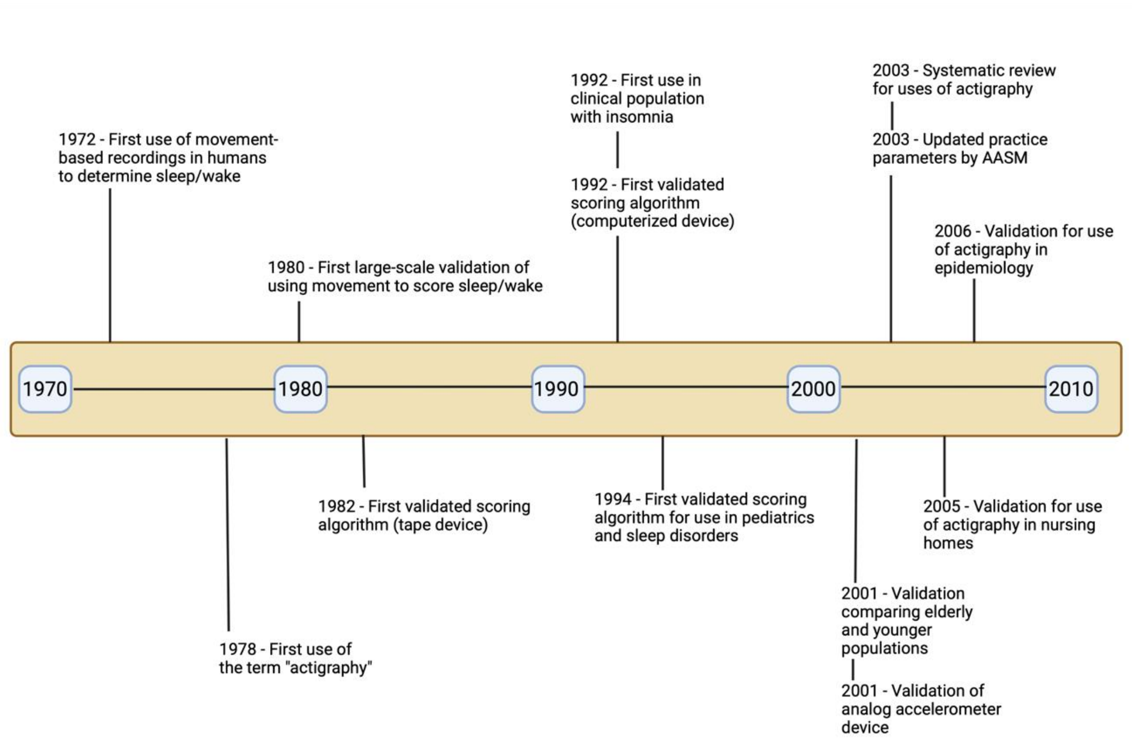
These devices demonstrated high correlation with PSG recordings of sleep and wake among the five participants that were enrolled in the study. More difficult to detect were nocturnal awakenings – a problem that persists with devices today (table 1).

Table 1. Comparison of PSG and actigraphy in five participants

Comparison of two methods of sleep measurement			
	Polygraph	**Actigraph**	
Sleep period	436 min	433 min	
	442	446	**r = 0.954**
	497	485	**t = 5.49**
	466	454	***P* < 0.01**
	512	528	
Sleep time	434 min	410 min	
	348	345	**r = 0.982**
	442	439	**t = 9.01**
	462	453	***P* < 0.005**
	502	473	
Wake time	94 min	100 min	
Within sleep	54	46	**r = 0.851**
	4	1	**t = 2.80**
	10	55	***P* < 0.05**
	2	23	

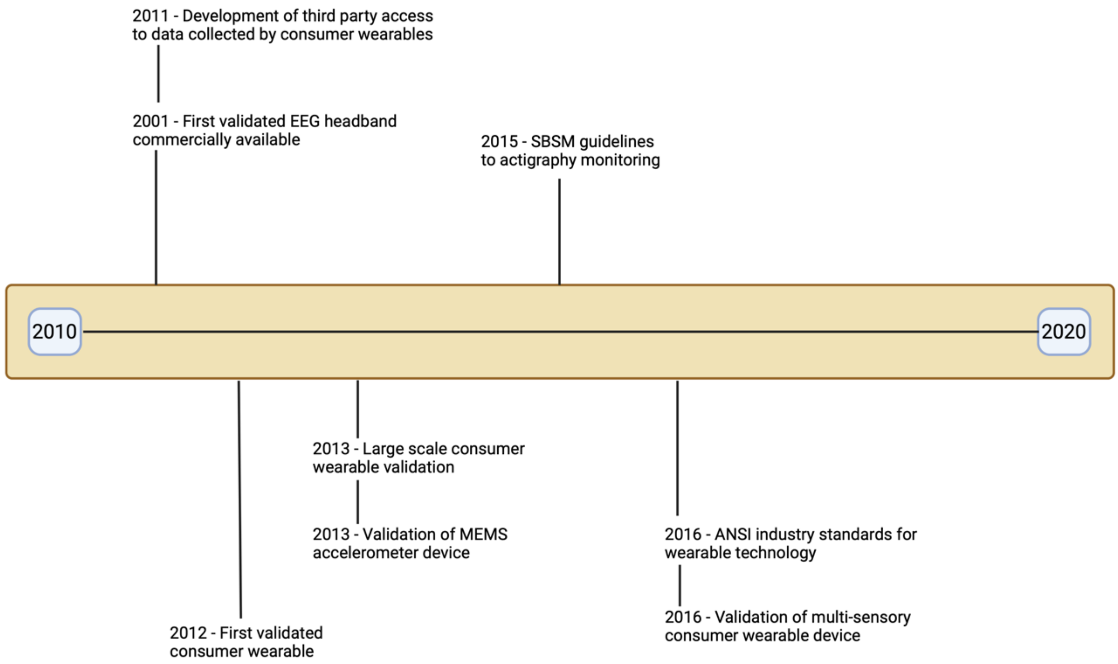
Source: Kripke *et al.*, 1978, p. 675

Figure 2. Key milestones in the history of wearable sleep assessment technology



Source: [online image of key milestones], n. d.

Figure 3. Key milestones in the history of wearable sleep assessment technology



Source: [online image of key milestones], n. d.

How do wearable technology work? Implications from sleep wearable tech

Movement

Wearable sleep technologies measure movement as the primary proxy for sleep. However, a person can be still, while awake and move during sleep. Discerning between the two can be done most efficiently by incorporating multisensory elements into devices, to build a clearer physiological picture of the state of consciousness that is occurring at any one moment.

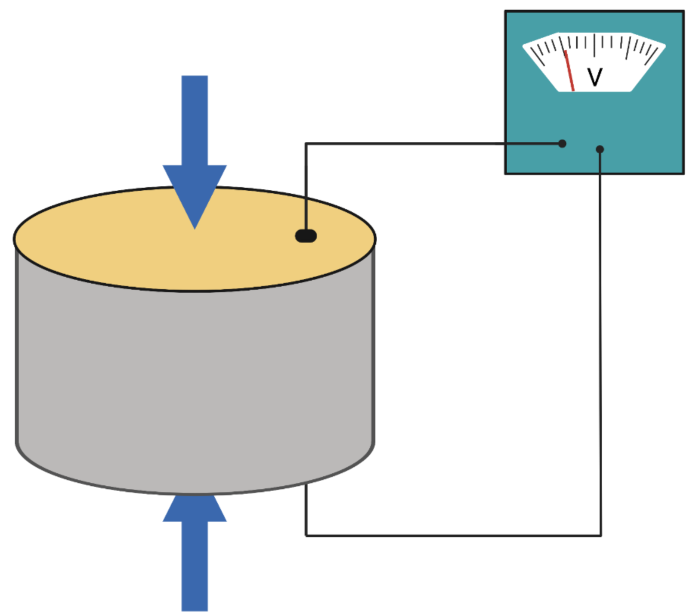
Measuring movement effectively begins with determining the kinds of movement that are most likely to represent wake and least likely to occur during sleep. Therefore, where on the body a device is placed is critical. Being able to gauge intensity of movement is also important, with more vigorous movements likely to occur during periods of wake.

Kripke's MediLog system could detect frequency of movement, but not intensity. The simple mechanism would be moved by the wearer, and this movement would trigger a change in voltage output that would register as a movement event. These movement events were assessed within a given timeframe, or epoch, akin to classic PSG scoring of sleep.

When piezoelectricity emerged, this advanced wearable technologies from movement transducers alone into true accelerometers. This meant that changes in voltage output could be used to quantify movement intensity rather than only recording the presence or absence of a movement event.

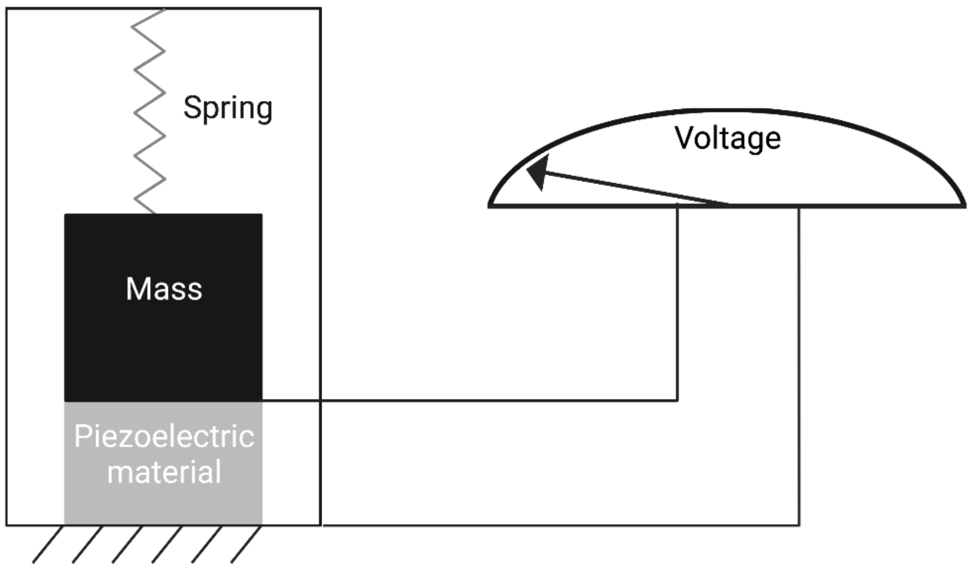
Piezoelectricity refers to the electric charge found in solid materials – such as crystals or ceramics – in response to pressure. It can be measured by attaching an electrode to one of these solid materials and recording the change in voltage in response to varying levels of mechanical stress (figure 3).

Figure 4. Principles of piezoelectricity



Source: [online image of principles of piezoelectricity], (n. d.), https://bit.ly/3eAUKDq.

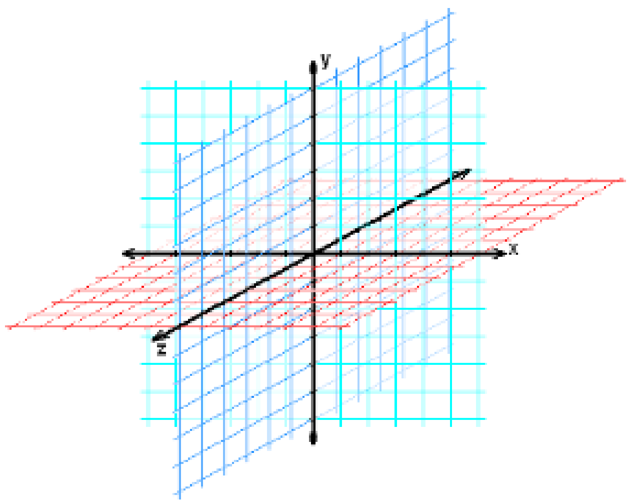
Figure 5. Acceleration acts on a mass that is restrained by a spring



Source: [online image of acceleration acts on a mass that is restrained by a spring], (n. d.), https://bit.ly/3D02fgl.

Acceleration acts on a mass that is restrained by a spring (figure 5). The internal component of an accelerometer will experience varying levels of squeeze, or pressure, as a function of the intensity of movement that is induced by the wearer. This can then be quantified.

Figure 6. Three-dimensional accelerometery



Source: [online image of three-dimensional accelerometery], (n. d.), https://bit.ly/3CFFvRL.

A critical advancement in the field came with the development of triaxial accelerometers. These devices use three accelerometers placed at 90-degree angles to one another, to reflect the real-life three-dimensional movements that wearers are likely to perform throughout the day. Triaxial accelerometers produce a single voltage output in response to the intensity of movement occurring at each of the three individual units.

Devices must be designed to effectively capture true movement that is limited to biological signals while filtering out noise. This is somewhat akin to the considerations given to excess noise that occurs during PSG recordings, such as air conditioning and other background activity that does not reflect the sleeper's physiology. However, there are still limitations, with many of today's devices recording activities that do not occur.

Extreme temperature changes can also alter the accuracy of movement recordings. Given that materials expand when they heat up, the likelihood of triggering a signal that movement has occurred increases in hot climates. This is particularly problematic in modern microelectromechanical systems (MEMS), which harness an array of accelerometers on a very small scale.

MEMS chips are present in today's sleep wearable devices, along with modern cell phones.

However, devices designed to discern between sleep and wake are often calibrated to a greater degree of movement sensitivity than cell phones, pedometers, or other devices targeted primarily at exercise. Sleep technologies also utilise specific algorithms that help to further predict patterns of sleep and wake.

Algorithms are created to predict sleep-wake episodes based on the activity preceding and following a specific sampling period. These periods or 'epochs' are typically 30-second windows so as to be comparable to PSG. While the 30-second duration is, somewhat, arbitrary today given the digital nature of objective sleep recordings, when PSG was first invented, the analog process meant that each sheet of paper could only hold 30 seconds worth of data. Despite technological advances, this number has remained standard in the field.

Original actigraphy recorded movement in two-minute epochs before reducing this to one-minute windows. During validation studies, PSG recordings had to be shifted from 30-second epochs to one, or even two-minute windows to be comparable to the wearable devices in question. Most of today's devices record sleep in 30 sec epochs because it has held as the 'gold standard' rubric for sleep staging, although some devices have shortened this to 15 second epochs.

Most modern devices now provide users with the complete raw data from each sampling point, which occurs many times a minute. While this can be useful, it can also be challenging to interpret. Within any one epoch, there is variability and noise. The advantage of a single data point – such as the maximum within an epoch – is that it can be easier to filter out the noise.

Devices can have different recording modes. The oldest of these is Zero Crossing Mode (ZCM), which originated from movement transducers. It captures whether a movement occurred or not, but not the intensity by registering each time the voltage crossed a pre-determined 'zero' mark that accounted for inherent error.

Time Above Threshold (TAT) measures the length of episodes above 'zero' and can be useful for detecting wakefulness. However, it also does not capture intensity and is less useful for detecting sleep.

Proportional Integral Mode (PIM) is the default recording mode found on most modern devices. It represents the area under the curve (AUC) values obtained for each epoch and while it is more sensitive than ZCM and TAT at recording frequency of movement, it also measures intensity.

The effectiveness of PIM in terms of minute-by-minute agreement with PSG was quantified in 2001 and shown to be more effective at assessing wake – which is inherently more challenging to detect than sleep – than ZCM and TAT (Jean-Louis *et al*., 2001).

Table 2. Comparison of recording modes

	AR%	MS%	MW%	SEN%	SPE%	SE%
SUMACT	94.4	3.6	2.0	97.9	30.3	96.4
MAXACT	91.4	3.2	5.4	94.3	37.3	92.7
Zero Crossing	95.0	3.7	1.3	98.7	27.7	97.3
Time Above Threshold	94.6	3.4	2.0	97.8	34.6	96.2
Preportional Integrating	96.5	1.7	1.8	97.2	43.1	95.4

[a]Parameters included minute-by-minute agreement rate (AR), percentage of PSG wakefulness epochs misscored as sleep (MS), percentage of PSG sleep epochs misscored as wakefulness (MW), sensitivity (SEN) and specificity (SPE) of the alogrithms, and derived sleep efficiency (SE).

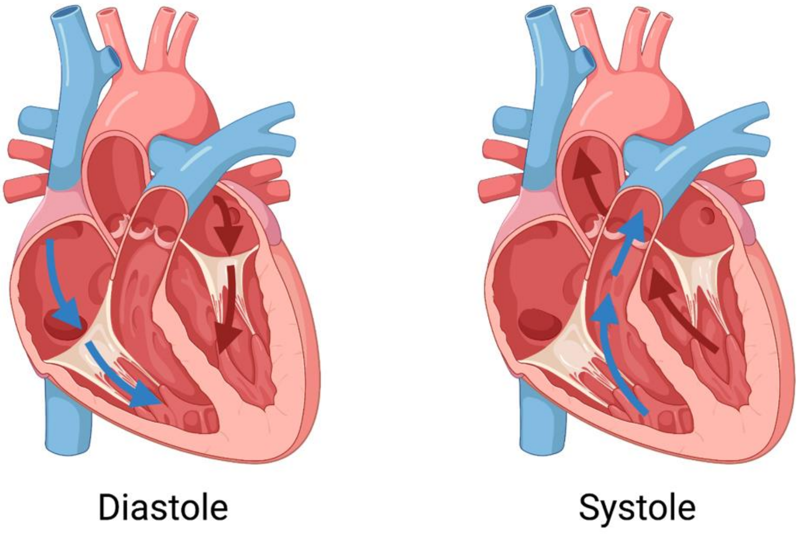
Source: Jean-Louis *et al*., 2001, p. 188.

A decade later in 2011, findings from a large study of older adults showed that PIM performed best for sleep duration, sleep efficiency, sleep latency, and WASO (Blackwell *et al*., 2011). TAT performed less well, but was comparable for sleep duration, sleep efficiency, and WASO. ZCM did not perform well for any sleep parameter, although it did perform moderately well for WASO.

Heart rate

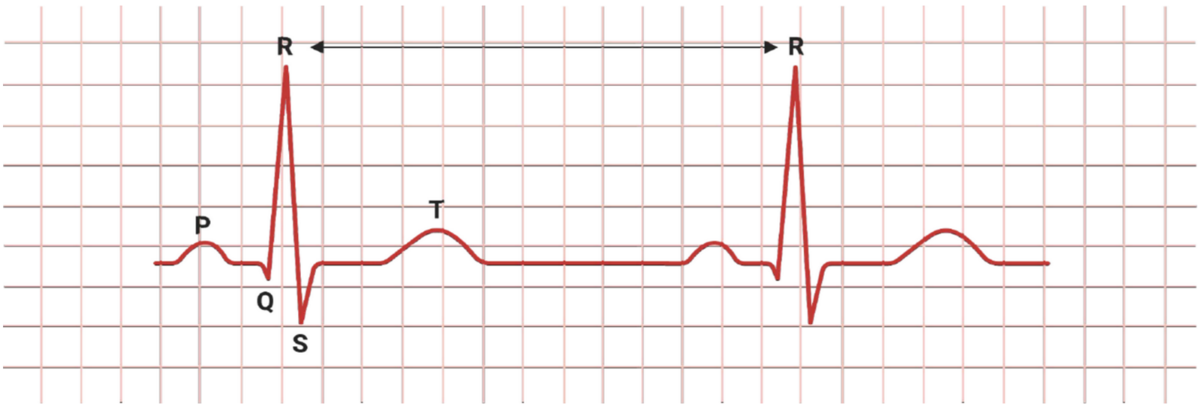
Each heartbeat consists of two major processes (figure 7). The first is diastole, which is the resting and filling of blood by the heart, and the second is systole, which is the ejection of blood through the aortic valve. An electrocardiogram (ECG or EKG) measures the electrical activity of a heartbeat using a series of electrodes applied to the skin on the chest. During each heartbeat, an orderly progression of electrical activity moves blood through the various chambers of the heart and out into the periphery. These different stages are recorded visually as a series of waves (figure 8).

Figure 7. Systole and diastole



Source: [online image of systole and diastole], n. d.

Figure 8. R-R Interval

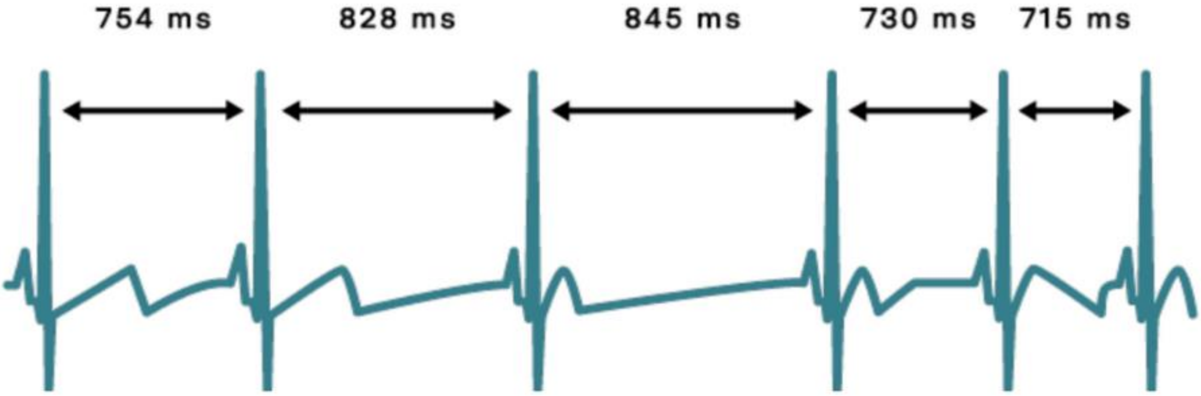


Source: [Online image of R-R Interval], n. d.

The distance between the same two points of any two consecutive heartbeats represent a single heartbeat's complete duration. Typically, the interval between two consecutive 'R' peaks (often referred to as the 'R-R interval') is used because these markers are the easiest to detect due to their indication of systole, or the large push of blood out of the heart and into circulation.

Heart rate variability (HRV) is a measure of the microsecond variability between those intervals, with greater variability representing better parasympathetic tone in response to stress. There are significant differences in HRV between individuals, in particular elite athletes, but, in general, a lower HRV represents a less adaptable heart. Vigorous exercise or training can temporarily decrease HRV, but sleep provides an opportunity for recovery. HRV is a KPI that is commonly tracked in professional athletes, and most commonly marketed wearable devices include HRV as a metric that is yielded from their wearable.

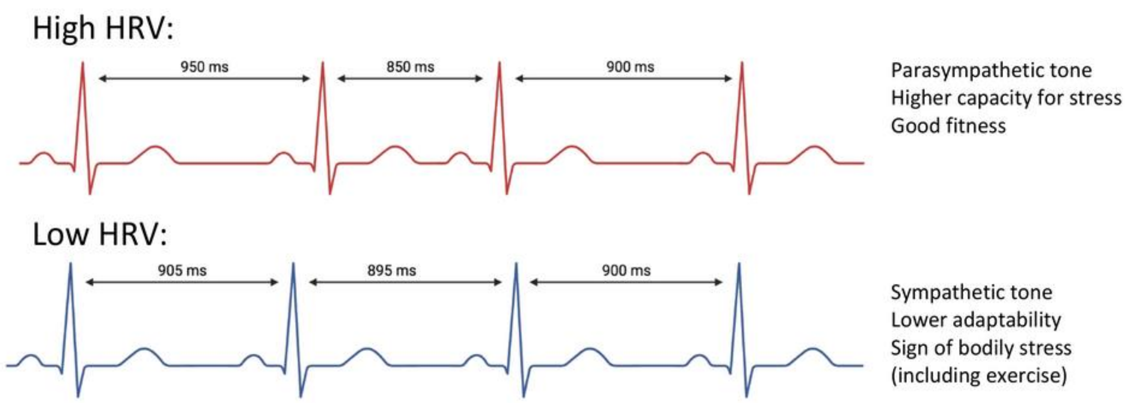
Figure 9. Heart rate variability (HRV)



Source: [online image of heart rate variability], (n. d.), https://bit.ly/3EGtzSh.

Nerve fibres communicate information about autonomic activity in the periphery to the brain, and the brain exerts top-down control over autonomic tone. Higher HRV has been associated with better cognitive performance and memory (Whitehurst *et al*., 2016). Chronic stress, however, has been shown to lower HRV (Thayer *et al*., 2012). While actigraphic devices do not measure brain activity, they can measure heart rate as a proxy for the heart-brain connection, mediated by the vagus nerve (figure 10).

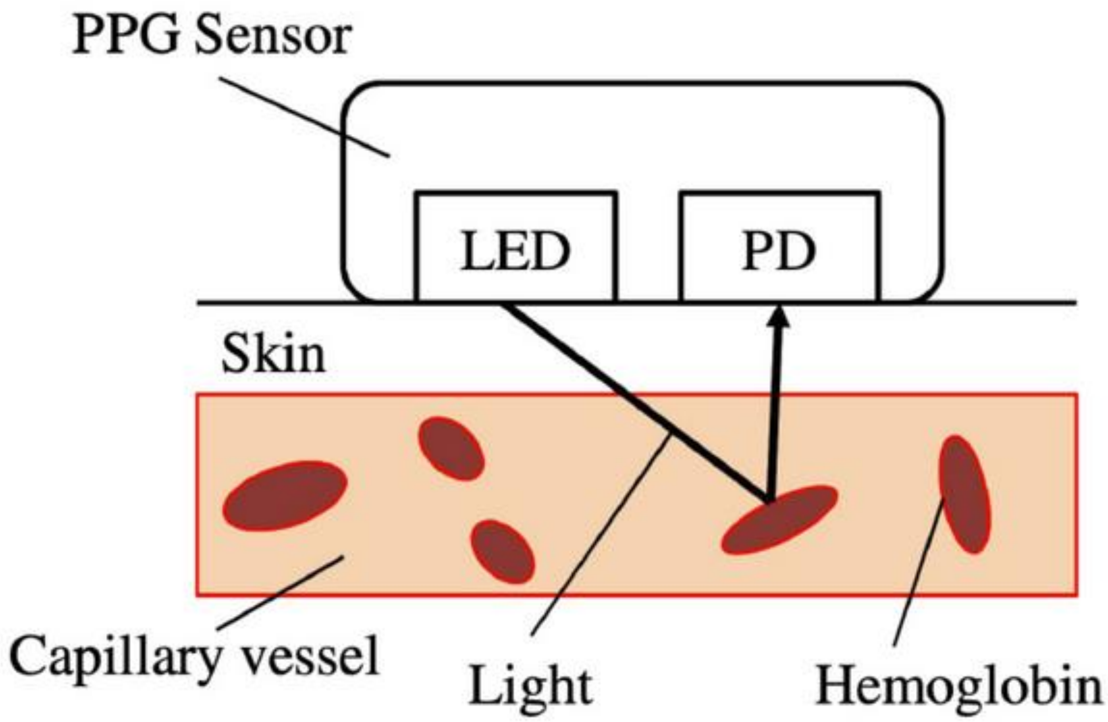
Figure 10. HRV as a measure of autonomic arousal



Source: [online image of HRV as a measure of autonomic arousal], n. d.

Photoplethysmography (PPG) is a simple technique that can be used to measure heart rate. It directs light from a light-emitting diode (LED) at the skin and records changes in absorption as the light is absorbed by blood vessels (figure 11).

Figure 11. Photoplethysmography (PPG)

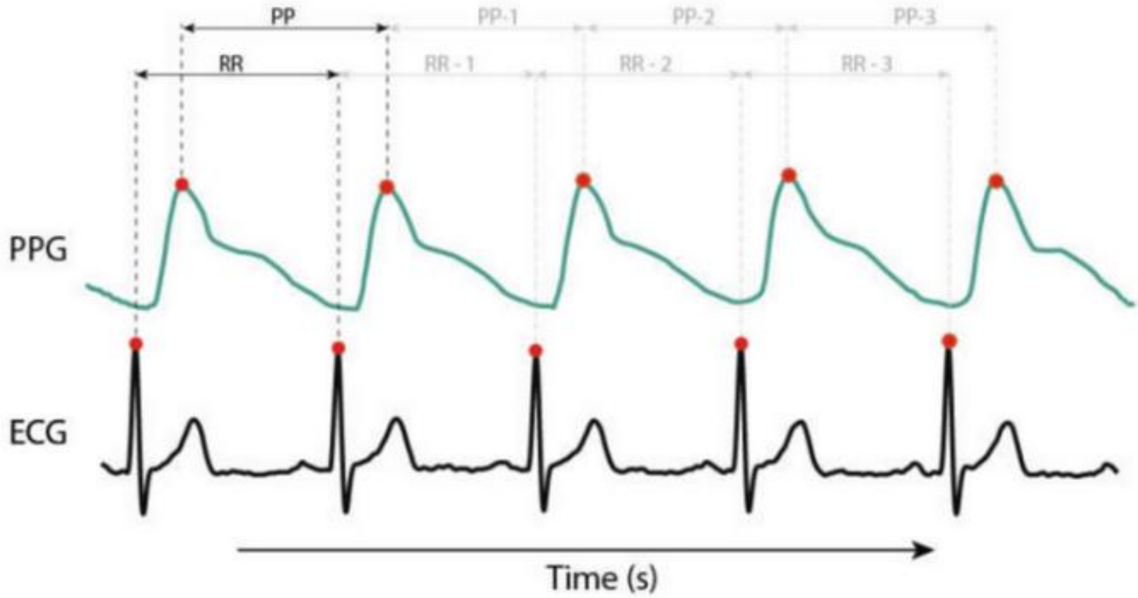


Source: Fukushima *et al*., 2012, https://bit.ly/3Mz7zKS.

As blood is pumped from the heart to the periphery, blood vessels pulse in response to expansion and contraction. Measuring the amount of light absorbed by these blood vessels at frequent intervals will detect changes in blood movement and thus heart rate. The pulse wave is the amount of light absorption and mirrors the heart rate.

This PPG signal is highly accurate for measuring heart rate data and aligned with ECG. However, there is a delay between the heart rate and pulse wave due to the time taken for blood to reach the periphery after leaving the heart (figure 12). This can be standardised using a time constant.

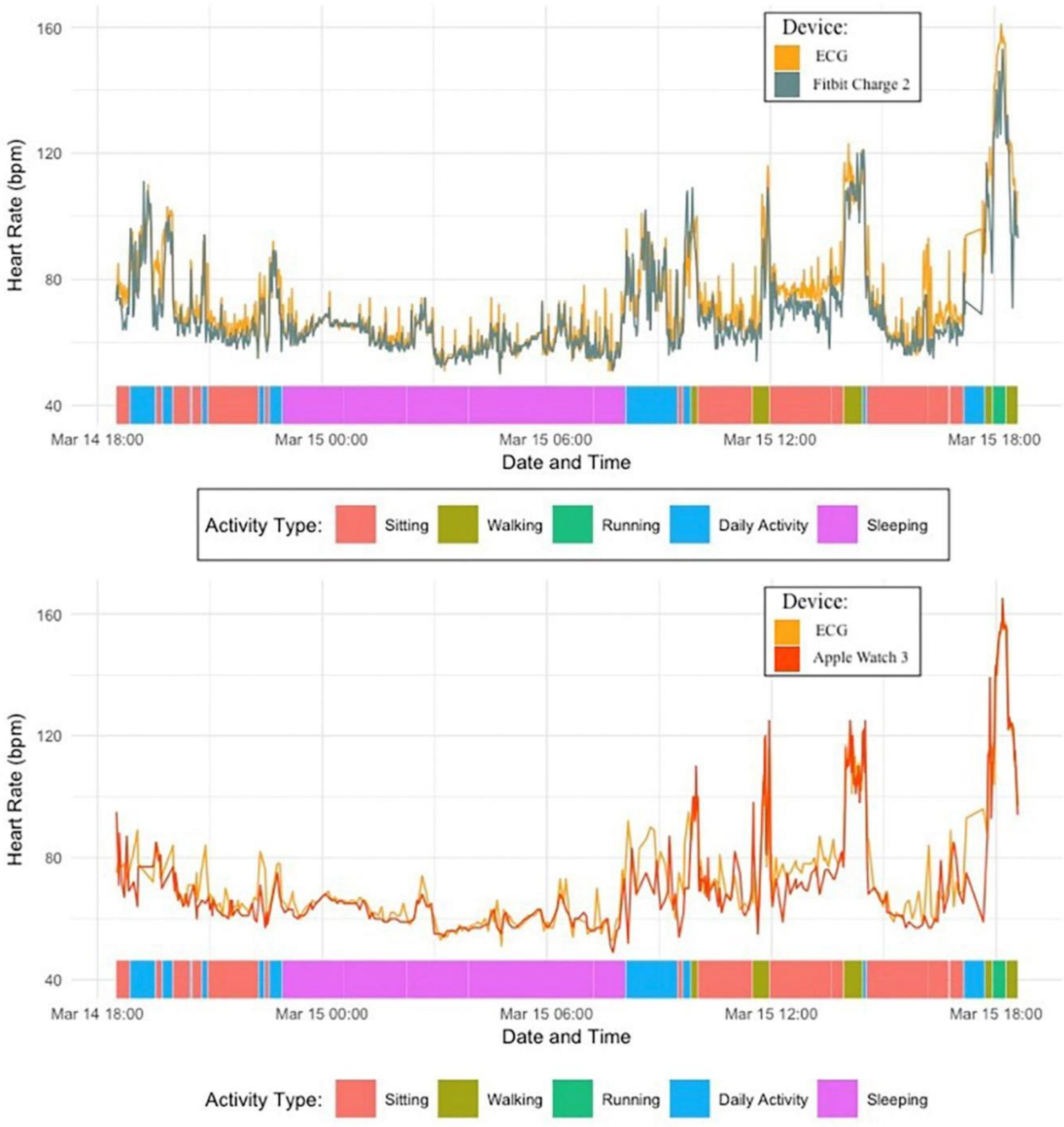
Figure 12. Pulse wave delay



Source: [online image of pulse wave delay], (n. d.), https://bit.ly/3S7fjou.

Most modern sleep technologies that incorporate PPG are highly comparable in this measurement, using green light wavelengths that reflect the desired depth of penetration into the skin, hitting only the outer portion of blood vessels and thus minimising noise (figure 11).

Figure 13. Heart rate measured using Fitbit Charge 2 and Apple Watch 3



Source: Nelson and Allen, 2019, https://bit.ly/3eC3Ek2.

Heart rate decreases and is typically less variable during sleep (figure 13). When combined with movement data, wearable devices that measure heart rate can build a clearer picture of sleep-wake behaviour. They can also approximate the time spent in different sleep stages with some reliability. When HRV is divided into different frequency bands, it implies different aspects of autonomic nervous system function. Parasympathetic nerves elicit a much faster response ($\leq$ 1 sec) than sympathetic nerves ($\geq$ 5 sec) (Nunan *et al*., 2010) and comprise high frequency (HF) and low frequency (LF) activity, respectively. When combined with movement data, this can begin to predict sleep architecture (table 3).

Table 3. Heart rate variability, autonomic arousal, and sleep staging

	Frequency (Hz)	ANS Indications	Correlated Sleep Stage
Very Low Frequency (VLF)	0.02 – 0.05	Sympathetic tone	Highest in REM
Low Frequency (LF)	0.05 – 0.15	Sympathovagal balance	Lowest in Stage 3 NREM
High Frequency (HF)	0.15 – 0.40	Parasympathetic tone	Highest in Stage 2 NREM
Total Power	0.00 – 0.40	--	Lowest in wake; highest in REM

Source: Prepared by the author based on Nunan et al. 2010.

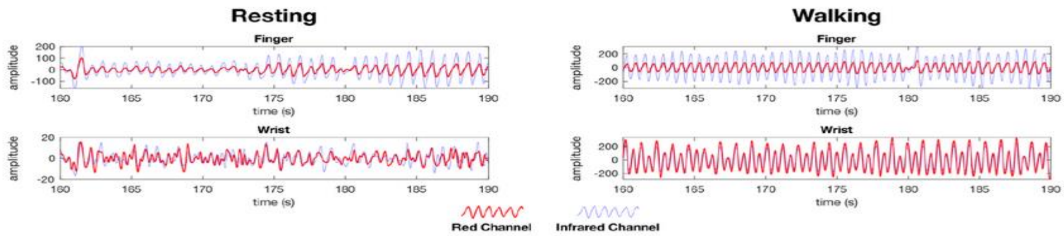
The first study to systematically assess cardiorespiratory signals to approximate sleep stages was done in 2006 among patients with obstructive sleep apnoea (OSA) (Redmond and Heneghan, 2006). They determined that measuring heart rate via ECG and respiration via ribcage expansion and contraction, sleep staging was comparable to that determined via EEG. In 2011, another study using Watch-PAT100 (PAT recorder; Itamar Medical, Caesarea, Israel), which is typically an OSA screening device but also uses actigraphy, showed good agreement for REM versus NREM sleep by looking at differences in peripheral and arterial tone (Hedner *et al*., 2011). Peripheral vasoconstriction is a well-documented hallmark feature of REM sleep.

Approximating sleep stages using Actiwatch combined with a heart rate monitoring was done in Nelson and Allen's study (2019). While these combined measured could predict sleep versus wake with 91.5% accuracy, accuracy reached a ceiling effect of 83% when it came to predicting sleep stages, a problem that persists to date.

In 2019, Longomore and colleagues investigated the efficacy of measuring heart rate at the finger and the wrist – the two locations typically used for today's wearable devices. The pulse is weaker to detect at the finger, as compared to the wrist, but tends to produce more stable data because the finger moves less frequently than the wrist does.

Figure 14. Wrist vs. finger-worn actigraphy

Location	Resting Median Error % (s.d.)			Walking Median Error % (s.d.)		
	Red	IR	Red & IR	Red	IR	Red and IR
Wrist	76 (±17)	62 (±32)	68 (±23)	10 (±10)	11 (±10)	11 (±10)
Finger	1.4 (±18)	1.2 (±16)	1.3 (±16)	6.8 (±11)	5.9 (±10)	6.5 (±10)



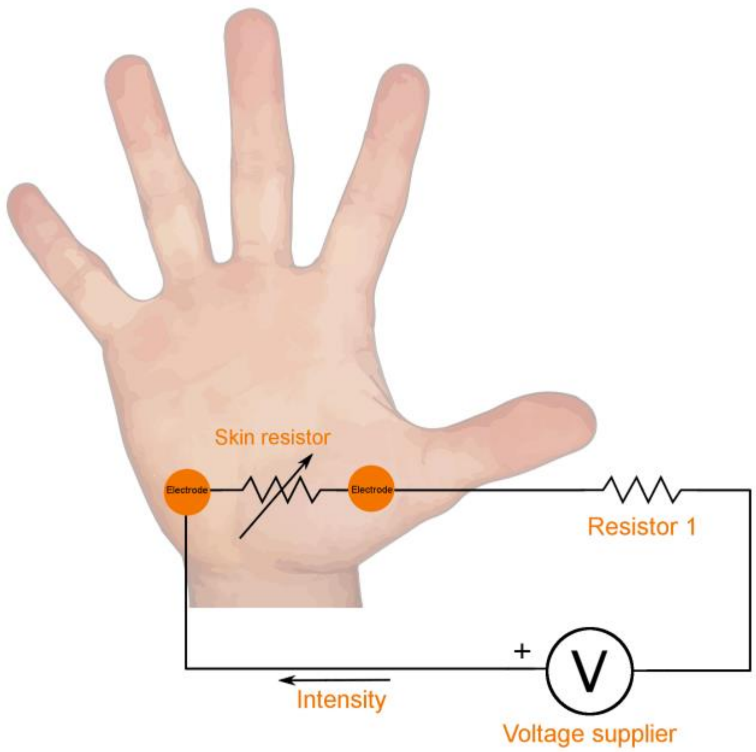
Source: Longomore *et al*., 2019, https://bit.ly/3MPhE6R.

Applying an algorithm developed based on a wrist-worn device to data produced from a ring is generally considered inappropriate, but, with the rise in popularity of rings worn on the finger, this must be taken into consideration.

Additional sensors

While movement and heart rate remain the key sensors in modern sleep wearable technologies, there are additional sensors that help to predict sleep versus wake and sleep staging that are used in both wearable and 'nearable' (devices used near the body but not worn) products.

Figure 15. Skin conductance



Source: [Untitled image about skin conductance], n. d., https://bit.ly/3CChESR

Pressure sensors are capacitive pressure transducers and are typically used in specialised mattress pads that measure sleep-wake behaviour. These use a piezoelectric element that records changes in voltage with changes in the distribution of pressure on the surface.

Another measure that is becoming increasingly popular is electrodermal activity. Sensors that measure the electrical activity of the skin can be used to produce dynamic signals that reflect autonomic arousal. Increased around serves as a stress marker.

Signals are driven by the function of sweat glands. The optimal location for detecting conductance through perspiration tends to be the palms; therefore, devices worn on the finger typically perform better in this area than devices worn on the wrist.

The SenseWear arm band is currently on the market and uses a triaxial accelerometer alongside skin temperature and conductance. It measures skin response, but it also has an accelerometer and measures skin temperature. Sleep timing has been well correlated with PSG in a 2013 study that included 107 OSA patients and 30 controls matched for age and body mass index (BMI) (Sharif and Bahammam, 2013).

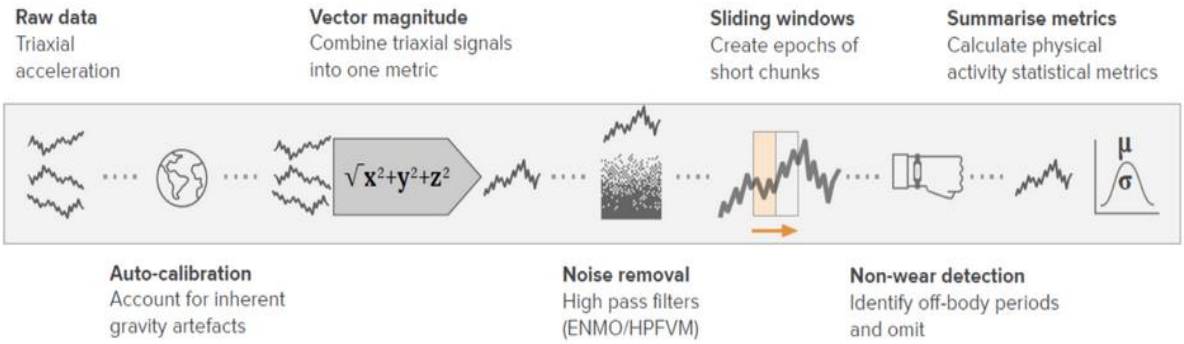
EMG can also be incorporated into wearable devices, similar to the electrodes placed on chin or legs during PSG, to help approximate sleep stages in the same way. Atonia present during REM sleep will be differentially measured than the normal muscle movements that occur during other stages of sleep.

Radar-based sensors are found in several commercial nearable devices and may one day interface with wearables. These sensors use an impulse radar system that generates pulses of radio frequency (RF) signals. Antennas measure reflections from the environment.

RF can penetrate soft materials such as clothing and bedding and can detect movement, respiration, and even heart rate by being able to measure the distance of velocity of targets. In a study comparing RF to PSG, agreement was approximately 78% (De Chazal *et al*., 2011).

Figure 16 captures the necessary adjustments that must be made for modern data processing and extraction, including adjusting for gravity, noise, the environment itself, and non-wear detection (Pérez-Pozuelo *et al*., 2022).

Figure 16. Adjustments for modern data processing and extraction



Source: Pérez-Pozuelo *et al*., 2022

Euclidean Norm Minus One (ENMO); High-pass Filtered Vector Magnitude (HPFVM)

Many consumer wearables do not incorporate non-wear detection because it typically drains battery life by constantly monitoring for signals.

In the next module, we will learn how to evaluate wearable technologies using the sleep wearable technology as a framework, with principles that can be applied to any wearable technology in the sports performance domain.

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