Commercial and Research-based Wearable Devices in Spinal Postural Analysis: A Systematic Review

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Abstract. The widespread use of ubiquitous computing has led to people spending more time in front of screens, causing poor posture. The COVID-19 pandemic and the shift towards remote work have only worsened the situation, as many people are now working from home with inadequate ergonomics. Maintaining a healthy posture is crucial for both physical and mental health, and poor posture can result in spinal problems. Wearable systems have been developed to monitor posture and provide instant feedback. Their goal is to improve posture over time by using these devices. This article will review commercially available, and research-based wearable devices used to analyse posture. The potential of these devices in the healthcare industry, particularly in preventing, monitoring, and treating spinal and musculoskeletal conditions, will also be discussed. The findings indicate that current devices can accurately assess posture in clinical settings, but further research is needed to validate the long-term effectiveness of these technologies and to improve their practicality for commercial use.

Keywords: postural analysis · wearable technology · commercial devices · spinal posture.

1 Introduction

Having poor posture can affect both physical and mental health. Poor posture can lead to physical discomforts, such as back pain, neck pain, and shoulder pain, which can affect productivity. It can also lead to poor circulation and decreased oxygen intake, leading to fatigue and difficulty concentrating. Mentally, poor posture can affect self-esteem and confidence. Standing or sitting with poor posture can give off the appearance of being unconfident or disinterested, which can negatively impact social interactions and opportunities. Poor posture can also lead to poor sleep quality, as it can cause discomfort and difficulty finding a comfortable position. In addition, poor posture can lead to long-term health problems, such as arthritis, osteoporosis, and degenerative joint diseases, which can significantly impact the overall quality of life. Therefore, poor posture can have significant negative impacts on both physical and mental health, and it is important to strive for good posture in order to avoid these disadvantages [33, 51, 16, 52].

Moreover, the term "posture" is often used in the context of sports and fitness, and health but the definition of this term can be quite vague and subjective. There are a variety of different factors that can contribute to poor spine posture, including muscle imbalances, poor core stability, and improper technique. This lack of clarity makes it difficult for coaches, athletes, medical experts, and researchers to accurately identify and correct poor spine posture, which can negatively impact performance and overall health.

One of the main challenges with defining poor spine posture is that it can vary depending on an individual's body type and physical abilities. Some individuals may have naturally fine spine posture due to their physical structure and muscle balance, while others may struggle with poor spine posture due to previous injuries or other physical limitations. This means that what constitutes poor spine posture for one person may not necessarily be the same for another, making it difficult to establish a clear and consistent definition.

Another issue with the definition of posture is that it can be influenced by a variety of different factors. For instance, poor spine posture can caused by muscle imbalances, where certain muscles are overdeveloped while others are underdeveloped. This can lead to poor alignment and stability, which can make it difficult to maintain good spine posture. Additionally, poor core stability can also contribute to poor spine posture, as the core muscles play a crucial role in maintaining proper alignment and balance.

The definition of posture can vary depending on the specific activity in which it is being applied. For example, in sports such as tennis, a good spine posture might involve a wide stance and a bent knee in order to generate power and control on shots. In contrast, the office working environment posture can be defined as the angle that hands make while resting on the table or the angle of the neck while looking at the screen.

It is crucial to identify poor posture early and maintain good posture to prevent injuries and the development of spinal disease. In medical field, human posture is assessed by the Bath Ankylosing Spondylitis Metrology Index (BASMI) using a measuring tape and goniometers to obtain the measurements. Incorrect use of the instruments, erratic or compensatory movements of the subject or observation errors can appear, which can cause a lack of accuracy and reproducibility [45, 11, 43]. On the other hand, the spine and sacroiliac joints create complicated motions that cannot be analysed using the BASMI approach. As a result, it is critical to research and develop new technology-based posture estimation techniques that can assess joints directly with acceptable accuracy, repeatability, and sensitivity to changes in information over time.

The human spine consists of 33 individual vertebrae separated by intervertebral discs and grouped into five regions: the cervical, thoracic, lumbar, sacral, and coccygeal regions. Each vertebra has a unique shape and size, with the cervical region having smaller and more mobile vertebrae than the lumbar region.

As shown in Figure 1, the cervical spine is the portion of the spine within the neck, and consists of 7 vertebrae (C1 to C7).

The 12 thoracic vertebrae (T1 to T12) are contained within the rib cage, and each vertebra articulates with a rib. These are far less mobile, and this more rigid structure of the thoracic spine provides the necessary support for the vital organs contained in the chest (heart and lungs). The lumbar spine is the lowest mobile segment and is commonly referred to as the lower back. It has 5 vertebrae (L1 to L5), and these are the largest vertebrae in the spine as they have the greatest load to bear.

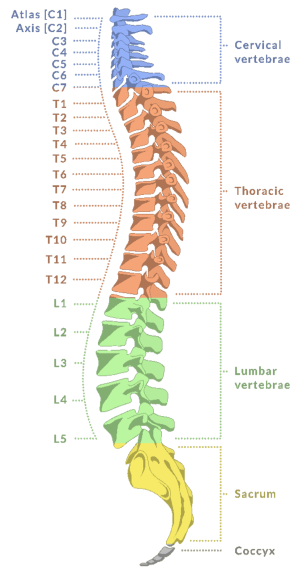

Fig. 1. Human Spine labelled with the joins name and group

Optical marker-based devices are a widely used technology for tracking motion and evaluating spinal mobility, but they have certain limitations in clinical settings due to their high cost, indoor-only capabilities, and need for specific equipment and conditions [21, 4, 6]. Researchers have attempted to overcome these issues by using technologies such as inertial measurement unit (IMU) to create wearable capture devices for human posture modelling [36, 75, 17, 20]. These wearables are more cost-effective and can be used in any location without the need for a complex setup.

Wearables are also widespread in the industrial and commercial markets for assisting users in improving their quality of life. For instance, they provide continuous and personalised health monitoring, physical activity, and vital signs while offering features like stress tracking, GPS tracking, and hands-free access to notifications and calls. Wearable devices for tracking spinal disorders during daily activity as an indication of health status are a trending venue for healthcare. With 239 million units in demand worldwide and over 1.2 billion devices expected to be in use by the end of 2025, with yearly sales approaching 400 million units in the year, the market forecast for wearables is optimistic [3, 59]. Therefore employing wearables for spinedisorder and correction feedback appears promising from a business perspective.

The introduction of new wearables and new sensor technologies has dramatically exceeded the limitations of traditional data capture methods, making it possible to acquire significant amounts of data[57]. However, with emergence of more complex data and gradual sharing of various clinical data sets, the sample size and potential predictor variables can exceed tens of thousands [44]. Traditional data analysis methods can no longer cope effectively, so alternative methods (e.g. complex data analysis) are needed to process such large amounts of information. Moreover, the fact that humans often present a much more complex posture in everyday life than in experimental settings has led to the validity of some of the datasets being questioned in practical applications [49]. As a result, one of the most critical challenges today is consistently collecting valid data over extended periods in complex environments outside the laboratory.

Machine learning (ML) has been shown to outperform classical computational methods in various tasks, including big data processing, data prediction, posture perdiction and object detection, thanks to rapid development of Artificial Intelligence (AI) field [30, 5]. A subset of ML, Deep Learning (DL), has led to significant advances and accuracy improvements in 2D human posture estimation tasks based on images and single-frame sequences [46]. The use of ML-derived algorithms and data models can enable the faster conversion of diverse and large databases into low resource-consuming applications on low-cost devices (e.g., smartphones, tablets, laptops) [62, 34], save significant manual time, and circumvent potential errors caused by humans to aid faster and more accurate real-time decision-making.

Furthermore, some studies have used multi-stage classification models to improve the recognition of complex postures. These models have achieved satisfactory accuracy rates in specific pose acquisition and localised body recognition. However, there are still significant limitations in full-body generic pose acquisition and in collecting data in complex environments in the real life. Several studies on postural assessment have also been developed. Wu et al.[77] proposed three criteria, namely joint angle, arm orientation and type of joint motion, that could be used to assess the forearm and upper arm. Khachai et al.[25] proposed a postural description language to redefine human posture and assess whole-body motion. However, they are difficult to assess quantitatively for non-standard body parts and have not been applied to a generalised postural assessment of the whole body. Meanwhile, ethicists have also raised risks and concerns about using ML for individual assessment and decision-making [39, 15, 65]. The risks are not only limited to a widespread lack of transparency in the data sets used for modelling, but the credibility of the decisions made cannot be validated as there is no uniform standard for posture assessment. The purpose of this systematic review is to carefully review and compare the recent advances and shortcomings in the use of wearable devices for estimating spinal posture, and to identify areas for further research and development. The specific research questions considered are as follows:

- **RQ1.** What are the recent studies and commercial wearable devices for Musculoskeletal posture detection ?
- **RQ2.** Are these wearable devices practical in a real-world setting?
- **RQ3.** What are the limitations of the devices that capture human Musculoskeletal posture ?

– **RQ4.** What are the data analysis methods used for estimating Musculoskeletal posture ?
– **RQ5.** How can ML techniques contribute to estimating and assessing human Musculoskeletal posture ?

2 Method

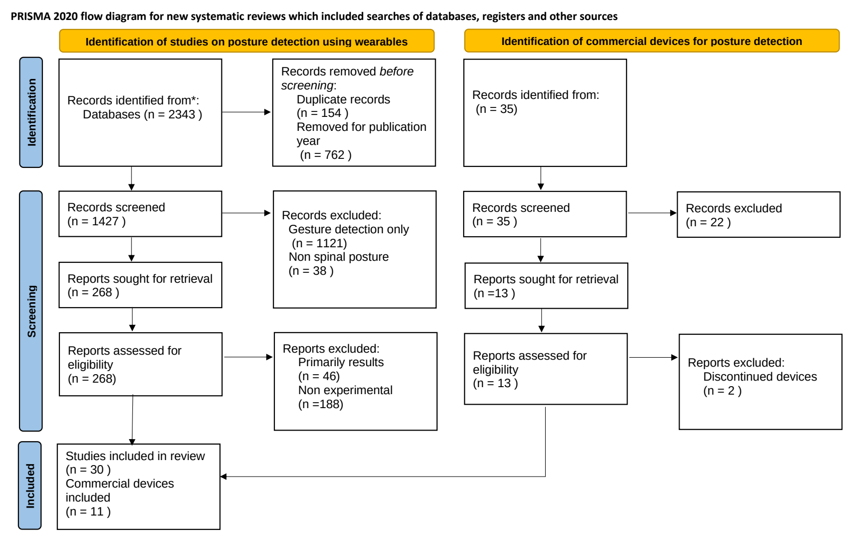

Fig. 2. PRISMA flowchart on academic and commercial wearable devices to estimate spinal posture

For this systematic review, the Reporting Items for Systematic Reviews and Meta Analyses Guidelines (PRISMA) were employed across five sources, namely: PubMed, MEDLINE, EMBASE, Cochrane, and Scopus. Following a general screening with a list of suitable key phrases, the final selection of key search terms was taken from pre-established headings on the OVID Medline (Med-line) database. Among the key search phrases were: ("human spine posture") AND ("recognition" OR "estimation" OR "evaluation" OR "capture") AND ("artificial Intelligence" OR "machine learning" OR "deep learning") AND ("wearable" , "sensor"). Spelling variants and synonyms were included and updated for each database as needed. Figure 2 depicts the PRISMA flow chart. The search results were limited to studies that met the following inclusion criteria:

Table 1. Summary of outcome from reviewed articlessss

Reference	Sensor	Region of Interest	Feedback System	# of participants	Environment	Data Analysis Method	Evaluation/validation	Posture definition
Bartalesi, R *et al.* 2010 [7]	Textile based piezoresistive sensor, IMU (3 DOF)	1: sacrum 2: spinous 3: T 12	No real-time feedback	–	Laboratory	measuring the correlation coefficient with the reference signal	Estimate error with reference signal	The curvature of lower back
O'Sullivan K, *et al.* 2012 [55]	BodyGuard: strain gauge	L3 to S2	Real-time biofeedback	12	Laboratory	Correlation in measurements	Comparing with marker-based motion analysis (video fluoroscopy)	Percentage of strain gauge elongation relative to range of motion (ROM), Pilot Study
Gopalai A, *et al.* 2012 [24]	MicroStrain's wireless IMU	1: Attached to trunk via waist band, 2: wobble board .	Real-time vibrotactile feedback	10	Laboratory	fuzzy logic based artificial intelligent system		Euler angular measurements trunk angle and wobble board angle Pilot study inspired by [26]
Lou E, *et al.* 2012 [40]	Smart garment	1: upper back 2: lower back .	Real-time vibrotactile feedback	1	Laboratory	correlation and difference between measured angles form proposed device and validation methods	Comparing with rotating wheel in static set up,and optical motion device in dynamic setup	Measurement of the kyphotic angle [41]
Wu W, *et al.* 2014 [76]	IMU (3 DoF)	Vest containing: 1: below neck, 2: chest, 3: centre of mass, 4: left hip, 5: right hip	No real-time feedback	10	Laboratory	Linear transfomation	Angle error computed by proposed method	Tilt angles from single IMU (3 DOF) on vest [38]
Tsuchiya Y,*et al.* 2014 [67]	Flex sensor, IMU (3 DOF)	Upper lumbar spine and sacrum, flex sensors between .	No real-time feedback	20	Laboratory	The cumulative error value of body coordinates	Compared to corresponding body coordinates from X-ray image	The center of gravity in the upper body and the waist shape [69]
Sardini E, *et al.* 2015 [63]	Inductive sensor	Inductive sensor sewn to the back and front shirt .	Real-time vibrotactile feedback	24	Laboratory	correlation coefficient and mean difference	Comparing with the optical system	Runk in the sagittal plane, and percentage of the Range of Motion (ROM) [54, 29]
Miyajima S,*et al.* 2015 [48]	IMU (6 DOF)	1: lumbar spine 2: thigh 3: calf	No real-time feedback	4	Laboratory/ Home	angle error in estimation of joint angle	Compared to SIMM[thre ref]	Estimating joint torque using three link angles of the body, thigh, and shank [2]
Gleadhill S, *et al.* 2016 [23]	SABEL Sense IMU (3 DOF)	1: C7, 2: T1, 2, 3: S1	No real-time feedback	11	Laboratory	Will Hopkins Typical Error, Pearson correlation, Bland Altman Limits of agremeent	Comparing with 3D MoCap	–
Ribeiro D, *et al.* 2016 [60]	Spineangel (IMU 6 DOF)	Attached to belt .	Real-time auditory alarm	4	In the Field	covariate measurement controlling with baseline imbalance	Evaluation with the Oswestry Disability Index (ODI)	Threshold of cumulative forward flexed trunk posture [61]
Lin W, *et al.* 2016 [37]	IMU (3 DOF)	1: lower cervical spine 2: middle of the chest 3: L3 (centre of mass) 4: right waist 5: left waist .	Real-time feedback via smartphone	–	–	maxumum error measured .	The maximum error of the tilting angle transformation using validation test [19]	The tilting angles of critical locations of the body[38]
Voinea G, *et al.* 2016 [71]	IMU (9 DOF)	Sensors affixed to shirt in upper thoracic to lower lumbar spine	No real-time feedback	40	Laboratory	cumulative error	Error from the mathematical model was measured in C2 and A4 posture in reconstruction	Measuring orientation angles to represents the curvature of the spine
Nath N, *et al.* 2017 [53]	Smartphone IMU (6 DOF)	1: upper arm 2: waist	No real-time feedback	16	Simulated working environment	an equation to measure trunk and shoulder flexions based on angular features	Comparing with observation-based measurements, Metric: minimum absolute errors	Angular rotations of different body parts [42]
Fathi A,*et al.* 2017 [19]	Shimmer IMU (6 DOF)	1: cervical spine 2: thoracic spine 3: lower lumbar spine .	Real-time feedback	–	Laboratory	Symbolic Aggregate approXimation	Metric : minimum lower bounding distance, and classification accuracy	Ankylosing spondylitis Hunchback and slouching back[1]
Valdivia S, *et al.* 2017 [70]	IMU (9 DOF)	waist	Real-time feedback via exergame	5	Laboratory	focused on System Usability Scale score rather than posture itself	Comparing with kintect version2 in terms of flexion angle measurement	Flexion angle [22]

Table 1. Continue: Summary of outcome from reviewed articles

Reference	Sensor	Region of Interest	Feedback System	# of participants	Environment	Data Analysis Method	Evaluation/validation	Posture definition
Xu J, *et al.* 2017 [78]	IMU (9 DOF) InvenSense	Eight IMUs placed on left and right sides of torso at L4/L5	Real-time vibrotactile feedback	–	Laboratory	statistical significants	RMS and percentage of time inside no zone while using system vs not using system	Used balance posture term by measuring trunk tilt and foot rotation angle [31] .
Hansraj K, *et al.* 2017 [27]	SPoMo (IMU 6 DOF)	1: upper back 2: lower back .	Real-time vibrotactile feedback	4	Laboratory	measuring Force To Cervical Spine at specific neck angles	Using Cosmosworks software, a finite element assessment package	The ears alignment with the shoulders and the angel wings or the shoulder blades [28, 13, 72]
Cornea, G *et al.* 2018 [61]	IMU (9 DOF)	5 sensors along spine	No real-time feedback	–	Laboratory	Mathematical model based on circle arcs	calculating the radius and the coordinates of the IMU sensors	circle arcs and radius model of spine to match its X-ray
Lim C, *et al.* 2018 [35]	IMU (3 DOF)	1: Lumber 2: cervical spine .	No real-time feedback	3	Laboratory	Error estimation in measuring angles	Comparing with goniometer and electrogoniometer	Calculation of the angle
Wang, Z,*et al.* 2019 [73]	IMU (9 DOF)	3 sensors on lower lumbar spine	No Real-time feedback	15	Laboratory, Swimming pool	An algorithm to combine orientation estimation with the human biomechanical model	Comparing with the NDI motion tracking system	Equilateral triangle bracket structure in the horizontal plane
Bootsman, R *et al.* 2019 [10]	Smart garment IMU (9 DOF) Lumo Back	Lower spine	Real-time feedback	60	Hospital	Qualitative data analysis	Three validated questionnaires	Lumbar flexion measurement
Stollenwerk, K*et al.* 2019 [66]	SpineTracker	Between C7 and, L4 vertebrae	Real-time feedback	360	Laboratory	The cumulative error value of body coordinates	Compared to corresponding body coordinates from X-ray image	The center of gravity in the upper body and the waist shape [69]
Caviedes, J, *et al.* 2020 [14]	StretchSense: strain gauge	upside-down triangle of sensors on posterior torso	Real-time biofeedback	6	Laboratory	a single class classifier	Sum of the Point-wise Mahalanobis Distances (SPMD)	curvature of spine inspired by specialised PT exercise therapy, Pilot Study
Wielgos, S *et al.* 2020 [74]	Magnetic sensors	On grid shirt align with spine	No Real-time feedback	4	Laboratory	Simulated curvatures of the spine	Preliminary results based on angle measurement	Measuring angles
Conforti, I *et al.* 2020 [18]	IMU (6 DOF)	Suprasternal notch, Pelvis, mid-thighs, mid-shanks, instep of the feet	No real-time feedback	26	Laboratory, Working Environment	Support vector machine	Accuracy in classification	range of motion of lower limb lumbosacral joint displacement of the trunk
Petropoulos, A*et al.* 2020 [58]	IMU (6 DOF)	1: upper back 2: lowerback	No real-time feedback	–	Laboratory	Angle error in estimation	Reporting RMSE in angle estimation	Estimating angle between lower and upper sensor parallel with spine
Kuo, Y *et al.* 2021 [32]	Lumo Lift	belowclavicle, and midway between the sternal notch	Real-time feedback	21	Laboratory	Correlation in measurement	Comparing with Vicon Motion system	Joint angles segment inclination angles, and pelvic plane angles
Carbonaro, N *et al.* 2021 [12]	IMU (9 DOF)	sacral level thoracic level head level	Real-time vibrotactile feedback	1	Operatory room	Qualitative data analysis	RULA scoring	flexion, lateral bending, and twisting angles of spine and neck
Michaud F, *et al.* 2022 [47]	IMU (9 DOF)	T1, T4, T7, T10 L1, L5	No real-time feedback	14	Laboratory	Measuring location of sensors and estimated position of sensor	Comparing with optical motion capture	3D human spine estimation through a subject-specific multibody model
Moon, K, *et al.* 2023 [50]	IMU (6 DOF)	pelvis, Two on either is of spine	No real-time feedback	1	Laboratory	Error estimation in measuring angles	Estimation of the matching error level from the predetermined template motion obtained from the robotic simulator	Calculation of 3D angles of the hip and spine in the sagittal

Table 2. Commercial Devices for Spinal Posture detection

	Upright Go S	**Upright Go 2**	**LumoBack**	**Alex**	**Nadi X**	**Sense-U**	**ZiktoWalk**	**Prana**	**Jins Meme**	**Sensoria**	**postureTracker**
Size (mm)	48 x 28	48 x 28	415 x 100	80 x 160	NA	35.6 x 35.6	13.6 x 47.3	31.8 x 6.4	NA	33 x 33	33 × 16
Weight (g)	12	11	25	25	NA	11.34	17.5	NA	36	7	10
Sensor location	Upper Back	Upper Back	Waist	Neck	Hips, knees, ankles	Clavicle	Waist	Waist	Nose bridge, ears	Foot, Upper Back	Lower back
Battery life (hours)	12	20	120	168	1.5	240	120	168	16	20	20
Feedback System	Visuo-haptic	Visuo-haptic	Visuo-haptic	Visual	Visuo-haptic	Visual	Visual	Visual	Visual	No Feedback	Visual
Data availability	No	No	No	No	No	No	No	No	No	Yes	Yes

- Articles involving wearable technologies which are able to monitor posture of human
- Data analysis methods were used for data analysis
- Control group experiments or accuracy validation were available
- Article published after 2010
- Articles written in English

We also have excluded following criteria from our screening:

- Articles that are only capable of identifying body positions such as walking, sitting, lying down
- Wearable technology that focus on monitoring posture parts other than spine

The initial database search yielded 2343 potentially relevant articles; however, 154 duplicates were excluded. After applying inclusion and exclusion criteria, 1159 articles were eliminated. The remaining 268 titles and abstracts were then scanned to identify potentially relevant studies. Of these, 234 did not meet the inclusion criteria due to: preliminary results (n=46), and non-experimental studies (n=188). As a result, data were extracted from 30 studies that met the inclusion and exclusion criteria.

After scanning chosen publications for bias using the Newcastle-Ottawa Scale of Quality Assessment. We explored the selected articles in terms of sensor technology, region of interest, feedback presents, participant number, lab or real-world setting, data analysis technique, assessment method, and the posture definition employed. Table 1 provides a thorough summary of the outcome.

Furthermore, another inquiry on Google and Espacenet was conducted to uncover the commercially available posture wearable technology. This study found and used 11 commercially available posture devices in total. “posture”, “wearable”, “device”, and “commercial” were utilised as search phrases. Wearables with posture-recording and monitoring capabilities met the inclusion requirements; however, devices that mechanically adjusted posture, like braces, or products whose device specs were unknown or unavailable were among the exclusion criteria. As demonstrated in Figure 2, the results of this investigation were contributed to the PRISMA as additional source of search results.

3 Findings

The study conducted a comprehensive review of 30 articles selected from a total of 2343 papers on human posture analysis. Out of the 30 selected articles, 14 (46%) used distance error measurement, 8 (26%) used model approximation, 5 (16%) used artificial intelligence, 2 (6%) used usability metric, and only 1 (3%) used qualitative measurements for their data analysis.

In terms of the experimental setting, most experiments were conducted in a laboratory environment (74%), 7 (23%) were conducted in a working environment, and the remaining experiment (3%) did not specify the environment setting. The acquisition points for human posture analysis varied from one local point to 20 points, with the majority of studies (83%) focusing on the spinal area for sensor placement. Additionally, 2 studies (6%) used a modified shirt, the same number of studies used an upside-down triangle shape for sensor placement, and one study (3%) used a belt for sensor placement.

In terms of sensor technology, the majority of studies (70%) used IMU sensors, 5 (16%) used commercial devices, 2 (6%) used strain gauge, 1 used textile, and 1 used a smart garment. The number of participants in the experiments varied from 1 to 360, with some studies not specifying the case study size. The definition of posture was not uniform, with each study defining it differently.

The study also reviewed 11 commercial devices, investigating their size, weight, body placement, presence of a feedback system, availability of collected data for researchers, and the presence of research studies. In terms of weight, wearables ranged from 7g to 36g. only 2 (18%) didn't specify the weight of the device. In terms of sensor placement, 3 (27%) focused on the upper body, 3 (27%) targeted the waist, and the rest aimed at the Neck, Clavicle, Nose ridge, ear, lower back, and foot. The battery life of the wearables covered a range of 1.5 hours to 168 hours. Regarding the presence of a feedback system, most devices (90%) had Mobile application feedback. In terms of the availability of data for researchers, only 2 (18%) had data available for other researchers to use. The details and features of commercial devices are available in Table 2.

4 Discussion

Wearables that monitor posture have the ability to prevent developing poor posture by providing real-time feedback and promoting the correction of poor posture. Many prototypes capable of assessing spinal position have been presented in the literature. A diverse set of technologies supports these systems. IMUs are the most regularly utilised, offering 3 to 10 Degrees of Freedom (DOF). Strain gauges, flex sensors, fibre-optic goniometers, inductive sensors, and ergonomic dosimeters are some other technologies employed in posture monitoring wearables [56, 9, 64, 68, 8]. A comparative detail of the studies is presented in Tables 1 and 2. This section discusses the details and our findings from the reviewed resources.

4.1 Posture definition

The definition of posture that each research study selected was surprisingly broad. While two studies developed their own unique definitions of posture and tested them in pilot studies, the majority employed some form of angular measurement to assess posture. However, the specific location and the combinations of angles and set-ups varied across studies. Defining posture presents a challenge as it is contingent on the underlying causes of poor posture, thereby influencing how it is measured. It is essential for the literature to establish a clear and standardised definition of posture to facilitate measurement and enable researchers to utilise a unified metric for comparing different models. However, the current wide range of methodological approaches for measuring posture presents a challenge in this regard. Comparing studies that use various measures for defining posture is difficult, given the lack of a standardised definition.

4.2 Sensor technology

An Inertial Measurement Unit (IMU) is a device that consists of sensors that measure acceleration, angular velocity, and sometimes magnetic field strength. These sensors can be used to determine the orientation, position, and movement of an object. IMUs are often used in wearable devices for posture detection because they are small, lightweight, and can operate without the need for external references. Several types of sensors are commonly used in IMUs, including accelerometers, gyroscopes, and magnetometers. Each of these sensors measures a different physical quantity, and the data from these sensors can be combined using algorithms to determine the orientation and movement of the device. The degrees of freedom (DOF) in IMU sensors refer to the number of independent axes along which an object's motion can be measured. Generally, an IMU sensor can have 3, 6, or 9 DOF. A 3 DOF IMU can measure acceleration along the three axes of X, Y, and Z, while a 6 DOF IMU can measure both acceleration and rotational velocity around these three axes. On the other hand, a 9 DOF IMU can measure all three axes of acceleration, rotational velocity, and the direction of the Earth's magnetic field. Generally, a higher number of DOF in an IMU sensor means more accurate measurements of an object's motion and orientation. Only 4 (13%) publications in this systematic review used IMU with 3 DOF, The majority, however, used IMU with 6 DOF that is possibly due to factors such as cost, power consumption, application requirements, and simplicity of data processing. 12 (40%) publications measured the posture concurrently with a combination of two to three sensors along with IMU. Three studies exclusively employed texture and pressure sensors, whereas one research incorporated an optical sensor (light).

4.3 Sensor Placement

Wearable placement of the body was an interesting aspect of this systematic review. While the majority of studies considered curvature and the spine's structure related to poor posture, each of them chose various spine locations for measurement.

14% of studies focused on the cervical, 21% targeted the sacrum and 28% aimed at Lumar, while the majority (35%) of studies considered the thoracal region of the spine for their measurement.

4.4 Environmental Setting

Experimental studies often rely on controlled environments to minimise confounding variables' influence and ensure that the results are reproducible. This is why many experiments are conducted indoors and in laboratory settings. In these controlled settings, researchers can carefully manipulate the independent variables and measure their effects on the dependent variables while keeping other variables constant. Additionally, laboratory equipment and instruments can be calibrated and standardised to reduce measurement errors, which is particularly important when conducting high-precision experiments. However, the controlled nature of laboratory experiments also limits their ecological validity or the extent to which the results can be generalised to real-life situations. Furthermore, laboratory equipment and facilities can be expensive or impractical for real-life usage. While laboratory experiments have their advantages, they may not always be practical or feasible when studying phenomena that occur in the real world or in outdoor environments. However, outdoor experiments also present many challenges, such as the lack of control over environmental conditions, difficulty in replicating the same conditions across multiple experiments, and the potential for confounding variables to influence the results. As a result, experimental designs for outdoor settings often involve compromises between control and ecological validity. In this systematic review majority, (84%) of experiments were conducted in a laboratory and controlled environment only five (16 %) experiments were adapted to real-life experience. It is necessary to design practical wearables in real work to be helpful and impactful.

4.5 Data Availability

In this systematic review, we observed that data for other researchers were only available in some cases. Publicly available data can encourage further analysis and replication of the findings. It also helps researchers in the field to improve existing work and develop more optimised outcomes. This can be particularly important in posture detection and public health, where access to data can inform policy decisions and lead to improvements in people's care. However, in other cases, the data may be restricted due to privacy concerns or ownership issues. However, the data may be restricted in other cases due to privacy concerns or ownership issues. For example, wearable technology such as fitness trackers or smartwatches can collect large amounts of data on individuals' health and behaviour, but this data may be subject to privacy laws or the terms of service of the device manufacturer. The lack of availability of data from wearable technology can pose challenges for researchers who are interested in studying health or behaviour. While wearable devices can provide valuable insights into individuals' activity, spine structure, and posture, access to this data may be limited by factors such as cost, privacy concerns, or proprietary algorithms. This can create barriers to replicating studies or conducting meta-analyses, which rely on the availability of large datasets. Additionally, the ownership of the data may be unclear, which can make it difficult for researchers to obtain permission to use the data or to share it with other researchers.

4.6 Data Analysis

In terms of data analysis, while existing and reviewed papers had valuable tools for evidence-based decision-making, the data analysis methods used in these reviews are often relatively basic. This can limit the accuracy of the outcome, as it may not fully capture the nuances of the underlying data. One potential way to improve the accuracy of systematic reviews is by incorporating AI and ML techniques. AI and ML can be used to analyse large datasets and identify patterns that may not be immediately apparent using traditional statistical methods. This can help to increase the accuracy of the outcome by providing a more nuanced understanding of the data. AI and ML can be particularly useful in scenarios with wearables that often involve significant and complex datasets. This can help to identify gaps or inconsistencies in the literature and provide insights into areas that may require further research.

5 Beneficiary In Well-being and Healthcare

Wearable technologies have the potential to revolutionise the way we monitor and improve our health and well-being, and one area where they have made significant strides is in the detection of human posture. These technologies can be used to not only identify poor posture, but also provide feedback and coaching to help individuals improve their posture and reduce the risk of injury or pain. In this systematic review, we also explore the application of wearable technologies for human posture detection and the benefits they offer for both individuals and healthcare professionals.

One of the primary benefits of wearable technologies for human posture detection is their ability to continuously monitor posture throughout the day. Traditional methods of posture assessment, such as manual observation or static photographs, are limited in their ability to capture posture changes over time or in different positions. Wearable technologies, on the other hand, can track posture in real-time, allowing for a more comprehensive understanding of an individual's posture habits and patterns.

One of the most significant advantages of wearable devices is their potential to facilitate behavioural modification and promote positive lifestyle changes. By continuously monitoring posture habits, these devices create a feedback loop that encourages individuals to adopt healthier postural habits in their daily lives. As users become more conscious of their posture, they are likely to make conscious choices to prioritise good posture, not just during device usage but throughout their day-to-day activities. This behavioural modification can extend beyond posture, leading to increased awareness of overall health and well-being.

In addition to providing individuals with a convenient and accurate way to monitor their posture, wearable technologies for posture detection also offer benefits for healthcare professionals. By providing continuous posture data, these technologies can help healthcare professionals identify patterns and risk factors for injury or pain, and provide more targeted interventions and treatment plans.

For example, a physical therapist working with a patient who suffers from chronic back pain could use wearable posture detection technology to identify specific postures or activities that may be contributing to the patient's pain, and develop a treatment plan based on this information. Moreover, using vision-based technology has raised concerns about the potential invasion of privacy, as they can capture personal information and activities without the individual's consent. Additionally, cameras can be hacked or accessed without the owner's knowledge, putting them at risk of cyber attacks or identity theft. Unlike vision-based technology, wearables do not capture visual data and instead rely on sensors to collect information. Thus, using wearables can maintain the benefits of technology while protecting privacy, making them a viable alternative to vision-based technology.

The boundary between smart health wearables and medical devices is becoming blurred with advancements in technology, allowing patients to take a more active role in their health and manage ongoing conditions. However, the use of commercial wearables in healthcare has both benefits and drawbacks. Healthcare professionals may be overwhelmed with the increase of patients bringing their own data to appointments, leading to confusion and tension. Alternatively, healthcare professionals and researchers could collaborate to validate wearable devices as a supportive tool in the healthcare system.

The use of wearable technology in the field of spine posture analysis offers several potential benefits, including:

- Early Detection of Postural Issues: Wearable technology enables real-time monitoring of spinal posture, which allows for early detection of postural issues. Early detection of these issues can lead to prompt intervention and prevent more serious problems from developing in the future.
- Improved Treatment Outcomes: By providing more accurate and detailed information about spinal posture, wearable technology can lead to improved treatment outcomes for individuals suffering from back pain, spinal injuries, or other postural problems.
- Increased Accessibility: Wearable technology offers an affordable and accessible solution for individuals to monitor their spinal posture, regardless of their location or access to healthcare facilities. This increased accessibility can lead to earlier and more effective treatment for postural issues.
- Better Understanding of Spinal Mechanics: Wearable technology can provide valuable data on spinal mechanics, which can help medical professionals better understand the causes of postural issues and develop more effective treatments.
- Improved Compliance: Wearable technology can provide real-time feedback on posture, which can encourage individuals to adopt better postural habits and improve compliance with treatment plans.

The use of wearables in healthcare is still in its early stages, and its potential applications and limitations are yet to be fully understood. Wearable technology has the potential to offer numerous benefits to healthcare providers and individuals alike. By enabling real-time monitoring and improved understanding of spinal mechanics, wearable technology can help prevent and treat postural problems, leading to improved health outcomes for individuals.

6 Conclusion

This paper has reviewed the current state of the art in wearable devices for monitoring and detecting spinal posture, as well as commercial devices. The current method for analysing posture is through radiography, but optical methods are emerging as a potential alternative. This paper shows that despite the benefits of using various technologies to measure posture, more research is needed to improve their accuracy, determine their clinical usefulness, and enhance their practicality before they can be widely adopted.

Furthermore, these laboratory-based methods are not suitable for daily posture monitoring. Wearable technology could fill this gap by providing objective measurements of posture. However, the lack of standardisation in posture definitions remains a challenge. Although there is a growing trend of commercial wearable devices using IMUs for continuous data collection, more research is needed to confirm their validity. Their data could potentially be used to detect spinal conditions earlier and more easily.

Our review highlights the advances made in this field, as well as the limitations that must be considered when designing and evaluating these devices. We have also identified several key concerns, including the availability of data, restrictions in experiment environment settings, data analysis, sensor technology and placement, and the potential application of these devices in healthcare.

One of the key challenges facing researchers and practitioners in this field is the need to balance the advantages of wearable devices with the limitations that arise from their use. While wearable devices offer many potential benefits, such as increased accuracy and real-time monitoring, they are also subject to limitations, such as the standardised definition of posture and employing AI for data analysis. Future research should continue to address these challenges and work towards developing more reliable and accurate wearable devices for monitoring spinal posture.

Overall, the findings of this paper emphasise the need for continued innovation in wearable technology, with a particular focus on the development of devices that can be used in various environmental settings, provide reliable and accurate data, and have clear applications in healthcare. By addressing these concerns, researchers and practitioners can work towards developing more effective interventions for spinal posture monitoring and detection, with the potential to improve patient outcomes and quality of life.

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