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Review

Use of Wearable Sensor Technology in Gait, Balance, and Range of Motion Analysis

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Abstract: More than 8.6 million people suffer from neurological disorders that affect their gait and balance. Physical therapists provide interventions to improve patient's functional outcomes, yet balance and gait are often evaluated in a subjective and observational manner. The use of quantitative methods allows for assessment and tracking of patient progress during and after rehabilitation or for early diagnosis of movement disorders. This paper surveys the state-of-the-art in wearable sensor technology in gait, balance, and range of motion research. It serves as a point of reference for future research, describing current solutions and challenges in the field. A two-level taxonomy of rehabilitation assessment is introduced with evaluation metrics and common algorithms utilized in wearable sensor systems.

Keywords: wearable sensors; gait analysis; balance; range of motion; rehabilitation; healthcare

1. Introduction

Researchers study gait, balance and joint kinematics in people with movement disorders. Movement disorders may be due to problems of musculoskeletal, neurologic or other body systems. In 2008, about 33 million American adults had balance problems caused by medications, ear infection, injuries or neurological disorders [1]. Some of the common neurological disorders that cause gait and balance problems are Stroke, Alzheimer's disease (AD), Parkinson's disease (PD), Multiple Sclerosis (MS), and Ataxia. The number of people affected by these neurological disorders are more than 18 million people worldwide [2–5].

Physical therapists help individuals with movement disorders by providing interventions to reduce pain; increase range of motion and muscle strength; improve balance; improve gait and mobility; and prevent falls [6]. Physical therapists often evaluate rehabilitation outcomes in a subjective manner, through visual observation, clinical impression, and through tests and measures. Researchers have developed applications to assess rehabilitation outcomes using novel technologies such as external sensors, smartphones, and wearable sensors. The performance of sensor systems depend entirely on the interaction of the subject with the sensor used; external sensors are deployed in the environment around the subject, while smartphones and wearable sensors are mounted on the subject [7].

Common external sensors are camera-based, floor-based sensors, or force platforms. A camera-based system can either use one or multiple cameras placed at points of interest around the environment where the subject will perform the specified exercise or activity, like walking or turning. Sensors used in floor-based systems are placed in mats on the floor to measure force and pressure when the subject walks on them [8]. Force platform-based systems, similar to floor-based systems, use force and pressure while a person is standing on the platform to measure postural stability or gait.

Floor-based sensors and force platform systems are used in research labs or clinically to provide very detailed spatiotemporal gait variables and postural stability measurements, respectively. The main drawbacks of these systems are their cost and lack of portability; they are primarily confined to research labs and rarely available for use in clinical settings. Additionally, camera-based systems are unable to track the subject outside of the camera's visibility, leading to purchasing additional sensors to increase the system's range of visibility, while increasing the cost of the overall system [7,9]. In addition, camera-based systems are computationally expensive to obtain accurate results and may raise privacy concerns. Camera-based systems have been used primarily to conduct motion analysis in research labs, but recently, camera systems have been deployed in people's homes to track their daily activities or assess their fall risk [10,11].

Unlike external sensors, wearable sensors are cheaper and mounted to the subject's body, eliminating cost and portability limitations set by external sensors [9]. The high level of portability allows physical therapists and researchers to analyze gait and balance not only in research laboratories but also in clinic, in patient's home or out the community. The accuracy of a wearable sensor system will depend on how many sensors are used, where and how are the sensors located, and other challenges that will be further discussed. There are many types of wearable sensors that are used in applications ranging from monitoring subject's physiologic responses like heart rate, ECG, or blood glucose [11], to measuring gait, balance, and RoM during movements like walking, turning, sit to stand or postural sway. Wearable sensors have been utilized in conjunction with tests and measures, like the Timed Up and Go, to provide more detailed and objective balance data [12]. Wearable sensors have also been used to study changes in gait and balance over time in people with neurodegenerative diseases and to investigate improvements post interventions [13].

This review paper will not cover external sensors, but will focus on the use of wearable sensors in gait, balance, and RoM analysis. Other papers have reviewed the use of wearable sensors in gait or balance, however, none have reviewed the literature on gait, balance, and lower extremity and trunk RoM [12,14,15]. It is important to review the literature in gait, balance, and RoM collectively since researchers and clinicians often evaluate the interplay between gait, balance, and lower extremity and trunk RoM. Therefore, this review surveys the wearable sensor system methodologies currently used to examine gait, balance, and RoM. Additionally, current reviews do not discuss the technical aspects in wearable sensor technologies that can affect the outcomes of gait, balance, and RoM measurements. This review discusses common design issues when using wearable sensors and describes how quantitative parameters are extracted from wearable sensors in gait, balance, and RoM research. Thus, the purpose is to review current literature on the use of wearable sensors in gait, balance, and ROM analysis.

2. Review Method

This review was performed following the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [16].

2.1. Literature Search Strategy

PubMed, Scopus, and IEEE Xplore were used to identify articles that use wearable sensor technology to measure and/or analyze gait, balance, and/or range of motion. The following keywords were used to search within title, abstract, and/or articles' keywords: "gait", "balance", "wearable sensor", "wearable device", "IMU", "EMG", "smartphone", "accelerometer", "gait variability", "inertial sensor", "postural sway", "range of motion", "gait analysis", "insole sensor", and combinations of all these keywords.

2.2. Study Selection: Inclusion Criteria and Quality Assessment

After articles were identified through electronic databases, they were screened by their title and abstract. Articles were included if they were written in English. Articles were excluded if they did not use any type of body worn wearable sensors to measure gait, balance, and/or RoM, were published before January 2009, were conference abstracts, review articles or case studies.

A quality assessment was performed for each of the included studies independently (Table 1). The quality assessment is based on three different sub-scales presented by Hagströmer et al.: internal validity (IV)—addresses methodological bias, external validity (EV)—addresses the extent that the findings can be generalized to the population based on the study subjects, and quality of the reported data (QV)—assesses if the information provided is sufficient and unbiased [17]. The quality assessment checklist used in this review is based on the 15-item checklist proposed by Ghislieri et al., which is similar to those commonly used in the literature for systematic reviews [17–21]. The score, or number of "Yes"s, was calculated for each article.

Articles were classified based on the score obtained: "high quality" if the score > 10, "moderate quality" if the score was between 5 and 10, and "low quality" if the score < 5. Only "high quality" articles were selected.

Table 1. Quality assessment checklist used in this survey.

Item	Criteria	Validity Type	Outcome
1	The purpose of the study is clearly stated	IV	Yes/No
2	The research question is relevant to the purpose of the study	EV	Yes/No
3	Inclusion and/or exclusion criteria are described	EV	Yes/No
4	Data collection clearly described	IV/EV	Yes/No
5	Same data collection procedure for all subjects	EV	Yes/No
6	Reliable data processing clearly described	IV/EV	Yes/No
7	Data loss <20%	EV	Yes/No
8	Outcomes are relevant to the topic	EV	Yes/No
9	Outcomes are same for all subjects	IV	Yes/No
10	Scientific question stated in the aim is answered	IV	Yes/No
11	Results are clearly presented and discussed	IV	Yes/No
12	Appropriate statistical analysis techniques used	QV	Yes/No
13	Statistical test used clearly stated	QV	Yes/No
14	Analytical software used is clearly stated and referenced	QV	Yes/No
15	Sufficient number of subjects	QV	Yes/No

3. Results

A total of 1677 articles were identified. After excluding 646 duplicates, 659 articles were screened based on their title and abstract, 131 were selected for full-text assessment. After excluding articles based on assessment results, 56 articles were included in this systematic review. A flow diagram showing the study selection is presented in Figure 1. Table 2 presents a description of the studies included providing the reference, the year of publication, and the objective of the study. Table 3 presents the main characteristics of the studies included such as parameters extracted, the population that participated in the study, sensors used, their locations, and their level of obtrusiveness.

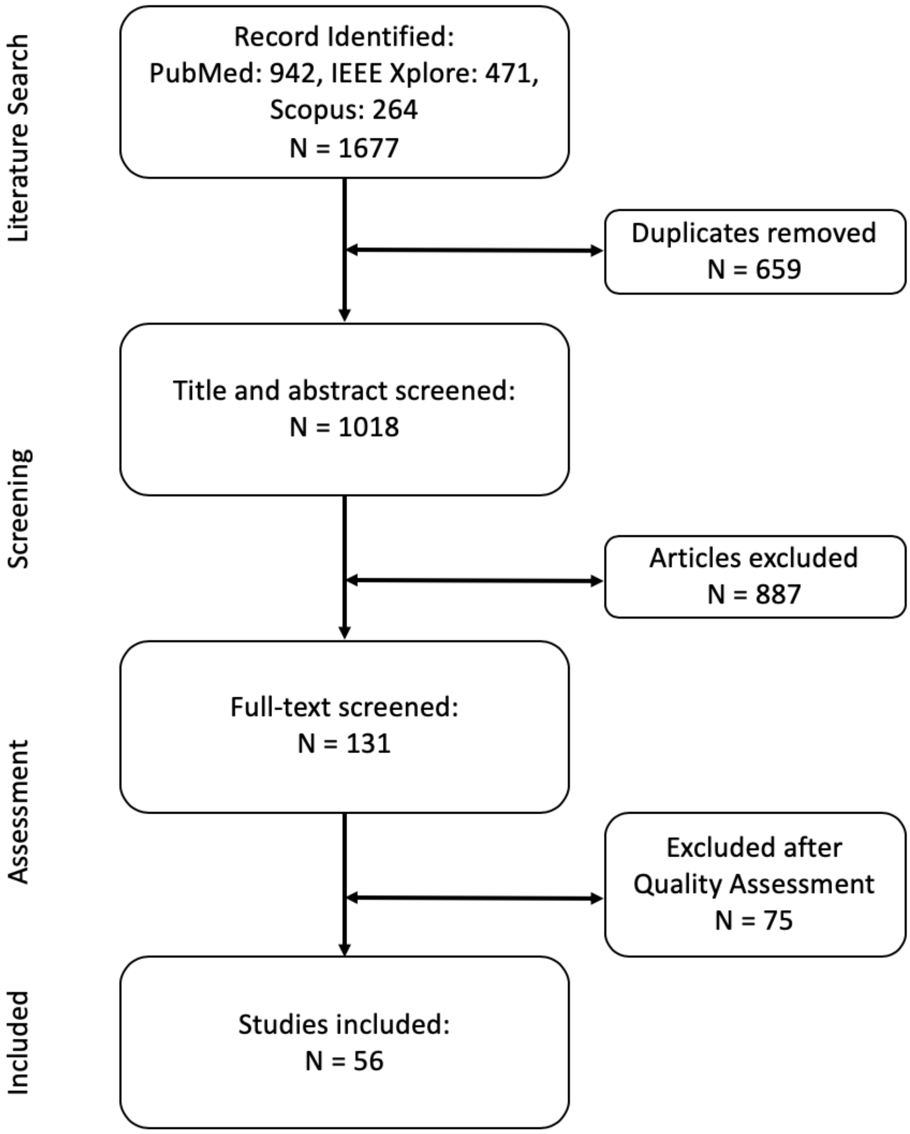

Figure 1. Flow Diagram of Search Strategy.

Table 2. Literature on Wearable Sensors in Gait, Balance, and RoM Research Included in the Review.

Reference	Year	Objective
Van den Noort et al. [22]	2009	Evaluate the use of goniometry in estimating the joint angle of the catch simultaneously with inertial sensors.
Franco et al. [23]	2012	Implement a Kalman filter using a smartphone to estimate 3-D angulation of the trunk.
Spain et al. [24]	2012	Study if wearable sensors can detect differences in balance and gait between people with MS with normal walking speeds and healthy controls.
Martori et al. [25]	2013	Develop a wearable motion analysis system to evaluate gait that consists on six IMUs.
Crea et al. [26]	2014	Describe a wearable pressure-sensitive insole sensor for lower-limb amputees feedbacks.
Dewey et al. [27]	2014	Assess suitability of instrumented gait and balance measures for PD diagnosis and estimation.
Hsu et al. [28]	2014	Develop gait and balance analysis algorithms to gather quantitative data considered early indicators of AD.
Patterson et al. [29]	2014	Compare a mobile technology application with a commonly used subjective balance assessment.
Tzallas et al. [30]	2014	Describe a system for continuous remote monitoring of patients with PD.
Wentick et al. [31]	2014	Investigate whether detection of gait initiation in transfemoral amputees can be useful for voluntary control of lower extremity prostheses.
Alberts et al. [32,33]	2015	Develop a biomechanically based quantification of the BESS using inertial sensors data. Determine whether inertial data provide sufficient resolution of center of gravity movements to quantify postural stability.
Bauer et al. [34]	2015	Evaluate IMU-system when assessing movement dysfunctions of concurrent validity and reliability.
Ellis & Zhu et al. [35,36]	2015	Describe a smartphone-based application to quantify gait variability.
Godfrey et al. [37]	2015	Investigate the use of a wearable sensor compared to laboratory reference.
Jaysrichai et al. [38]	2015	Measure the knee joint angle using IMUs and reference it with a motion capture system.
Kanzler et al. [39]	2015	Present a method for calculating continuous heel and toe clearance and foot angle in the sagittal plane without knowing shoe dimensions.
Lee & Kumar et al. [40,41]	2015	Design and validate a smartphone-based system for motor assessment using IMUs.
Lin et al. [42]	2015	Present and evaluate the step count performance of a smart insole system.
Postolache et al. [43]	2015	Develop a system to objectively record ground reaction forces, acceleration and direction of the feet using wearable sensors.

Table 2. *Cont.*

Reference	Year	Objective
Sijobert et al. [44]	2015	Present an algorithm to estimate stride length using an accelerometer and a gyroscope.
Nouredanesh et al. [45,46]	2015-16	Develop a method that automatically distinguishes compensatory balance responses from regular stepping pattern.
Bertolotti et al. [47]	2016	Assemble an IMU to provide measurements of limb movements and balance abilities.
Del Din et al. [48]	2015	Quantify a comprehensive range of gait parameters using a single tri-axial accelerometer. Compare gait data of older adults with PD subjects.
Horak et al. [49]	2016	Study balance and gait to represent independent domains of mobility in PD.
Lee et al. [50]	2016	Compare Multiscale Entropy (MSE) analysis of acceleration data with other features to observe falling behavior and traditional clinical scales to evaluate falling behavior.
LeMoyne et al. [51]	2016	Facilitate the acuity of the timed 25 foot walk test with the synthesis of wearable and sensors and machine learning.
Li et al. [52]	2016	Develop a sit to stand detection system to raise an alarm when a individuals stand up without proper technique or assistance.
Storm et al. [53]	2016	Evaluate accuracy of two algorithms for detection of gait events and temporal parameters during free-living walking.
Wang et al. [54]	2016	Improve autocorrelation method for gait analysis using EMG signals collected from six muscle groups of the lower limbs in hemiparetic subjects.
Andó et al. [55]	2017	Propose a multi-sensor architecture for postural sway assessment in elderly and in people with neurological disorders.
Iijima et al. [56]	2017	Assess quantitatively the gait disorders in the daily lives ofpatients with PD using with a newly developed portable gait rhythmogram.
Lebel et al. [57]	2017	Assess attitude and heading reference system at multiple segments and joints.
Robert-Lachaine et al. [58]	2017	Determine the technological error and biomechanical model differences between IMUs and an optoelectronic system.
Schlachetzki et al. [59]	2017	Develop a gait analysis system with wearable sensors to assess gait parameters in PD.
Shazad et al. [60]	2017	Provide an objective, cost-effective method to obtain balance and mobility based fall-risk in older adults.
Aich et al. [61]	2018	Quantify gait parameters using wearable accelerometers; compare five estimated gait parameters with a 3D motion capture system automatic discrimination of FoG patients from no FoG patients using machine learning.

Table 2. *Cont.*

Reference	Year	Objective
Diaz et al. [62]	2018	Propose methods to estimate step length and step width using wearable sensors.
Stack et al. [63]	2018	Detect instability using wearable sensors.
Zhang et al. [64]	2018	Propose a new gait symmetry index to quantify gait symmetry using one accelerometer.
Chomiak et al. [65]	2019	Assess the accuracy and reliability of a wearable sensor system for bio-feedback training.
Chomiak et al. [66]	2019	Describe a pattern recognition algorithm for the automated detection of gait-cycle breakdown and freezing episodes.
Grinberg et al. [67]	2019	Investigate different types of 3-meter tandem walking tests in fully ambulatory PwMS.
Hsied et al. [68]	2019	Determine if a smartphone can measure static postural stability and distinguish elderly with fall risk.
Mazzeta et al. [69]	2019	Propose a wearable sensor system for auto-continuous analysis of FoG in PD patients.
Mikos et al. [70]	2019	Demonstrate the integration of an FoG detection system into a single sensor node.
Ngueleu et al. [71]	2019	Equip an insole with pressure sensors to detect steps.
Phan et al. [72]	2019	Investigate wearable sensor technology to identify the kinematic features associated with gait abnormalities seen in cerebellar ataxia.
Reeves et al. [73]	2019	Determine the between-day reliability of peroneus longus EMG in healthy subjects while walking.
Rivolta et al. [74]	2019	Investigate the use of wearable accelerometer to evaluate the fall risk determined by the Tinetti clinical scale.
Tang et al. [75]	2019	Propose an objective approach to access functional balance using an insole wearable sensor and an accelerometer.
Weiss et al. [76]	2019	Evaluate strategies employed by PD patients when transitioning from turning to sitting.
Zhao et al. [77]	2019	Present an adaptive method for gait detection.

Table 3. Main Characteristics of Wearable Sensors in Gait, Balance, and RoM Research Included in the Review.

Reference	Analysis	Parameters Extracted	Population	Sensor(s) Used	Sensor(s) Location	Obtrusiveness Level
Van den Noort et al. [22]	ROM	Knee Angle Ankle Angle	1 healthy	IMU	Thigh	Medium
Franco et al. [23]	Balance ROM	Trunk angles Sway ranges	20 healthy	Smart	Lumbar	Low
Martori et al. [25]	Gait ROM	Stride length Cadence Knee flexion	10 healthy	IMU	Sternum Waist Thighs Shanks	High
Crea et al. [26]	Gait	Swing time Stance time Cadence	10 healthy	Pressure	Insole	Low
Dewey et al. [27]	Gait Balance	Velocity Cadence Arm swing Sway area Jerk Path length Sway distance	135 PD	IMU	Ankles Wrists Lumbar Sternum	High
Hsu et al. [28]	Gait Balance	Stride time Stride Velocity Stance time Swing time Cadence	21 AD 50 healthy	IMU	Feet Waist	Medium
Patterson et al. [29]	Balance	Postural measure	21 healthy	Smart	Hold on chest	Low
Tzallas et al. [30]	Gait	Not specified	20 PD short-term 24 PD long-term	IMU	Ankles Wrists Waist	High
Wentick et al. [31]	Gait	Gait initiation	3 transfemoral amputees 3 through the knee amputees	IMU EMG	Upper leg	High

Table 3. *Cont.*

Reference	Analysis	Parameters Extracted	Population	Sensor(s) Used	Sensor(s) Location	Obtrusiveness Level
Alberts et al. [32,33]	Balance	Path length RMS Equilibrium score	49 healthy for one study 32 healthy for other study	Smart	Lumbar	Low
Bauer et al. [34]	ROM	Flexion Extension Lateral flexion	22 asymptomatic for validity 24 asymptomatic for reliability	IMU	Right thigh Sacrum L1 back level T1 back level	Medium
Ellis & Zhu et al. [35,36]	Gait	Step time Step length Variability	12 healthy elderly 12 PD	Smart	Abdomen	Low
Godfrey et al. [37]	Gait	Step length Step velocity Asymmetry	40 healthy young 40 healthy old	IMU	Lumbar	Low
Jaysrichai et al. [38]	ROM	Knee angle	10 healthy	IMU	Shanks Thighs	Medium
Kanzler et al. [39]	Gait	Heel clearance Toe clearance Foot angle	20 healthy	IMU	Ankle	Low
Lee & Kumar et al. [40,41]	ROM	Joint angles	19 healthy 20 disable	IMU Smart	Thighs Shanks Ankles	High
Lin et al. [42]	Gait	Step count	10 healthy	Pressure	Insole	Low
Postolache et al. [43]	Gait	Step length Stride length Cadence Gait Speed	6 healthy	IMU Pressure	Shanks Insole	Low
Sijobert et al. [44]	Gait	Stride length	10 healthy 12 PD	IMU	Shanks	Low

Table 3. *Cont.*

Reference	Analysis	Parameters Extracted	Population	Sensor(s) Used	Sensor(s) Location	Obtrusiveness Level
Nouredanesh et al. [45,46]	Gait Balance	Normal step Side step Crossover step	5 healthy	IMU EMG	Thighs Shanks Lumbar	Medium
Bertolotti et al. [47]	Balance ROM	Trunk inclination Sway path Sway area Sway mean velocity	10 healthy	IMU	Lumbar	Low
Del Din et al. [48]	Gait	Stride time Stance time Swing time Step velocity Step length Variability Diff. Asymmetry	5 healthy	IMU	Lumbar	Low
Horak et al. [49]	Gait Balance	Postural measures Trunk acceleration Gait speed Cadence	10 healthy 12 PD	IMU	Lumbar Shanks Arms	High
Lee et al. [50]	Gait Balance	Jerk Sway range Sit-to-stand time Mean & STD Step length	65 elderly	IMU	Lumbar	Low
LeMoyne et al. [51]	Gait	Stride time Gyroscope statistics	1 healthy 1 FA	IMU	Ankles	Low
Li et al. [52]	Gait Balance	Trunk angle Muscle strength	6 healthy	EMG Smart	Lumbar Thighs	Medium
Storm et al. [53]	Gait	Stride time Step time Stance times	10 healthy	IMU	Lumbar Ankles	Low

Table 3. *Cont.*

Reference	Analysis	Parameters Extracted	Population	Sensor(s) Used	Sensor(s) Location	Obtrusiveness Level
Wang et al. [54]	Gait	Autocorrelation	10 healthy 1 hemipheris	EMG	Legs muscle	High
Andó et al. [55]	Balance	Sway range Sway mean velocity Sway mean frequency	22 healthy	IMU	Waist Sternum	High
Iijima et al. [56]	Gait	Gait cycle Cadence Acceleration magnitude	14 PD	IMU	Waist	Low
Lebel et al. [57]	Gait ROM	Multiple ROM angles	20 asymptomatic	IMU	Left feet Pelvis Back Head Left Calf Left Thigh	High
Robert-Lachaine et al. [58]	ROM	Multiple ROM angles	12 healthy	IMU	Feet Shanks Arms Thighs Pelvis Sternum Head	High
Schlachetzki et al. [59]	Gait	Stride length Stride time Velocity Gait phases times Foot clearance Heel-strike Toe-off angles	63 PD	IMU	Ankle	Low

Table 3. *Cont.*

Reference	Analysis	Parameters Extracted	Population	Sensor(s) Used	Sensor(s) Location	Obtrusiveness Level
Shazad et al. [60]	Gait Balance	Step count Step frequency Avg. step length Walking speed	23 elderly	IMU	Waist	Low
Aich et al. [61]	Gait	Step time Stride time Step length Stride length Walking speed	51 PD	IMU	Ankles	Low
Diaz et al. [62]	Gait	Step length Step width	4 healthy	IMU	Lumbar Thighs Shanks	Medium
Stack et al. [63]	Gait Balance	TUG Times Turns' Step Count	4 healthy	IMU	Wrists Ankle Waist	Medium
Zhang et al. [64]	Gait	Symmetry	16 Post-Stroke 9 healthy	IMU	Feet Lower Back	Low
Chomiak et al. [65]	Gait	Walking speed Cadence Step length	15 healthy	IMU Smart	Knee	Low
Chomiak et al. [66]	Gait	Rence quantification analysis	9 healthy 21 PD	Smart	Thigh	Low
Grinberg et al. [67]	Gait	Velocity Cadence Double support Swing phase	25 MS 25 healthy	IMU	Feet Lower Back	Low
Hsied et al. [68]	Balance	RMS AP & ML movements	30 elderly	Smart	Hold on chest	Low
Mazzeta et al. [69]	Gait	Step time Ratio: Max value/sEMG	7 PD	IMU EMG	IMU-calf EMG-lower leg	High

Table 3. *Cont.*

Reference	Analysis	Parameters Extracted	Population	Sensor(s) Used	Sensor(s) Location	Obtrusiveness Level
Mikos et al. [70]	Gait	Frequency RMS & STD Range Stride length Stride time	63 PD	IMU	Ankles	Low
Ngueleu et al. [71]	Gait	Step Count	20 healthy	Pressure	Insole	Low
Phan et al. [72]	Gait	PCA generated features	29 cerebellar ataxia 22 healthy	IMU	Ankles	Low
Reeves et al. [73]	Gait	Peroneus longus	10 healthy	EMG	Right leg (SENIAM guideline)	Medium
Rivolta et al. [74]	Gait Balance ROM	Accelerometer features Tilt angle	79 hospitalized	IMU	Chest	Low
Tang et al. [75]	Gait Balance	RMS & STD Entropy Mean absolute deviation Lempel-ziv Dominant frequency	33 elderly	IMU Pressure	Waist pouch Insole	Low
Weiss et al. [76]	Balance	TUG times	96 PD	IMU	Lumbar	Low
Zhao et al. [77]	Gait	Gait cycle phases	9 healthy	IMU	Feet	Low

3.1. Common Wearable Sensors Used in Gait, Balance, and RoM Analysis

Wearable sensors are devices that are mounted to a person's body in order to gather information; such as movement or heart rate. Wearable sensors typically are inexpensive and small in size. Wearable sensors are playing an increasing role in balance and gait assessment in rehabilitation research. Three important advantages of wearable sensors for assessment of gait and balance disorders include [12]:

- obtain objective measures that characterize how and why functional performance of gait and balance are impaired,
- increase the sensitivity of gait and balance measures,
- increase the opportunity for immediate biofeedback provided to patients.

3.1.1. Inertial Measurement Units and Magnetometers

Inertial measurement units (IMUs) are devices that typically contain an accelerometer, a gyroscope, and sometimes, a non-inertial sensor called a magnetometer [78]. There are numerous types of IMUs developed by different companies and the size and weight of these devices are similar. The primary difference between sensors developed by different companies is in the software, in the algorithms used to analyze the data and the housing in which they are mounted. The housing varies depending on the battery and on-board storage. The information collected from these devices depends on the subject's movements performed while wearing the devices.

Accelerometers are the most common sensor used in gait, balance, and RoM research using IMU devices. Accelerometers are embedded within wearable sensors and the data is often given in three dimensions, acceleration forces in the X, Y, and Z axes. These forces may be caused by the constant force of gravity pulling at the feet or caused by moving or vibrating the accelerometer. Some researchers prefer a single signal of acceleration in order to be orientation invariant, thus, avoiding misalignment issues [79]. To achieve this, the magnitude of the acceleration using three-dimensional data is calculated using Equation (1), where a_x, a_y, and a_z are the accelerations in the X, Y, and Z axes, respectively.

$$a_m = \sqrt{a_x^2 + a_y^2 + a_z^2} \tag{1}$$

A gyroscope is a sensor that uses the Earth's gravity to help determine the orientation and angular velocity. Usually, the design consists of a freely-rotating disk mounted into a spinning axis in the center of a larger and more stable wheel. When the axis turns, the disk remains stationary to indicate central gravitational pull. The main difference between the accelerometer and gyroscope is that one can sense rotation and the other cannot. In a stationary scenario, the accelerometer can determine orientation with relation to Earth's surface, but when acceleration is applied to the device, the accelerometer is unable to differentiate between that movement and the acceleration provided through gravitational pull.

Magnetometer is a non-inertial sensor that measures magnetic fields. A simple type of magnetometer is a compass, which provides a simple orientation in relation to the Earth's magnetic field. Magnetometers, in ubiquitous computing applications, are often used to improve measurements regarding orientation, especially heading. A challenge in the application of magnetometer is that magnetic disturbances limits the accuracy of their measurements. Fortunately, there are ways to compensate for these errors, which will be discussed in Section 4.11.

3.1.2. Smart Devices

Smart devices, such as smartphones and smart watches, are very popular because of their low cost, high availability, and capability to behave as an IMU device. Smart devices contain similar componentry as IMUs including accelerometers, gyroscopes, and magnetometers. Researchers investigate the potential use of smart devices to assess gait, balance, and RoM to reduce the level of obtrusiveness that using multiple devices can introduce and to increase portability. There are studies that implement smart devices to measure trunk movements and postural stability to assess balance [23,29,32,33,52,68]. Other studies quantify gait parameters, including symmetry and variability [35,36,65,66].

3.1.3. Electromyography (EMG) Sensors

Electromyography (EMG) sensors use electrodes to record electrical activity from subject's muscle tissue. There are two types of EMG sensors; surface electrodes and needle electrodes. Needle electrode exams are more specific and accurate. EMG sensors can detect whenever a muscle is at rest or active; a negative electrical potential difference is maintained across the muscle when the muscle is resting, while a positive potential travels along the length of the fiber when the nerve activates the muscle fiber [80].

EMG is an essential tool in diagnostic evaluation of patients with peripheral neurologic disorders, such as peripheral neuropathy, Guillain Barre or ALS [81]. EMG has contributed in multiple clinical areas to enhance the management of patients with neuromuscular disorders. including neurology, neurosurgery and orthopedics [82]. EMG is often used in combination with nerve conduction velocity tests. EMG and nerve conduction velocity provide different information about the peripheral nervous system, but when analyzed together, aid in accurate diagnosis [81]. Unfortunately, EMG has limitations and considerations [81,83,84]:

- technical limitations may be present in cases of obesity or advanced age,
- EMG cannot be used for all muscles for all activities,
- EMG does not give RoM information,
- electrode placement is vital,
- traditional EMG cannot detect passive movements,
- for surface EMG (SEMG), skin must be cleaned and static charges on the skin can alter the signals.

EMG and SEMG have been used to identify certain gait characteristics, distinguish compensatory balance responses, and develop and improve methods used to assess balance. Continuous EMG analysis in patients with neurological disorders provide relevant diagnostic contributions in terms of nosological classification, localization of focal impairments, detection of pathophysiological mechanisms, and functional assessment to supplement the clinical evaluation of neuromuscular disorders [31,52,69,73].

3.1.4. Insole Pressure and Force Sensors

Besides measuring body movement with IMUs and smart devices and measuring muscle electrical activity with EMG, there are sensors that can measure ground reaction forces applied by the subject. The pressure sensor is typically located in the insole of the subject's shoes, and it can measure the plantar foot surface in 3 dimensions. The most common insole sensors are capacitive, resistive piezoelectric, and piezoresistive sensors, and which is selected depends on the range of pressure it can stand and it's sensitivity [8]. Insole pressure sensors are known for being unobtrusive and for their potential in monitoring daily activities since people wear shoes for multiple hours a day. They are typically used in gait analysis to count steps and extract time and distance based parameters. In balance analysis, they are typically used to measure center of pressure to evaluate postural stability [19,26,42,43,71].

The most common wearable devices used by the studies included in this review are IMUs (71.43% of studies). 21.43% of articles used smart devices in their studies, while 8.93% and 8.93% used EMGs and pressure/insole sensors, respectively.

4. Design Issues in Gait, Balance and RoM Wearable Systems

The following outlines the most important challenges to consider in the design and implementation of systems that use wearable sensor technology to assess and track gait, balance, and RoM.

4.1. Obtrusiveness

The number of wearable sensors used in a system can be associated with the level of obtrusiveness of the system. It is known that having more sources of data in a system will provide more information. However, there is the disadvantage of decreased subject comfort as the number of sensors increases. Additionally, not all sensors are completely wireless since there are sensors that require the use of wires or electrodes, such as the EMG devices, to extract information, also affecting the level of obtrusiveness. Researchers often encounter this problem: accuracy versus subject comfort. They have to decide to either build a system with high accuracy using multiple sensors or build a system with lower accuracy and less data using fewer sensors. Less sensors allows the subject to be more comfortable and avoids interfering with trial performance or daily activities. Decreasing the number of sensors can be beneficial in terms of complexity, cost, and the amount of data to process. From the studies included in this review, 33 had a low level obtrusiveness. On the other hand, 10 were considered to have a medium level obtrusiveness, and 13 high level obtrusiveness.

4.2. Sensor Location

Wearable sensors eliminate the location limitation set by external sensors, but they yield another complication. Selecting locations on the subject's body to mount the sensors is a difficult decision, especially when the number of sensors available is limited. It is extremely important to decide optimal locations since the performance of the system and the data obtained depends on it. Studies using wearable sensors vary greatly in terms of body locations selected to mount sensors, however, the most common areas are the sternum, waist, lumbar, lower back, and different upper or lower extremity location such as wrists, thighs, ankle, heels, and feet. The selection of sensor locations will depend on the gait, balance, and RoM parameters to be measured. For static balance assessment the most common locations are lumbar, waist, and/or holding the device in the chest/sternum due to the capability of measuring trunk sway at these locations (Table 3). The most reliable step count comes from insole pressure sensor since it can detect the pressure applied to the sensor once a subject is performing a step [26,42,43,71]. Studies that use IMUs for gait analysis tend to mount the devices on locations below the knee joint, such as feet, ankles and shanks, due to the high movements involved in those areas when a person is walking (Table 3).

4.3. Sensor-to-Segment Alignment

After sensor locations are selected, another problem is known as sensor-to-segment alignment. Sensor-to-segment alignment is known as the orientation of each sensor relative to the assigned segment previously selected. A study indicated that the position of the sensor relative to the segment is usually far less important for obtaining valid segment orientations than the sensor-to-segment alignment [85,86]. Calibration procedures to address this problem have been proposed, such as static pose calibration, requiring the user to take on specific poses, functional calibration, requiring the user to perform movements around defined axes, and technical calibration, requiring manual alignment with respect to the bone structure [85,87–89]. These procedures still have potentially large human-induced errors and researchers have started to study ways to integrate machine learning and deep learning techniques to help improve inaccuracies [45,46,51,62,70].

4.4. Soft Tissue Artifact

A challenge in human motion analysis is posed by soft tissue artifact (STA). STA occurs from unequal movement of soft tissue layers (muscle, tendon, and dermis) between the bone and the skin surface [90]. Typically, relative translation and relative rotation are assumed to show the majority of STA, in which yields to be the components targeted for mitigation [91]. Another way to mitigate STA is by processing the translational acceleration and rotational velocity measured by an IMU [92]. Few studies included in this review handled soft tissue artifact in different ways. A common way is to place the devices over the bones and not over the muscles to reduce soft tissue artifact [58]. Additionally, using bundles and straps and having care in positioning the bundles can minimize soft tissue artifact [57].

Additionally, STA also occurs in optoelectronic systems when placing markers to the subject's segments. This needs to be taken into consideration since optoelectronic systems are often used to validate wearable sensor measurements [22,57,58,61,62]. Few ways to minimize this issue is by having the marker within the field of view of at least two cameras, markers attached to the same segment should be distributed to minimize position error propagation to bone orientation, and the movement between underlying bones and the markers should be minimal [93–97].

4.5. Processing

Once the data is collected, the researcher has to decide how to process the data and this largely depends on the system used. If a wearable sensor system doesn't have the capability of running the algorithms locally, servers are preferred since they have a large amount of storage space, processing power, and energy capabilities that allow complex data and algorithms. This approach is really common when machine learning techniques are used because these techniques often require high computational and processing power in order to train the models [45,46,61,62,70]. Systems connected to smartphones can run the algorithms locally if the complexity of the data and algorithms allow it, which depends on the device's limitations of storage, battery, and processing power. Twelve studies included in this review followed the smart device based approach (Table 3). Depending on the processing approach, it may affect the waiting time of the subjects between each trial because the computational cost and processing power influence how fast the users can get the results.

4.6. Energy Consumption

Communication is usually the most energy consuming operation, therefore researchers should minimize the amount of data transmitted. Short range wireless networks, such as Bluetooth or Wi-Fi, should be preferred over long range networks since they use less power. There are methods to reduce the energy consumption, such as data aggregation and compression, but they may jeopardize the system's performance.

The number of sensors used have also an impact on the system's energy consumption. It is obvious that the more sensor used, the more energy the system consumes. This is another reason why studies tend to use fewer sensors. Another direct and simple solution to this issue is; when the sensors are not being used, they can be turned off.

4.7. Mobility

A common reason to use wearable sensors is to provide a high level of mobility and portability. Systems that use servers to analyze the data often require access to the Internet. This makes the system location dependent since they would not work in locations where Internet is not available such as outdoors. This leads to a system that is not completely mobile. Studies that use smart devices usually do not have this issue because of the high capability of connecting to the Internet and run their own methods to evaluate the subject's gait, balance, and RoM regardless of the location being assessed (Table 3).

4.8. Cost

As previously mentioned, wearable sensors are cheaper than external sensors. However, this does not mean that cost is not an issue with wearable sensors. Cost can increase for multiple reasons, such as the number of sensors used, type, brand, and computer equipment and software needed to process the data. Researchers and clinicians with low resources may not be able to afford costly wearable sensor systems. That is why some researchers tend to evaluate the subjects using smart devices, such as smartphones, since nowadays millions of people already owns one (Table 3). Others prefer to build their own device using their own specifications to reduce the cost [47].

4.9. Noise

Noise is irregular fluctuations within the signal monitored. If noise is not filtered out, the results attained may be inaccurate. Wearable sensor noise is generated by the electrical and mechanical components. Common considerations to reduce noise in a system using accelerometers are cables and shield [47]. Most wearable sensors are wireless, eliminating cable noise. Modern wearable devices shield the sensors embedded in the device to protect them from noises produced by external signals. Sometimes these techniques are not sufficient and the measured signal contains measurement errors. In this case, noise is known to be the high-frequency portion of the measurement errors and thresholds and filtering techniques are used to clean the signals extracted from the sensors [34,44–46,54].

4.10. Thresholds

A threshold is a limit used to trigger an action when that limit is surpassed. Various systems use thresholds to make decisions and conclusions about the data's behavior. The most common solution is to set thresholds that generalizes the data as much as possible. Additionally, there are studies that investigated the use of thresholds with filtering techniques to extract useful gait, balance, and RoM parameters from wearable sensors [32,33,44–46,54]. Another way to avoid setting thresholds is by using machine learning techniques. By using these techniques, the algorithms are trained to learn the most optimal threshold for a specific problem or measurement [51,60–62,66,70,85].

Systems should provide the option to adjust thresholds since they should be optimized to the movements to give the most reliable and accurate measurements. Otherwise, the data yields misleading results, which may affect decisions made by researchers of professionals making rehabilitation decisions.

4.11. Magnetic Disturbances

A challenge in the application of IMUs is that magnetic field is known to be inhomogeneous in indoor environments and near ferromagnetic materials. These disturbances limit the accuracy of measured parameters in two ways: sensor orientation estimates are deteriorated, and magnetic disturbances may limit the accuracy of the sensor-to-segment calibration [98]. To avoid magnetic disturbances, there are researchers that consider to use non-magnetic equipment to perform the assessment, such as a couch with wooden frames [22]. There are others that use Kalman filters and sensor fusion techniques to minimize the disturbance applied to the signals being evaluated [23,58,98,99].

4.12. Sensor Fusion

Wearable sensor systems relying on single or multiple sensors present limitations such as sensor deprivation, limited spatial coverage, and imprecision [100,101]. Sensor fusion is an effective solution to address these problems. Sensor fusion can be *competitive*, *complementary*, and *cooperative* [102]. Competitive fusion uses multiple equivalent sources of information to obtain redundancy and self-calibration. In complementary fusion each sensor captures different aspects of what is being monitored to improve system accuracy and reliability. Cooperative fusion is when multiple sensor signals are needed to obtain information that wasn't obtained by any of the signals independently [103]. When it comes to data processing level, sensor fusion is divided into three categories:

- *data-level fusion*: implements de-nosing, feature extraction, data classification, and data compression,
- *feature-level fusion*: creates a new high-dimension feature set that represents the input for classification or pattern recognition, and
- *decision-level fusion*: utilizes the abstracted information from either data-level or feature-level fusion to make a decision [103].

The fusion level used in a wearable sensor system will affect other issues such as processing, information loss, and performance. There are instances when sensor fusion is necessary to provide more accurate measurements. For example, when researchers want to know the orientation of an IMU, it may not be sufficient to just use an accelerometer because this may yield inaccurate results. It is not possible to extract heading of the sensor with just an accelerometer but fusing an accelerometer and magnetometer provides this additional information critical to examine postural control and ROM [98]. Fusing the accelerometer, gyroscope, and magnetometer data helps to improve the accuracy of these measurements.

From the studies included in this review, 87.50% used data-level fusion, 33.93% used feature level fusion, and 33.93% used decision-level fusion.

5. A Taxonomy for Gait, Balance, RoM Analysis

A new taxonomy for wearable sensor technology that allows comparison of different systems that share similar characteristics and capabilities is presented in Figure 2. In this survey, the systems are categorized into two levels. The first level specifies the analysis to be performed, which can be either *gait analysis*, *balance assessment*, or *Range of Motion (RoM) analysis*. The second level specifies the categories of parameters extracted from the analysis, which can include *rhythm and phase*, *pace*, *variability*, *postural control*, or *asymmetry*. Rhythm and phase parameters are variables that reflect gait rhythm, timing, and duration; pace parameters give information about speed and/or length measurements; postural control is an integrative process used to maintain body's position relative to gravity and of its segments relative to each other; asymmetry parameters are those that look for differences between limbs; and variability is the fluctuation of parameters, which can offer a complementary way of quantifying and indicating mobility deficits [104].

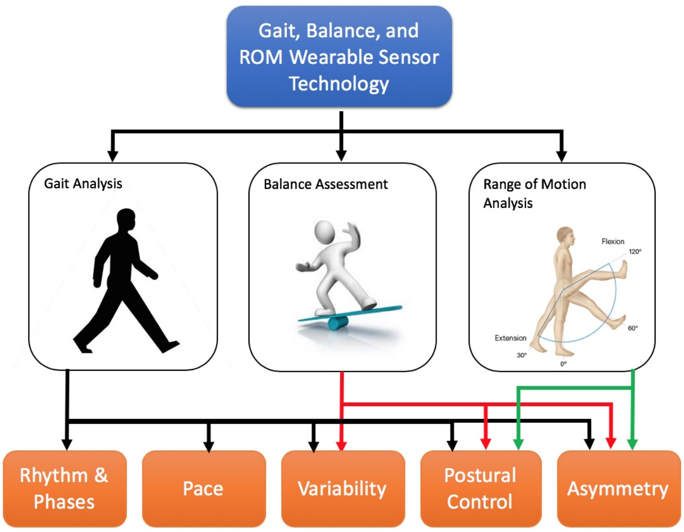

Figure 2. Taxonomy of Wearable Sensor Technology for Gait, Balance, and ROM Research.

5.1. Gait Analysis

One of the main goals of physical therapy and rehabilitation is that ambulatory patients achieve independent walking. Physical therapists use *gait analysis* to determine what causes patients to walk the way that they do. The goal of clinical gait analysis is to assist in plan of care decision-making for patients to help ameliorate the gait deviations so that the patient may walk more efficiently and independently [105]. Additionally, gait analysis in research studies the natural history of change in walking over time in neurodegenerative diseases or changes in gait after implementing interventions [12,13].

Walking is the result of a cyclic series of movements that can be characterized by a description of its fundamental unit, the *gait cycle*. A gait cycle is the time period of events during locomotion in which one heel makes contact with the ground and that same foot makes contact with the ground again; a single gait cycle is also known as *stride*. A step is the sequence of events that occurs within successive heel contacts of opposite feet. Step and/or stride detection is the first task that researchers try to accomplish when using wearable sensors to conduct gait analysis. The most common method to perform step and/or stride detection using IMU and smart devices is by using peak detection algorithms on accelerometer data [28,35,36,48]. Step and/or stride detection is easier when using insole pressure sensors since the pressure applied to the sensor when the foot is in contact with the ground is higher than when it is not in contact with the ground [31,46,52,54,69,73]. However, people that are affected by neurological disorders tend to shuffle and/or drag their feet when walking, performing short and dragged steps, which makes it harder to detect heel strikes or foot contact [106].

5.1.1. Gait Analysis: Rhythm and Phases

The most common gait parameters associated with rhythm and phases of gait are *gait cycles phases*, *stance time*, *swing time*, *step time*, *stride time*, *cadence*, and *walking ratio* [80,104].

In the gait cycle, there are two main phases called stance phase and swing phase. In the stance phase, the foot is in contact with the floor, while in the swing phase, the foot is moving through the air without making contact with the floor. However, researchers continue to expand the gait phases involved in a gait cycle to have a deeper and more detailed understanding of the gait cycle. Taborri et al. standardized the name of the different gait phases, going from the two main phases, stance phase and swing phase, to a granularity of phases in which the one that has the most phases contains eight phases: initial contact, loading response, mid stance, terminal stance, pre swing, initial swing, mid swing, and terminal swing [107].

Researchers measure the time it takes subjects to complete each phase of gait. Swing time is the time that passes during swing phase, starting as soon as the foot gets off the floor until it makes contact with the floor again. Stance time is the time that passes during the stance phase, starting once the foot makes contact with the floor until it moves off the floor again. Researchers have found that stance phase is longer when the subject has a balance problem [104]. Stride time is the duration of a stride and the same procedure used to measure swing time and stance time can be used to calculate stride time. It can also be measured by adding up the swing time plus the stance time. Step time is the duration of a step. When data is recorded from wearable sensors, the data includes a timestamp. A timestamp is the time registered to a file or log that records when an event or data is added, removed, or modified. It is possible to calculate time based parameters by subtracting the timestamp of when the previous event occurred minus the timestamp of when the current event occurred [26,28,35,36,48,51,53,61,70].

Cadence is the rate at which a subject walks, expressed in steps per minute. Researchers have found that cadence is usually between 98–138 steps per minute for healthy women and 91–135 steps per minute for healthy men, between the ages of 18–49 [108]. Researchers often approximate cadence by using a mean step time. As an example, if a subject's mean step time is around 0.5 s, the subject will execute approximately 120 steps in a minute. Using mean step time may not be ideal when the subject's walking pattern is asymmetrical. Cadence has been used to give quantitative data that serve as early indicators of neurological disorders, assess the daily living walking activities, and provide immediate bio-feedbacks [25,26,28,43,56,65].

Walking ratio represents the relationship between frequency and amplitude of movements of the legs. It can be calculated by dividing the mean step length by the cadence. Researchers have found that the mean walking ratio is 0.58 and it decreases when the person walks with fast, shorter steps such as in person with Parkinson's disease or Alzheimers Disease [104].

5.1.2. Gait Analysis: Pace

The parameters that represents pace include *step length*, *stride length*, and *walking speed* (or gait velocity).

Step length is the distance between one foot's heel-strike to the opposite foot's heel strike when walking. Stride length is the distance travelled by a person when they perform a stride; i.e., the distance from one foot's heel-strike to the next heel-strike of the same foot. Step and stride length can be calculated once the steps are detected. Knowing the step and stride lengths helps to determine how symmetric the subject is walking. Researchers have discovered that step length is affected linearly by walking frequency and acceleration variance [109]. Walking frequency (WF) can be calculated using Equation (2), where WF_k is the walking frequency for step k and $t_k - t_{k-1}$ is the step time for step k. Acceleration variance (AV) can be calculated using Equation (3), where AV_k is the acceleration variance for step k, n_k is the number of samples during the sequence of step k, $a_{k,i}$ is the acceleration at time i-th on step k, and $\bar{a_k}$ is the acceleration mean during the same sequence of step k.

$$WF_k = \frac{1}{t_k - t_{k-1}} \tag{2}$$

$$AV_k = \frac{1}{n_k - 1} \sum_{i=1}^{n_k} (a_{k,i} - \bar{a}_k)^2 \tag{3}$$

After walking frequency and acceleration variance are calculated, then step length (SL) can be determined using a linear approximation (Equation (4)), where α, β and γ are the step length estimation constant parameters for the linear equation [109].

$$SL_k = \alpha * WF_k + \beta * AV_k + \gamma \tag{4}$$

Other researchers have calculated step length using the change of height of the center of mass h (vertical position) and the length of a pendulum l (sensor height from the ground), as shown in Equation (5) [48,110]. Once step lengths are calculated, stride length can be determined by adding the left step length to the right step length.

$$SL = 2 * \sqrt{2lh - h^2} \tag{5}$$

Step length and stride length has been used in the literature to compare the variability pre- and post-training as well as the variability between healthy subjects and subjects with a particular neurological disorder [25,35–37,43,44,50,60,62,65,70].

Gait velocity, also known as walking speed, is the distance travelled in a given period of time and is thought to be indicative of a person's functional capacity [111,112]. Gait speed represents the overall performance of the walking pattern. According to Baker, it can be calculated using Equation (6), where gait velocity (GV) is expressed in meters per second, cadence is in steps per minute, and stride length (SL) is in meters [80]. Researchers have found that while cadence increases linearly, step length increases logarithmically, and it tends to stabilize at high speeds but changes at low speeds [104]. Gait velocity is correlated with functional ability and balance confidence and can be used to determine outcomes such as functional status, discharge location, and the need of rehabilitation [111].

$$GV = \frac{Cadence \times SL}{120} \tag{6}$$

Gait velocity estimation algorithms can be divided into three categories: abstraction model, human gait model, and direct integration [113]. Abstraction model takes advantage of machine learning techniques to approximate the speed and decide to ignore the details of the human gait biomechanics; human gait models estimate the gait velocity by using the stride length of the subject; and lastly, direct integration method is when the acceleration of the sensor is integrated in the global coordinate system from the starting point to obtain instantaneous sensor velocity and the associated stride length. Direct integration is the most common approach used in gait and balance studies [113]. Direct integration seems like a straight-forward approach, but the accuracy of the integration can be inaccurate since the gravitational force is difficult to separate from the inertial force.

Walking speed is considered the "sixth vital sign" for its capabilities, reliability, and sensitivity that it can measure to assess and monitor overall health [111,112]. These led researchers to use walking speed to provide bio-feedback training, assess fall-risk and server as an indicator of a neurological disorder [28,43,49,60,61,65].

5.1.3. Gait Analysis: Variability

Variability can be expressed in terms of measures of dispersion, such as standard deviation and/or coefficient of variation [114]. Variability can be detected temporally or spatially, similar to asymmetry. Research informs that variability in spatiotemporal parameters predicts mobility deficits and future falls better than other gait parameters [104]. On the other hand, researchers have concerns about the best way to measure variability. This leads to questions about how many parameters to use to measure variability; for example, whether to measure it temporally or spatially, and whether to measure variability for each lower limb separately or combined.

Gouelle et al. proposed a new way to quantify fluctuation magnitude using the Gait Deviation Index as reference and developed a *Gait Variability Index* (GVI) [115,116]. The GVI is based on nine weighted (using Principal Component Analysis) gait parameters: step length, stride length, step time, stride time, swing time, stance time, single support time, double support time, and velocity. It uses the difference between the variability of an individual compared with a reference group. The value obtained is transformed into a score with 100 and 10 representing the mean and standard deviation, respectively, of the reference.

Non-linear variability is also gaining acceptance within the gait analysis community, such as Lyapunov exponent (LyE). Huisinga et al. quantified the temporal structure of the trunk acceleration time series from both direction using LyE and approximate entropy [117]. The largest LyE is a measure of the rate at which nearby trajectories in state space diverge s lack of divergence in the acceleration pattern will produce small values for the LyE and vice versa [117]. They demonstrated that in people with multiple sclerosis the acceleration time series increased LyE in both medio-lateral and antero-posterior directions, which indicates excessive divergence and reduced behavioral complexity as compared to healthy subjects [117].

Another way to measure variability using wearable devices is to extract statistical parameters. Two of the most common statistical parameters used to represent variability are standard deviation and coefficient of variation [35,36,48,116]. These are calculated by using spatiotemporal parameters such as step length, step time, single support time, and others, since they have shown in the literature to being able to assess fall risk. However, these are sometimes not recommended since these measures of dispersion can present bias and alter the results: standard deviation is sensitive to the scale, and coefficient of variation tends to infinity when the mean is close to 0 [116].

5.1.4. Gait Analysis: Postural Control

The main parameters in this category are *step width* and *foot angle*. Step width measures the separation of the feet while walking. Step width is usually 8-12 centimeters in children and adults [104]. Changes in step width can be seen when people have balance problems and when patients walk faster. People with a balance disorder usually expand their step width; while people that walk faster tend to decrease their step width. The foot angle can be defined as the angle of rotation during stance. Usually, the angle ranges from 0-15 degrees in normal, healthy adults. Excessive foot angle or toe out can be an indication of walking abnormalities and is often seen in children with cerebral palsy or adults with stroke [104]. Unfortunately, these parameters are complex to measure using wearable sensors and accurate methods to extract these parameters using wearable sensors are limited [62].

Another common criterion studied by researchers and related to postural control is the walk deviation. Walk deviation is when a person attempts to walk in a straight line but is unable to achieve it and strays off the line. Perez and Labrador calculated walk deviation from a walking path using the rotation vector sensor of a smartphone [118]. They incorporated used of the Functional Gait Assessment (FGA) walking path level markers (Figure 3).

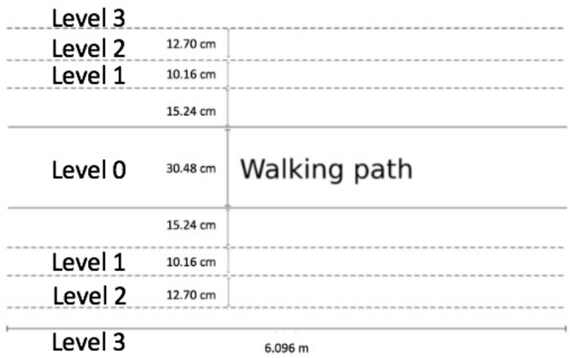

Figure 3. FGA Walking Path with 4-Level Deviation Scale.

The FGA determines the risk of falling by assessing postural stability during gait. To perform the FGA, they used a 6.096 meter long walkway with a 30.48 centimeters (cm) lateral path. To assess walk deviation, markers are placed on both sides of the walkway, each one corresponding to a specific deviation level. The level range is from 0 to 3, level 0 meaning no or small deviation and level 3 meaning high deviation.

Perez and Labrador detected the deviation D_i for $step_i$ by using the step length and the angle of rotation for that specific step (Equation (7), Figure 4) [118,119]. The angle of rotation is extracted from the rotation vector samples.

$$D_i = SL * sin(\theta_i) \tag{7}$$

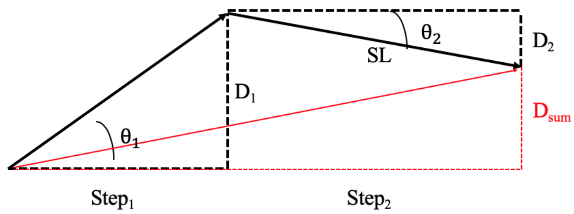

Figure 4. Step Deviation Calculation Visualization.

Additionally, the cumulative deviation can be calculated (Equation (8)) to check the total deviation from the starting to end point [118], where D^0_{sum} is equal to 0.

$$D^i_{sum} = D_i + D^{i-1}_{sum} \tag{8}$$

5.1.5. Gait Analysis: Asymmetry

Gait asymmetry can be expressed in two different ways: *temporal asymmetry* and *spatial asymmetry* [104]. In spatial asymmetry, the step length values are unequal, while in temporal asymmetry there is a difference in time spent in swing and/or stance phase between the two feet. In a temporal symmetric walking pattern, the steps and strides are equal. In the case of a temporal asymmetric walking pattern, step lengths are different between the two legs but stride lengths are equal. Two common ways to represent symmetry are by differences or ratios [37,48]. In differences, the values are subtracted (i.e., left-right) from each other, in which 0 represents perfect symmetry. Using ratios, the values are divided (e.g., left/right), in which 1 represents perfect symmetry.

Another two approaches have been used to represent symmetry: Dynamic Time Warping (DTW) algorithm and Autocorrelation. DTW is popular because it is extremely efficient in measuring time-series similarities, thus minimizing the effects of shifting and distortion in time, and allowing transformation of time series in order to detect similar shapes with different phases [120]. The algorithm can be applied by comparing two acceleration signals of different steps to see if there are any differences between one step and the other.

Autocorrelation is the correlation between a signal with a delay copy of itself and has been widely used to find repeated patterns in a signal [118,119]. Accelerometer signals from wearable sensors provide information to be used in the algorithm. Researchers have demonstrated that low values in the coefficient of the first and second dominant period represent a low regularity between steps and cycles and the ratio of both coefficients represents symmetry between left and right steps [121]. Researchers used these techniques to check similarities between different steps and to capture a walking pattern problem if an impediment was present [54,118,119].

Gait asymmetry has shown to be an important marker of mobility impairment [64]. Recently, a Gait Symmetry Index (GSI) that uses one accelerometer placed at the lower back was proposed [64]. GSI uses autocorrelation coefficients of vertical (AR_v), frontal (AR_f), and lateral (AR_l) accererelations at the location in which the device is attached as the function of time lag t. The sum of positive autocorrelation coefficients of the three axes represent the coefficient of stride cycle repetition (Equation (9)) [64]. When C_{stride} has the maximum value, the stride time is equal to t. The norm of the autocorrelation coefficients represents the coefficient of step repetition (Equation (10)). For a perfect symmetric walking pattern, is assumed that two consecutive steps have the same step time, half of the stride time [64]. GSI is represented as the normalized $C_{step}(0.5 * Time_{stride})$, where the normalized coefficient is $\sqrt{3}$ since is the maximum value that C_{step} can obtain at zero-lag (t = 0) (Equation (11)) [64].

$$C_{stride}(t) = AR_v(t) + AR_f(t) + AR_l(t); if AR(t) < 0, AR(t) = 0 \tag{9}$$

$$C_{step}(t) = \sqrt{AR_v(t) + AR_f(t) + AR_l(t)} \tag{10}$$

$$GSI = \frac{C_{step}(0.5 * Time_{stride})}{\sqrt{3}} \tag{11}$$

5.2. Analysis of Postural Control and Balance

Patients may have balance problems due to neurologic or musculoskeletal disorders. Balance exercises performed as part of a rehabilitation program can help address these problems and can help prevent falls. Physical therapists teach patients static and dynamic balance exercises in both sitting and standing; activities increase in difficulty as balance improves over time. If the patient keeps improving, more complex balance activities can be introduced; such as during walking or standing on compliant surfaces.

Physical therapists use tests to assess patients' balance. Some common non-instrumented tests used by physical therapists include [52,122–130]:

- Romberg Test,
- Limits of Stability Test,
- Single Leg Stance Test (SLST),
- 5 Times Sit to Stand (STS) Test,
- Functional Reach Test (FRT),
- Clinical Test of Sensory Interaction and Balance (CTSIB),
- Timed Up and Go (TUG) Test,
- Tinetti Test,
- Berg Balance Scale (BBS), and
- BESTest.

These tests have semi-objective components; by using rating scales, scores and timed performance, however, they lack objective data. This yield to the use of instruments that can objectively measure the subject's locomotion quantitatively. By combining both techniques, researchers can conduct these tests by using instruments, such as the Romberg Test or Limits of Stability Test with force platforms, in order to have a complete assessment with both components: rating scales/scores and quantitative data about the subject's locomotion. Force platforms are the most common sensor for instrumented balance assessment. They quantitatively measure center of pressure and center of mass displacement of a subject while the subject is standing on the force platform performing static and/or dynamic tasks, such as Romberg Test. The problem with force platforms is that they are often expensive and are not portable.

Researchers have begun to integrate the use of wearable sensors for balance assessment because they are more portable and less expensive. Non-wearable instrumented tests, such as dynamic posturography, and non-instrumented tests are still the gold standard methodologies to assess balance. They are often used to evaluate performance of the wearable sensors systems. For example, researchers used wearable sensors to measure subject's balance as they were performing the BBS [60]. Another study determined a smartphone could measure static postural stability and distinguish elderly at risk to fall, and they validated the performance of the smart device using a force platform [68]. Additionally, other balance studies have used wearable sensors during gait activities to provide information about subject's dynamic balance [24,49,50].

5.2.1. Postural Sway

A common parameter used by researchers and clinicians in static balance assessment is *postural sway*. Postural sway is the horizontal movement of the person's center of mass (CoM) in all directions. Postural sway during quiet stance has helped differentiate age-matched healthy controls from those with early untreated Parkinson's Disease and helped determine changes with disease progression in early PD [131]. Studies that use IMUs and smart devices vary in terms of where to place the sensor to measure postural sway. The studies in this review vary in terms of the sensor's location used to measure postural sway. There are some that attach the device to the lower back or lumbar spine [23,32,33,47,49,50,52,55] while others have the subject hold the device on their chest/sternum with their dominant hand [29,68]. The most common measures that describes postural sway are *sway area*, *sway range*, *sway velocity*, and *sway jerk*.

Sway area approximates the area enclosed by the acceleration path in each axis of movement [132]. Studies vary between enclosing the path with a circle or enclosing the path with an ellipse. In both approaches, the acceleration in both the mediolateral (ML) and anteroposterior (AP) direction can be extracted using the acceleration signal at the X-axis and the acceleration signal at the Z-axis, respectively. Figure 5 shows the typical 'Spaghetti' plot that represents the acceleration sway path using ML and AP planes.

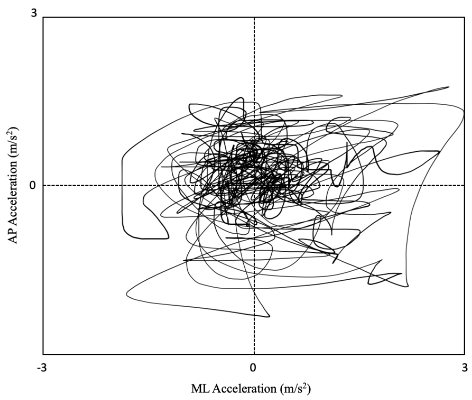

Figure 5. Postural Sway Acceleration in ML and AP Planes ('Spaghetti' Plot).

The acceleration path can be enclosed using an ellipse fitting or ellipse enclosing algorithms [133]. These algorithms can be difficult to implement with datasets that have a lot of data points. To reduce the size of the problem, researchers often use an approach called *convex hull*. A convex hull is a subset of points that defines a convex polygon that encloses all the points in the set [133]. The minimum enclosing ellipse for the convex hull is the same as the minimum enclosing ellipse for the set of points (Figure 6).

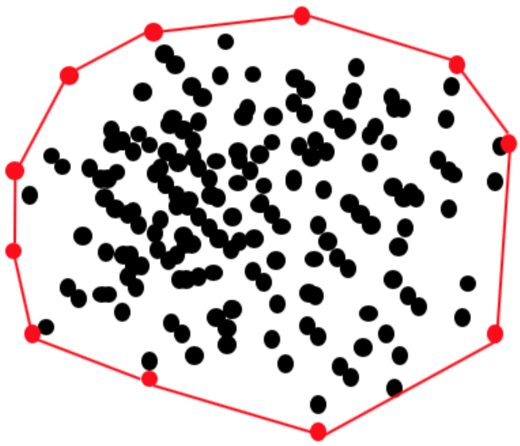

Figure 6. Convex Hull Example.

Sway range is the maximum distance between any two points in the accelerometer data [132]. Sway range estimates how wide the acceleration was at a particular assessment time point. It can be calculated in all the different axes using Equation (12), where P_{axis} is the set of points in a particular axis [132].

$$Range_{axis} = |max(P_{axis}) - min(P_{axis})| \tag{12}$$

Sway velocity is the velocity at which the trunk sways. Similar to gait velocity, sway velocity can be estimated using abstraction models or by direct integration.

Sway jerk is the smoothness of the trunk sway. One of the first reviews on jerk defined the term as the "rate of change of acceleration" [134]. Flash and Hogan (1985) formulated a mathematical model to predict features of coordination of voluntary human arm movements. More recently, jerk is used in many varied applications including postural sway analysis using sway jerk. Sway jerk is typically calculated for the ML-AP plane using Equation (13), where t is the time that the trial lasted and N the size of the set of points of the acceleration signal [132]. Since Equation (13) involves integration of time derivatives of acceleration components, it is important to make sure that the signal is clean and does not contain much noise since dealing with noisy differentiation signal may amplify the noises on the signal to be estimated.

$$Jerk_{ML-AP} = \frac{1}{t}\sum_{i=1}^{N-1}\sqrt{(AP_{i+1} - AP_i)^2 + (ML_{i+1} - ML_i)^2} \tag{13}$$

5.2.2. Postural Sway: Asymmetry and Variability

Physical therapists often use Modified Clinical Test of Sensory Interaction and Balance (mCTSIB) when evaluating postural sway [135]. In the mCTSIB, subjects have to complete four trials in four different conditions: *eyes open-firm surface*, *eyes closed-firm surface*, *eyes open-foam surface*, and *eyes closed-foam surface*. After completing the trials, the physical therapists calculate the asymmetry and variability between the measurements extracted in the different conditions. The asymmetry and variability extracted from the trials between eyes open vs eyes closed are known as the visual dependence, while the asymmetry and variability extracted from the trials between hard surface vs foam surface are known as the surface dependence.

5.3. Analysis of Joint Range of Motion

Range of motion (RoM) is the distance a subject's joints can be moved in a certain direction and is measured in degrees. The goniometer is an instrument used widely by physical therapists to measure RoM angles [136]. RoM testing is an integral part of any physical therapy examination, and generally RoM is examined before physical therapy treatment begins. RoM testing can be performed on specific joints, and if limited motion is found, the physical therapist determines if the cause is muscle tightness, pain, or tightness of ligaments or tendons [137]. Common RoM angles measured by physical therapists are at the shoulder, elbow, hip, knee, and ankle joints and spine angle/inclication (Figure 7).

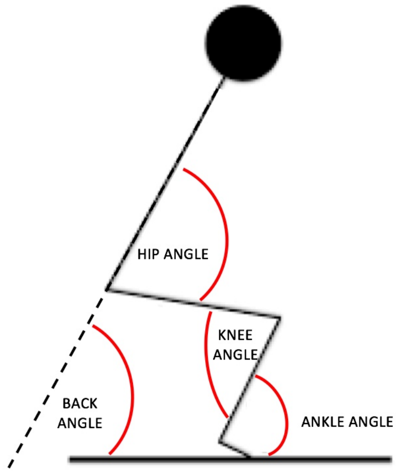

Figure 7. RoM Angles Measured While Squatting.

RoM is divided into three main types [137]:

- passive RoM: physical therapist is moving the subject's joint and no active movement is performed by the subject,
- active assistive RoM: the subject can perform movements but cannot complete it because of pain or muscle weakness; assistance of the physical therapist is needed, and
- active RoM: the subject can perform the movement without manual assistance from the therapist.

One common way to get RoM measurements is to calculated pitch, roll, and yaw angles. Pitch and roll angles can be computed using an accelerometer. A simple way to compute pitch and roll angles is using Equations (14) and (15), where Acc_x, Acc_y, and Acc_z are the normalized accelerometer values in the X, Y, and Z axis respectively and $\frac{180}{\pi}$ is used to convert the angles from radians to degrees [138].

$$Roll = atan(\frac{Acc_y}{Acc_z}) * \frac{180}{\pi} \tag{14}$$

$$Pitch = atan(\frac{-Acc_x}{\sqrt{Acc_y^2 + Acc_z^2}}) * \frac{180}{\pi} \tag{15}$$

However, there is a constraint using this method to extract the angles. These equations, besides being simple, are known to only work for the unrealistic assumption of zero or constant velocity. Additionally, there is no way to calculate the yaw angle (heading). Yaw angle can be measured by rate of gyroscope and magnetometer and not only with accelerometer values [138]. Additionally, roll, pitch, and yaw angles are not widely used in joint analysis in the recent years.

Some studies measure RoM by using unit quaternions and/or Euler angles [22,40,65]. A quaternion is a 4-tuple whose primary application is in a quaternion rotation operator that can offer fundamental computational, operational, and/or implementation and data handling over conventional rotation matrices [139]. The problem with unit quaternions is that the four quaternion parameters do not have intuitive meaning, a quaternion must have a unity norm to be a pure rotation, and it is harder to understand [140]. Euler angles are popular since they are easy to understand and use. Certain important functions of Euler angles have singularities and they are less accurate than unit quaternions when measuring incremental changes over time [140]. However, according to the International Society of Biomechanics (ISB) recommendations, Euler angles are preferred for joint coordinate systems of various upper body and lower body joints for the reporting of human joint motion [141,142].

Joint coordinate system has been established by the ISB in order to report joint motion. There are two main reasons of why the joint coordinate system has been established: (1) lack of standard reporting for joint motion in biomechanics for human movements, making comparisons among studies more difficult, (2) and the advantage of reporting joint motion in clinically relevant terms, making interpretations easier for clinicians and researchers [141]. The joint coordinate system recommend by the ISB established a Cartesian coordinate system for each of the two adjacent body segments that are defined based on bony landmarks [141]. The system is established for both two cases: fixed body and "floating" or moving body and includes three rotational and three translational components. For joint coordinate systems illustrations, refer to studies by Wu et al. [141,142].

The location of the sensors depends on which RoM angles are intended to be measured. One study introduced the use of a smartphone mounted to subject's back to measure back inclination while subjects stood up and sat down [52]. Other researchers mounted IMUs to the thighs and shanks to extract Euler angles and measure knee flexion [25]. Kanzler et al. mounted an IMU on a shoe while subjects performed walking exercises to measure ankle joint angles using quaternions [39].

5.4. Validation against a Gold Standard

Gold standard methods in this review are categorized into two types: non-instrumented and instrumented. The non-instrumented gold standard methods in gait, balance, and RoM analysis are composed of subjective assessments, such as the assessments mentioned in Section 5.2, whereby expert give a score to the subject based on subjective observation. On the other hand, instrumented gold standard methods in gait, balance, and RoM analysis are the goniometer, optoelectronic systems, and force platforms due to the capability of attaining objective data. Validation against gold standard was presented by some of the articles selected in this review to validate the accuracy and application of wearable sensors to quantify gait, balance, and RoM parameters. A total of 57.14% of the articles included in this systematic review validated their results against a gold standard, 26.79% validated against a non-instrumented gold standard method, and 47.86% validated against an instrumented gold standard system.

6. Discussion

This systematic review discusses the evidence for the use of wearable sensors to enhance gait, balance, and RoM analysis in both research and in clinic. An overview of the most common wearable devices, their technical issues, and the parameters generated to define gait, balance, and RoM was provided. Wearable sensor systems have made it possible to obtain locomotion measurements in real time by placing devices on different parts of the body. Additionally, wearable sensors can be used anywhere to provide less expensive and portable gait, balance, and RoM analysis measurements. The literature on this topic is extensive and it is clearly the trend in developing and improving wearable gait, balance, and RoM analysis systems.

6.1. Revealing Features in Population

Researchers perform gait, balance, and RoM analysis using wearable sensors for several purposes including: to reveal features that describe a population, to study changes in patient characteristics over time, and to analyze the effect of interventions. This is possible due to the capability of wearable sensors to provide quantitative and objective measurements of gait, balance, and RoM parameters. People with neurological disorders and the elderly [24,27,28,48,49,72,76] and the elderly [50,63,68,75] are common target populations. Often, the goal of studies that focus on these populations is to assess the efficacy of rehabilitation or pharmacologic interventions or to evaluate falling behavior.

A study of individuals with Alzheimer's Disease (AD) showed that the number of strides, stride length, stride speed, and stride time extracted from wearable devices served as strong indicators for early diagnosis of AD [28]. Another study showed that, for quiet stance with eyes closed, people with Multiple Sclerosis (MS) have a greater sway acceleration amplitude than healthy controls [24]. Moreover, multiple studies that investigated people with Parkinson's disease (PD) have shown that wearable sensor measurements serve as indicators to distinguish between people with PD and healthy subjects and also serve as an assessment of the efficacy of rehabilitation and drug interventions [27,48,49,56,59,76].

Research with elderly populations has shown that postural sway parameters, statistical features, such as mean and coefficient of variation, and step length extracted from wearable devices can be used to categorize falling behavior [50]. However, another study of the elderly demonstrated that smart devices are not recommended for regular stance in conditions such as eyes open, eyes closed, and dual task since they demonstrated weak to moderate correlations between the force plate center of pressure and smart device measures. Although, they found that the correlations between the force plate center of pressure and smart device measures were high for semi-tandem, tandem, and single leg stance conditions, showing the possibilities of the use of smart devices to evaluate such conditions [68].

These studies show the ability to perform tele-health rehabilitation to monitor home exercise programs, especially for targeted populations who may have difficulty going to a research laboratory to perform the assessments. Additionally, wearable devices show a high possibility to assess the quality of natural locomotion out in the community. It is important to note that these systems should be validated against gold standard assessments and instruments to show more clinically relevant parameters. Comparing wearable devices to gold standards methodologies proof the feasibility, reliability, and validity of wearable devices for gait, balance, and ROM analysis.

6.2. Biofeedback

Researchers have used objective measurements extracted from wearable sensors to provide biofeedback [23,26]. Biofeedback information can be provided visually, auditorily, and/or tactilely. Visual biofeedback can be difficult when using wearable devices for assessment. However, using smart devices this issue can be addressed since most of the smart devices provide small and portable screens. Additionally, auditory biofeedback can be implemented in such devices by using earphones, adding the capability of having both types of feedback occurring at the same time. This dual feedback can be used with one portable device and can be very beneficial for patients who benefit from feedback, such as those with Parkinson's disease [23,65]. On the other hand, tactile biofeedback systems are designed to provide stimulation to the surface of the skin with electrical signals or vibrations [26]. Tactile biofeedback is not recommended since applying such stimulations can be obtrusive and it can affect subject performance during the assessment; particularly, if they are performing gait, balance or other functional tasks.

6.3. Wearable Sensor Technology Validation

It is important to highlight that in gait, balance, and ROM analysis there are gold standard assessments and instruments. These gold standard methodologies are often used to evaluate the performance of parameter quantification when using wearable devices. In balance analysis, a study concluded that there is a strong inverse correlation between the Balance Error Scoring System (BESS) and inertial sensor measurements [29]. However, another study used the BESS and a force platform to validate the use of smart devices and track center of gravity movement of the subject [32,33]. They found a mean absolute error between 5.87% to 10.42% compared to the force platform measures. On the other hand, a study used the Tinetti Test, BESTest, an optoelectronic system, and a force platform to validate IMUs measurements [47]. They reported correlations between 0.5980 and 0.8658 for static exercises with eyes open or eyes closed when comparing the force platform measurements and the center of mass displacement estimation from the IMUs [47].

In gait analysis, optoelectronic systems and pressure mats are the most common gold standard instruments used to validate wearable sensor measurements. High correlations between pace, postural, rhythm and phases parameters have been documented in the literature. On the other hand, that is not always the case for variability and symmetry measurements. A study conducted a detailed investigation to explain the poor agreement between parameters extracted from wearable devices and a pressure mat [37]. The study determined that the poor agreement was due to inherent differences between the two systems rather than an inability of the wearable sensor to measure the gait characteristics [37].

In ROM analysis, a study concluded that although goniometry is a reasonably accurate method to measure joint angles in static situations, it is not precise to measure the angle of catch in individual patients [22]. However, there are studies that have evaluated the validity of IMUs and smart devices to measure joint angles against an optoelectronic system. These studies demonstrate that wearable devices are reliable to measure joint angles, where the error usually ranges between 1°–6° [34,38–41,58].

Studies included in this review that validated their results with gold standard methodologies show discrepancies related to assessment of gait, balance, and ROM. Some studies highly recommend the use of wearable sensors to assess balance; others report variable and not as strong results. However, they introduced the possibilities for future use of wearable devices and suggest potential improvements. Additionally, these results highlight the importance of caution when selecting a reference system for validation studies. Validity is important since it will help ensure that researchers truly measure gait, balance, and ROM in an accurate and objective manner.

6.4. Machine Learning in Gait, Balance, and RoM

Machine learning has been playing an important role in gait, balance, and RoM analysis in recent years. Machine learning techniques can be used to quantify gait, balance, and ROM parameters [35,36,62,66,70], distinguish between populations and conditions [45,46,51,61], and estimate assessments scores [74,75]. The techniques used in the literature showed the efficiency of machine learning to reduce and create gait, balance, and RoM parameters. Machine learning has the capability to converge to global optimum, even in non-linear datasets. Additionally, studies in this review that used machine learning techniques showed the highest accuracy, 88–99%, for both parameter quantification and population/condition classification. Moreover, recent studies showed that gait and balance assessments scores, such as Berg Balance Score and Tinetti Test Scores, can be estimated by using features extracted from wearable devices and machine learning models [74,75].

However, the amount of data from different subjects and the time needed to train the algorithms in order to have a reliable and accurate model is immense. Additionally, most of the research builds classification models focused on a binary classification, healthy versus non-healthy, limiting the adaptability and reliability for different targeted population. Also, the selection of features might be constrained by the number of subjects that participate in the study [74]. At last, when using models based on activities from gold standard assessments, the person needs to perform all the activities in which the model was constructed. Therefore, the model may not be feasible in a free living environment due to that some activities may be difficult to perform in such environment [75].

6.5. Limitations

Some of the studies included in this review had similar limitations: small sample size, lack of description of inclusion/exclusion criteria, and data loss was not reported. Additionally, there were studies that did not provide sufficient information about the protocols followed to perform assessments, making it difficult to make comparisons among studies. A limitation of the studies is that the results presented mostly represent the use of wearable sensors in controlled environments or laboratory settings. Furthermore, most of the studies did not include a long-term follow-up assessment. Research in work and home environments as well as long-term follow-up studies are needed in order to consider the use of wearable sensor technologies to assess gait, balance, and RoM in daily life. By monitoring activities of daily living, early detection of walking deviations and assessments of the ability of an individual to live independently in their community will be more complete, reliable, and correlated to individual's usual behavior. Another limitation is that optimum sensor locations to extract gait, balance, and RoM parameters are still inconclusive due to the variety of locations used in the literature. This affected the level of obtrusiveness in some studies since they used multiple devices attempting to get as much reliable data as possible. Knowledge of the most optimal sensor locations will help future research to reduce processing power and energy consumption needed to extract gait, balance, and RoM parameters. Furthermore, this will also decrease the level of obtrusiveness. If obtrusiveness is minimized, it may not interfere with trial results as much since the subjects may feel more comfortable participating in the trial.

7. Conclusions and Future Research

This paper is a systematic review of the literature in wearable sensor technology for analysis of gait, balance, and RoM. There is a high demand for wearable sensor technology in these analyses due to the high level of portability that they afford. Wearable sensor systems allow clinicians and researchers to analyze gait, balance and RoM not only in the research lab, but also in the clinic and out the community. But, before wearable sensors can be useful as clinical devices, methods must be valid and reliable, and the data provided by these systems should be accurate, informative and practical. At present, most body worn sensor systems are not affordable for most clinics and require experience in data analysis to interpret the results.

The studies reviewed in this paper have contributed to information on the use of wearable sensors in gait, balance and RoM analysis, however, further validation and improvements in these systems are needed. Based on this review of the literature, future research should focus on the design of wearable sensor systems that are affordable and more simple to use clinically or in the community. Calculations for gait parameters such as step length, step width, and walk deviation using wearable sensors need to be improved upon. Balance assessment using wearable sensors could be further developed with parameters that are correlated with gait parameters. Lastly, the integration of values extracted from time-series symmetry calculation, such as dynamic time warping and autocorrelation, to measure gait variability using wearable sensors should be investigated.

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Abbreviations

The following abbreviations are used in this manuscript:

AD	Alzheimer's Disease
AP	Anteroposterior
AV	Acceleration Variance
BESS	Balance Error Scoring System
BBS	Berg Balance Score
CoM	Center of Mass
CTSIB	Clinical Test of Sensory Interaction and Balance
DTW	Dynamic Time Warping
EMG	Electromyography
FA	Friedreich's ataxia
FGA	Functional Gait Assessment
FoG	Freezing of Gait
FRT	Functional Reach Test
GVI	Gait Variability Index
IMU	Inertial Measurement Unit
ISB	International Society of Biomechanics
KNN	K-Nearest Neighbors
LyE	Lyapunov Exponent
MAE	Mean Absolute Error
ML	Mediolateral
MS	Multiple Sclerosis
PCC	Pearson Correlation Coefficient
PD	Parkinson's Disease
RMSE	Root Mean Square Error
RoM	Range of Motion
SEM	Standard Error of Measurement
SEMG	Surface Electromyography
SL	Step length
SLST	Single Leg Stance Test
STA	Soft Tissue Artifact
STD	Standard Deviation
STS	Sit to Stand
SVM	Support Vector Machine
TUG	Time Up and Go
WF	Walking Frequency

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