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Review Article

Application of Wearable Technologies in Fall Risk Assessment and Improvement in Patients with Peripheral Neuropathy: A Systematic Review

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Background. Peripheral neuropathy is regarded as one of the leading causes of fatal and nonfatal falls. Wearable sensors, due to their increasing availability and flexibility of setting and space, are used widely to obtain wearer's kinematic data to analyze one's balance capacities for the evaluation of risk of fall. There is yet to have a review study focusing on the application of wearable sensors in the scope of fall risk for patients with peripheral neuropathy. *Objective.* To investigate the methods by which researchers adopt to assess risk of fall in peripheral neuropathy patients and potentially shed light on future researches. *Methods.* A systematic review design was used to identify articles on fall risk assessment and balance training using wearable sensors in patients with peripheral neuropathy. The study is aimed at extracting the following information: the type of sensors, the type of signal and data processing employed, the scales and tests used in the study, and the type of application. *Results.* We identified 351 studies, from which 8 were included. An average sample size of 35.6 patients enrolled the studies. The accelerometer was the most common wearable sensor used. 10-meter walk test was the preferable procedure for assessing risk of fall. *Conclusion.* This review examined several key components in studies on assessing and improving the risk of fall using wearable sensors. We identified the preferred functional test (10-meter walk test), sensor technology (accelerometer), locations (torso and lower legs), and fall risk improvement methods (prostheses). However, due to the limited number of articles specializing in this field of research, a consensus on patient sample size and procedures is not reached. We would recommend future researches to examine more parameters and adopt a fusion sensor setup.

1. Introduction

Peripheral neuropathy (PN) is one of the most frequent causes for neurology outpatient visits, with a prevalence of 1-12% in all age groups [1, 2]. It refers to a wide series of symptoms impairing the peripheral nerve system; affecting the distal motor, sensory, and autonomic fibers [3]; and thus causing impaired balance, loss of tactile sensations, and allodynia [4]. Common causes include systemic diseases (i.e., diabetes mellitus (DM)), genetic disorders (i.e., Charcot-Marie-Tooth disease), toxic exposure, and chemotherapy [5, 6]. Especially with DM reaching increasing proportions in the world, high occurrence of diabetic peripheral neuropathy (DPN) of nearly 50% in DM populations was reported [7, 8].

PN is thought of as a major risk factor of falls [9]. Hindfoot reflex loss, decreased vibratory sense, damaged proprioception, and strength all contribute to the higher odds of fall [10]. Fall is identified as a leading cause of injury, disability, and death by the Centers for Disease Control and Prevention [11] that results in over 50 billion dollars of medical bills in the U.S. alone [12], causing financial burdens on the healthcare system and individuals. Fall risk assessments are therefore crucial in analyzing the risk factor and characteristics of people who are more prone to falling.

Traditionally, assessment of fall risks relied heavily on gait and balance monitoring in laboratory settings using motion capture or clinical tools. While these methods are accurate, they have innate limitations, requiring for a dedicated test space, costly equipment, or the presence of healthcare professionals for data interpretation [13]. In contrast, wearable sensor devices utilizing accelerometers or gyroscopes are most used to accurately record the body's kinematic data in a relatively compact and boundless chassis [14]. They are attached to various locations on the patient's body (i.e., waist, ankle, or shin) and retrieve accurate motion data.

Unfortunately, researchers have yet to reach a consensus on the methodology by which they evaluate the risk of fall. Plenty of researches focused on exploring the risk of fall assessment in healthy individuals or the elderly [15–17]. But only a handful of them are specifically targeting the PN population. Considering that there is currently no review article focusing on the application of wearable in fall risk assessment in PN patients, our study is aimed at performing a systematic review analysis to provide insight for future studies.

2. Method

Our research adopts a systematic review strategy in accordance with PRISMA recommendations [18].

2.1. Database Search Strategy. PubMed, Embase, Scopus, IEEE Xplore, and Web of Science databases were chosen to include both engineering and medical journals in the search process. The following terms were used to search the database on March 23, 2022: neuropathy or "peripheral neuropathy" or "peripheral nervous system diseases", device or wearable or accelerometer, risk or detect* or predict* or prevent*, and fall* or stumble or misstep. The search query is summarized in Table 1.

2.2. Inclusion and Exclusion Criteria. The inclusion criteria of the search were as follows: (1) to identify articles published in English; (2) used portable wearable devices to detect, predict, or improve fall risks; and (3) research subjects clinically diagnosed with peripheral neuropathy. The exclusion criteria of the search were as follows: (1) review articles, conference abstracts, books, patents, or case studies; (2) did not specify the use of wearable devices; and (3) published in a language other than English.

2.3. Data Analysis. Our study designed a table prior to data extraction. Target data included author, utilization of wearable for rehabilitation, PN sample size, cause of PN, wearable sensor type, location of the wearable, data acquirement procedure, and clinical measurement for fall risk stratification or assessment.

3. Results

3.1. Selection Process. A total of 351 records were identified from the 5 electronic databases as summarized in Figure 1. Of these, we identified 8 articles meeting our criteria to be included in the systematic review [19–26]. Of which, 5 applied wearable sensors to assess risk of falling, 1 utilized wearable sensors to improve gait and balance in effort to mitigate risk of falling, and another 2 did both.

3.2. Risk of Fall Assessment

3.2.1. Sensors. Three types of sensors are recognized in the 6 studies assessing the risk of fall. All of the studies used accelerometers. Three of the studies used the combination of accelerometers, gyroscopes, and magnetometers [27]. One study used a combination of accelerometers and gyroscopes. The number of sensors and the locations of the sensors also varied. Four studies used multiple sensors to capture motion data. Gait analysis and balance evaluation required a different number of sensors. On average, 3.2 sensors were needed to complete gait performance evaluation, and 2.75 sensors were needed for balance evaluation. The torso and lower legs are the most common placement of sensors. In the 2 studies using only 1 sensor, both of them were placed at chest level. The details of risk of fall assessment are shown in Table 2.

3.2.2. Sample. In the studies, a total of 214 PN subjects were enrolled, an average of 35.6 per study. The average age for the subjects was 74.2. Only DPN or CIPN are included in these studies, 3 had CIPN subjects, 2 had DPN patients, and another 1 had both.

3.2.3. Clinical Fall Assessment. We sought to identify the clinical tools used to evaluate the subject's fear of fall or fall tendencies. Past fall events in the 12-month period were surveyed in 5 studies, with 3 of them recording the recalled number of past falls and 2 taking yes/no answers. Fall Efficacy Scale-International (FES-I) was used in 4 of the studies. FES-I is a validated tool in assessing concerns for fall and fall risks, with good reliability [28, 29]. The FES-I score in PN subjects among studies varied. One study adopted the Tinetti score. The Tinetti score was designed as a quick scale to evaluate gait and balance with good validity [30, 31].

3.2.4. Procedures. The functional test procedures during which wearables were applied to measure gait and balance in the studies include timed up and go (TUG), walk with varied length or duration with or without turns required, 48-hour physical activity, and 30-second standing balance test Table 3.

3.3. Risk of Fall Improvement. We identified 3 articles focusing on the use of wearable technology to train PN patients to improve their gait and balance functions in an effort to reduce fall risks. Two of them used a wearable sensory prosthesis that detects center of plantar pressure and provides directional tactile vibrational stimuli to signal the patient at the lower leg level. One used a triaxial accelerometer, gyroscope, and magnetometers to capture patient motion; then, data was used to assist balance training simultaneously. Training time varies as depicted in Table 4.

3.3.1. Procedures. As is summarized in Table 3, both studies using prostheses adopted functional gait assessment, 10-meter walk test (10MWT), and 4-stage balance test; one additionally included timed up and go test. The study using interactive balance training strategy included 30-second standing balance test and 10-meter walk test.

Table 1: Search queries used for each database.

Database	Query	Hits
Scopus	TITLE-ABS-KEY ((neuropathy OR "peripheral neuropathy" OR "peripheral nervous system diseases") AND (device OR wearable OR accelerometer) AND (risk OR detect* OR predict* OR prevent*) AND (fall* OR stumble OR misstep))	70
IEEE Xplore	(neuropathy OR "peripheral neuropathy" OR "peripheral nervous system diseases") AND (device OR wearable OR accelerometer) AND (risk OR detect* OR predict* OR prevent*) AND (fall* OR stumble OR misstep)	3
Web of Science	(TS=(neuropathy) OR TS=(peripheral neuropathy) OR TS=("peripheral nervous system diseases")) AND (TS=(device) OR TS=(wearable) OR TS=(accelerometer)) AND (TS=(prevent) OR TS=(risk) OR TS=(detect*) OR TS=(predict*)) AND (TS=(fall*) OR TS=(stumble) OR TS=(misstep))	102
PubMed	("peripheral neuropathy" OR "peripheral nervous system diseases" [MeSH] OR neuropathy) AND (device OR wearable OR accelerometer) AND (risk OR detect* OR predict* OR prevent*) AND ("accidental falls" [MesH] OR fall* or stumble or misstep)	90
Embase	("peripheral neuropathy"/exp OR "peripheral nervous system diseases" OR neuropathy) AND (device OR wearable OR accelerometer) AND (risk OR detect* OR predict* OR prevent*) AND (fall* OR stumble OR misstep OR "falling"/exp)	86

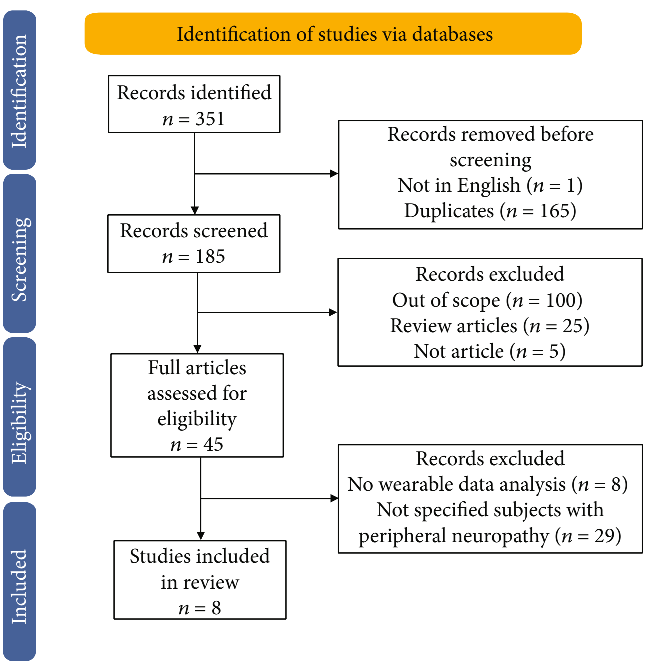

Figure 1: Study selection. Preferred Items for Systematic Reviews and Meta-Analyses (PRISMA) flow diagram. Out of 351 identified studies and after application of the inclusion and exclusion criteria, 8 studies were included.

3.3.2. Summary of Papers. Zahiri et al. [19] stratified patients according to clinical diagnoses and the quantifiable vibration perception threshold (VPT) test and found that ankle sway and stride time had a significant correlation with motor deterioration. Najafi et al. [22] proposed that by novel algorithm, one accelerometer can monitor three main postures (sitting, standing, and lying), assessing the risk of falling. Lalli et al. [23] discovered that variability for step length and velocity is the distinguishing parameter for PN. Kang et al. [25] assessed the relationship between postural sway and fall risk with or without visual cues. In another research, Kang et al. [26] monitored the daily physical activity over the span of 48 hours, proposing that walking bouts and total step counts have a strong correlation to fall risk assessment.

Schwenk et al. [20] utilized a five-sensor setup to conduct sensor-based balance training to improve patients' balance functions. After four weeks of training, the subjects significantly improved sway of ankle, hip, and mediolateral center of mass. Since sensory loss is a major symptom for PN patients, Oddsson et al. [21] tested a sensory prosthesis on patients over a period of 10 weeks. A decrease in fall risk factors and fall rate was observed in the patients. The same prosthesis was used by Koehler-McNicholas et al. [24] to validate the short-term effect; over half of the participants reported improved gait scores.

4. Discussion

The use of wearable sensor types and locations had shown a degree of homogeneity, preferring the combination of accelerometer, gyroscope, and magnetometer. Only 1 article [22] described the specific algorithm in denoising and removing signal artifacts to assess risk of fall. We believe the fact that many researchers used wearables from the same commercial wearable sensor company and that sensors have become more available and affordable played a major role. The most used sensors were validated sensors such as PAMSys [32], LEGSys [33], and BalanSens from the same company BioSensics. Overall, the most frequently used sensor was an accelerometer, which corroborates with other reviews on wearable sensor fall detection [13, 34]. The torso and lower legs were the most common locations for sensor fixation.

Only DPN and CIPN patients have been recruited in these studies, while they do represent the majority of patients with PN, whether PN caused by other diseases or factors share the same characteristics in gait and balance remains to be tested. Future studies should also focus on the difference in fall risk impact among different causes of PN since the mechanism varies.

The use of FES-I and past fall recollection as an indicator for fall risk assessment is present in most articles. Recording the number of falls in the past 12 months rather than binary

Table 2: Articles selected for fall risk assessment.

Year	Author	Cause	Sample	Sensor	Numbers	Clinical measures	Procedure	Frequency
2013	Najafi et al. [22]	DM	$N = 8$	Accelerometer	1 (chest)	Tinetti score	Traditional timed up and go	40 Hz
2013	Lalli et al. [23]	DM	$N = 42$	Accelerometer, gyroscope, magnetometer	2 (both shins)	Reports of past falls	50-meter walk with one 90-degree turn	N/S
2016	Schwenk et al. [20]	CIPN	$N = 22$	Accelerometer, gyroscope, magnetometer	Gait: 4 (each shank and thigh); balance: 3 (each shank and lower back)	FES-I, reports of past falls	30-second standing and 10-minute walk	100 Hz
2019	Zahiri et al. [19]	CIPN	$N = 58$	Accelerometer, gyroscope, magnetometer	5 (each shin thigh and lower back)	FES-I, past falls event (yes/no)	15-meter walk at self-selected speed	100 Hz
2020	Kang et al. [26]	DM, CIPN	DPN ($n = 23$), CIPN ($n = 26$)	Accelerometer	1 (chest)	FES-I, reports of past falls	Physical activity over 48 hours	50 Hz
2021	Kang et al. [25]	CIPN	$N = 35$	Accelerometer, gyroscope, magnetometer	Gait:4 (2 each shin); balance: 2 (1 shin, 1 lower back)	FES-I, past fall event (yes/no)	1. Walk for 12 meters. 2. Stand for 30 seconds	100 Hz

Table 3: Functional test description.

Functional test	Description	Frequency
10-meter walk test (10MWT)	Walk at a self-selected speed for 10 meters. Some studies have slightly longer distance.	5
30-second standing test	30 seconds of standing in 2 circumstances: (1) feet close together (but not touching) with eyes open (EO) and (2) feet close together and eyes closed (EC). One study required an additional circumstance of semitandem position with EO.	3
Timed up and go	Sit-to-stand and walk 10 meters roundtrip and then turn and stand-to-sit.	2
Functional gait assessment	Includes a 10-item scale where each item is scored from 0 to 3.	2
4-stage balance test	Four gradually more challenging postures the subject performs: (1) stand with feet side by side, (2) stand with feet in semitandem stance, (3) stand with feet in tandem stance, and (4) stand on one leg. Subjects pass if they can hold the stance for 10 seconds and then move on to the next stance.	2
Physical activity over 48 hours	A total 48-hour period (except for water activity and sleep).	1
50-meter walk with one 90-degree turn	Walk at normal pace for 50 meters with one 90-degree turn with no rest time permitted.	1

Table 4: Articles selected for fall risk improvement.

Year	Author	Subjects	Sensor	Mechanism	Training duration	Procedures
2016	Schwenk et al. [20]	CIPN ($n = 22$)	Accelerometer, gyroscope, magnetometer	Interactive balance training	4 weeks	30-second standing balance test, 10-meter walk test
2019	Koehler-McNicholas et al. [24]	PN ($n = 31$)	Pressure sensor	Sensory substitution	10 minutes	Functional gait assessment, 10-meter walk test, 4-stage balance test
2020	Oddsson et al. [21]	PN ($n = 45$)	Pressure sensor	Sensory substitution	10 weeks	Functional gait assessment, 10-meter walk test, 4-stage balance test, timed up and go

yes/no answers provides more data for the accurate estimation of the patients' fall risk. But patients' recollection may present itself as a bias. None of the articles included another pool of PN patients to validate the correlation between sensor data and fall risks. This might be due to the difficulty in volunteer recruitment. Future researches could incorporate fall detection wearables to correlate actual fall events to ensure accuracy.

The 10-meter walk test was the preferred procedure for gait analysis, followed by the 30-second standing test for balance evaluation. We presumed that this is partly due to the fact that they are easier to perform with minimal setup to prepare. They are well-researched and validated tests with high reliability [35–38]. One study required subjects to record 48 hours of daily physical activity. Daily activities over a prolonged period of time can accurately represent the natural gait and posture for the test subjects. Since it was done using a single sensor setup, only step counts, walking bouts, and postural data were collected, making it hard to take all activities into accurate assessment. It would be interesting to see if multiple sensors can represent daily activities more precisely.

For risk of fall improvement studies, the two using the sensory substitution method applied the same prosthesis. The device provides real-time tactile feedback, and significant improvements of gait and balance was achieved even after 10 minutes of training. The interactive balance training study utilized sensor data for error-dependent training, indicating the real-time feedback-enabled restore of sensory mapping could improve gait and balance. Future studies should investigate the ideal combination of the methods and schematic training techniques.

A rather small number of articles were included in our review. Our paper is focused on articles that expressively selected patients with peripheral neuropathy (PN) as their subjects. We did in fact find quite a large number of current articles on fall prediction and intervention for healthy individuals or the elderly, or patients with Parkinson's disease. We excluded those articles that did not include clinically diagnosed PN patients. Admittedly, fall risk assessment methods could share a certain level of resemblance among different groups. Due to the fact that PN is unique in its etiology and pathology, gait patterns and fall mechanisms could vary. As a result, the significance and threshold of corresponding assessment tool could differ widely. We believe that methods and thresholds formulated from data collected from other groups (mostly healthy adults) would be of poor value to the future researches on fall risk assessment of patients with PN.

As a relatively novel field for risk assessment and improvement, research methods and sensor types used in general fall risk researches could be migrated to that of PN patient. Multiple novel wearable sensors could be put into use. For example, plantar inclinometer, electromyography, and pressure sensor could be promising [39]. Adaptive/dynamic threshold selection is becoming increasingly crucial to provide personalized care [40]. Utilizing the smartphone as an input of integrated sensors has also proved practical [41]. Researchers should also calculate the precision, specificity, accuracy, and F1-measure of the selected methods [42]. Future researches should also focus on applying deep learning algorithms to extrapolate gait patterns of higher fall risk among PN patients [43]. The fusion of multiple sensors is also crucial to negate noises and boost robustness of real-time analysis of fall risks in gait analysis [44]. We would also advocate for more sophisticated and validated sensor systems such as APDM [45] to be utilized by future researches.

5. Conclusions

This review examined several key components in studies on assessing and improving the risk of fall using wearable sensors. We identified the preferred functional test (10-meter walk test), sensor technology (accelerometer), locations (torso and lower legs), and fall risk improvement methods (prostheses). However, due to the limited number of articles specializing in this field of research, a consensus on patient sample size and procedures is not reached. We would recommend future researches to examine more parameters and adopt a fusion sensor setup.

Data Availability

Data are available from PubMed, Embase, Scopus, IEEE Xplore, and Web of Science.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

Authors' Contributions

Qiyang Pan and Yungu Chen contributed equally to this work.

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