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Freezing of Gait Prediction and Monitoring in the Treatment of Parkinson's Disease

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Abstract. Wearable sensing offers a promising path for continuous monitoring and early intervention of freezing of gait (FOG) in Parkin- son's disease (PD), yet heterogeneity in sensor type/placement, ground- truthing, and validation metrics hampers comparability and transla- tion. This scoping review (1) catalogs sensor types and placements; (2) compares performance across sensor modalities and placements under comparable measurement regimes (with emphasis on accuracy) and analyzes how metric definitions shape results; and (3) identifies gaps for real-world deployment and standardization. We searched PubMed, Embase, IEEE Xplore, and Web of Science (2015–June 2025). Inclusion required a wearable approach targeting FOG/abnormal gait, at least one evaluation metric, and PD participants/data; two reviewers screened/extracted independently with third-party adjudication. Across the studies summarized in Tables 1–3, wearable sensing for Parkinson's disease (PD) freezing of gait (FOG) remains dominated by inertial measurement units (IMUs) with a variety of body placements (waist/lower-back, shank/ankle, foot, and multi-node configurations). According to the table, best accuracies locate roughly 71% to 99%, reflecting both differences in task definition (FOG detection, or broader gait abnormality) and heterogeneity in ground- truthing and validation protocols. A consistent pattern emerges: placement matters, and how we validate models strongly shapes apparent performance. We conclude FOG wearables are IMU-centric and placement-sensitive; standardizing labels/metrics and prioritizing subject-independent, home validation—alongside sparse, placement- optimized designs, >24-h runtime, on-device inference, privacy, and adherence/burden reporting—are key to translation.

Keywords: component, formatting, style, styling, insert.

1. Introduction

Parkinson's Disease (PD), a common and intricate neurodegener- ative condition, impacts the central nervous system and is notably frequent in older adults [1]. Amid the trend of global population aging, the pathological processes and clinical consequences of PD have become pivotal issues in public health. PD is pathologically characterized by the gradual deterioration of dopaminergic neurons within the midbrain's substantia nigra, leading to a substantial de- crease in dopamine concentrations in the basal ganglia and, in turn, impairing signal transmission routes in the motor cortex. Studies show that when typical PD symptoms appear, as many as 80% of the brain's dopamine-synthesizing cells in patients would have already died off. This irreversible neuronal impairment directly triggers a range of motor symptoms like bradykinesia, muscular stiffness, resting tremor, and gait issues, along with non-motor manifestations including sleep disturbances, emotional dysregulation, cognitive impairment, and autonomic dysfunction [2].

Globally, PD's annual incidence is approximated to be 5–35 cases per 100,000 people, a range possibly due to differences in the demographic compositions of study populations or methodological variations. PD seldom occurs before the age of 50, yet its incidence increases by 5–10 folds among those aged 60–90. On a global scale, PD's prevalence is conservatively put at 0.3%, while it rises sharply to 3% in individuals over 80. Forecasts from the World Health Organization's Neurological Diseases Program further highlight its

seriousness: by 2040, PD is projected to become the world's second leading cause of death [3-5]. These data not only highlight PD's threat to individual health but also reveal the potential burden it poses to public health systems.

Among PD's diverse symptoms, freezing of gait (FoG) is a severe, disabling movement disorder unique to advanced-stage patients, exerting the most profound impact on quality of life. FoG is defined as "a brief pause or marked deceleration of both feet despite a clear intention to walk, preventing normal forward movement." [6] Its clinical manifestations are highly heterogeneous, encompassing resting tremor (alternating leg tremors), bradykine- sia (short, shuffling strides), and complete immobility (rare)—a diversity that has hindered the development of a unified clinical definition. Epidemiological studies show that approximately 50% of PD patients experience FoG, with this proportion rising to 60%–80% in advanced stages [7]. In a 2007 survey of 6,620 PD patients, Macht et al. found that 47% of participants frequently encountered FoG, with a significantly higher incidence in male patients than in female patients [8].

FoG episodes exhibit strong contextual dependence, typically occurring during gait initiation, turns, traversal of narrow spaces (e.g., doorways, corridors), or dual-task performance (e.g., walking while talking). Triggering factors include environmental constraints (e.g., crowded areas), distraction, and time pressure, while allevi- ating factors include emotional arousal, rhythmic auditory cues, and stepping targets. The unpredictability of these episodes not only elevates patients' fall risk,but also leads to loss of mobility independence, social isolation, and a precipitous decline in quality of life. Case reviews suggest FoG's pathological mechanisms may involve impaired coordination between somatic sensory functions and the brain's motor cortex, i.e., the brain's inability to promptly process path-related signal changes; however, the specific molecular and neural circuit mechanisms remain to be fully elucidated [9].

Accurate assessment and monitoring of FoG are critical for improving PD patients' prognosis, yet traditional methods suffer from notable limitations. In clinical practice, subjective rating scales are the most widely used assessment tools, including the Unified Parkinson's Disease Rating Scale (UPDRS), Modified Hoehn-Yahr Scale (mHY), and Freezing of Gait Questionnaire (FoG-Q). These tools, however, rely on evaluators' subjective judgments, fail to quantify key parameters such as episode frequency and duration, and are highly susceptible to environmental interference. Notably, FoG attack rates in clinical settings are significantly lower than in home environments, resulting in biased assessment outcomes.

This review focuses on FoG detection research using wearable devices from 2015 to 2025, aiming to systematically summarize technological advancements and existing challenges. By analyzing sensor types, placement locations, and performance disparities, we reveal the advantages and limitations of current studies. The review

will primarily explore three key questions: how to enhance result comparability through standardized evaluation metrics (e.g., accu- racy, sensitivity, F1 score); how to optimize sensor configurations to balance detection performance and wearability; and how to develop cross-individual, cross-scenario models to facilitate clinical transla- tion. Ultimately, this work provides a theoretical basis and practical guidance to advance wearable technology from the laboratory to PD patients' daily lives, enabling real-time monitoring and intervention of FoG.

2. Literature review

To evaluate freezing of gait (FOG) and associated gait abnor malities in Parkinson's disease, several methods have been put forth. Early research mostly used clinical rating scales, including the Freezing of Gait Questionnaire (FoG-Q), Modified Hoehn-Yahr Scale (mHY), and Unified Parkinson's Disease Rating Scale (UPDRS), in addition toclinicianobservation during outpatient visits [2,7]. Although these tools are widely used in routine care and are simple to administer, they are subjective, only offer coarse-grained information on the frequency and duration of episodes, and are heavily influenced by the clinic environment and visit timing, where FOG is frequently less common than at home [7,8]. Laboratory¬based systems like force plates, optoelectronic motion capture, and instrumented walkways have been used to measure kinematics and kinetics in detail in order to gather more objective gait data [9,10]. However, these systems are expensive, require specialized facilities, and typically capture only short, highly structured walking tasks that may not reflect day-to-day gait variability.

With the spread of low-cost inertial measurement units (IMUs) and mobile devices, many studies have explored body-worn sensing for FOG detection and monitoring in more natural settings. Most work uses one or more IMUs placed on the waist or lower back, shank/ankle, feet, chest, or wrists to detect FOG episodes or more broadly classify gait states in people with Parkinson's disease [10-14]. Reported best accuracies for FOG detection or abnormal gait classification typically range from about 75% to over 95%, depending on the task definition, sensor configuration, and validation protocol [15-19]. In addition to single modality IMU systems, multimodal approaches have combined IMUs with physiological and mechanical signals such as surface electromyography, electrodermal activity, electrocardiography, plantar pressure, and strain or piezoelectric sensors to jointly characterize tremor, dyskinesia, balance, and FOG-related gait changes [12,20-22]. These richer sensing configurations can capture more aspects of motor and non-motor function, but often increase complexity, cost, and burden on patients.

Technology for FOG detection and cueing strategies has been compiled in a number of narrative and systematic reviews, frequently concentrating on algorithm development, particular device classes, or digital indicators of FOG severity [23-26]. Nevertheless, previous reviews often combine wearable and non-wearable systems, pool different outcome definitions (e.g., general motor state, fall risk, and FOG detection), or offer scant insight into the effects of validation regime and sensor placement on reported performance. Specifically, there is still disagreement about the best places for wearable sensors to balance accuracy, usability, and long-term wearability, as well as how evaluation metrics (such as F1 score, sensitivity, specificity, and accuracy) and ground-truthing techniques (such as video annotation, UPDRS based labels, and self-report) influence apparent results [13,27-29].

In this context, the present scoping review concentrates specifically on wearable-sensor–based FOG detection and prediction in Parkinson's disease from 2015 to 2025. Building on the databases and inclusion criteria described in the Methods section, we aggregate 40 eligible studies using wearable devices for FOG or closely related gait outcomes. Our synthesis emphasizes three aspects: (1) how sensor types and placements (waist, legs, ankles, feet, chest, and multi-node configurations) are distributed across the literature; (2) how reported performance depends on placement and validation strategy, including the choice of evaluation metrics; and (3) which gaps remain for translation to long-term, home and community deployment, such as small sample sizes, limited subject independent testing, and incomplete reporting of adherence or user burden. By structuring the review around these questions, we aim to provide a clearer map of current evidence and practical guidance for designing future wearable systems for FOG monitoring in real world settings.

3. Methods

3.1. Information sources

We searched the entire literature for articles published between 2015 and June 2025 using PubMed, Embase, IEEE Xplore, the ACM Digital Library, and the Web of Science. The search strategy was refined with input from a professional research librarian to enhance its rigor and completeness. All retrieved records were imported into Zotero and Obsidian, two web-based tools commonly used for systematic review management. In order to find any more pertinent articles, the reference lists of the research that were initially included were also manually examined.

3.2. Literature search

To find pertinent research on (i) Parkinson's illness, (ii) freez- ing of gait (FOG) prediction or monitoring, and (iii) wearable sensor technologies, a thorough literature search was carried out. To increase sensitivity and guarantee comprehensive coverage of the subject, the search method combined free-text keywords with controlled vocabulary terms.”Parkinson,” ”prediction,” ”monitor,” ”freezing of gait,” ”FOG,” ”wearable sensor,” ”mobile device,” and ”mobile app” were among the keywords.

3.3. Criteria

Articles were collected if they were published in ten years and written in English.

1. Involve participants diagnosed with Parkinson's disease or use data collected from such participants

2. Wearable device.

Any wearable device or sensor (i.e., a device worn on the body) intended for the automated detection of abnormal gait patterns was considered eligible. This includes the identification of early indicators of freezing of gait (FOG), such as decreased stride length, increased step frequency, altered angular velocity during turning movements, and tremor. Additionally, surface electromyography (sEMG) signals were included as a means to differentiate between true motor arrest and FOG episodes. The term ”device” is defined as a wearable system embedded with sensors capable of detecting and recording the aforementioned physiological and kinematic parameters.

3. Capability mentioned.

At least one evaluation metric (e.g., Accuracy, sensitivity) shall appear in the article to indicate the performance of the device in monitoring and predicting FOG in Parkinson's disease.

3.4. Screening

Three steps were taken in order to screen for possibly eligible studies: full-text screening, title and abstract screening, duplication removal, and data extraction and validation. Duplicate records were found and eliminated from the obtained publications using Zotero and Obsidian. To make sure that every study was assessed just once, manual checks were performed to eliminate any duplicates

that these tools were unable to find. The titles and abstracts of the remaining records were separately examined by two review authors (Author A and Author B) using the inclusion and exclusion criteria. To verify their eligibility, the whole texts were assessed independently by the same two review authors. Disagreements between the two reviewers were initially settled through lengthy discussions during the screening phase. A third reviewer (Author C) was consulted to settle the matter if an agreement could not be achieved. Author (A) finished extracting, classifying, and annotating all of the data following the final validation of the included studies' eligibility, and Author (B) then confirmed this.

3.5. Data

For the extracted continuous variables—such as sample size, number of sensor types, use of large models and apps, and predic- tion accuracy—the mean and standard deviation were computed. Charts were then generated for sensor type and prediction accuracy to enable more intuitive comparisons.

3.6. Objective

When people with Parkinson's disease experience freezing of gait (FOG), they may suddenly feel as if their feet are "stuck" to the floor, making it hard to move forward. This phenomenon is one of the key motor disturbances of the disease, especially in advanced stages. FOG not only increases the likelihood of falls and fractures but also exacerbates existing mobility impairments. Anticipating FOG events can help reduce injuries in this population. This scoping review aims to systematically examine studies published from 2015 through June 2025 on wearable-sensor–based approaches for detecting and forecasting FOG in Parkinson's disease. Specifically, we (1) summarize sensor types and placement sites (waist, shank, foot, multi-node), (2) compare performance outcomes across sensor configurations, and

(3) highlight implementation challenges such as labeling protocols, reporting consistency, and transferability to real-world settings.

1. Catalog sensor types and placements (waist/shank/foot/multi- node).
2. Quantify performance differences by sensor type and placement.
3. Identify gaps for real-world deployment (labeling protocols, reporting consistency, transferability).

3.7. Diagram

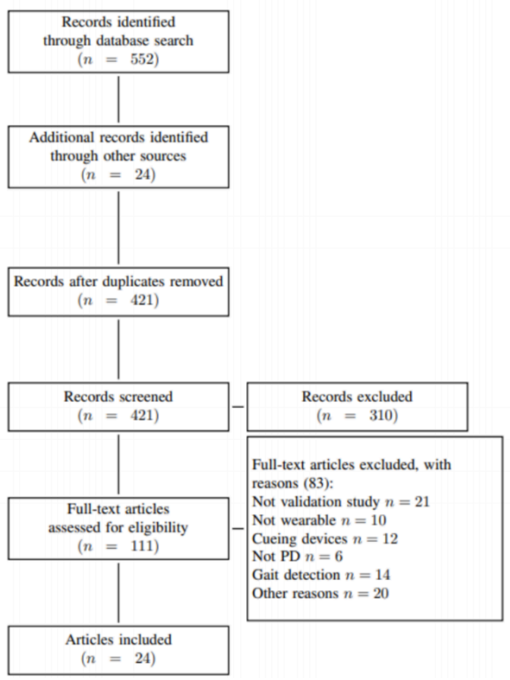

Figure 1. PRISMA-style flow diagram

4. Result

4.1. Literature search

The literature search produced 640 research articles in total, with 107 duplicates, leaving 533 articles to be screened. 35 articles were excluded as review articles while 128 articles were identified as no wearable sensor or did not meet criteria. Meanwhile, 213 articles were algorithm target and 56 articles did not have evaluation metric. 29 of the articles were commentary article, and 6 of them could not retrieve full text and 2 of them could not be read. After excluded those papers, only 64 articles for eligibility. After reviewing full text, 29 articles were left as final included articles. The sensor that was used most frequently was IMU. All the data was shown in Table1.

4.2. Table1

Table I: Summary of wearable device studies for Parkinson's disease monitoring and intervention

ID	Study	Sample Size	Wearable Device Used	Sensor Type	Prediction Task	Evaluation Metrics	Best Accuracy	Ground Truth
1	[10]	Dev: 10 PD; Test: 24 PD	Shank, thigh, lower back	IMU	Subject-independent FOG detection (ASD)	Sensitivity, Specificity, F1	Sensitivity 94–96%Specificity 79–84%	Video labeling
2	[11]	25 PD	Waist	IMU	Balance rehabilitation	Accuracy, ROC	94.4%	Lab-based testing
3	[12]	20 PD	Lower back + Waist	IMU	Motor state classification	AUC, Sensitivity	AUC 0.91	UPDRS scoring
4	[13]	27 PD	Feet	IMU	Gait classification	Accuracy	89.8%	Lab-based testing
5	[14]	30 (15 PD, 15 HC)	Trouser pocket + Waist	IMU	Activity classification	Accuracy	93.3%	Video labeling
6	[15]	56 PD	Waist	IMU	FOG classification	Accuracy	86.1%	Video annotation

Table 1. (continued)

7	[16]	15 PD, 8 HC	Trunk / upper back	IMU	Unstructured movement classification	Accuracy, AUC	100% (chair test)	Video annotation
8	[17]	106 PD, 105 HC	In-shoe; phone at pocket/waist	IMU + microphone	gait classification	Accuracy	bigger than 94%	UPDRS + video annotation
9	[18]	11 PD	Wrist (EDA), chest patch (ECG), ankle/shank IMU, scalp (EEG)	IMU, ECG, EDA, EMG, EEG	Multisymptom quantification (tremor, gait, cognition)	Correlation, RMSE	RMSE 0.12 0.34	Clinician-annotated events
10	[19]	10 PD	Lower back + left/right shanks	Inertial sensors	UPDRS gait evaluation	RMSE, correlation	0.85 correlation	Clinician UPDRS
11	[20]	71 PD	Left waist	IMU	FOG detection	Sensitivity	82 %	Self report + video detection
12	[21]	65 PD + 28 HC	Chest, lower back, wrists, ankles	IMU	Bradykinesia, tremor, dyskinesia, FoG, gait/balance detection	Accuracy	0.96/0.98/0.83	Self-report and Video-based expert labeling
13	[22]	15 PD	Chest	IMU	Detect Anticipatory Postural Adjustments	Sensitivity	85.7%	Force-plate Center of pressure onset + video detection
14	[23]	11 PD	Chest + wrist + ankle	IMU + PPG + EDA	Forecast FOG 1-5 ahead	Accuracy	71.3%	Video-based expert labeling

Abbreviations: PD = Parkinson’s Disease; HC = Healthy Controls; FOG = Freezing of Gait; UPDRS = Unified Parkinson’s Disease Rating Scale; IMU = Inertial Measurement Unit; EMG = Electromyography; sEMG = Surface Electromyography; ECG = Electrocardiography; EDA = Electrodermal Activity; EEG = Electroencephalography; RMSE = Root Mean Square Error; AUC = Area Under Curve; ICC = Intra-class correlation coefficient; PPG = Photoplethysmography; ROC = Receiver Operating Characteristic; FFT = Fast Fourier Transform; HRV = Heart Rate Variability; DBS = Deep Brain Stimulation; IoT = Internet of Things; ML = Machine Learning; SEM = Structural Equation Modeling; NW =

Table 2. Summary of wearable device studies for Parkinson’s disease monitoring and intervention

ID	Study	Sample Size	Wearable Device Used	Sensor Type	Prediction Task	Evaluation Metrics	Best Accuracy	Ground Truth
15	[24]	30 PD	Wrist	IMU	Tremor detection	F1 score	92%	Video-based expert labeling
16	[25]	10 PD	Ankle	IMU	Swing angular range and stride time	Accuracy	84%	Video detection
17	[26]	101 PD	Waist	IMU	FOG detection	F1-score	82 %	Video annotation
18	[27]	21 PD	Right ankle	IMU	FOG detection in semi-free-living situation	F1 score	86%	Multi-angle video detection
19	[28]	20 PD	Chest, wrist, ankle	IMU	loss of alternating stepping, complete cessation, or trembling	Accuracy	Ankle 80%, Foot 78%, Chest 72%	Video detection
20	[29]	50 PD	Wrist and chest	IMU	FOG detection	Accuracy	99.7%	UPDRS +

Table 2. (continued)

								neurologist video review
21	[30]	23 PD	Waist	IMU	FOG detection	Sensitivity, Specificity	75%, 76%	Video analysis
22	[31]	30 (21 PD)	Thigh	IMU + voice cues	Gait-cycle breakdown	Accuracy	95%	Clinical labeling + video review
23	[32]	20 PD	Waist ,feet	FSR + IMU + laser	Step Time variability	Accuracy	99.2%	Video labeling + UPDRS
24	[33]	14 PD	Feet ,knee	Force sensors + bend sensors	FoG characterization	Step-Time variability	80% accuracy	Clinical video labels
25	[34]	7 PD	Ankles	IMU + CNN DGAD	FoG prediction	Specificity	98.6%	Video labels
26	[35]	32 PD	Ankles	IMU + sEMG	FoG subtype classification	Accuracy	98.4%	Clinical video labels
27	[36]	20 PD	Feet	Pressure	FOG detection	Accuracy	90%	Clinician video annotation

Table 3. Summary of wearable device studies for Parkinson’s disease monitoring and intervention

ID	Study	Sample Size	Wearable Device Used	Sensor Type	Prediction Task	Evaluation Metrics	Best Accuracy	Ground Truth
28	[37]	147 PD + 83 HC	Legs,lumbar	IMU	FoG severity continuum	ICC	89%	NFOG-Q + video
29	[38]	39 PD	Left hip	IMU + Bluetooth	FoG detection	Accuracy	85%	UPDRS + Clinical interview + Neurologist evaluation
30	[39]	15 PD	Shank-mounted IMUs	IMU	FoG transition detection	Accuracy	94.5%	Expert video annotation
31	[40]	12	Waist, thigh, shin, feet	IMU + ESKF	Gait phase detection	Accuracy	99.11%	3D motion
32	[41]	2 PD	Wrists, thighs, calves, waist	IMU + quaternion	FOG detection	Accuracy	Qualitatively consider this to be accurate	Clinician video annotation
33	[42]	11PD	Ankles	IMU + CNN	FOG detection	F1-score, Accuracy	86.4%, 87.2%	Expert video labels
34	[43]	26 PD	Ankles	IMU + Transformer	FoG detection	Accuracy	96.5%	Clinician LOSO labels
35	[44]	32 PD	Both shins	IMU + K-index	FoG detection	Specificity	97.6%	Clinical video reference
36	[45]	12 PD	Left shank	IMU	FoG prediction	Accuracy	96.97%	Video + physician annotation
37	[46]	13 PD	Plantar,quadriceps,shank	IMU + strain + piezoelectric	FoG detection	Accuracy	94.2%	CNN/SVM vs video
38	[47]	25 PD + 18 HC	Both feet	IMU	Stride length	Accuracy	86.2%	Optoelectronic validation
39	[48]	16 PD	Both feet	IMU	FoG detection	accuracy	81.03%	Video annotation

Table 3. (continued)

40	[49]	10 PD	Epson BT-200 smart glasses	IMU + AR visual cues	FOG detection	Accuracy	92.86%	Video-based gait analysis

4.3. Study characteristics

The earliest publication year among these papers is 2015, while the most recent year is 2025. The sample size of these papers ranged from 2 to 147 PD (Parkinson's Disease Patient), with 6 papers among 40 have healthy controls.

For wearable sensor types, IMU was used most frequently. And sensors were often placed in waist, legs and feet as top three sensor position.

Accuracy, sensitivity, and specificity were the top three evaluation mentioned in studies, which were mostly ranged from 75% to 99%. High accuracy could be seen in those papers.

Video labeling was the most commonly used ground truth method among all papers, followed by UPDRS, self-report and lab-test.

4.4. Sample size

The sample size of the studies ranged from 2 to 147 PD (Parkinson's Disease Patient), which was further classified into three levels according to the number of PD: less than 25, 25 to 50, and more than 50. 23 of 40 studies included only less than 25 PD, while those studies with 25 to 50 PD (N = 8 of 40) and more than 50 PD (N = 3 of 40) took 20% and 7.5%, respectively.

Among them, approximately 6 of 40 studies included HC (health controls). And half of the studies with HC included less than 25 participants, while the other half included more than 50 participants (N=3 of 6).

4.5. Wearable sensor types

Most of the sensors (N = 37 of 40) used in the experiments were IMUs, which took about 92.5%. Among them, approximately 40.5% of them (N = 15 of 37) content more than one sensor despite the IMU sensor. Force sensor, pressure sensor, and internal sensor were also mentioned in studies, which all took 2.5% among all studies (N = 1 of 40).

4.6. Wearable sensor placement

Almost 100% of the studies had more than one sensor placement. This article concluded all the placement in every article.

According to Table 1, 17 of 40 studies placed sensors on the legs (including the thighs, shins, calves, quadriceps, shins, and trouser pockets), which had the highest percentage among all positions .

The waist sensors (N = 12 out of 40) and the ankle sensors (N = 10 out of 40) took the second and third positions, which were 30% and 25% of all articles separately.

The limbs were also another important placement. The wrist (N = 8 of 40) and feet (including the smart insole) (N = 8 of 40) both took 20%.

There were also sensors on chest and lower back. 7 of 40 studies placed sensors on the chest , and 4 of 40 placed them on the lower back .

Other positions such as upper back, trunk, scalp, knee, hip, and smart glasses were each used in 1 of 40 studies.

4.7. Evaluation metrics

Studies often showed many different kinds of parameters from evaluation , such as accuracy, sensitivity, specificity, F1 score and others. Among all those articles, 26 of 40 mentioned accuracy, and the accuracy rate ranged mostly from 85% to 99.11%.

5 of 40 papers mentioned sensitivity, 5 of 40 papers mentioned mentioned F1 score , and 4 of 40 papers contained specificity (N = 4 of 40). And exact percentage of sensitivity ranged from 75% to 96.7%, and F1 score ranged from 82% to 92%, while specificity ranged from 76% to 98%.

4.8. Precision and placement

As there were articles with different evaluation metrics and sensors, to make statistic conclusion more direct, this section only chose studies using IMU and whose evaluation metrics is accuracy to find out the relationship between precision and sensor placement. Therefore, only 25 articles were selected in the section for data analysis.

Among those, 44% of the articles mentioned sensors on legs (N = 11 of 25) and the average accuracy was 96.4%. 28% of sensors were placed on waist (N = 7 of 25), with average accuracy of 95.2%. And 28% of sensors were placed on ankle(s) (N = 7 of 25) with 85.8% average accuracy. Those were the top three amount of sensor position, and the rest of the data could be seen in Figure 2.

4.9. Ground truth method

In order to evaluate the device in automatical detection in free living fields, under which circumstance the patient maintain their normal daily life conditions, thus enhance further development in real life, 100% of the studies used one or more validation methods in which the ground truth methods were used to record the episode

of FoG and were compared with the FoG detected by the device.

31 of 40 studies used video labeling, which more than one experts were engaged in the test and would label all the FoG episodes in video. This method might cause misjudgment since the videos were manually labeled, leading to the errors in final result. However, it was the most direct way for ground truth method.

5 of 40 studies used UPDRS , which included both self-report and expert assessment. UPDRS contains patient’s emotion, daily activity, motion examination and complication, is a useful tool when assessing Parkinson’s disease.

3 of 40 studies used self-report and 3 of 40 used lab test. 2 of 40 used 3D motion capture , and force plate , LOSO label and Optoelectronic validation were each used in 1 of 40 studies.

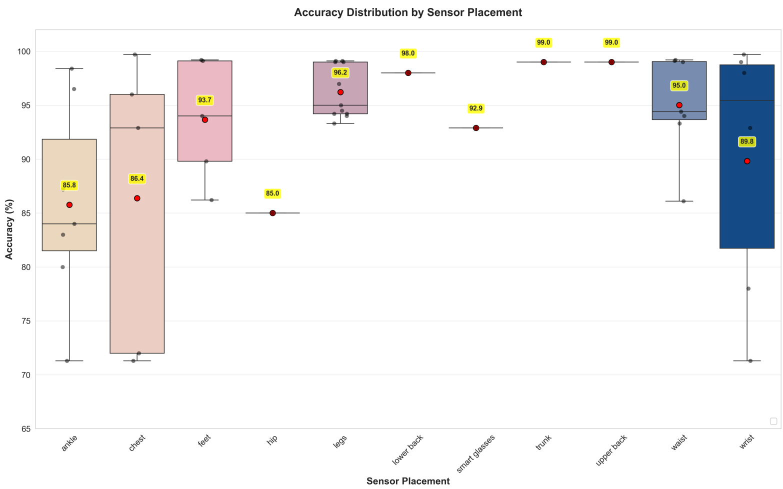

Figure 2. Accuracy distribution by sensor placement

5. Discussion

Our analysis additionally verifies that portable FOG tracking for Parkinson’s disease predominantly relies on inertial measurement units, covering investigations conducted from 2015 through 2025 and demonstrating notable reported precisions, approximately 75 to 99 percent across diverse assessments, categorizations, and confirmation methods. Broadly speaking, the findings suggest two primary determinants of effectiveness: sensor positioning and the validation along with measuring protocols employed by the frame- works.

As highlighted, IMUs featured in 92.5 percent of reviewed studies where device specifics could be extracted, frequently sup- plemented by pressure sensing or surface electromyography in a smaller fraction. In terms of attachment, the most common areas were legs, accounting for 42.5 percent, followed by waist at 30 percent and ankle at 25 percent; additional sites incorporated wrist or foot, each at 20 percent, chest reported by 17.5 percent, and lower back by 10 percent. Other less frequent placements included upper back, trunk, scalp, knee, hip, or smart glasses, each appearing infrequently. Such distribution illustrates a practical balance: distal points like shank or foot offer refined data on step timing and turning dynamics, whereas trunk or waist positions deliver broader stability metrics with improved practicality.

To conduct a fair comparison, the analysis focused solely on investigations utilizing IMUs, specifically those reporting accu- racy metrics (25 studies). Three distinct trends emerged. Initially, sensors positioned on the thigh, shank, or inside the trouser leg demonstrated the highest average accuracy (96.4%). Next, devices mounted on the waist or lower back yielded slightly lower yet notable results (95.2%), suggesting single node trunk-based sensing remains effective during regulated motion. Lastly, configurations limited to the ankle underperformed (mean 85.8%), likely because ankle-only data heavily depends on sensor alignment, possible issues with footwear, and interference from non freezing of gait movements where proximal data is absent. These observations, aligning with the superior figures linked to elevated placements, support the practical suggestion to favor leg (shigh or upper leg) or leg plus waist arrangements when the primary objective involves freezing of gait detection.

Within the subset of 40 papers containing quantifiable data, accuracy figures appeared in 65 percent (26/40), generally ranging from 85 to 99.11 percent. Only 12.5 percent provided sensitivity (5/40) or F1 scores (5/40), while merely 10 percent included speci- ficity (4/40). Given that FOG commonly involves class imbalance, relying solely on accuracy metrics can distort evaluations:

omitting infrequent FOG episodes minimally impacts accuracy but substan- tially lowers recall and F1. Moreover, studies inconsistently mixed event level and window level assessments, alongside varying time thresholds, rendering cross paper comparisons unreliable. Adopting uniform reporting of precision, recall, F1 scores, alongside PR-AUC and ROC-AUC, paired with explicit tolerance definitions, would significantly enhance clarity.

Currently, the field continues to grapple with several persistent obstacles. First, inconsistent reference standards and metrics ex- ist, comparing dual annotator video reviews, UPDRS scales, and patient self reports, alongside discrepancies between event based and window based analyses with flexible time margins. Second, limited sample sizes and dataset shifts degrade model efficacy under subject independent or real world home conditions. Lastly, trade offs persist between practical constraints and algorithmic performance, where multi node setups offer superior accuracy but impose greater wearability and power demands, whereas waist only configurations prioritize comfort at the expense of specificity. We suggest: Normalize labels (dual-rater video or UPDRS-mapped with explicit onset/offset/tolerance), results stratification based on validation regime and placement, and preference for rollout with sparse, place-optimized configurations (leg±waist), ¿24-h duration, on-device inference, and privacy-protecting sync; report user burden and adherence as well as accuracy.

5.1. Ground truth and metrics

Labeling based on videos and reporting which emphasizes accu- racy are prevalent, yet labeling guidelines as well as metric fineness differ, hindering comparative studies across. We recommend a mini- mum common set of measures (accuracy, F1, ROC-AUC, PR-AUC) as well as baseline labeling procedure to enhance comparability as well as reproducibility.

5.2. Shortcomings of this review

Our metaanalysis is limited by the heterogeneity evident in Results (different tasks, labels, measures, and constructs used for validation) as well as variation within the denominator within subsections (e.g., 29 ultimate included vs. a 40-study subset out- puttable device/metric cells). We did not conduct a meta-analysis because the outcomes were incompatible, as well as because the Englishlanguage, 2015-2025 time frame possibly excluding past research or research conducted outside the English language.

5.3. Prospective pathways

Regularize reporting (event/window, tolerance, parallel metric set, labelling workflow). Perform larger, subject-independently, home/community validations. Compare single- vs few-node placements on limb-based minimal placements for marginal benefit vs burden and expense. Investigate semi- /self-supervised and feder- ated learning to minimize label requirements and offset domain shift. Allow lightweight in-the-wild confirmations to facilitate scal- ing long-term studies. This analysis finds that IMU designs that draw guidance from placement, measured with common labels and measures in subject-agnostic situations, hold the greatest claim to the long-term tracking of FOG. It is essential that reporting and methodologies conform to these guidelines, while simultaneously working to minimize wear, optimize use, and privacy, so as to span the distance between optimally positive results in the lab and effective, sustainable care as practiced.

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