Exploring Parkinson's Disease Datasets: Key Findings, Challenges, and Recommendations for Motor Symptom Analysis

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***Abstract*— Parkinson's Disease (PD) is a progressive neurodegenerative disorder characterized by motor symptoms such as bradykinesia, tremor, or freezing of gait (FoG). Over the past decade, the rise of low-cost sensing technology has facilitated data collection, leading to the creation of datasets capturing motor symptoms and enabling advancements through machine (ML) and deep (DL) learning techniques for early diagnosis, precise symptom monitoring, and personalized treatment strategies in PD management. However, limited patient accessibility and dataset availability continue to pose challenges for widespread implementation and cross-dataset studies. This paper surveys the 17 (seventeen) most widely used PD motor symptom analysis datasets, examining their features, modalities, and data sources while addressing the variability challenges across datasets.**

***Index Terms*—Parkinson's Disease (PD), Motor Symptoms Recognition, PD Datasets, Machine Learning (ML), Deep Learning, Cross-Dataset Analysis, Sensors**

I. Introduction

Parkinson's Disease (PD) is a significantly debilitating neurodegenerative disorder that, in the past two decades, has seen a significant increase in both incidence and years of life affected by disability [1]. PD is characterized by a wide variety of motor symptoms, including tremors, bradykinesia, rigidity, gait disturbances, freezing of gait (FoG), and postural instability [2]. These motor manifestations are among the disease's most visible and impactful symptoms, playing a critical role in diagnosing, monitoring, and managing the disease. Studying such symptoms is crucial not only for early detection and personalized treatment but also for advancing the understanding of the underlying pathophysiology of the disease [3], [4].

An accurate assessment of motor symptoms enables clinicians to evaluate disease progression and optimize therapeutic interventions, ultimately improving patients' quality of life [4]. However, studying motor symptoms in PD presents several challenges. Traditional assessment methods, such as the Unified Parkinson's Disease Rating Scale (UPDRS), often rely on subjective evaluations, introducing variability in symptom interpretation [5]. Beyond these methodological limitations, several additional factors hinder progress in this field. The heterogeneous and fluctuating nature of motor symptoms, the limited availability of objective monitoring tools, restricted patient accessibility, and small, unbalanced datasets create significant obstacles [5]. Moreover, distinguishing PD symptoms from those of similar disorders adds another layer of complexity.

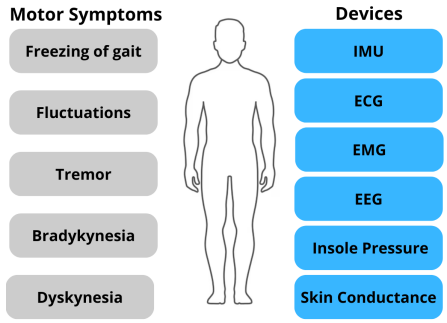

Fig. 1. Main motor symptoms of Parkinson's disease (left) and sensors used to detect and monitor these symptoms automatically.

Compounding these issues, the availability of public or private datasets is minimal and offers only a fragmented view of PD. Most datasets are collected in clinical settings, using varied sensor types, symptom focuses, and task protocols, making it difficult to generalize findings or develop comprehensive, robust recogniton models [5].

In recent years, the integration of machine (ML) and deep (DL) learning techniques with data from sensors and motion capture systems has shown promise in addressing these challenges (see Figure 1), enabling precise and scalable analysis to support diagnosis and disease progression tracking in PD [4], [6]. These technologies offer objective, real-time monitoring, reducing reliance on subjective clinical assessments and enabling continuous symptom tracking outside of clinical settings.

Building on these advancements, transfer learning (TL) has emerged as a powerful solution to overcome the data scarcity inherent in PD research. By leveraging preexisting datasets—including those from related neurological disorders

or movement analysis studies—TL enables models to learn generalizable patterns that can be fine-tuned for PD-specific tasks, improving robustness even with limited patient-specific data [7]. However, despite its potential, cross-dataset variability, domain adaptation, and dataset accessibility remain key challenges in ensuring the effective application of TL or other advanced techniques for PD symptom recognition.

Objective: Addressing these limitations is crucial for advancing the field and enhancing the effectiveness of technology-driven PD management. To this end, there is an urgent need to systematically analyze and consolidate knowledge from existing studies. A clear and structured aggregation of available datasets can help reduce the abovementioned limitations, mainly through multi- and cross-dataset analyses. While previous literature reviews have explored wearable technologies or ML/DL-based methods applied to PD [6], [8]–[10], no prior study has systematically reviewed existing datasets. Specifically, there is no comprehensive resource detailing dataset availability, the use of wearable technologies and their setup, and the demographic and clinical characteristics of the included participants. To determine whether prior surveys/systematic reviews exist on such topics, we conducted a systematic search using Scopus. The search query was designed to retrieve review papers focusing on datasets for motor symptom analysis in PD. The query used (Table I) resulted in 31 articles. However, upon manual inspection, none of these articles specifically focus on surveying datasets used for motor symptom analysis in PD.

Contribution: Complementing prior works, this article provides an overview of principal datasets—both publicly available and restricted-access—that focus on wearables-based PD motor symptom analyses. To assist researchers in dataset selection and integration, we categorize these datasets based on: (i) availability (open-source vs. non-open-source), (ii) focus on FoG vs. PD motor symptoms in general, (iii) wearable sensing technology, and (iv) on-body sensor placement and setup. Following this strategy, we identified nine publicly available datasets shown in Figure 2 and eight non-public shown in Figure 3) wearables-based datasets for PD motor systems analyses, providing information perceived by diverse types of sensors such as accelerometer (ACC), gyroscope (GYRO), electroencephalography (EEG), electromyography (EMG), skin conductance (SC), smart insoles (INSOLE), and electrocardiography (ECG). By structuring this information, we aim to facilitate dataset accessibility and cross-dataset analytics, as well as future improvement of the understanding of PD motor symptoms. Additionally, we provide detailed insights into the clinical parameters and demographic characteristics of the involved PwPD (People with Parkinson's Disease). This guidance supports the development of more effective and personalized studies, simplifying the process of addressing key research questions, such as:

To design a recognition model for a specific motor symptom, which combination of datasets would best fit my goal, considering the subject's clinical/demographic requirements and the devices' type, position, and setup?

Paper Organization: Section III explores the primary datasets, categorizing them based on their focus and availability while also detailing their key characteristics and clinical

TABLE I
SCOPUS RESEARCH QUERY.

"Parkinson's Disease" OR "PD"	AND
"motor symptoms" OR "bradykinesia" OR "tremor" OR "freezing of gait"	AND
"machine learning" OR "deep learning" OR "artificial intelligence"	AND
"dataset" OR "datasets" OR "data sources"	AND
"survey" OR "review" OR "systematic review" OR "overview"	

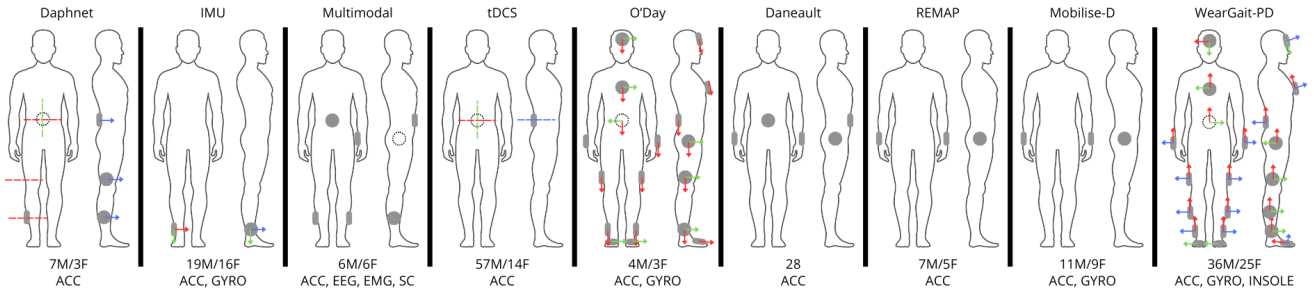

Fig. 2. Sensor type, position, orientation in publicly available PD datasets. (→ (red) for the x-axis, → (green) for the y-axis, and → (blue) for the z-axis).

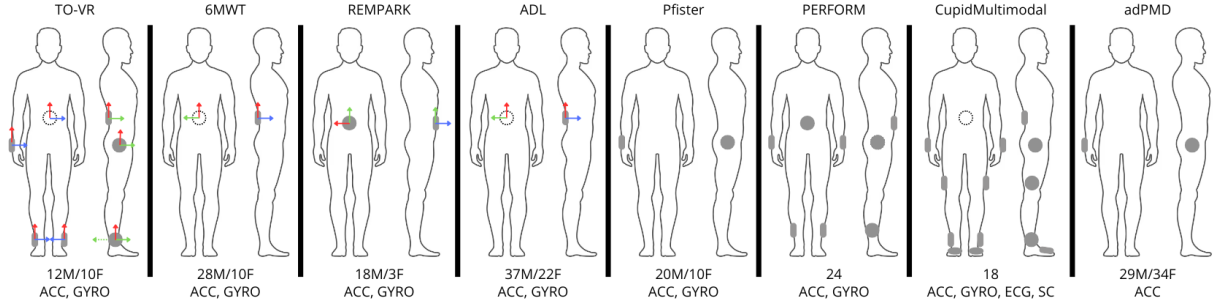

Fig. 3. Sensor type, position, and orientation in non-public PD datasets. (→ (red) for the x-axis, → (green) for the y-axis, and → (blue) for the z-axis).

relevance. Section IV examines the strengths and limitations of these datasets, offering recommendations and outlining future research directions. Finally, Section V summarizes the key findings and conclusions drawn from this study.

II. Overview of Sensing Technologies

This section provides a detailed overview of various sensing technologies and their relevance to monitoring and recognizing motor symptoms in PD.

- **Inertial Measurement Units (IMUs):** IMUs are widely used in PD to measure motion-related parameters such as acceleration, angular velocity, and orientation. By attaching IMUs to specific body locations (e.g., wrist, ankle, or chest), researchers can detect motor symptoms such as tremors, bradykinesia, and gait abnormalities. *Commercial Examples:* Shimmer3 IMU, XSens MTw Awinda, Noraxon Ultium Motion, and Bosch BNO055. Some commercial solutions comprise hardware and software (e.g., APDM Opal, Physiolog GaitUp, and PD-specific wearable systems – Sense4Care STAT-ON, Kinesia 360, Personal Kinetigraph, PD Monitor.
- **Electrocardiography (ECG):** ECG sensors measure the electrical activity of the heart, offering insights into cardiovascular changes that can correlate with non-motor symptoms of PD, such as autonomic dysfunction. *Commercial Examples:* BioHarness 3, AliveCor KardiaMobile, Zephyr BioPatch, and Polar H10.
- **Electromyography (EMG):** EMG sensors monitor muscle activity, making them valuable for analyzing muscle stiffness, rigidity, and other motor impairments in PwPD. *Commercial Examples:* Delsys Trigno, Myon 320, Noraxon Ultium EMG, and Biometrics Ltd DataLOG.
- **Electroencephalography (EEG):** EEG sensors capture brain activity and can provide data related to neurological changes in PD, helping researchers understand how the disease impacts motor control at a neural level. *Commercial Examples:* OpenBCI Ultracortex, Muse 2, Emotiv Epoc+, and Brain Products LiveAmp.
- **Insole Pressure Sensors:** These sensors measure foot pressure distribution and gait patterns, which are critical for assessing gait disturbances and balance issues commonly observed in PD. *Commercial Examples:* Tekscan F-Scan, Moticon ReGo, Loadsol, and XSENSOR insoles.
- **Skin Conductance Sensors:** Skin conductance sensors measure changes in the electrical properties of the skin, which can reflect autonomic nervous system activity. These are useful for monitoring stress, arousal, and non-motor symptoms in PwPD. *Commercial Examples:* Empatica E4, Shimmer3 GSR+, and BITalino EDA.

A large variety of sensors has been used to monitor movement and physiological parameters in PwPD. Inertial Measurement Units (IMUs) represent the most widely used technology in PD, due to their capability of accurately measure motion-related parameters such as acceleration, angular velocity, and orientation. Motor symptoms such as tremor, bradykinesia, and gait abnormalities can be tracked by attaching IMUs to specific body locations (e.g., wrist, ankle, or chest) [9]. Electrocardiography (ECG) measures the electrical activity of the heart, offering insights into cardiovascular changes that can correlate with non-motor symptoms of PD, such as autonomic dysfunction. Electromyography (EMG) monitor muscle activity, essential for analyzing muscle stiffness, rigidity, and other motor impairments in PwPD. Electroencephalography (EEG) captures brain activity and can provide data related to neurological changes in PD, helping researchers understand how the disease impacts motor control at a neural level. Insole Pressure Sensors measure foot pressure distribution and gait patterns, which are critical for assessing gait disturbances and balance issues commonly observed in PwPD. Skin conductance sensors measure changes in the electrical properties of the skin, which can reflect autonomic nervous system activity. These are useful for monitoring stress, arousal, and non-motor symptoms in PwPD.

Each of these sensing technologies plays a unique role in providing a comprehensive understanding of PD motor symptoms, enabling researchers and clinicians to tailor interventions and improve patient outcomes. In the next section, we introduce the main datasets that utilize these technologies to monitor PwPD.

III. Exploration of Datasets for PD Research

This section provides an overview of the most well-known wearable-based datasets for PD research. Section III-A presents the datasets in terms of the used sensor type, their position on the body, and their orientation. Section III-B details the datasets in terms of specific symptoms under investigation, comparing studies focusing on FoG or PD motor symptoms in general. Finally, Section III-C reports participants' demographic and clinical information.

A. Sensors Type and on Body Position

Figures 2 and 3 illustrate the dataset name, sensor type, placements, orientation, and dimension in terms of involved PwPD for the publicly available and non-publicly available datasets, respectively. As clearly shown, the accelerometer is the most commonly used sensor type (100% of cases), followed by the gyroscope (65% of cases). Skin conductance sensors were used in two datasets, in combination with EEG, EMG, or ECG sensors. Finally, one dataset included smart pressure insoles.

Overall, most datasets (82%) exclusively provided motion signals through inertial sensors. At the same time, multimodal physical/physiological data were exploited in three datasets (i.e., Multimodal [11], WearGait-PD [12], Cupid Multimodal [13]), all focused on FoG. While sensor positioning is described in all studies, the information on sensor orientation is totally (47% cases) or partially (11% cases) missing.

Moreover, Figure 4 illustrates the distribution of sensor positions across datasets. The wrist and lower back are the most common locations, reflecting their clinical relevance for monitoring tremors, bradykinesia, and postural stability. The preference for wrist-mounted sensors aligns with their usability and convenience [14], while lower-back sensors effectively capture gait dynamics and fall [15].

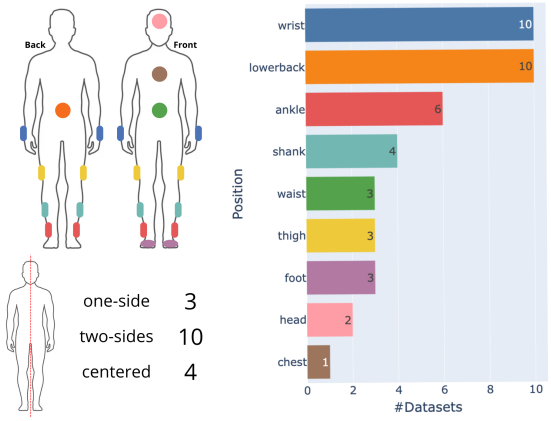

Fig. 4. Distribution of sensor placements across datasets.

As shown, there is an under-representation of head-mounted sensors, which could provide valuable insights into head tremors and balance-related symptoms. Additionally, sensors on the chest and thigh are less frequently used despite their potential for monitoring vital signs (e.g., heart rate, respiration) and leg movements, respectively.

Finally, analyzing Figure 4 in terms of body side (i.e., center, two sides, and one side), we notice that 3 datasets use one-sided placement, which may cause asymmetrical data and lower accuracy for bilateral symptoms. Two-sided placements (in 10 datasets) are more common, ensuring balance and symmetry but less practical for real-world use. Central placements (in 4 datasets) provide robust gait and posture data but miss PD lateral asymmetries and limb-specific movements.

B. Target Symptoms

The introduced PD datasets can mainly be divided into two main categories: (i) studies dedicated explicitly to FoG (Table II) and (ii) studies that encompass a broader range of motor symptoms, including but not limited to FoG (Table III). This distinction is vital, as FoG-targeted datasets often involve specific tasks and sensor placements tailored to capture this particular phenomenon. In contrast, broader datasets aim to provide insights into an extended set of motor impairments such as tremors, bradykinesia, dyskinesia, and FoG.

Table II provides key insights into the frequency, duration, and characteristics of FoG events across different datasets. A high degree of variability is evident, particularly in the number of FoG events recorded, their duration, and duration statistical properties (min, max, mean, and standard deviation). A critical aspect of this variability is the inclusion of medication status (ON/OFF phases), activity labels, and standardized PD tests. For instance, some datasets offer detailed contextual information, including medication status and activity labels (e.g., CupidMultimodal [13]), which can enhance FoG analysis by linking events to real-world conditions. In contrast, others, such as PERFORM-Long [16], primarily provide raw data without additional annotations. This variability underscores the importance of careful dataset selection when designing cross-dataset studies or developing machine-learning models for FoG analysis.

Table III provides an overview of datasets that aim to capture a wide range of motor impairments, offering a broader perspective on PD symptomatology. However, a key limitation is the lack of detailed symptom annotations, which can restrict their applicability for symptom-specific analyses. Additionally, medication status (ON/OFF phases) and daily activity labels (ADLs) are inconsistently reported across datasets. This inconsistency can impact the generalizability of findings, as medication fluctuations and activity contexts play a crucial role in PD symptom expression. Furthermore, while some datasets include clinical assessments, others provide only raw sensor data without clinical correlations. Given these variations, researchers must carefully evaluate dataset suitability based on symptom annotations, medication tracking, activity labeling, and clinical assessments to ensure meaningful insights into PD motor symptom progression and its impact on daily life.

C. Demographic and Clinical Information

Tables IV and V present participants' demographic and clinical characteristics in datasets specifically focused on FoG and general PD motor symptoms, respectively.

As shown, sample sizes vary significantly, ranging from 7 participants (in [14]) to 71 participants (in [22]). Only three datasets include more than 50 subjects ([12], [22], [26]), emphasizing a key limitation: small sample sizes restrict the generalizability of findings due to the high inter- and intra-subject variability in PD symptom expression and movement patterns.

Demographic data indicate that most datasets involve middle-aged to elderly participants (mean age: 60–70 years), aligning with the typical onset and progression of PD. Gender distribution varies considerably, with some datasets under-representing female participants. While this often reflects the higher prevalence of PD in males, it also introduces bias that can limit the applicability of research findings. Additionally, the years since diagnosis (YoD) vary widely across datasets, reflecting the heterogeneity in disease progression among participants.

The recorded tasks range from basic walking exercises to dual-task challenges and simulated daily activities. FoG-focused datasets (Table IV) primarily include gait-related tasks, such as: (i) supervised walking (e.g., straight-line, zigzag, random walking), (ii) turning movements (e.g., figure-eight, 180° and 360° turns), and (iii) dual-task conditions involving cognitive (e.g., counting backward) or motor (e.g., navigating obstacles, passing through doorways, carrying a full glass of water) challenges. Simulated ADLs remain

TABLE II
SUMMARY OF DATASETS FOCUSING ON FOG.

Dataset	# Patients (M/F)	Dataset Duration (FoG seconds)	# FoG Events	FoG Stats [Min, Max, Mean, Std]	Medication Status	Activity Labels	PD Tests
Daphnet [17]	10 (7/3)	30000	273	[0.5, 40.5, 7.3, 6.7]	on-off	no	n/a
IMU [18]	35 (19/16)	n/a (1611)	n/a	n/a	on	no	UPDRS, NFOG-Q, MMSE MOCA, FAB, HADS
Multimodal [11]	12 (6/6)	13320 (5280)	334	[1, 201, 8.2, n/a]	off	no	UPDRS, FOG-Q, MMSE, MOCA
CupidMultimodal [13]	18 (n/a)	n/a	184	[0.12, 98.88, 8.84, 14.87]	on	yes	UPDRS, FOG-Q
REMPARK [19]	21 (18/3)	n/a (5580)	1321	[3.2, 38, 5.4, n/a]	on-off	no	UPDRS, FOG-Q, MMSE
6MWT [20]	38 (28/10)	13140 (240)	33	[0, 21, n/a, n/a]	on	yes	UPDRS
TO-VR [21]	22 (12/10)	6474 (1074)	101	[0.6, 108, 9.2, 16.9]	off	yes	UPDRS, H&Y, FOG-Q MOCA, FES-I, PDQ-8
tDCS [22]	71 (57/14)	55140 (17100)	100	[0.18, 687.62, 15.12, 51.90]	on-off	no	UPDRS, NFOG-Q
Oday [14]	7 (4/3)	5328 (1272)	211	[n/a, n/a, 7.8, n/a]	off	no	n/a
PERFORM-Short [16]	24 (n/a)	29500	824	[n/a, n/a, n/a, n/a]	on-off	no	UPDRS
PERFORM-Long [16]	24 (n/a)	1587994	13042	[n/a, n/a, n/a, n/a]	on-off	no	UPDRS
wear-GaitPD [12]	61 (36/25)	n/a	41	[n/a, n/a, n/a, n/a]	on-off	yes	UPDRS

NFOG-Q: New Freezing of Gait Questionnaire; MMSE: Mini-Mental State Exam; MOCA: Montreal Cognitive Assessment; FAB: Frontal Assessment Battery; HADS: Hospital Anxiety and Depression Scale; H&Y: Hoehn and Yahr; FES-I: Fall Efficacy Scale-International; PDQ-8: 8-item Parkinson's Disease Questionnaire.

TABLE III
OVERVIEW OF DATASETS RELATED TO MOTOR SYMPTOMS IN PD THAT DO NOT SPECIFICALLY TARGET FOG.

Dataset	Motor Symptoms	Dataset Duration	Symptoms Duration	# Symptom Events	Medication Status	Activity Labels	PD Tests
Daneault [23]	tremor, brady, dys	n/a	n/a	n/a	on-off	yes	UPDRS
REMAP [24]	n/a	n/a	n/a	n/a	on-off	yes	UPDRS, PIGD, NMSS, PDSS, PDQ, TUG, RSBDQ
HRMS* [25]	dys, brady	519660	n/a	n/a	on-off	no	UPDRS, MOCA
ADL [26]	n/a	n/a	n/a	n/a	on	yes	UPDRS
PERFORM-Short [16]	tremor, brady, LID, FoG	119518	n/a	n/a	on-off	no	UPDRS
PERFORM-Long [16]	tremor, brady, LID, FoG	6404861	n/a	n/a	on-off	no	UPDRS
adPMD [27]	n/a	43200	n/a	n/a	on-off	yes	UPDRS
Mobilise-D [28]	n/a	n/a	n/a	n/a	on-off	no	UPDRS

dys: dyskinesia; brady: bradykinesia; LID: Levodopa-induced dyskinesia ; UPDRS: Unified Parkinson's Disease Rating Scale; PIGD: Postural instability and gait disorders; NMSS: Non-Motor Symptoms Scale; PDSS: Parkinson's Sleep Scale; PDQ: Parkinson's Disease Questionnaire; TUG: Timed Up-and-Go; RSBDQ: REM Sleep Behaviour Disorder Questionnaire; MOCA: Montreal Cognitive Assessment

underrepresented in these datasets despite their relevance for real-world applications. In contrast, datasets focusing on other PD motor symptoms (Table V) include a broader range of activities, such as standing, postural transitions, and balance tasks. Notably, some datasets also capture data during supervised or unsupervised free-living activities, improving ecological validity.

Finally, among the 17 surveyed datasets, only REMPARK [19] and REMAP [24] datasets concern home-collected data, Cupid [13] and PERFORM [16] dataset both concern home and clinical environment and all the other dataset concern only clinical collected data.

IV. DISCUSSION

This study highlights the diversity and challenges in datasets that monitor PD motor symptoms through different wearable sensing technologies. While progress has been made in data collection and analysis, several key issues remain.

Sensor placements, particularly on the lower back, are widely used due to their stability and ability to capture gait and posture data with minimal artifacts [29], [30]. However, reliance on specific placements can limit generalizability across datasets with different sensor configurations [4]. Similarly, asymmetry in PD symptoms—where one side is more affected—poses challenges when datasets only include unilateral sensor placements, restricting the ability to assess bilateral disease progression and provide deeper insights into PD dynamics [31]. Another challenge is sensor orientation inconsistencies across datasets, which make data integration and reuse difficult. Combining datasets without standardized sensor alignment and orientation documentation increases the risk of errors and unreliable models, especially when scaling AI solutions across different experimental setups.

Further reinforcing these challenges, Tables III, IV, and V reveal gaps in dataset documentation, with missing details on symptom characteristics, medication status, activity labels, and clinical assessments. These inconsistencies hinder dataset comparability, limit generalizability, and affect the development of reliable ML models. Standardized reporting of demographic, clinical, and symptom-related data improves

TABLE IV
DEMOGRAPHIC AND CLINICAL INFORMATION FOR DATASETS FOCUSING ON FOG.

Dataset	# Patients (M/F)	Age	YoD	MoCA	MMSE	UPDRS	FoG-Q	H&Y	Tasks Performed
Daphnet [17]	10 (7/3)	66.5±4.8	13.7±9.67	n/a	n/a	n/a	n/a	2.6±0.65	1. Straight-line walking 2. Walking with pauses 3. Turning 4. Gait freezing events 5. Short resting intervals
IMU [18]	35 (19/16)	62.5±10.59	8.23±3.99	n/a	n/a	2: 8.54±3.78 3: 31.83±14.99	17.72±5.63	2.91±0.5	1. Walking 2. 360-degree turns 3. Resting periods 4. Straight-line and zigzag walking 5. Obstacle avoidance
Multimodal [11]	12 (6/6)	69.1±7.9	9.3±6.8	23.6±3.6	28.2±1.5	1: 10.4 ± 5.5 2: 16.3 ± 10.6 3: 45.0 ± 16.0 4: 2.2 ± 2.9	16.2±4.2	n/a	1. Walking with sensors 2. Performing figure eights 3. Walking at variable speeds 4. Ascending and descending stairs
Cupid Multimodal [13]	18 (n/a)	68.9±10.2	8.8±4.6	n/a	n/a	3: 41.7 ± 10.2	19.7 ± 7.1	2 to 4	1. Walking tasks 2. Obstacle avoidance 3. Dual-task activities 4. Gait freezing simulation
REMPARK [19]	21 (18/3)	69.29±9.72	10.3±3.96	n/a	27.75±1.87	3: 36.3± 14.02 (OFF) 3: 16.15± 9.4 (ON)	15.8±4.11	3.07±0.43	1. Simulated ADLs 2. Free-living activities 3. Walking during medication ON/OFF states 4. Task-specific monitoring
6MWT [20]	38 (28/10)	70±5.1	12±6	n/a	27±2	n/a	n/a	3	1. Six-minute walking test 2. Timed distance walking 3. Recording heart rate and stride length
TO-VR [21]	22 (12/10)	65±4	10±4.2	n/a	n/a	n/a	n/a	2.5	1. Virtual reality walking 2. Interactive gait tasks 3. Cognitive task challenges during walking
tDCS [22]	71 (57/14)	63±3.5	8±3.8	24±2.5	28±1	3: n/a	18±6	2.7	1. Walking 2. Dual-task cognitive challenges 3. Continuous walking for fatigue assessment
Oday [14]	7 (4/3)	68±6	14±7.1	23±3	27±2	n/a	n/a	3.1	1. Gait analysis 2. Walking during ADLs 3. Step count and stride analysis 4. Motion symmetry testing
PERFORM [16]	24 (n/a)	69±7	15±8	22±4	26±3	n/a	n/a	2.9	1. Simulated daily living tasks 2. Turning 3. Step-to-step coordination 4. Gait rhythm analysis
wearGait [12]	61 (36/25)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	1. Motion analysis 2. Walking across flat surfaces 3. Walking in a crowded environment 4. Navigating narrow spaces

YoD: Years of Diagnosis; MoCA: Montreal Cognitive Assessment; MMSE: Mini-Mental State Examination; H&Y: Hoehn & Yahr Scale

TABLE V
DEMOGRAPHIC AND CLINICAL INFORMATION FOR DATASETS FOCUSED ON MOTOR SYMPTOMS IN GENERAL.

Dataset	# Patients (M/F)	Age	YoD	MoCA	MMSE	UPDRS	FoG-Q	H&Y	Tasks Performed
Daneault [23]	28 (n/a)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	1. Standing 2. Straight-line walking 3. Balance tasks 4. Sitting-to-standing transitions 5. Gait monitoring during rest
REMAP [24]	12 (7/5)	61.25±8.5	8.2±6.5	n/a	n/a	n/a	n/a	2.3±0.8	1. Free-living monitoring 2. Walking tasks 3. Resting periods 4. Step length and speed measurement
HRMS* [25]	30 (20/10)	67.1±10.2	11.0±5.1	25.7±2.8	n/a	3 (ON): 21.6±15.3	n/a	n/a	1. Free-living monitoring 2. Short walking bouts 3. Resting 4. Monitoring walking patterns during transitions 5. Gait analysis using wearable sensors
ADL [26]	59 (37/22)	69.2±10.2	6.7±5.3	n/a	n/a	n/a	n/a	2.14±0.8	1. ADL simulation 2. Gait and balance analysis 3. Postural control tests 4. Navigating everyday obstacles 5. Sit-to-stand movements
PERFORM [16]	12 (n/a)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	1. Extended free-living monitoring 2. Detailed walking analysis 3. Step frequency tracking 4. Task-related movement assessments 5. Long-term variability studies
adPMD [27]	15 (10/5)	64±4.5	9±4	26±3	29±1	n/a	n/a	2.8	1. Free-living monitoring 2. Sensor-based gait analysis 3. Step length and symmetry evaluation 4. Walking under variable conditions 5. Short bursts of high-intensity walking
Mobilise-D [28]	n/a (n/a)	n/a	n/a	n/a	n/a	n/a	n/a	n/a	1. Gait analysis in daily life 2. Walking with variable surfaces 3. Step consistency monitoring 4. Transitioning between walking speeds 5. Adaptive gait tasks

YoD: Years of Diagnosis; MoCA: Montreal Cognitive Assessment; MMSE: Mini-Mental State Examination; H&Y: Hoehn & Yahr Scale

research reproducibility and enhances PD symptom analysis. Additionally, PD progression heterogeneity complicates dataset standardization. Many datasets lack information on disease stage and duration, making representing the entire PD spectrum challenging. A more stratified approach, including patients at different stages, is needed to ensure balanced datasets without introducing bias.

Towards addressing these limitations, Table VI provides actionable recommendations for dataset selection, sensor configurations, and AI techniques. However, the standardization of experimental protocols remains an open challenge. We encourage scientific bodies to establish guidelines, building on the Movement Disorder Society Task Force roadmap [32], to ensure consistent and reliable digital measures from wearable technologies.

V. CONCLUSIONS

This paper presents the first overview of primary datasets available for PD motor symptom research, categorizing them based on their focus on FoG or other motor symptoms. It highlights key challenges related to sensor placement, asymmetry, patient selection, and data integration, which must be addressed to enhance the generalizability and applicability of research findings.

By providing a structured analysis of existing datasets, this study serves as a practical guide for researchers in selecting the most appropriate datasets and configurations for their studies. This effort is intended to facilitate the development

of advanced ML/DL models, clinical applications, and real-world monitoring solutions for PD symptom assessment.

Future research should focus on overcoming these limitations by establishing unified benchmarks, adopting standardized methodologies, and promoting collaborative approaches. Developing interoperable datasets and aligning experimental protocols will be essential to drive innovation in PD monitoring and management, ultimately leading to improved patient care and quality of life.

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TABLE VI
KEY FINDINGS, RECOMMENDATIONS, AND FUTURE DIRECTIONS.

Finding	Recommendations and Future Directions
Data Accessibility and Standardization	
Limited accessibility to high-quality datasets hinders reproducibility and external validation.	Establish open repositories for PD datasets and encourage public sharing while ensuring compliance with ethical guidelines (e.g., GDPR).
Variability in data collection protocols, sensor types, and task designs complicates cross-dataset learning.	Develop standardized protocols for sensor placements, orientation, and task designs to improve comparability across datasets.
Datasets lack open-source availability, reducing reproducibility.	Prefer open-source or publicly available datasets to foster collaboration and reproducibility in the research community.
Dataset Size, Diversity, and Integration	
Small sample sizes limit the generalizability of findings to the broader PD population.	Select datasets with large sample sizes to ensure statistical power and robustness. Prioritize datasets with diverse demographics (e.g., age, gender, ethnicity) and clinical characteristics (e.g., disease severity, comorbidities).
Focus is often on moderate stages of PD, neglecting early-stage data critical for early diagnosis.	Focus on datasets where disease duration is minimal to improve early-stage PD detection and diagnosis.
Heterogeneity in datasets for disease severity classification is limited.	Promote datasets with variability in clinical information and disease duration to capture the spectrum of disease progression.
Limited dataset integration affects model robustness.	Combine multiple datasets, when feasible, to enhance model robustness and enable cross-dataset generalization.
Task and Activity Variety	
Focus on controlled tasks over real-world, free-living activities reduces ecological validity.	Opt for datasets that include a wide range of activities or tasks, especially those reflecting free-living or naturalistic settings to better represent real-world behavior.
Simulated activities of daily living (ADLs) are underrepresented.	Include tasks representative of ADLs in datasets to improve the ecological validity of models.
Validation and Testing	
Lack of rigorous validation protocols affects model generalizability.	Employ rigorous validation schemes (e.g., leave-one-subject-out cross-validation) and validate algorithms on independent datasets to ensure robustness across populations and sensor setups.
Sensor Placement and Configuration	
Dominance of wrist and lower-back sensor placements, with limited use of head-mounted or chest-mounted sensors.	Diversify sensor placements to include head-mounted sensors for head tremors and chest-mounted sensors for vital sign monitoring.
One-sided sensor placements may lead to asymmetrical data collection, reducing accuracy for detecting bilateral symptoms.	Opt for two-sided or central placements to improve balance and enhance detection of lateralized symptoms.
Differences in sensor settings (e.g., orientation, sampling rates) affect performance.	Address differences in sensor settings across datasets to enable cross-dataset generalization and performance in heterogeneous environments.
Contextual and Longitudinal Data	
Datasets often lack contextual metadata to interpret sensor readings.	Select datasets that include contextual metadata (e.g., activity logs) to improve model interpretability.
Limited availability of longitudinal datasets for disease progression monitoring.	Use datasets that include longitudinal data to capture disease progression and enable long-term outcome predictions.
AI and Computational Techniques	
Limited use of advanced AI techniques for symptom detection and dataset integration.	Employ multimodal AI, transfer learning, and federated learning to enhance symptom detection and integrate datasets efficiently.
Lack of real-time applicability in current models due to hardware limitations.	Develop AI models optimized for resource-constrained edge devices to enable real-time symptom monitoring.
Clinical Relevance	
Datasets often lack clinical validation and fail to capture heterogeneous patient demographics.	Collaborate with clinicians during dataset design and ensure inclusion of diverse demographics to improve clinical relevance.
Focus on motor symptoms over non-motor symptoms limits comprehensive PD management strategies.	Align dataset development with clinical priorities by incorporating both motor and non-motor symptoms into data collection protocols.

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