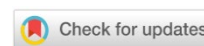


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Wearable Digital Devices as a Tool for Objective Assessment of Motor Disorders in Parkinson's Disease: A Review of Current Studies

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Abstract

Introduction. Parkinson's disease (PD) requires objective and continuous monitoring of motor symptoms. Wearable sensors are a promising tool for improving diagnostic accuracy and monitoring disease dynamics. However, they are underutilized in clinical practice due to the lack of uniform standards and limited data reproducibility. The presented study fills this gap. The objectives of the research are to analyze current approaches to the use of wearable systems for monitoring motor symptoms of PD, identify limitations (including those related to validation standards), and determine ways to overcome them for the efficient use of sensors in clinical practice.

Materials and Methods. Using the Prisma 2020 methodology, a literature search was conducted for the years 2020–2025 in PubMed, Scopus, Web of Science, and Elibrary.ru. Peer-reviewed studies on the development, validation, and application of wearable devices for assessing gait, tremor, bradykinesia, and dyskinesia were examined. Nine key terms in digital medicine and neurodiagnostics in Russian and English were used for the search: “Parkinson's disease”, “digital biomarkers”, “wearable devices”, and others. The final sample of 48 studies was dominated by meta-analytics (31%) and clinical studies (29%). Nineteen percent of the sources discussed the development of monitoring systems, 15% were longitudinal studies, and 6% were systematic reviews.

Results. Descriptions of nine wearable devices for monitoring motor performance in patients with PD were compared. The types of metrics, clinical scenarios, and tasks were considered. Two concepts of the devices under study were outlined:

- minimalism (one sensor, high comfort level, focus on integral indices);
- real-time detection (emphasis on episodes and instant recognition).

These two cases required different labeling standards, analysis windows, and clinical significance criteria. To improve the comparability of results, a “minimum validation set” specific to the class of problems was needed. Conditions for overcoming these contradictions were:

- unification of data collection protocols, metric sets, and indicators;
- external and multicenter validation (labeling, accuracy criteria);
- algorithm stability to device changes;
- clinical utility criteria.

Discussion. The widespread use of wearable devices for analyzing motor symptoms in patients with PD is hampered by a lack of analytical and clinical validation standards and economic ambiguity of implementation. In general, five of the devices reviewed show promise. However, clinical data on their efficiency and impact on quality of life are insufficient, as research is primarily focused on the potential of the concepts (accuracy of the algorithms) rather than the practical value and readiness for everyday use of real devices. There is little research on external (multicenter) transferability, unified endpoints, and clinical utility.

Conclusion. Current data on the capabilities and limitations of wearable sensors for Parkinson's disease has been systematized. Widespread adoption of such devices is impossible without standardization and unified criteria for efficiency, safety, and economic viability. Addressing these identified challenges will transform approaches to diagnosis and treatment, making wearable systems a key tool in personalized medicine.

Keywords: Parkinson's disease, wearable sensors, inertial measurement units (IMU), digital biomarkers, motor symptom monitoring, clinical validation, personalized medicine

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Обзор предметного поля

Цифровые носимые устройства как инструмент объективной оценки моторных нарушений при болезни Паркинсона: обзор современных исследований

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Аннотация

Введение. Болезнь Паркинсона (БП) требует объективного и непрерывного мониторинга моторных симптомов. Носимые сенсоры — перспективный инструмент для повышения точности диагностики и контроля динамики заболевания. Его недостаточно задействуют в клинической практике из-за отсутствия единых стандартов и ограниченной воспроизводимости данных. Представленное исследование заполняет этот пробел. Цели научной работы: анализ современных подходов к использованию носимых систем для мониторинга моторных симптомов БП, выявление ограничений (в том числе по стандартам валидации), определение пути их преодоления для эффективного применения сенсоров в клинической практике.

Материалы и методы. По методологии Prisma 2020 выполнен поиск литературы за 2020–2025 годы в базах данных PubMed, Scopus, Web of Science и Elibrary.ru. Изучались рецензируемые исследования по разработке, валидации и применению носимых устройств для оценки походки, тремора, брадикинезии и дискинезии. Для поиска использовались девять ключевых терминов цифровой медицины и нейродиагностики на русском и английском языках: «болезнь Паркинсона», «цифровые биомаркеры», «носимые устройства» и др. В финальной выборке из 48 исследований основное место заняли метааналитические (31 %) и клинические (29 %). В 19 % источников речь шла о разработках систем мониторинга, 15 % — лонгитюдные исследования, 6 % — систематические обзоры.

Результаты исследования. Сопоставляются описания девяти носимых устройств для отслеживания особенностей моторики пациентов с БП. Учитываются типы метрик, клинических сценариев и задач. Обозначены две концепции исследуемых гаджетов:

- минимализм (один датчик, высокий уровень комфорта, фокус на интегральных индексах);
- детекция в реальном времени (акцент на эпизодах и моментальном распознавании).

В двух этих случаях нужны разные эталоны разметки, окна анализа и критерии клинической значимости. Для повышения сопоставимости результатов необходим «минимальный набор валидации», специфический для класса задач. Условия преодоления противоречий:

- унификация протоколов сбора данных, набора метрик, индикации;
- внешняя и межцентровая валидация (разметка, критерии точности);
- устойчивость алгоритмов к смене устройства;
- критерии клинической полезности.

Обсуждение. Массовому использованию носимых устройств для анализа моторных симптомов пациентов с БП препятствуют недостаток стандартов аналитической, клинической валидации и экономическая неоднозначность внедрения. В целом перспективны пять рассмотренных устройств. Однако клинические данные об их эффективности и влиянии на качество жизни недостаточны, т. к. исследуется главным образом потенциал концепций (точность алгоритмов), а не прикладная ценность и готовность к повседневному использованию реальных устройств. Редко изучается внешний (межцентровый) перенос, единые конечные точки и клиническая полезность.

Заключение. Систематизированы современные данные о возможностях и ограничениях носимых сенсоров при болезни Паркинсона. Широкое распространение таких гаджетов невозможно без стандартизации, единых критериев эффективности, безопасности и экономической целесообразности. Решение выявленных проблем позволит изменить подход к диагностике и лечению, сделать носимые системы ключевым инструментом персонализированной медицины.

Ключевые слова: болезнь Паркинсона, носимые сенсоры, инерциальные измерительные устройства, цифровые биомаркеры, мониторинг двигательных симптомов, клиническая валидация, персонализированная медицина

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Для цитирования. Щеглов Б.О., Яковенко А.А., Артеменко А.Ф., Ледков Е.А., Биктимиров А.Р. Цифровые носимые устройства как инструмент объективной оценки моторных нарушений при болезни Паркинсона: обзор современных исследований. *Advanced Engineering Research (Rostov-on-Don)*. 2026;26(1):2257. <https://doi.org/10.23947/2687-1653-2026-26-1-2257>

Introduction. Parkinson's disease (PD) is a neurodegenerative disorder with a wide range of motor and non-motor manifestations. The principle motor symptoms include resting tremor, bradykinesia, and postural instability. Non-motor manifestations primarily include autonomic dysfunction, as well as behavioral and cognitive deficits [1]. Parkinson's disease is one of the most common neurodegenerative pathologies. The progressive loss of the patient's independence and the need for long-term medical monitoring and care reduce the quality of life for the patients and their families, placing additional strain on the healthcare system. At the late stages of the disease, levodopa treatment is often accompanied by the development of motor complications. One of these is the so-called “wearing-off phenomenon”, in which the duration of the drug therapeutic effect gradually decreases. In this work, we will refer to this as the off-effect. Delayed and random “on — off” fluctuations are also known. These are characterized by unpredictable changes in motor activity, regardless of the time of drug administration [2].

Motor fluctuations and dyskinesias significantly impair quality of life, increase the risk of falls, and complicate patient management. They require timely and often individualized treatment adjustment, which further complicates the situation. Traditional methods for assessing PD symptoms rely primarily on subjective clinical observations, patient diaries, and questionnaires. The known weaknesses of such approaches include:

- potential for systematic errors;
- individual variability;
- overreliance on observer's qualification [3].

Moreover, such methods typically reflect the patient's condition only during interactions with doctors or short tests. This is insufficient to reliably detect short-term off/on episodes. Consequently, the possibility of timely treatment adjustments and personalized management is limited.

The development of flexible electronics and artificial intelligence technologies opens up new prospects for healthcare, including the creation of wearable monitoring systems, brain-computer-interface solutions, and integration with the Internet of Things [4]. Flexible wearable medical electronic devices are capable of recording blood pressure, respiratory rate, body temperature [5], electrophysiological activity. This supports prolonged recording of key parameters [6], provides continuous collection of data on the state of the body, and opens up the possibility of improving the quality of personalized medical decisions [7].

In the context of PD, continuous recording of motor patterns in natural settings helps bridge the gap between actual symptom dynamics and their episodic clinical assessment. Clinicians gain continuous access to the data, specifically, to track daily variability and episodes of motor fluctuations.

Wearable devices have transformed approaches to monitoring and treating Parkinson's disease [8]. Objective, continuous remote monitoring of motor symptom dynamics has become possible [9]. Compact and lightweight wearable devices are attached to the patient's body and record physiological parameters: movement, tremor, gait, balance, as well as cognitive and behavioral characteristics, including sleep disturbances [10]. Sensor technologies are used to record and transmit data: accelerometers, gyroscopes [11], magnetometers, and electromyographic sensors [12]. All this allows for a comprehensive assessment of motor and non-motor symptoms of the disease [13].

The greatest clinical utility is provided by solutions that allow for the comparison of digital indicators with clinical scales (for example, UPDRS — Unified Parkinson's Disease Rating Scale) and identification of changes that are significant for adjustment of therapy, specifically in the case of motor fluctuations.

Modern approaches to sensor monitoring involve the use of:

- multi-point systems with sensors placed in different areas of the body [14];
- minimalist solutions — for example, sensors integrated into shoes, wrist devices, smartphones, or bracelets [15].

In recent years, data analysis methods that utilize threshold algorithms, automatic classification, and deep neural networks have become widespread. This allows for the creation of inexpensive and noninvasive remote viewing systems [16]. Information received from sensors can be processed both in real time [17] and retrospectively [18]. Machine learning has opened up new possibilities for recording disease progression, assessing treatment efficacy, and generally analyzing the patient's quality of life [19]. However, the results of a number of studies remain methodologically heterogeneous. Variations in protocols, metrics, samples, and testing conditions hinder direct comparison of solutions and the transfer of findings to routine clinical practice.

Contemporary research demonstrates significant interest in the use of wearable sensors and machine learning algorithms for medical purposes [20]. As a result, diagnostic capabilities are expanding, and intelligent systems for making medical decisions are developing [21]. Algorithm validation and data interpretation [22] require the participation of specialists from various fields — neurologists, physiotherapists, biostatisticians, psychologists, and medical engineers. [23]. Collaboration between multidisciplinary teams improves the accuracy [24] and clinical validity [25] of algorithmic models. However, it is at the clinical and analytical validation stage that the lack of unified approaches is most noticeable: there are no generally accepted data collection protocols, and quality and reproducibility criteria are not agreed upon. Therefore, digital platforms need unified requirements for biomarker comparability.

Previously published reviews focused primarily on specific aspects of wearable technology applications. Examples included the use of mobile apps or inertial sensors to predict motor and non-motor symptoms of PD using machine learning methods [26, 27].

To further develop this area of study, the following tasks must be addressed:

- compare different classes of wearable sensor systems across scenarios (medical facility vs. home, short-term testing vs. long-term monitoring);
- conduct a comparative analysis of the algorithms and metrics used, identifying the applicability limits and methodological limitations;
- define criteria for “good” clinical and analytical validation;
- identify the reasons for the low comparability of results across studies.

There are no publicly available publications that address these issues.

Thus, the knowledge gap arises mainly from the shortcomings of previous literature reviews and their inadequate focus on the problem. Furthermore, there is a lack of an integrated picture combining technologies, evidence quality, and standardization (validation) requirements. All of this is necessary to improve the quality of personalized care for patients with PD.

The objectives of this review are to analyze current wearable digital devices for monitoring motor symptoms of PD, identify key limitations and shortcomings of validation, and identify methods to overcome them for efficient use in clinical practice.

Achieving these stated objectives requires addressing the following tasks.

1. Systematization of the types of wearable sensor systems used in PD, as well as their target clinical tasks (determination of gait, tremor, bradykinesia, dyskinesia, fluctuations).
2. Classification of data analysis and machine learning algorithms.
3. Comparison of clinical and technical metrics of the efficiency of developed methods and devices.
4. Analysis of the quality of available studies (samples, testing conditions, reproducibility, external validation).
5. Identifying unresolved issues in digital biomarker standardization and validation.
6. Comparison of platforms of interest in the context of the problem under study.
7. Identification of practically oriented directions for further research (protocols, endpoints, data collection and storage infrastructure).

Materials and Methods. The study is based on a systematic search and analysis of peer-reviewed scientific publications devoted to the development, architecture, and operational logic of digital systems designed to assess neurological dysfunction in patients with PD. This work was conducted in accordance with the Prisma 2020 guidelines.

The search period was from 2020 to 2025. Publications were reviewed in the international bibliographic databases PubMed, Scopus, Web of Science (WoS), as well as the Russian scientific electronic library Elibrary.ru. In addition, a manual search of the reference lists of key publications and a selection of relevant full-text conference proceedings were performed. The objective of the source selection was to identify relevant data on the principles of the design and operation of digital platforms used for the diagnosis, monitoring, and rehabilitation of patients with PD (Table 1).

Table 1

Selection of Sources for Prisma 2020 Methodology Review

Identification				Total*
Database records	Number of sources	Additional sources	Number of sources	
PubMed: $n = 80$ Scopus: $n = 105$ Web of Science: $n = 88$ Elibrary.ru: $n = 15$	288	References: $n = 6$ Conference Proceedings: $n = 4$	10	298
Screening by titles and abstracts				
Duplication	210	Exclusion by target indicators	160	50
Eliminating duplicates: $n = 88$		Irrelevant topic: $n = 70$ Not about Parkinson's disease: $n = 42$ Not about wearables: $n = 35$ Publications before 2020: $n = 13$		
Full-text correspondence assessment				
Exception due to unavailability of full text: $n = 2$	48	—	—	48
Final selection				
Qualitative synthesis	33	Meta-analysis	15	48
Clinical studies: $n = 14$ Systems development: $n = 9$ Longitudinal studies: $n = 7$ Systematic reviews: $n = 3$		Consolidation of data from multiple studies: $n = 15$		

Notes: * Total number of sources by stage and overall selection.

Some data in Table 1 are visualized for greater clarity. The figures are presented as percentages and rounded to whole numbers. As we can see, the most common basis for exclusion from the final sample was the results of title and abstract analysis. Irrelevance was identified in 64% of cases. A significant proportion (more than a third) was due to duplication (Fig. 1).

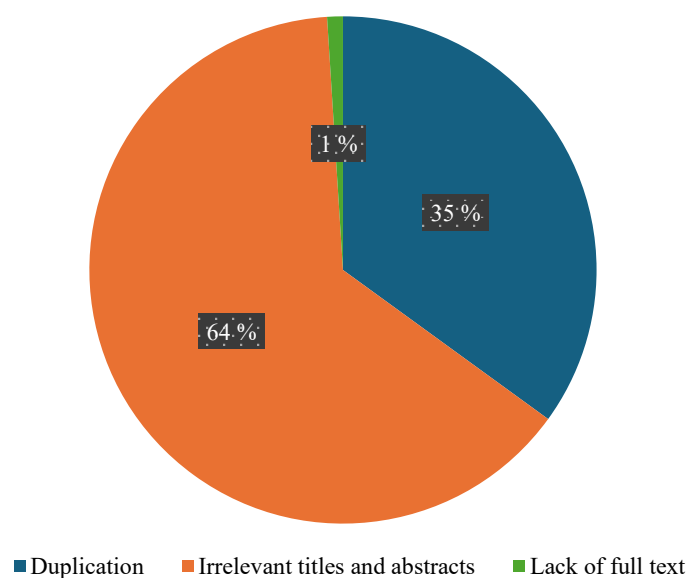


Fig. 1. Reasons for excluding sources from the review

Processing the information summarized in Table 1 revealed an extremely small number of systematic reviews (Fig. 2). Such sources accounted for only 6% of the total number of materials included in the final sample. Investigating the reasons for this imbalance is beyond the scope of this study. It is worth noting that the largest share of the sample consisted of studies consolidating data from multiple publications (meta-analyses, 31%). Almost the same proportion (29%) were clinical studies.

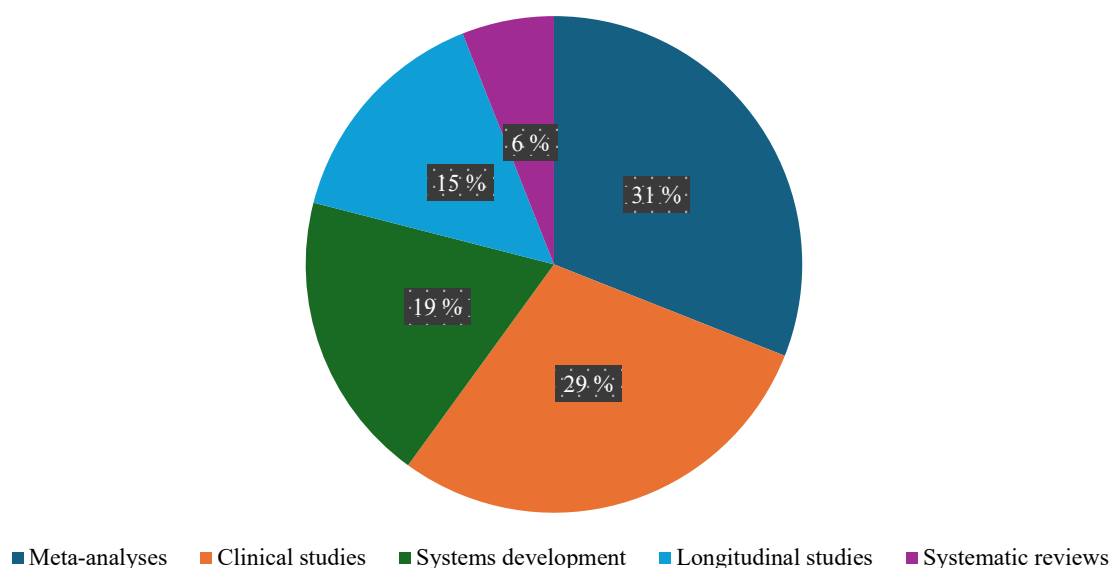


Fig. 2. Types of studies in the final sample

Key terms in digital medicine and neurodiagnostics were used for the search:

- Parkinson's disease;
- digital biomarkers;
- wearable devices;
- computer vision;
- machine learning;
- telemedicine platforms;
- neurological assessment systems;
- mobile health (mHealth);
- cloud diagnostics.

Search queries were generated in Russian and English. Publications available in Russian and/or English were included in the analysis.

Articles were selected based on relevance, scientific significance, and novelty. Priority was given to original research, comprehensive analytical reviews, and publications describing architectural solutions, algorithmic approaches, and clinical studies of digital systems.

The review included materials that met five criteria:

- appearance in 2020–2025;
- publication in peer-reviewed sources;
- full-text availability;
- subject: patients with PD;
- subject: wearable and/or digital systems used for diagnosis, monitoring, or quantification of neurological dysfunction.

Regarding the last criterion, we should clarify that this primarily concerns motor symptoms: tremor, bradykinesia, dyskinesia, gait, and postural stability. Publications describing the sensor platform, processing algorithms, and/or clinical trial results were taken into account.

Resources meeting the following seven criteria were excluded from the review:

- publication before 2020;
- studies not on PD;
- studies without analysis of wearable digital devices (e.g., purely molecular or pharmacological);
- studies on non-motor symptoms without connection to motor status monitoring;
- publications with insufficient data volume to extract key parameters (metrics, protocol, system characteristics);
- materials with duplicate data;
- unavailability of full text.

Let us clarify the last point. The review did not include so-called “gray literature”, such as dissertations and non-peer-reviewed preprints. Conference proceedings were only considered if they had a full-text publication and data extraction capabilities.

Two independent reviewers conducted the selection process at two stages. The first stage involved screening titles and abstracts, and the second — full-text evaluation. Disagreements between the reviewers were resolved through discussion. In the absence of consensus, a third reviewer was brought in. Blinded review was not used. According to Prisma (Table 1), 288 records were identified in the following databases: PubMed — 80, Scopus — 105, Web of Science — 88, and Elibrary.ru — 15. Additionally, 10 sources were found (6 from reference lists, 4 from conference proceedings). After removing 88 duplicates, 210 records remained.

At the screening stage, 160 publications were excluded:

- 70 were irrelevant;
- 42 were not about Parkinson's disease;
- 35 were not about wearable devices;
- 13 were published before 2020.

Accordingly, 50 articles remained in the list for evaluation. Two of these were excluded due to the unavailability of the full-text version. Ultimately, 33 studies were included in the qualitative synthesis, and 15 — in the meta-analyses. A total of 48.

The methodology involved a critical analysis and systematization of data to identify key areas for the development of digital technologies for Parkinson's disease monitoring. It was important to identify patterns in the architecture and operating logic of the systems, as well as compare the advantages and limitations of various solutions.

To provide reproducibility of the analysis, standardized data extraction was performed for each included study. The following factors were considered:

- type of digital system and sensor platform;
- sensor location;
- measurement mode and duration;
- clinical scenario (clinical and home);
- target symptoms;
- processing and machine learning algorithms;
- quality and validity metrics;
- study parameters (sample size, presence of a control group, duration of observation);
- information on clinical and/or external validation.

The studies were then grouped into four predetermined analytical categories.

The first was the functional task of the system. This included diagnostics, fluctuation monitoring, symptom and therapy assessment, as well as rehabilitation and feedback.

The second was the type of sensor platform. This could include single-point and multi-point IMU (inertial measurement units), smartphones, smartwatches, or multimodal solutions.

The third was the target motor phenotype (gait, tremor, bradykinesia, dyskinesia, balance).

The fourth was the level of clinical or analytical validation (comparison with clinical scales, presence of external validation, real-world testing, protocol reproducibility).

To move from individual studies to general conclusions, we compared the results within each group using common criteria (quality metrics, design, limitations). This allowed us to identify recurring patterns and systemic barriers to implementation.

Research Results. The study examined data on the potential applications of various sensor classes in power supply diagnostics and digitalization (Table 2).

Table 2

Comparative Analysis of Devices for Diagnostics and Digitalization of PD

Device / sensor	Examples	Advantages	Disadvantages / limitations	Reference
Accelerometer	IMU component; used in PKG ¹	Acceleration measurements, posture and movement pattern analysis. Basis for integrated motor performance indicators	Incomplete motion picture (3D reconstruction often requires IMU). There are questions about signal interpretation	[28] [29]
Gyroscope	IMU component; DynaPort7	Recording rotational movements and angular velocity. Analysis of gait, symmetry, and posture	Incomplete information on orientation and linear displacements. Processing and interpretation required	[29] [30] [31] [32] [33]
Magnetometer	IMU component	Tracking spatial orientation through magnetic field changes	Limitations on clinical interpretation. Requires integration with other sensors and algorithms	[28] [29] [31] [34] [35]
IMU: accelerometer + gyroscope + magnetometer	IMU modules (general class); PDMonitor	3D reconstruction of linear and angular displacements. Objective, continuous, long-term observations outside the clinic. Reduction of the Hawthorne effect	Weak data integration into practice. Decreased compliance among some patients. Specialized analytics tools and standardization of platforms, algorithms, and metrics are needed	[31] [32] [36] [37] [38]
Wearable motion sensors (general class)	IMU, accelerometers and others	Lightweight, compact, and energy performance. Continuous, objective monitoring. Differentiation between healthy and impaired movement patterns. Monitoring progression, activity, and therapy efficacy. Physician's findings on tremor, bradykinesia, and gait are taken into account	Challenges with clinical interpretation of multidimensional signals, regulatory compliance, privacy, and ethics. Decreased compliance in some patients. Need for standardization. Limited data on efficacy and user quality of life. Issues regarding economic viability	[30] [33] [37] [39] [40]
Approved ² clinical remote monitoring systems	PDMonitor, PKG, Stat-On, Kinesia360, KinesiaU	Widely used in clinical practice	Limited clinical data on efficacy and impact on patient quality of life. Organizational and ethical barriers	[41] [42] [43]
Multisensor with cloud architecture	Mobility Lab, PDMonitor 5 IMU + SmartBox	Daily activity analysis. Gait, tremor, and bradykinesia assessment. Data collection, processing, and cloud transmission	Data security risks. Clinical integration issues. Patients must wear multiple sensors	[44] [45] [46]

¹ Personal Kineti Graph

² In the Russian Federation, such systems require, first and foremost, approval from the Ministry of Health and the Federal Service for Surveillance in Healthcare (Roszdravnadzor).

Wrist device with accelerometer	PKG	High sensitivity. Standard scales. Measurements of tremor, dyskinesia, and bradykinesia. Integral indicators of fluctuations, dyskinesias, and immobility for therapy adjustment	Insufficient data on economic efficiency. Dependence of metrics on processing algorithms	[47] [48] [49]
Lumbar device with real-time ML ³	Stat-On	Detection of gait freezing, falls, and dyskinesia. Sensitivity over 93%	Difficulties in data interpretation. Limitations of practical integration. Issues of standardization and compliance	[47] [48]

To reduce descriptiveness and improve the comparability of approaches, the results were further structured by the types of metrics used in evaluating efficiency and validation, as well as by types of clinical tasks and clinical application scenarios:

- office vs. home;
- short-term tests vs. long-term monitoring.

Four typical clinical tasks were identified:

- 1) quantitative assessment of the severity of motor symptoms (tremor, bradykinesia, dyskinesia, postural instability, gait parameters);
- 2) detection of events and motor complications (off⁴ episodes, gait freezing, falls)
- 3) monitoring of dynamics, progression and responses to therapy (daily activity profiles, fluctuations);
- 4) clinical decision support (reports for the physician, remote management).

This approach provides the discussion beyond the use of specific sensors. The study allows for assessment of the clinical problem the system addresses and how convincingly this is supported by metrics and validation.

The study results were further interpreted taking into account the clinical scenario:

- a) under controlled conditions (office, laboratory test) high repeatability of measurements is achieved and high accuracy is recorded more often;
- b) long-term monitoring at home has higher ecological validity and the ability to record fluctuations, while the requirements for compliance, algorithm stability, and data interoperability are stricter.

To unify the comparison of efficiency, we conditionally distinguish three groups of metrics (Table 3):

- 1) algorithmic metrics of recognition and classification (accuracy, sensitivity, specificity, AUC⁵);
- 2) metrics of agreement with clinical scales (correlation, agreement with UPDRS, etc.);
- 3) metrics of clinical utility (impact on therapy adjustment, QoL⁶, event rate, clinical and economic indicators).

It is the metrics from the third group, critical for implementation, that are encountered significantly less frequently, which limits the evidence base for the practical efficiency of a number of solutions.

Table 3

Analytical Framework for Comparing the Studies Included in the Review

Dimension of comparison	What is being compared	Examples of indicators	Limitations to widespread adoption
Task type	Monitoring and evaluation of symptoms, events, dynamics, decision support	Tremor, bradykinesia, dyskinesia, freezing, falls, off, daily profiles, physician report	Disparate goals, incomparable data sets, incorrect labeling
Clinical scenario	Office (test) and home (long-term wearing)	Results in controlled tests, variability	Compliance issues, context issues, signal drift, protocol differences
Metrics	Algorithmic and clinical agreement, clinical utility	Accuracy, sensitivity, specificity, agreement with UPDRS, impact on quality of life	Heterogeneity of endpoints, lack of clinical utility assessments
Validation	Internal, external, multicenter	Internal and external validation	Lack of external validation standard and reproducibility protocols

³ Machine Learning

⁴ In this case, “off” and “on” episodes refer to fluctuations in the patient's motor activity. “Off” indication shows limited mobility, motor difficulties, and stasis lasting from a few seconds to several minutes.

⁵ Area Under Curve

⁶ Quality of Life

Inertial sensors, or motion sensors, are compact electronic devices for measuring acceleration, angular velocity, and magnetic field characteristics [28]. Based on these parameters, the orientation and motion of an object in three-dimensional space are determined. The most common types of inertial sensors are accelerometers, gyroscopes, and magnetometers. [29]. Due to their low weight, compactness and low power consumption, wearable motion sensors are widely used for routine continuous and objective monitoring of patients with PD outside the clinic [30]. The clinical utility of a particular sensor solution is determined not only by the sensor composition, but also by which clinical conditions can be reproducibly measured (task) and under what conditions (scenario).

The accelerometer records acceleration dynamics, allowing for posture and movement analysis, while the gyroscope records rotational movements and angular velocity. The magnetometer displays changes in the magnetic field to track spatial orientation. Sensors are placed on the wrist, shin, waist, thigh, and foot. When combined, the three sensors (accelerometer, gyroscope, and magnetometer) form an inertial measurement unit (IMU), providing a three-dimensional reconstruction of linear and angular movements [31].

An objective assessment of the situation requires minimizing the Hawthorne effect. In this case, we are talking about the patient being aware of the monitoring, watching his movements, and, if possible, controlling them [32]. The resulting picture is unnatural. Gadgets allow for objectivity, as they support long-term monitoring outside of a clinical setting.

From an analytical perspective, IMU often prove to be a competitive advantage in tasks such as tracking gait, posture, and complex motor skills (where 3D kinematics is critical).

Single-axis or single-type sensors (e.g., just an accelerometer) are sufficient for narrow tasks such as tremor assessment under specific conditions. However, they are more difficult to integrate with different scenarios and protocols.

Inertial sensors have demonstrated high efficiency in differentiating the motor patterns of PD patients and healthy volunteers. This provides the basis for the application of machine learning algorithms in identifying diagnostically significant features [33]. The devices also make it possible to track disease progression [34], identify changes in motor activity over time [35], and evaluate the therapy efficacy [36].

Observations based on inertial sensor data enable physicians to make informed decisions about treatment adjustments, including based on the severity of tremor, bradykinesia, and gait disturbances [37].

In recent years, inertial sensors have been actively used to develop digital biomarkers for the progression of Parkinson's disease [38]. Here are some comprehensive studies in this area: Personalized Parkinson Project, Cincinnati Cohort Biomarker Program, Watch-PD, Oxford Parkinson Disease Centre Discovery Cohort and Alameda [39]. These devices enable objective evaluation of the efficiency of new therapeutic approaches, taking into account drug therapy, physical therapy, and deep brain stimulation [40]. Continuous data recording in natural settings provides a more reliable assessment of the impact of therapy on motor activity. This increases the accuracy of clinical trials and the efficacy of personalized treatment regimens [41]. However, even in large-scale projects, the issue of unifying endpoints, protocols, and validation of digital biomarkers remains critical for reproducing and comparing results across different centers and platforms.

Devices such as the aforementioned PDMonitor, PKG, Stat-ON, Kinesia360, and KinesiaU [42] are widely used in clinical practice. PDMonitor is classified as a Class IIa medical device. The solution combines five IMU sensors placed on the wrists, shins, and waist, and a SmartBox system that collects, processes, and transmits data to the cloud [43]. This allows for the analysis of a patient's motor activity throughout the day and the assessment of the likelihood of off-time based on information on gait, tremor, and bradykinesia [44].

Compared to single-sensor solutions, multi-sensor solutions (like PDMonitor) offer superior coverage of motor phenotypes and noise immunity to individual channels. However, wearing multiple sensors requires higher compliance and more complex integration into clinical workflows.

The PKG wrist device measures tremor, dyskinesia, and bradykinesia with high sensitivity [45]. Accelerometer data is used to generate integrated indicators of motor fluctuations, the degree of dyskinesia, and the duration of inactive periods, allowing the physician to objectively assess the severity of symptoms and correct therapy [46]. Stat-on uses real-time machine learning algorithms to record signals from inertial sensors located in the lumbar region [47]. The device, with a sensitivity of over 93%, identifies episodes of gait freezing, falls, and trunk dyskinesia [48].

In the analytical comparison, we can talk about two different concepts:

- PKG — minimalism (one sensor, high level of comfort, focus on integral indices);
- Stat-on — real-time event detection (emphasis on episodes and instant recognition).

We emphasize the particular importance of standardizing protocols for event labeling and analysis, as well as criteria for comparison with clinical assessment. This provides the ability to compare metrics across different platforms.

The KinesiaOne system and its expanded version, Kinesia360, combine wearable sensors and tablet software to provide an objective assessment of tremor, bradykinesia, and other motor manifestations of the disease. Cloud-based neural networks process this data and calculate symptom severity using scores corresponding to clinical scales.

DynaPort7 is a combination of gyroscopes and accelerometers with a 100 Hz recording frequency. The solution accurately analyzes gait parameters, movement symmetry, and supports postural control.

The Mobility Lab system, comprised of wireless sensors and specialized software, provides a quantitative assessment of gait and balance. It can be used to detect subtle or mild signs of Parkinsonian gait and freezing episodes. The literature review allows us to suggest practical steps to overcome the limitations outlined above and to specify implementation paths for solutions. Let us present this as a sequence of actions:

- 1) unification of data collection protocols (minimum set of tests or modes, placement of sensors, monitoring duration, data requirements);
- 2) standardization of a set of metrics and reporting indicators for specific tasks (separately for symptom assessment, episode detection and fluctuations);
- 3) mandatory external and, if possible, multicenter validation with a description of the markings and criteria for accuracy and correctness;
- 4) testing the stability of algorithms to device changes (software versions) and to work in home conditions;
- 5) clinical utility studies (impact on therapy adjustment, quality of life, safety and clinical and economic outcomes);
- 6) integration into clinical processes (interpretable reports, compatibility with medical information systems) while maintaining ethical standards and ensuring data protection.

Discussion. Thus, the differences in competing approaches to implementing devices for recording the condition of patients with PD into clinical practice are well-known. They differ not only in terms of hardware but also in terms of clinical verification logic. Manufacturers focus their solutions on:

- scales (linked to symptom scores);
- events (episode detection).

Clearly, these two approaches have different validation standards and endpoints.

Numerous studies and a wide selection of regulatory-approved systems fail to address a significant issue. This concerns the incomplete development of unified and generally accepted validation standards for wearable solutions in PD. In this review, “good” validation of a digital system is defined as a combination of:

- analytical validity (stability and reproducibility of measurements and processing, resistance to noise and sensor drift);
- clinical validity (alignment of digital indicators with clinical scales and/or clinically significant conditions, such as “off”);
- clinical utility (evidence of impact on physician decisions, outcomes, quality of life, and economic indicators).

It should be noted that, in practice, numerous studies focus on demonstrating algorithmic accuracy under controlled conditions. External validation on independent samples, multicenter reproducibility, and clinical utility assessment are considered much less frequently.

There are other factors that limit the comparability of results across platforms and hinder the development of universal clinical endpoints. These include:

- protocol variability (sensor placement, recording duration, testing conditions);
- differences in metrics and understanding of target states (definition of off-label, episode labeling, accuracy, AUC, correlation with UPDRS).

Information obtained through wearable sensor devices allows for personalized therapeutic strategies, optimized drug dosing, and assessment of treatment efficacy in both clinical and home settings. Sensor systems can detect even subtle changes in motor function that may go unnoticed during routine doctor visits, making them indispensable for the early detection of disease progression or treatment response. The integration of physiological data obtained from wearable devices opens up possibilities for adaptive deep brain stimulation. For example, ankle movement velocity recorded by inertial sensors can be used as a control parameter to dynamically adjust subthalamic nucleus stimulation to correct freezing. Furthermore, these technologies create an infrastructure for remote monitoring and telemedicine consultations. Patients receive care without leaving their homes, reducing the burden on healthcare facilities.

However, the clinical significance of such decisions is most convincingly supported where studies include:

- comparison with clinical scales (for example, MDS UPDRS⁷);
- external validation;
- evaluation of results in natural settings.

In the absence of the listed elements, developments often remain prototypes due to the difficulties of integration with other centers and platforms.

⁷ Movement Disorder Society-sponsored revision of the Unified Parkinson's Disease Rating Scale.

The widespread adoption of wearable sensors is associated with methodological and organizational limitations. These are due not only to the technology but also to the methodological nature of the evidence. Some factors that reduce the comparability of study results include:

- small sample sizes;
- protocol specifics;
- differences in target definitions (e.g., “off” criteria and “freeze” labeling rules);
- limited external validation.

The complexity of integrating sensory data into routine clinical practice is primarily due to the need for specialized knowledge and analytical tools to interpret the multidimensional signals received from devices. Recent studies have demonstrated the possibility of simplifying motor assessment protocols using a single sensor placed in the lumbar region for typical motor tests such as the “time-up-and-go” test [46]. It has been found that automatic segmentation and extraction of a limited number of parameters can provide diagnostic accuracy [47] comparable to more complex systems. This opens the way to the introduction of sensor technologies into everyday practice without excessive computational load [48]. However, with this approach, compliance with the requirements of standardized validation is critical [49]:

- stability of metrics when changing conditions (office — home);
- reproducibility when changing the version of the algorithm and device.

Ethical issues and the risk of personal information leakage when using sensor data should be addressed separately. Such information must be fully protected from unauthorized use. Without safeguards, data should not be collected and transmitted.

Educational efforts must also be organized to explain the benefits and risks of digital monitoring to patients and their families. Ethical aspects and issues related to personal data handling should be considered at the early stages of development. This is especially important in cases of:

- using open source principles;
- expanding patient rights to access data;
- implementing metaconsent models.

An additional limitation is that not all patients with Parkinson's disease can effectively use wearable devices. Cognitive and motor impairments, as well as tremors, reduce compliance. Smartphone-based cognitive test results correlate with traditional neuropsychological assessments, but require adaptation for patients with severe motor impairments.

Standardization of hardware platforms, signal processing algorithms, and output clinical metrics remains a prerequisite for unifying approaches and incorporating sensor systems into diagnostic guidelines. However, current practice does not meet these objectives. The literature review has revealed that studies use different endpoints and different sets of metrics, and the success of studies and finished models is defined differently. For example, clinical interpretability is not assessed by accuracy or AUC, which complicates the development of uniform quality criteria for digital biomarkers.

We should also note the economic ambiguity of the large-scale implementation of the described solutions. From this perspective, devices such as PKG, Stat-on, Kinesia360, KinesiaU, and PDMonitor should be considered generally promising. However, clinical data on their effectiveness and impact on quality of life remains insufficient. The literature review provided an explanation for this discrepancy. The authors of the publications primarily work with concepts, proving their potential. This is quite far from the actual practical value of the solutions, that is, their clinical utility and cost-effectiveness.

In this review, the lack of validation standards is considered as a separate systemic barrier to implementation. For reproducible and comparable use of digital biomarkers in PD, the following validation and utility requirements must be met:

- analytical validation — measurement stability, controllability of error sources (sampling frequency, sensor drift, preprocessing), reproducibility of feature (index) calculations);
- clinical validation — proven compliance of digital indicators with clinically significant conditions or scales (e.g., UPDRS), evaluation in target application scenarios (office, home), external validation using independent data;
- clinical utility – evidence that the use of a digital biomarker improves decision-making (therapy adjustment), patient outcomes, or quality of life at an acceptable cost.

In practice, the literature most often presents first- and partially second-level elements (especially in controlled tests). External (multicenter) transferability, common endpoints, and clinical utility assessments are less common. This creates a gap between demonstrating the algorithm accuracy and the technology readiness for routine use.

We emphasize that separate guidelines and programs for digital endpoints in clinical trials are insufficient. To improve the comparability of results, a “minimum validation set” is needed, one specific to each of the two classes of tasks:

- symptom severity assessment (for scale-based systems),
- detection of off-states, freezes, and falls (for event-based systems).

The development of wearable sensors for Parkinson's disease management is linked to advances in artificial intelligence and machine learning. A key area is the integration of deep neural networks with inertial sensors for time series analysis. Existing models do not yet provide consistent results when processing multidimensional biomechanical data in real time. A promising solution in this regard is the use of distributed wearable sensors that enable autonomous data collection and analysis with the capability for rapid decision-making. At the same time, AI progress must be accompanied by methodologically transparent validation, which includes:

- protocol reporting;
- prevention of overfitting;
- validation on independent samples;
- analysis of robustness to real-life variations.

The integration of sensor systems with mobile apps and smart devices enhances patient engagement in self-monitoring, improves therapy adherence, and facilitates the development of personalized treatment trajectories. Experimental studies using inertial sensors and convolutional neural networks have demonstrated the feasibility of accurately measuring gait freezing episodes at home with high patient compliance. However, the level of evidence for such results depends on the quality of the episode labeling and the availability of external validation. Failure to meet the labeling and external validation requirements will limit the comparison of models and their transfer to clinical settings.

Conclusion. The authors of this review, based on the analysis of peer-reviewed publications from 2020–2025, accomplished two scientific objectives:

- systematized modern approaches to the use of wearable digital devices for objective monitoring of motor symptoms in Parkinson's disease;
- compared the main classes of sensor systems (primarily IMU platforms and clinically used wearable gadgets), their target clinical tasks (gait, tremor, bradykinesia, dyskinesia, motor fluctuations), as well as typical clinical use scenarios (office — home, short-term tests — long-term monitoring).

The classification of processing algorithms and machine learning approaches have shown that the most convincing results are obtained in tasks of quantitative motor assessment and recognition of individual phenotypes under controlled conditions. Outside the clinic, in the patient's daily life, the quality and reproducibility of results can decrease due to differences in protocols, measurement conditions, and compliance.

The key outcome of the review is the identification of a systemic problem with digital biomarker validation standards for Parkinson's disease. The literature lacks unified requirements for data collection protocols, a set of metrics, evidence of clinical utility (impact on treatment adjustment, quality of life, and economic indicators). There are no criteria for the reproducibility and comparability of results generated by different sensor platforms. Ultimately, it can be argued that the widespread adoption of wearable sensors for patients with Parkinson's disease is hampered not only by technical limitations but also by insufficient standardization of analytical and clinical validation procedures.

Based on the review results, the authors identified the following priority objectives for theoretical and applied research in this area:

- standardization of protocols and endpoints;
- development of external (multicenter) validation;
- assessment of the robustness of algorithms in real-world settings;
- detailed study on clinical utility and clinical-economic effectiveness.

In the long term, it is required to establish collaboration between researchers, clinicians, engineers, industry representatives, and regulatory authorities. This will enable the development of standardized, reliable, and clinically validated solutions for digital Parkinson's disease monitoring in the context of precision medicine.

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