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Review

Biomechanics of Parkinson's Disease with Systems Based on Expert Knowledge and Machine Learning: A Scoping Review

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Abstract: Patients with Parkinson's disease (PD) can present several biomechanical alterations, such as tremors, rigidity, bradykinesia, postural instability, and gait alterations. The Movement Disorder Society–Unified Parkinson's Disease Rating Scale (MDS-UPDRS) has a good reputation for uniformly evaluating motor and non-motor aspects of PD. However, motor clinical assessment depends on visual observations, which are mostly qualitative, with subtle differences not recognized. Many works have examined evaluations and analyses of these biomechanical alterations. However, there are no reviews on this topic. This paper presents a scoping review of computer models based on expert knowledge and machine learning (ML). The eligibility criteria and sources of evidence are represented by papers in journals indexed in the Journal Citation Report (JCR), and this paper analyzes the data, methods, results, and application opportunities in clinical environments or as support for new research. Finally, we analyze the results' explainability and the acceptance of such systems as tools to help physicians, both now and in future contributions. Many researchers have addressed PD biomechanics by using explainable artificial intelligence or combining several analysis models to provide explainable and transparent results, considering possible biases and precision and creating trust and security when using the models.

Keywords: Parkinson; human reasoning; knowledge; machine learning; expert system; explicable; artificial intelligence; fuzzy inference system

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1. Introduction

The Movement Disorder Society–Unified Parkinson's Disease Rating Scale (MDS-UPDRS) [1] has become highly recognized. It considers the non-motor and motor aspects of PD. However, the MDS-UPDRS guidelines for motor examination (Part III) are intended for evaluation by an expert rater. Therefore, the assessments use visual interpretations, which are more qualitative than quantitative, and subtle distinctions are not recognized [2]. An expert rater performs a patient's motor evaluation and provides an appraisal or rating based on their perception, which may vary from another expert's opinion. Monitoring disease progress or the patients' evolution with confidence, among other relevant aspects, can be difficult. Computerized systems based on expert knowledge, machine learning (ML), and measurements have advantages, such as quantified and repeatable results for the same patient's behavior.

However, different approaches or methods, such as fuzzy inference systems and ML models, have advantages and limitations. Interpretability involves understanding the models' internal workings; explainability expounds on the decisions made. Therefore, interpretability requires more detail than explainability [3]. Consequently, results can be very interesting and appropriate for diverse specialists. In some cases, computer models require numerous or balanced data, and others use expert knowledge. Their results may be more or less explainable, influencing their acceptance in clinical environments. Explainability helps to describe the results and their possible biases, precision, and transparency, in addition to creating trust and security when putting the models into production (ready to be used), adopting a responsible approach [4,5].

Many works have been published on interpretability and explainability, which are considered essential principles for ML models in diverse applications, including medicine, natural sciences, economics, and law [6–11]. Despite the highly significant advances in several ML models, they often lack transparency; their black-box nature allows for powerful predictions, but the results cannot be directly explained [8]. However, interpretability is frequently contingent on the application domain. Depending on the type of application, authors should consider ML models with the most adequate interpretability and explainability or use interpretable models. A widely cited specialized work on the subject is "Stop explaining black box ML models for high stakes decisions and use interpretable models instead" [12].

Following the PRISMA extension for scoping reviews [13,14], our paper considers models based on expert knowledge and ML methods. PD motor signs in Part III (motor examination) of the MDS-UPDRS were initially considered, such as "speech, facial expression, rigidity, finger tapping, hand movements, pronation-supination movements of hands, toe tapping, leg agility, arising from chair, gait, freezing of gait, postural stability, posture, global spontaneity of movement (body bradykinesia), postural tremor of the hands, kinetic tremor of the hands, rest tremor amplitude, constancy of rest tremor" [1]. However, a subset of these motor signs was emphasized because others have scarcely been addressed computationally. Nevertheless, the presented works allowed us to consider interpretability and explicability and generalize application opportunities in clinical environments or as support for new research.

The eligibility criteria and sources were scientific articles in journals indexed in the Journal Citation Report (JCR) and their analyzed data, methods, results, and application opportunities in clinical environments or as a basis for new research. Likewise, the measurements, devices, sampling rates, preprocessing, and study participants were considered.

2. Methods

This review included English-language documents published online from 2015 to 2024 in journals indexed in the JCR, as these have more consultations and citations. All information sources were obtained from the bibliographic databases of Elsevier, Springer, IEEE, MDPI, Wiley Online Library, World Scientific Publishing Co Pte Ltd., and Websites, without the need for additional contact with authors or the identification of supplementary sources.

The bibliographic databases are freely accessible to subscribed academic institutions or open access publications. The selected sources address computer models on the biomechanics of PD.

Appraisal of Individual Sources of Evidence

Measurements of two tremor types using accelerometers were evaluated in 42 patients with PD [15,16]. Specific features were compared, such as the peak frequency, peak frequency amplitude, and root mean square (RMS) amplitude. Accelerometers included in smartphones and smartwatches were used in [17]. However, the signals from these device types are restricted by their constructive characteristics, such as the resolution or frequent calibrations of the magnetometers. Likewise, the three previous works did not use fuzzy inference systems or ML methods. The work in [17] states that ML algorithms could be beneficial in discriminating features more precisely and making differential diagnoses of other tremor types.

Linear regression, applied to process tremors in [18], uses mathematical expressions, and the model may be difficult to understand. Some classifiers used to determine the severity of tremors employ support vector machines (SVMs), decision trees (DTs), k-nearest neighbor (KNN), and neural networks [19]. However, the classification does not show disease progression until the tremors exceed determined thresholds; likewise, its results are hardly explainable.

Tremor severity quantification using wrist sensor-based signals acquired from 92 PD patients is presented in [20]. The tremor score prediction algorithm uses a convolutional neural network (CNN) with deep learning, reporting an average accuracy of 85% and a linear weighted kappa of 0.85. The authors claim that optimizing the structure's design could improve the estimation accuracy. PD was identified based on a handwritten dynamics assessment with a CNN using a deep learning approach in [21]. In both works, improving explainable results for clinical utilization may be worth considering.

A wearable system for motor assessment to support the diagnosis of PD is presented in [22]; several motion parameters are extracted, although the classification only distinguishes healthy control subjects and patients. Many spatiotemporal and frequency parameters are calculated in the study to improve visual examinations. Supervised learning classifiers are applied, such as SVM, random forest (RF), and Naïve Bayes (NB).

A wearable sensor system and ML algorithms are presented in [23]. The sensor system comprises three inertial measurement units (IMUs), four custom mechanomyography (MMG) sensors, and one force sensor. The system predicts Unified Parkinson's Disease Rating Scale (UPDRS) scores based on a quantitative assessment of rigidity, bradykinesia, and tremor in Parkinson's patients. A total of 23 patients were examined using the sensors, together with exams conducted by clinicians, with ten healthy subjects as a control group. The reported prediction result for the UPDRS scores for all symptoms was 85.4%, matching, on average, the physicians' assessments. Three classifiers were selected based on a preselection process using 13 typical classification methods. However, the study covered many items of the MDSUPDRS through wearable sensors and ML algorithms, and a computational method was not developed to evaluate individual items in detail; likewise, the explainability of the results must be considered.

The remote measurement and home monitoring of tremors are addressed in [24], but the methods are not presented in detail. An ML method using signals from a triaxial accelerometer attached to patients' waists was used to assess bradykinetic gait in [25]. It employed an SVM to identify parts of the gait signals. The stride frequency content was used to determine bradykinetic walking bouts and estimate bradykinesia severity using an epsilon support vector regression model. A total of 12 PD patients with idiopathic PD participated in the experiments without healthy control subjects, but it would be interesting to use more than one sensor.

Insole and IMU-based solutions for assessing gait impairment to support clinical practice instrumentation are presented in [26]. The assessment applied two datasets obtained from a clinical study. However, the MDS-UPDRS guidelines were not strictly followed; therefore, the study did not intend to detail the evaluations' specific causes or their relationships with biomechanical indicators.

Current and future perspectives on hand-tracking methods employing deep learning and video-based assessments are presented in [27], which examines many studies on video-based assessments and inertial signals.

We note that evaluations and analyses are more precise and robust when combining techniques consisting of videos and inertial signals, as well as ML models and systems based on expert knowledge, for example, for exercises established in the MDS-UPDRS, such as pronation/supination of the hand, hand postural tremors, hand kinetic tremors, hand rest tremors, and gait.

An analysis of turns during gait in individuals with PD was conducted in [28], comparing biomechanical strategies and their clinical subtypes. The cross-sectional study included 43 individuals with idiopathic PD, divided into subgroups: akineto-rigid, dominant tremor, and mixed. The authors found no statistically significant difference among the subgroups.

A biomechanical posture analysis with ML was conducted in healthy individuals in [29], exploring the data through principal component and cluster analyses. A group of 200 healthy subjects with a mean age of 24.4 ± 4.2 years was photographed from dorsal, frontal, and lateral views. The study found potential new patterns in postural analyses, with possible applications in physical therapy, ergonomics, and sports.

A PD gait classifier [30] based on spatial–temporal gait features acquired from 23 patients and 26 age-matched controls was applied with multiple regression normalization, which considered the subjects' age, gender, height, body mass, and self-selected walking speed to identify differences between PD patients and controls, evaluating the effectiveness of classification ML after gait normalization. Significant differences between the PD patients and healthy control subjects were found to be related to the stride length, step length, and double support time after data normalization.

One study used ML algorithms to distinguish patients with PD from matched healthy subjects, discriminating PD stages using spatial–temporal parameters, including asymmetry and variability [31]. Gait information was analyzed in 63 people with PD with a distinct severity of motor symptoms and in 63 subjects from a matched control group with a self-selected walking speed. It achieved an accuracy of 84.6%, a precision of 0.923, and a recall of 0.800 using the NB algorithm for the PD diagnosis. The most relevant gait features for PD diagnosis were step width variability, step length, velocity, and width. RF performed better in PD stage recognition than the other ML algorithms studied. The two gait features found to be outstanding in PD stage identification were stride width variability and step double support time variability. The ML algorithms studied were DT, NB, RF, SVM, multilayer perceptron (MLP), and logistic regression (LR).

An ML technique employing an incremental SVM and modified Frank–Wolfe method was used to classify and predict PD in [32]. Data were taken from the PPMI database [33] and downloaded on 24 April 2018. The technique's results were compared with other state-of-the-art techniques. In [34], an exploratory ML study was used to evaluate hand rest tremors in both healthy and PD individuals. Time and frequency domain characteristics were used to feed seven ML algorithms: logistic regression, support vector classifier, KNN, RF, linear discriminant analysis, DT, and Gaussian NB. However, the work did not follow the MDS-UPDRS guidelines for evaluating hand rest tremors.

ML approaches to human movement analysis are examined in the short editorial [35], which states that human movement is inherently complex, dynamic, highly non-linear, and multi-dimensional. ML models tackle this complexity by conducting three tasks: classification, predictive modeling, and dimensionality reduction. Combining an unsupervised principal component analysis (PCA), a linear discriminant analysis, and a Gaussian mixture model can allow for pattern recognition. Likewise, computer vision and estimations of kinetics and kinematics using wearable sensors, as well as artificial intelligence, are highlighted in the document.

A study examining musculoskeletal biomechanics with ML highlights deep learning for describing musculoskeletal dynamics. The study approximates "the posture-dependent moment arm and muscle length relationships of the human arm and hand muscles" [36]. The authors use a light gradient boosting machine and an artificial neural network (ANN) to solve the wrapping kinematics of the arm and hand muscles with several degrees of freedom.

Using videos to assess finger-tapping in PD offers results that can be integrated into clinical decision-making processes [37]. This work used 75 videos of 50 PD patients. Expert assessors agreed that the classification performance and the characteristics chosen by the decision tree aligned with clinical knowledge. The DT approach was primarily the classification method to improve interpretability and quantification. As a limitation, the authors recognized that the number of patient videos used to train the model was small; a more extensive dataset would enhance the model's generalizability and robustness.

Combining ANNs and fuzzy logic systems allows for the development of intelligent and adaptive systems. ANNs can learn, and computer models based on fuzzy reasoning offer excellent systems in medical approaches. A neuro-fuzzy system integrates adaptive structures and can perform pattern recognition in medical applications [38] and expert systems to help physicians. Different types of cooperative fuzzy neural networks are presented in [38].

Type-2 fuzzy systems are frequently used to predict PD. Fuzzy logic shows greater precision in PD detection than common ML approaches [39]. Hybrid methods combine supervised learning, unsupervised learning, and feature selection methods. The membership functions of a type-1 fuzzy system fuzzify the inputs, mapping them to single numbers. Nevertheless, these numbers are denoted as intervals in a type-2 fuzzy approach, adding a dimension to the membership function definition [39]. Results have confirmed that combining the Expectation–Maximization (EM) technique, backward stepwise regression, and a type-2 Sugeno fuzzy inference system provides the greatest accuracy in predicting Motor-UPDRS and Total-UPDRS outcomes.

Other combined methods use deep learning and neuro-fuzzy techniques orientated toward the early diagnosis of PD [40] based on the Motor-UPDRS. These combinations apply an ensemble learning approach that can learn online from large clinical datasets. Neuro-fuzzy and Deep Belief Network (DBN) approaches are used. EM, a clustering method, is used to handle datasets. The PCA technique is used to remove data noise. KNN is used to manipulate missing data. Incremental ML is used to improve the methods' efficiency. Findings have revealed that this approach can improve the prediction accuracy of the UPDRS and the time complexity of preceding systems in large datasets.

A neuro-fuzzy system using a learning method for an interpretable classifier analyzing the gait cycle in PD is presented in [41]. Wearable sensors were used to measure the vertical ground reaction force (vGRF). The method uses the features obtained from these signals. The authors believe that experts can verify the decision made by this method. A type-2 fuzzy system increases robustness in the case of noisy sensor data. The initial fuzzy rules are created utilizing KNN. Later, a quasi-Levenberg–Marquardt learning approach is employed to fine-tune the initial rules, minimizing the cross-entropy loss function and using a trust region optimization method. Lastly, online learning improves rules and helps identify new labeled samples. The model's performance is contrasted with that of previous supervised and unsupervised ML systems, and patients and healthy subjects participated in the experiments.

An approach using a PD dataset of speech cues and integrating two methods, namely, Ensembles of Self-Organizing Map and a neuro-fuzzy and unsupervised learning algorithm, was used to predict UPDRS outcomes in PD [42]. The authors found that the method effectively predicts UPDRS outcomes by combining speech signals. The statistical analysis presented in [43] examined twenty-four people with PD who were separated into two subtypes: tremor-dominant and postural instability and gait disturbance subtypes. The assessed outcome measures were sit-to-walk overall performance and kinetic and kinematic data.

A biomechanical system is compared with an observational rating scale tremor assessment in [44]. The work compares a biomechanical system and the MDS-UPDRS regarding test–retest reliability. The authors claim that the comparison eliminates some of the tools' inconsistencies and assists as a guideline for selecting a tool that can improve tremor assessments. Nevertheless, further work is necessary to consider other variabilities that influence the overall situation. This review presents several works that quantify tremors following the MDS-UPDRS guidelines, presenting two evaluations—one based on the MDS-UPDRS and the other quantified to two decimal places—allowing for better monitoring of the motor evolution of patients.

A comparison of kinetic–rigid and hyperkinetic PD considering postural adjustments and biomechanics based on starting gait with obstacles is presented in [45]. The work reports a cross-sectional study of thirty-three volunteers separated into two groups according to clinical motor manifestations. Another paper studied computerized assessment methods to classify the motor dysfunction of patients with PD on a clinical scale [46]. The biomechanical parameters of six exercises measured through wearable inertial sensors were used. Feature selection methods, SVM, logistic regression, and neural networks allowed the classification of the two groups of patients. However, the authors claim that the significant features are only valid when using this dataset to classify the two groups of patients.

Some initial biomechanical PD characteristics may appear in hand-drawn images. A computer-assisted diagnosis of PD was made using fuzzy optimum-path forest and Restricted Boltzmann Machines in [47]. The work compared these results with those of baseline models, such as SVMs, KNN, and the optimum-path forest (OPF) classifier. The authors show that the proposed model mostly outperforms the baselines, and that the fuzzy OPF is an alternative method for detecting PD. In [48], a methodology for detecting PD based on a neuro-fuzzy system with minimized feature selection is presented. In [49], a classification method with a three-stage fuzzy system for PD diagnosis is presented, and it uses dynamic handwriting analysis. A biomechanical signal analysis for gait evaluation in PD is presented in [50], employing biomechanical signals acquired with the wireless sensor networks Bluetooth and XBee. The model presents good results for assessment according to the parameters established by the MDS-UPDRS; however, this work performed a partial gait analysis as the sensors were only placed on the ankles. Swinging arms were not considered, which may play an important role in PD gait. In [51], the detection of PD with keystroke data is presented; ML models were developed using keyboard keystroke dynamics.

Several works evaluate and quantify the biomechanical alterations presented by Parkinson's patients, such as turns, rigidity in the arms and legs, rest tremors, hand tremors, kinetic tremors, reemergence tremors, and walk alterations. They address individual items of the MDS-UPDRS in detail, conducting qualitative assessments following the MDS-UPDRS guidelines that are familiar to medical experts and performing quantitative evaluations of up to two decimal places, facilitating motor evolution monitoring. All these works were based on measurements of 60 patients with PD at different stages and 20 healthy control subjects. In total, 400 measurement sessions were performed for eight exercises, each bilateral (800 measurements), established using the MDS-UPDRS. Each computerized measurement session took 30 min and was repeated every three to six months. These works used fuzzy inference systems, but the research could be improved by using hybrid methods, i.e., fuzzy logic and ML. Computer science and medicine experts participated in the design and validation, as the systems were based on human reasoning and expert knowledge. Six IMUs were used. Two were placed on the upper extremities (one on each hand), two were placed on the trunk, and two were placed on the lower extremities (on the ankles to reduce the accelerometer noise when the foot contacts the ground). A gyroscope, accelerometer, and magnetometer were included in each IMU. Data acquisition employed a sampling frequency of 50 samples per second. IMU–computer communication used Bluetooth. Figure 1 shows the distribution of the sensors. The following nine referenced works used these measurements to assess each item individually [50,52–59].

A fuzzy inference model was used to evaluate turn in PD patients [52], using four biomechanical characteristics during gait. The model design was based on clinician expert knowledge. The model outputs were verified through comparison with expert evaluations. The results were explicable, and the model has already been applied in clinical environments as an expert system to help physicians.

A pronation and supination analysis was conducted based on biomechanical signals from PD patients [53]. Using eight biomechanical features, a fuzzy inference model was used to evaluate upper extremity rigidity based on the MDS-UPDRS.

Rest tremor was quantified based on fuzzy inference systems and wearable sensors [54]. A tremor severity estimation model using a Takagi–Sugeno-type fuzzy inference system was used. The model used the MDS-UPDRS to perform rest tremor quantification, which was found to be instantly applicable to clinical environments. Rest tremor amplitude data concerning the timeline were reported. Adding a continuous range improved the resolution of the tremor ratings.

A computer model based on a fuzzy inference system was developed for leg agility quantification and an assessment of Parkinson's patients [55]. Leg agility is an item of the MDS-UPDRS; nevertheless, only a visual analysis of the features is conducted, leading to subjectivity. The proposed model can capture all details regardless of the task speed, reducing the inherent uncertainty of an examiner's observations. This model is feasible for quantifying and assessing leg agility based on inertial signals. Experts in computer science and medicine participated in the design and result validation.

Figure 1. Six sensors (IMU) are distributed on the trunk and upper and lower extremities.

A fuzzy inference model based on triaxial signals for pronation and supination assessments in PD patients is presented in [56]. This model considers biomechanical affectations not included in the MDS-UPDRS. It uses a weighted score for the medical experts and fuzzy inference models using an Analytic Hierarchy Process [60,61]. Twelve different biomechanical characteristics are quantified based on IMUs. This study [61] evaluates the wobble of the arm and the change in the speed rate during hand movements at different stages of the exercise.

Computer models for evaluating hand tremors in Parkinson's patients are presented in [57], using five biomechanical indicators that characterize the hand tremors. The three fuzzy inference models recognize postural or resting tremors, differentiating them from normal hand movements, and, if detected, their severity is evaluated. The evaluations follow the MDS-UPDRS guidelines, providing an assessment with an accuracy of two decimal digits. They are applicable in clinical environments due to their simplicity. Experts in medicine and computer science participated in the design and validation.

A computer method for pronation/supination assessments in PD based on latent space representations of biomechanical indicators is presented in [59], using scalable and adaptable computing systems. It quickly adapts to new expert knowledge and includes new characteristics in a self-supervised training approach. The method employs a training phase with an encoder/decoder to represent the patients' biomechanical indicators in latent space; later, based on clinical knowledge, each patient's latent space representation is labeled according to the MDS-UPDRS. Figure 2 presents an overview of this computer method.

A kinetic tremor analysis was conducted using wearable sensors and fuzzy inference systems in PD patients in [58], evaluating kinetic tremors of the hands. It evaluated patients based on the MDS-UPDRS; additionally, the method achieved an accurate evaluation using approaches such as the amplitude of the tremors in the different stages of the finger-to-nose exercise, the frequencies of the tremors, and voluntary movements. The five biomechanical characteristics used to evaluate each patient included the tremor amplitude before reaching the finger, during the transition, and before reaching the nose, as well as tremor and voluntary movement frequencies.

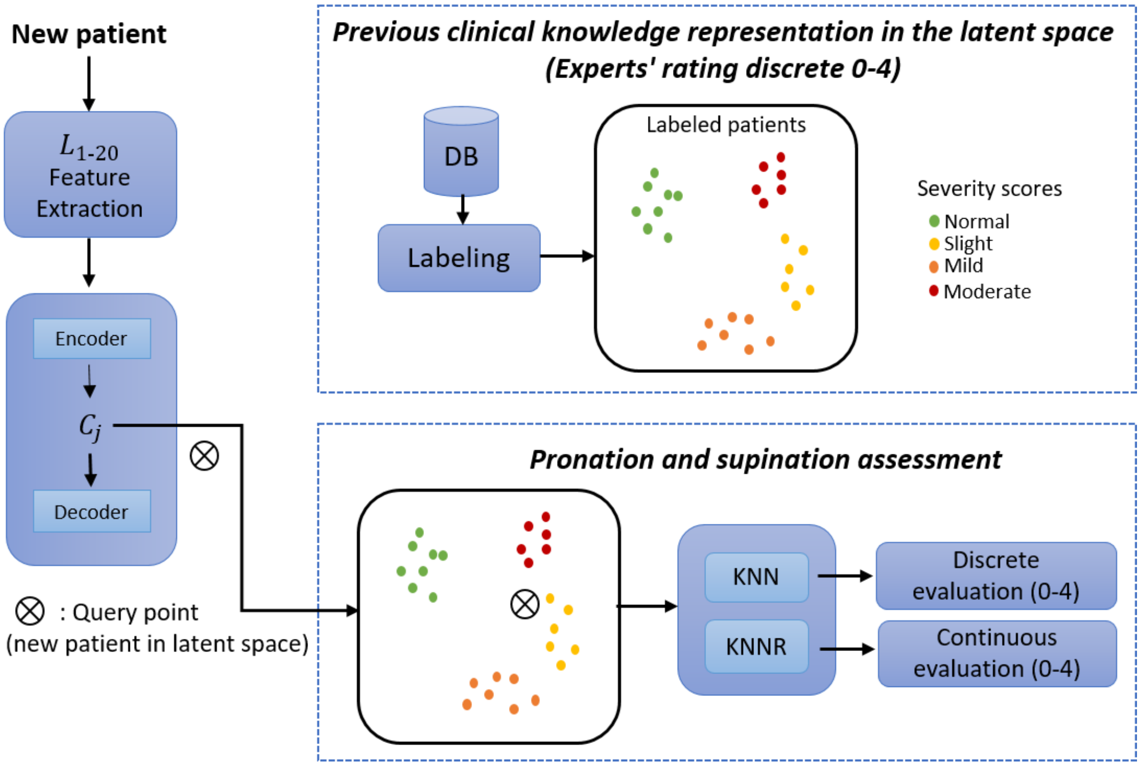

Figure 2. Overview of the computer method (modified graphical abstract of [59]).

3. Results

This section presents Table 1, which shows the sources of evidence selected, evaluated for eligibility, and included in the review.

Table 1. Sources of evidence included in the review.

	Source of Evidence	Characteristics	Critical Appraisal	Relevant Information Related to the Review
1.	"Wrist Sensor-Based Tremor Severity Quantification in Parkinson's Disease Using Convolutional Neural Network" [20].	Tremor score prediction algorithm uses a CNN with a deep learning architecture.	The explainability of results for use in clinical environments should be considered.	Application opportunities in clinical environments as a tool to help physicians.
2.	"Wearable System to Objectify Assessment of Motor Tasks for Supporting Parkinson's Disease Diagnosis" [22].	Spatiotemporal and frequency parameters are calculated. Supervised learning classifiers, such as SVM, RF, and NB, are applied.	Classification is only performed between healthy control subjects and patients.	Visual examinations can be improved in clinical environments. Support for specialized diagnosis.
3.	"A Heterogeneous Sensing Suite for Multisymptom Quantification of Parkinson's Disease" [23].	One force sensor, three IMUs, and four MMG sensors are used. A quantitative assessment of bradykinesia, rigidity, and tremor is conducted in 23 PD patients. Three base classifiers are used (ML).	It covers several items of the MDS-UPDRS and may be unable to evaluate individual items in detail. Explainability must be considered.	Detailed evaluations of individual items. Result explainability in clinical environments.
4.	"Estimating Bradykinesia Severity in Parkinson's Disease by Analysing Gait through a Waist-Worn Sensor" [25].	Signals are provided by a triaxial accelerometer placed on the waist of PD patients. It uses SVM and an epsilon support vector regression model.	A total of 12 PD patients with idiopathic PD participated in the experiments. Healthy control subjects did not participate in the tests—only a sensor.	Biomechanics of PD with systems based on ML and inertial sensors.

Table 1. *Cont.*

	Source of Evidence	Characteristics	Critical Appraisal	Relevant Information Related to the Review
5.	"Deep Learning for Hand Tracking in Parkinson's Disease Video-Based Assessment: Current and Future Perspectives" [27].	On-hand tracking and many studies on video-based assessment and inertial signals are examined.	Assessments are more precise and robust, combining videos, inertial signals, ML, and systems based on expert knowledge.	Biomechanics of the pronation/supination of the hand, hand postural tremor, hand kinetic tremor, and hand rest tremor.
6.	"Classification of Parkinson's Disease Gait Using Spatial-Temporal Gait Features" [30].	Based on spatial–temporal gait features, multiple regression normalization is applied, considering subject age, height, body mass, gender, and self-selected walking speed, evaluating the effectiveness of ML.	Important differences in the stride length, step length, and double support time are identified between PD patients and healthy control subjects.	Biomechanics of gait in PD patients.
7.	"Machine Learning Models for Parkinson's Disease Detection and Stage Classification Based on Spatial-Temporal Gait Parameters" [31].	ML algorithms are used to distinguish patients with PD from matched healthy subjects, discriminating PD stages.	RF performs better than the other ML algorithms studied. The most relevant gait features in PD diagnosis are step length, velocity, and width, and step width variability.	ML algorithms, such as NB, SVM, DT, RF, LR, and MLP, are analyzed for PD detection and stage classification.
8.	"Solving Musculoskeletal Biomechanics with Machine Learning" [36].	Musculoskeletal biomechanics. Deep learning describes musculoskeletal dynamics. The study approximates "the posture-dependent moment arm and muscle length relationships of the human arm and hand muscles".	A light gradient-boosting machine and a fully connected artificial neural network are used to solve the wrapping kinematics of the muscles for the arms and hands.	Possible applications of ML to analyze the biomechanics of PD.
9.	"Clinically Informed Automated Assessment of Finger Tapping Videos in Parkinson's Disease" [37].	This work offers results that can be integrated into clinical decision-making processes. The work used 75 videos of 50 PD patients. The DT approach was the primary classification method used to improve interpretability and quantification.	Expert assessors agreed that the classification performance and the features selected by the DT aligned with clinical knowledge.	Interpretability and quantification were considered. The authors recognized that a more extensive dataset would enhance the model's generalizability and robustness.
10.	"Accuracy Analysis of Type-2 Fuzzy System in Predicting Parkinson's Disease Using Biomedical Voice Measures" [39].	A hybrid method combines supervised learning, unsupervised learning, and feature selection techniques. The membership functions of a type-1 fuzzy system fuzzify the inputs, mapping them to single numbers. Nevertheless, these numbers are represented as intervals in a type-2 fuzzy system, adding a dimension to the definition of the membership function.	Results confirmed that combining the EM technique, backward stepwise regression, and type-2 Sugeno fuzzy inference system led to the best accuracy in predicting the Motor-UPDRS and Total-UPDRS outcomes.	Hybrid methods combining ML and fuzzy inference systems can lead to excellent results in a clinical environment. These hybrid methods can be more robust and precise.
11.	"Early Diagnosis of Parkinson's Disease: A Combined Method Using Deep Learning and Neuro-Fuzzy Techniques" [40].	Combining deep learning and neuro-fuzzy techniques. It uses an ensemble learning approach with the ability to learn online from large clinical datasets. DBN and neuro-fuzzy approaches are used. EM handles datasets. The PCA technique removes the data noise. KNN is used to manipulate missing data.	Incremental ML improves the method's efficiency. Findings reveal that the approach can improve the UPDRS prediction accuracy and the time complexity. It is only compared with preceding methods to manipulate large datasets.	The hybrid method can improve the UPDRS prediction accuracy and the time complexity, combining ML and neuro-fuzzy techniques.

Table 1. *Cont.*

	Source of Evidence	Characteristics	Critical Appraisal	Relevant Information Related to the Review
12.	"A Type-2 Neuro-Fuzzy System with a Novel Learning Method for Parkinson's Disease Diagnosis" [41].	The gait cycle in PD is analyzed. Wearable sensors are used to measure the vGRF. The method uses features obtained from these signals. Fuzzy systems are combined with ML models.	An interpretable classifier; the authors believe that experts can verify the decision made by the proposed method. The performance is compared with that of previously supervised and unsupervised ML approaches. The MDS-UPDRS guidelines are not used.	Neuro-fuzzy systems can improve PD diagnosis (using the gait cycle in PD). However, other signs of PD patients are not measured.
13.	"Fuzzy Inference Model Evaluating Turn for Parkinson's Disease Patients" [52].	Four biomechanical characteristics are used for turn assessments during gait, and the model design is based on clinician expert knowledge.	Model outputs are verified through comparison with expert evaluations. The model has already been applied in clinical environments as an expert system to help physicians.	Based on the MDS-UPDRS. Interpretability and explicability. Application opportunities in clinical environments.
14.	"Pronation and Supination Analysis Based on Biomechanical Signals from Parkinson's Disease patients" [53].	Using eight biomechanical features, a fuzzy inference model is used to evaluate upper extremity rigidity based on the MDS-UPDRS.	Results are verified with expert evaluations. The model has already been applied in clinical environments as an expert system to help physicians.	Interpretability and explicability. Application opportunities in clinical environments.
15.	"Rest Tremor Quantification Based on Fuzzy Inference Systems and Wearable Sensors" [54].	A tremor severity estimation model using a Takagi–Sugeno-type fuzzy inference system is presented. The model performs rest tremor quantification using the MDS-UPDRS. This method is applicable to clinical environments.	Rest tremor amplitude data concerning the timeline are provided. Adding a continuous range improves the resolution of tremor ratings.	Interpretability and explicability. Application opportunities in clinical environments.
16.	"Computer Model for Leg Agility Quantification and Assessment for Parkinson's Disease Patients" [55].	A model based on a fuzzy inference system is presented. Leg agility is an item of the MDS-UPDRS; nevertheless, only a visual analysis of the features is conducted, leading to subjectivity. Experts in computer science and medicine participated in the design and result validation.	The model captures all details, regardless of the task speed, reducing the inherent uncertainty of an examiner's observations. This model is feasible for quantifying and assessing leg agility based on inertial signals.	Interpretability and explicability. Application opportunities in clinical environments.
17.	"Fuzzy Inference Model Based on Triaxial Signals for Pronation and Supination Assessment in Parkinson's Disease Patients" [56].	A model considering biomechanical affectations not included in the MDS-UPDRS is presented. The wobble in the arm and the change in speed rate during hand movements at different stages of the exercise are evaluated in this paper. Design and validation by experts in medicine and computer science.	It uses a weighted score for medical experts and fuzzy inference models using an Analytic Hierarchy Process. Twelve biomechanical characteristics are quantified.	Interpretability and explicability. Application opportunities in clinical environments.
18.	"Computer Models Evaluating Hand Tremors in Parkinson's Patients" [57].	Models using five biomechanical indicators of hand tremors are presented. The three fuzzy inference models recognize postural or resting tremors, differentiating them from normal hand movements, and, if they are detected, then their severity is evaluated.	The models follow the MDS-UPDRS guidelines, conducting an assessment with an accuracy of two decimal digits. Experts in medicine and computer science participated in the design and validation.	Interpretability and explicability. Application opportunities in clinical environments.

Table 1. *Cont.*

	Source of Evidence	Characteristics	Critical Appraisal	Relevant Information Related to the Review
19.	"A Computer Method for Pronation-Supination Assessment in Parkinson's Disease Based on Latent Space Representations of Biomechanical Indicators" [59].	The method uses a training phase using an encoder/decoder to represent the patients' biomechanical indicators in latent space; later, based on clinical knowledge, each patient's latent space representation is labeled according to the MDS-UPDRS.	The method uses scalable and adaptable computing systems. It can quickly adapt to new expert knowledge and includes new characteristics in a self-supervised training approach.	Interpretability and less explicability. More easily scalable. Application opportunities in clinical environments.
20.	"Kinetic Tremor Analysis Using Wearable Sensors and Fuzzy Inference Systems in Parkinson's Disease" [58].	A method for evaluating a patient's kinetic hand tremors based on the MDS-UPDRS is presented; additionally, the method achieves an accurate evaluation by using approaches, such as the amplitude of the tremors in the different stages of the finger-to-nose exercise, the frequencies of the tremors, and voluntary movements.	The five biomechanical characteristics used to evaluate each patient are tremor amplitude before reaching the finger, during the transition, and before reaching the nose, as well as tremor and voluntary movement frequencies.	Interpretability and explicability. Application opportunities in clinical environments.

4. Discussion

4.1. Summary of Evidence and General Considerations

Multiple studies address PD biomechanics using systems based on expert knowledge and ML, but not all follow the MDS-UPDRS guidelines. However, the MDS-UPDRS has obtained notoriety and is widely used in evaluations of non-motor and motor disturbances. If computerized models use measurements, then their assessments, both qualitative and quantitative, can be repeatable, given the same patient behavior.

Models based on fuzzy inference systems and ML have advantages and limitations. In medical applications, and particularly in works on the biomechanics of Parkinson's disease, interpretable models represent good practice. In this sense, interpretability involves understanding the internal workings of the models; explainability helps to describe the results and their precision, possible biases, and transparency. These factors create trust and security when models are put into production and promote a responsible approach to their use.

ML methods generally require numerous or balanced data or use black box models. Fuzzy systems demand expert knowledge, and interdisciplinary research improves both design and result validations, influencing the systems' acceptance in clinical environments. Any explainable artificial intelligence model is recommendable for applications involving humans, such as biomechanics; thus, their results can be motivating or appropriate for non-specialists in computer science, increasing the possibilities for use in medical practice. These principles formed part of the qualification criteria for the studies in this review. Other elements were considered in the qualification process, such as the analyzed data, wearable system use, whether classification was only conducted between healthy control subjects and patients, MDS-UPDRS's evaluated items, detailed evaluations of individual items, hybrid methods, and application opportunities in clinical environments.

The evaluated studies used different data sources. Several works used data obtained from inertial sensors, force sensors, and triaxial accelerometers or video-based data. These characteristics were identified for each work and were subject to critical appraisal. The studies' conclusions were affected by the variation in their data sources. Table 1 presents 20 evidence sources that meet the proposed eligibility criteria. Each selected source includes its characteristics, a critical appraisal, and the relevant information related to the review.

How accurate and clinically applicable are the machine learning techniques presented for PD assessments (e.g., SVM, neural networks)? The answer depends on how the authors have developed their applications to be more interpretable and explainable, crucial considerations in medical applications. In this sense, noninterpretable ML models, for example, deep learning, artificial neural networks (ANNs), and SVM, have great predictive capabilities, high performance in pattern recognition, and increasing importance in analyzing and modeling scientific data across various areas [62]. However, noninterpretable ML models are frequently presented as black boxes, limiting their acceptance in critical decision-making procedures [62]. When developing high-stakes decision applications, it is essential to consider the evaluated proposals in specialized scientific and technological works, such as [3,6–8,10,12,62] to name just a few, which evaluate the interpretability and explainability of ML techniques considered to be noninterpretable and intrinsically interpretable.

Explainable artificial intelligence (XAI) in interdisciplinary research directions [63] and the evolution from black box to glass box [64] highlight the advancements in XAI and its application in diverse scenarios and ongoing challenges, emphasizing perspectives and interdisciplinary collaboration. Other artificial intelligence techniques, such as fuzzy inference systems, are interpretable and explainable, facilitating multidisciplinary collaboration during design, validation, and use in clinical environments. Likewise, hybrid models are a growing trend in applications related to the biomechanics of Parkinson's disease, such as neuro-fuzzy systems and combined ML models, as the potential of each artificial intelligence technique is exploited, reducing limitations and disadvantages. A fuzzy inference system (FIS) uses fuzzy logic to associate inputs and outputs. It utilizes fuzzy reasoning and rules (If/Then) similar to human reasoning. FIS can be applied to making decisions, recognizing patterns, and simulating biological or physical systems, intelligent automatic control, and expert systems, among other applications [65]. Neuro-fuzzy systems (NFSs) combine the human-like reasoning of FIS and ML models as neural networks. NFSs can be used in diverse applications [38,41,66].

Interestingly, some works, for example, [34], use neuro-fuzzy systems; however, they do not use the MDS-UPDRS, which is widely used in clinical environments and is familiar to medical experts. In addition, the classification of PD gait [30] requires data on the age, gender, height, body mass, and self-selected walking speed of patients to evaluate ML effectiveness. Nevertheless, several fuzzy boundaries of membership functions in fuzzy inference systems allow for classification without data on the age, height, body mass, and gender of patients, although they may be incorporated for additional analysis.

ML models for PD detection and stage classification [31] only use gait parameters; however, other works report patients with disturbances in tremors and upper extremity rigidity without gait alterations.

The progress in wireless and miniaturized wearable sensors has improved sensor-based Parkinson's biomechanics analysis. They are inexpensive, accurate, easy to calibrate, and can detect a wide range of motor changes. These characteristics contribute to their potential use in multiple clinical settings and portable assessments. No difficulties have been reported regarding their use. The analysis of their signals can be verified in several ways, including comparisons with expert evaluations or with optical- and vision-based reference systems, usually installed in specialized laboratories at a considerably high cost. Adequate system validation based on inertial sensors may involve comparison against robust 3D motion analysis [67].

The selection of the sampling frequency is essential in digital signal processing applications; it is not sufficient that Shannon's sampling theorem is fulfilled [68,69]. Analyzing Parkinson's disease motor symptoms requires calculating the signals' peak values. A minimum sampling rate of 50 samples per second ensures that the signal is sampled five times for the highest frequency harmonic, which is 10 Hz for a postural tremor [70]. If the measurement system does not allow a higher sampling frequency, then the signals must be interpolated to obtain a higher equivalent sampling frequency, as was the case in [55], as the impact of the feet with the ground produces higher frequency harmonics.

Common limitations of some of the revised studies are the lack of interpretability and explainability of the results and the small number of patients analyzed; classification between only healthy control subjects and patients; not all works following the MDS-

UPDRS guidelines; and no detailed evaluations of the items presented. In this review, suggestions that can help to overcome these limitations by improving further research are highlighted.

External validation of the proposed models using independent datasets from different regions or clinical settings is recommended for several works. Another validation method is cross-validation with external datasets to ensure broader applicability. Some examples of the validation techniques applied include data acquired in various clinical environments, patients at different stages of PD, comparisons between PD patients and healthy control subjects, patients' assessments in medical consultations spaced X months apart, assessments with no change in the medication doses taken between 4 and 5 h before the evaluation, and patients' assessments for consultations spaced a month apart and at separate medication times.

Several algorithms have been applied to the biomechanics of Parkinson's disease using machine learning. ML expert researchers know that the most frequently used algorithms can be grouped into supervised, unsupervised, and reinforcement learning algorithms [71]. Supervised learning requires labeled input/output data for training and tests, including SVM, Naïve Bayes Classification (NBC), Mathematical Regression, DTs, and ANNs [72]. Unsupervised learning does not require labeled input/output data and involves clustering and the Hidden Markov Model (HMM) [72]. Reinforcement learning employs trial and error, and the algorithm interacts with an environment to achieve an objective [71,72]. Further, random forest (RF) is a supervised ML algorithm with a treelike structure. RF uses a collection of decision trees to make predictions [71,73]. Deep learning is a machine learning algorithm with intrinsic learning rules and representative data sample levels using large neural networks with multiple layers; it has been well received for its automatic feature extraction capabilities, being applied in diverse areas such as [74–76].

The strengths and weaknesses of these ML algorithms generally depend on the application type, such as industrial, environmental, biomedical, social, or marketing. Although documents on their main features exist, general comparisons of some ML algorithms are linked to specific applications [73,77–80]; for Parkinson's disease recognition [81–84] and Parkinson's disease progression [85]. In Parkinson's biomechanics, the strengths and weaknesses would depend on how the authors applied their ML algorithms or combined them with other artificial intelligence methods, including fuzzy inference systems [52–59]. The publications on Parkinson's biomechanics that apply one or several ML methods evaluate their specific results in an individualized manner. However, for high-stakes decisions, such as diverse medical applications, it is recommended that references that emphasize using interpretable models, such as [12], and explainability and interpretability concepts [63] are consulted.

4.2. Recommendations and Best Practice

Recommendations and best practice for integrating machine learning models into clinical workflows facilitating model deployments are as follows: a large set of patients should be used covering the stages of Parkinson's disease to be assessed or analyzed; the data must represent the variety in PD patients' alterations or impairments described in the MDS-UPDRS guidelines for motor examination (Part III); physicians and expert raters should participate in the design, measurement supervision, and verification of the developed models, which is facilitated by the systems being based on expert knowledge [65,86–88] or interpretable and explainable ML models being used [3,12,63,64]; data should be acquired from a subset of healthy control subjects of all genders, ages, and physical characteristics compatible with the PD patients; if necessary, external validations and independent datasets from different regions or clinical environments can be considered, with diverse validation techniques to ensure broad applicability.

Based on ML models and expert knowledge, the analyzed studies consider the ethical implications of diagnosing, monitoring, and conducting motor evaluations in PD patients. The published works cite the authorizations of bioethics committees and the informed consent of patients and healthy control subjects. A particular focus was on patient data privacy and security. Ethical implications must continue to be addressed, because the research involves humans, which is easier when studies are conducted with the participation of a multidisciplinary team, following best practices.

4.3. Limitations

There are no key limitations that should be highlighted. Numerous papers on the biomechanics of PD that applied systems based on expert knowledge and ML were reviewed; 20 papers were selected, including aspects that represent multiple published works on the subject.

4.4. Conclusions

The sources of evidence include papers in journals indexed in the JCR that analyze the data, methods, results, and application opportunities in clinical environments or as support for new research. Works with less explicable results can form a basis for future contributions combining several ML models, fuzzy inference systems, vision, and statistical analyses.

Although the MDS-UPDRS has gained recognition, the assessment uses visual interpretations, making it more qualitative than quantitative, and subtle distinctions are not recognized. In this sense, computerized systems that employ measurements improve assessments, which can be qualitative and quantitative, showing repeatability, given the same patient behavior. When the requirements of interpretability and explicability are sufficient, they can constitute expert systems that help physicians.

Currently, many researchers are addressing the biomechanics of PD. This scoping review can support future research, especially regarding the interpretability and explainability of results in terms of the acceptability of such systems as tools to help physicians. Interpretability involves understanding the internal workings of models; explainability centers on explaining the decisions made. The biomechanics of PD based on explainable artificial intelligence or combining several analysis models provides explainable and transparent results, as well as possible biases and precision, creating trust and security when the models are put into production and promoting a responsible approach to their use.

If the economic conditions of clinical environments are favorable, combining certain measurement technologies, such as inertial sensors (wearable sensors) with video-based data, pressure-sensitive walkways, and robust 3D motion analysis, can improve PD biomechanics assessments.

Interpretable and explainable measurement-based models for the biomechanics of Parkinson's disease can provide physicians with quantitative and qualitative motor evaluations in PD patients. The assessments are repeatable (the same inputs produce the same outputs) without depending on subjective factors. Their results facilitate patient tracking and can correlate medication doses with motor conditions, as well as suitable intervals for follow-up consultations with doctors.

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