Sensor-Based Locomotion Data Mining for Supporting the Diagnosis of Neurodegenerative Disorders: A Survey

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Locomotion characteristics and movement patterns are reliable indicators of neurodegenerative diseases (NDDs). This survey provides a systematic literature review of locomotion data mining systems for supporting NDD diagnosis. We discuss techniques for discovering low-level locomotion indicators, sensor data acquisition and processing methods, and NDD detection algorithms. The survey presents a comprehensive discussion on the main challenges for this active area, including the addressed diseases, locomotion data types, duration of monitoring, employed algorithms, and experimental validation strategies. We also identify prominent open challenges and research directions regarding ethics and privacy issues, technological and usability aspects, and availability of public benchmarks.

CCS Concepts: • **Human-centered computing** → **Ubiquitous computing**; • **Applied computing** → **Health informatics**; • **Information systems** → **Data mining**; • **Computing methodologies** → *Intelligent agents;*

Additional Key Words and Phrases: Pervasive healthcare, neurodegenerative disorders, location data mining, cognitive decline

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1 INTRODUCTION

With the demographic change toward an elderly population, the proportion of elderly people is increasing and it is projected that the old-age dependency ratio alone in the European Union will increase from 27.5% in 2013 to 49.4% in 2050. Aging is associated with decline in cognitive function and mobility, and it has a significant impact on society [98]. For example, in 2013, the number of **People with Dementia (PwD)** was more than 35 million worldwide, and this number is expected to double by 2030, reaching 115 million by 2050 [87]. With the shift toward an elderly

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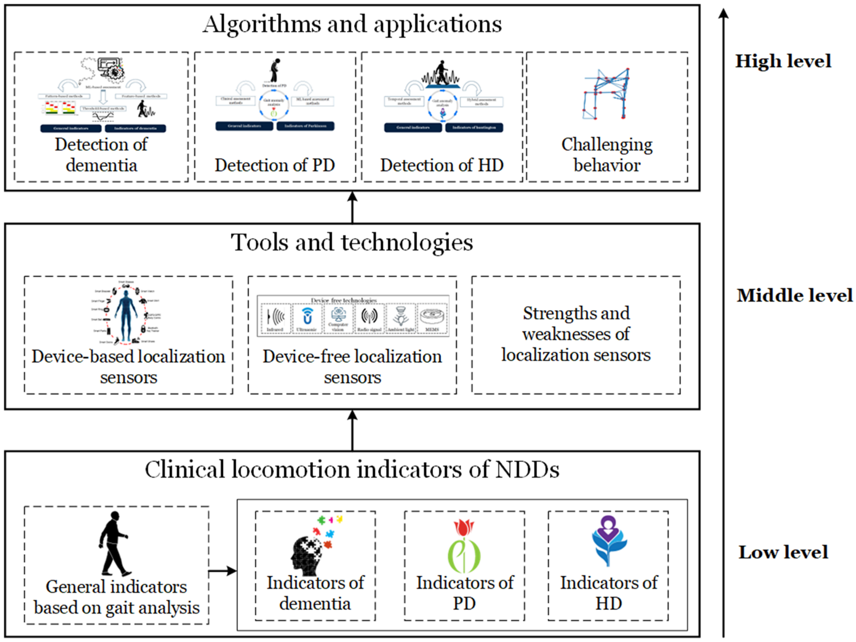


Fig. 1. Survey scenario.

population, it is also expected that the shortage in professional caregivers will increase. Early detection of age-related cognitive impairments could potentially help them find timely therapies and be independent and socially active for a longer time. Automated intelligent technologies could provide easier and more accessible ways of early diagnosis of cognitive impairments. Several works showed that **Neurodegenerative Diseases (NDDs)** are strongly related to locomotion anomalies [62, 103, 110]. Thanks to the widespread availability of positioning infrastructures and inexpensive portable devices to track locomotion, there is increasing interest in exploiting locomotion sensor data and AI algorithms to support the diagnosis of NDDs. To evaluate the potential of automated technologies to detect cognitive decline, in this survey we analyze the locomotion-based indicators of NDDs and then look at different methods and sensor-based technologies for detection of cognitive impairments based on locomotion data. We concentrate on those studies that tackle the recognition of locomotion anomalies for NDD recognition, but we do not consider works that target the recognition of locomotion anomalies irrespectively of an NDD diagnosis. Consequently, we consider only those works that are supported by an extensive experimental evaluation that includes both cognitively impaired subjects and **Healthy Control Subjects (HCSs)**.

We concentrate on three widespread types of cognitive decline in the elderly population: **Alzheimer's Disease (AD)**, **Huntington's Disease (HD)**, and **Parkinson's Disease (PD)**. To our knowledge, this is the most elaborated overview of the state of the art in detection of cognitive impairments for the elderly from locomotion data, and it provides a practical guide for the basis from which future technologies could be developed.

1.1 Survey Structure

The structure of our survey is illustrated in Figure 1. We divided the study into three different parts, which correspond to the main building blocks of AI-based systems for NDD assessment. The lowest level is related to primary or complex gait indicators, which are used for the diagnosis of NDDs according to clinical theory and practice. Those indicators provide the clinical ground for designing an NDD detection system, as they identify which raw data are necessary for the assessment. The middle level regards existing tools and technologies to acquire locomotion data at coarse- and fine-grained levels in different environments, including wearable and infrastructure-based systems. Finally, the highest level reports and discusses algorithms and applications that process locomotion data for supporting the diagnosis of NDDs and for recognizing challenging behaviors that may put the safety of cognitively impaired subjects at risk. As explained at the end of this section, each level is addressed in a specific section of our article.

1.2 Contributions

The contributions of this work are as follows. We provide a systematic literature review of existing technologies and algorithms for detection of locomotion anomalies as indicators for three types of cognitive diseases: AD, HD, and PD. To our knowledge, this is the most extensive survey on this topic. Additionally, we analyze the usage of existing technologies and algorithms for the detection of locomotion anomalies and discuss the weaknesses and strengths in utilizing them. Based on our analysis of existing technologies and algorithms, we discuss future directions, in which the field of automated detection of locomotion anomalies could develop to increase the quality of existing technologies and in that manner to improve the well-being of elderly people suffering from NDDs.

1.3 Summary of Methodology and Main Findings

We queried the most prominent scientific search engines with a handcrafted query to retrieve the paper candidates. From a pool of 1,277 retrieved articles, we selected and surveyed 128 papers that matched our criteria regarding types of clinical indicators, sensor technologies, experimental setup, and algorithm types. The survey indicates that the number of scientific works exploiting AI and locomotion sensor data for the diagnosis of NDDs has been strongly growing, especially since 2010. Most papers address the detection of dementia and PD, which are the most common NDDs, and a few address HD. Most works are based on indoor locomotion monitoring, and a few consider more complex outdoor movement patterns. Several different **Machine Learning (ML)** algorithms are used for NDD detection. The most common approach is to use classical ML algorithms such as **Random Forest (RF)** or **Support Vector Machine (SVM)**, whereas a few works adopt deep learning methods. Some works relying on fine-grained motion indicators that rely on statistical measures and thresholds to produce a prediction. The duration of monitoring ranges from a few minutes for gait analysis to hours, days, or weeks for more complex patterns. The majority of the experiments were held in controlled laboratory environments, but a large percentage of them were conducted in naturalistic real-world environments such as the individual's home. The results show that this kind of technologies may effectively support the diagnosis of NDDs and help simplify patient management. However, as explained in Section 7, the review showed that the state of the art falls short in addressing different challenging issues.

The article is structured as follows. Section 2 introduces the three types of NDDs, their clinical symptoms, and locomotion indicators. In Section 3, we describe the procedure used in this study and the types of papers included. Section 4 analyzes the clinical locomotion indicators of NDDs. Section 5 presents the technologies and tools used for the detection of locomotion indicators. Section 6 discusses the existing algorithms for detecting NDDs based on sensing technologies. The article concludes in Section 7 with a discussion of the shortcomings of existing technologies and methods and the potential future directions in detecting cognitive impairments in the elderly based on locomotion data.

Table 1. Symptoms of AD

Early Stage	Middle Stage	Advanced Stage
Forgetfulness	Having difficulty in remembering recent events and people's names	Having difficulty in walking
Losing track of time	Getting lost at home and having difficulty in communication	Experiencing behavior changes that may escalate aggression
Getting lost in familiar places	Needing help with personal care	Having an increasing need for assisted self-care
–	Experiencing behavior changes, including wandering and repeated questioning	–

2 BACKGROUND

In what follows, we briefly introduce the three types of NDDs and their clinical symptoms and locomotion indicators.

2.1 Alzheimer's Disease

AD is the most familiar type of dementia, and it is considered as a syndrome that has a chronic or progressive nature. It is defined as declination in cognitive function beyond what might be expected from normal aging. **People with Dementia (PwD)** suffer from a lack of memory and thinking capability, learning ability, and inability to communicate. The impairment in cognitive function is generally accompanied and periodically preceded by weakening in emotional control and social manners. It is regarded as a predominantly cognitive disorder. Gait abnormalities can also be noticed in the disease's early stages, including decreased walking speed, step length, step frequency, and increased gait variability. Dementia is considered one of the main reasons for disability and dependency among older adults worldwide. It can be troublesome for PwD, caregivers, and family members. Lack of awareness and understanding of dementia are being observed that cause stigmatization and hindrances to diagnosis and care. The effect of dementia on caregivers, families, and the community is quite diverse. It can be biological, psychological, social, and economic. It might be challenging to detect dementia early since each individual is affected by the disease differently, relying on the effect of the disease and the individual's personality before becoming sick. According to the World Health Organization[1] approximately 50 million people are diagnosed with dementia, and the most common symptoms of dementia can be classified into three stages: early, middle, and late. Some common symptoms for these stages are listed in Table 1. It can be noticed that the severity of the symptoms advances with progression of the disease.

2.2 Parkinson's Disease

PD is regarded as the most familiar movement disorder, involving more than 6 million individuals worldwide. PD can have an early onset, although it primarily affects people over the age of 55 years, and progression of the disease slowly increases after the age of 65 [38, 105]. The World Health Organization ranks PD as the second most familiar NDD. It hampers the nerve cells in the brain that generate dopamine. Dopamine is necessary for transmitting messages to control and coordinate movement. Approximately 0.1% to 0.2% of the dopaminergic neurons are lost per year during normal aging. This speed is significantly accelerated in **People with Parkinson's Disease (PwPD)**, and signs become apparent when nearly 70% to 80% of these neurons have been lost.

PwPD experience both motor and nonmotor symptoms. The most common motor symptoms during the early stages of PD are resting tremors, rigidity, and bradykinesia, which are explained as follows:

[1] https://www.who.int/.

Table 2. Symptoms of HD

Movement Disorder	Cognitive Disorder	Psychiatric Disorders
Involuntary jerking or writhing movements (chorea)	Difficulty in organizing or focusing on tasks	Irritability
Rigidity or muscle contracture (dystonia)	Lack of flexibility to get stuck on a behavior/action	Social withdrawal
Abnormal eye movements	Lack of impulse control that can result in outbursts, acting without thinking	Insomnia
Impaired gait, posture	Difficulty in learning new information	Fatigue and loss of energy
Difficulty with talking/swallowing	Slowness in processing thoughts or in finding words	Frequent thoughts of death or suicide

(1) *Tremor/shaking* [105]: This starts in a limb, often the patient's hand. Patients might experience rubbing of their thumb and forefinger back and forth, called a *pill-rolling tremor*. The patient's hand may shake when it is at rest.
(2) *Bradykinesia* [105]: PD may slow the patient's action over time, making simple tasks complicated and time consuming.
(3) *Rigid muscles* [105]: Muscle stiffness may appear in any portion of the body. As a result, the stiff muscles cause pain and restrict the range of movement.
(4) *Impaired posture and balance* [105]: Posture may become stooped. Patients might suffer from imbalance movement as a consequence of PD.

The hardship in controlling movement caused by PD harms the social and psychological situation of the patient, who feels secluded and ineffective in accomplishing simple tasks. PwPD in the middle stage experience cramping (dystonia), dyskinesia, loss of postural reflexes, and **Freezing of Gait (FOG)**. FOG is one of the most common motor signs of PD and appears during advanced stages of the disease. It is defined by a brief episode of involuntary lack of locomotion, a feeling of being stuck in place when attempting to take a step or navigating through or turning around barriers [89].

2.3 Huntington's Disease

HD is defined as a progressive inherited NDD, inducing involuntary movement and cognitive problems, harshly impacting quality of life. It is caused by a cytosine-adenine-guanine (CAG) repeat mutation in the *HTT* gene [39]. It has a comprehensive effect on a person's functional capabilities, resulting in motor, cognitive, and psychiatric disorders. The signs of HD can form at any age, but they usually arise in people aged 30 to 40 years, and the beginning of the disease is diagnosed clinically when motor abnormalities form. Impairment in motor control is regarded as the most familiar sign of HD, ordered by chorea and dystonia. This, merged with the cognitive and behavioral symptoms, can impact day-to-day tasks. Nevertheless, cognitive and behavioral symptoms [39] can be noticed many years (even decades) before motor symptoms, which progressively affect the quality of life of **People with Huntington's Disease (PwHD)**.

When HD forms at an early age, signs are identical to those of PD, and the disease may advance faster. Drugs are available to aid the symptoms of HD, but remedies cannot prevent the physical, cognitive, and behavioral deterioration associated with the condition [8]. Therefore, most of the current research in this area is based on detecting HD at an early stage so that patients may benefit from prospective medical interventions that may assist in slowing advances of the disease. The most common symptoms of HD are mentioned in Table 2.

3 MATERIALS AND METHODS

In this section, we explain the methodology used in our survey. We conducted a systematic review to select the relevant studies considered in this article. We focused on locomotion-based data mining techniques experimented on a significant number of patients, including both HCSs and people with NDDs. In the following, we report our search strategy, including inclusion and exclusion criteria, as well as statistics about the selected research works.

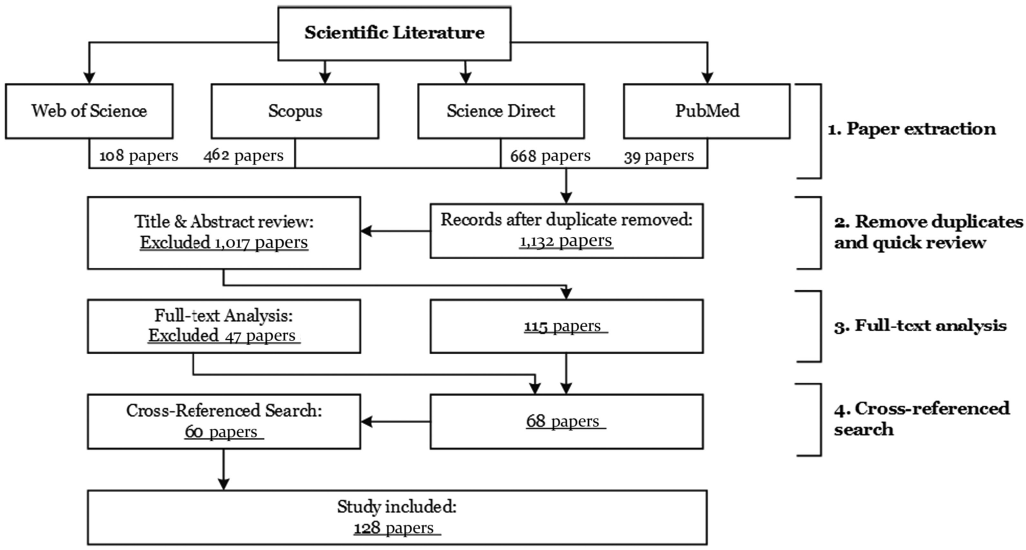


Fig. 2. Flowchart of our literature search and selection method.

3.1 Search and Selection Strategy

Figure 2 illustrates our literature search and selection method. We queried different scientific search engines—Web of Science, ScienceDirect, PubMed, and Scopus—considering academic studies published in peer-reviewed journals and in proceedings of international conferences. We handcrafted a search query to identify relevant papers published between 1975 and October 2020, considering terms appearing in the title, abstract, or keywords of the papers. Our search query is reported in Table 3. Its syntax is slightly different depending on the functionality of the considered database, without impacting the semantics of the query. Our literature search and selection method is divided into four phases.

Paper Extraction. The whole query is divided into six parts connected by the "AND" operator. The first part of the search query includes different terms to identify "neurodegenerative disorders." Since the target group of our study is elderly people, in the second part of the query we retrieve only publications specifically related to that age group. In the third part, we select only papers related to the use of sensor devices and pervasive computing technologies. The fourth part retrieves only papers related to locomotion data mining. The fifth part selects only papers related to different monitoring methods. The last part retrieves only papers published in conference proceedings or scientific journals that were published after 1974. The query retrieved 1,277 papers in total.

Duplicates Removal and Quick Review. In the second phase, initially we performed duplicates removal, keeping 1,132 papers. Then, we applied a quick review procedure to those papers to ensure that they met our inclusion criteria. The title, abstract, and keywords of each paper were evaluated by two of this article's authors to ensure that they actually met the inclusion criteria specified in the query string. In case of disagreement, the paper was discussed between all of this articles's authors to reach a consensus. As expected, the search query provided a relatively large number of false positives. Most papers were excluded because they did not rely on sensor devices or pervasive computing technologies, or considered diseases not related to neurocognitive disorders. After this operation, we retained 128 papers.

Full Text Analysis. In the third phase, the full text of each remaining paper was assessed by two of this article's authors to exclude those papers that were preliminary versions of extended papers

Table 3. Literature Search Query

TITLE-ABSTRACT-KEYWORDS((“cognitive impairment” OR “cognitive problem” OR “cognitive issue” OR “cognitive decline” OR “cognitive assessment” OR “dementia” OR “mci” OR “mild cognitive impairment (MCI)” OR “alzheimer’s disease” OR “neurodegenerative”)
AND (“elderly” OR “senior” OR “Aging Adults” OR “aging” OR “older adult” OR “adult”)
AND (“internet of things (IoT)” OR “indoor” OR “outdoor” OR “wearable” OR “ambient intelligence (AmI)” OR “ambient assisted living” OR “aal” OR “healthcare application” OR “positioning technology” OR “ambient sensors” OR “Global Positioning System (GPS)” OR “accelerometer” OR “gyroscope” OR “environmental sensors” OR “inertial sensor” OR “mobile” OR “Intelligent Assistive” OR “assistive Device” OR “device free” OR “intelligent systems” OR “smartphone” OR “non-invasive” OR “human computer interaction” OR “hci” OR “mobile health” OR “smart homes”)
AND (“locomotion anomaly” OR “locomotion pattern” OR “locomotion” OR “abnormal movement pattern” OR “trajectory” OR “wandering” OR “disorientation “ OR “movement traces “ OR “ambulatory gait analysis” OR “abnormal locomotion” OR “abnormality” OR “gait” OR “mobility” OR “motor impairments” OR “motor assessment” OR “motor function” OR “acceleration” OR “spatial” OR “gait variability” OR “gait-cycle” OR “functional assessment” OR “motor dysfunction”)
AND (“monitoring” OR “detection” OR “analysis” OR “non-intrusive” OR “unobtrusive” OR “reconstruction” OR “gait monitoring” OR “gait detection” OR “remote monitoring” OR “trajectory mining”))
AND (LIMIT-TO (DOCUMENT TYPE,“(PEER REVIEWED JOURNAL) ARTICLE”) OR LIMIT-TO (DOCUMENT TYPE,“CONFERENCE PAPER”) OR LIMIT-TO (DOCUMENT TYPE,“REVIEW”)) **AND** PUBYEAR > 1974

already included in our search, and to keep only those papers that met our inclusion criteria. In this regard, we excluded those works that lacked a significant experimental evaluation with both cognitively impaired seniors and HCSs. In case of disagreement, the paper was discussed by all of this article’s authors to make a decision. After this phase, we retained 68 papers.

Cross-Referenced Search. In the fourth phase, we checked the references of the remaining publications to look for further relevant publications matching our search criteria to be included in our survey. We also looked for additional relevant papers published by the same authors of the included papers. Thanks to this search, we added 60 more papers. The full list of the reviewed papers can be found in the supplementary materials.

3.2 Comprehensive Science Mapping Analysis

Recently bibliometric measurements have been increasingly expanding across various fields [2, 3, 55]. This technique is particularly suited for implementing the comprehensive science mapping analysis of published studies of fragmented and controversial streams of research. As mentioned previously, the papers in this survey can be divided into three main categories regarding the NDDs and locomotion anomaly as follows: PD, HD, and dementia. The total number of published and selected papers in this survey considering different databases are mentioned in Figure 2.

From another point of view, Figure 3 shows the number of selected papers by each category compared to total number of the papers from the same category considering their publisher. As can be seen, the selected papers in the Web of Science search engine represent the highest number of total papers among the others.

3.2.1 Annual Scientific Production. Among the 128 included papers, 33 were survey or review papers. Figure 4(a) represents the temporal trend of papers included in our survey, and it shows an exponential increase in the number of papers related to sensor-based locomotion data mining for NDD diagnosis.

3.2.2 Word Cloud. Word clouds are introduced as a tool to identify the most essential topics dealing with a particular subject [2, 55]. Figure 4(b) presents the most frequent words adopted by previous studies extracted by our search and selection strategy explained in Section 3.1. These keywords, which are repeated more than 30 times considering all selected papers, demonstrate that most of them are focused on the gait aspect of the cognitive disease that interests the authors.

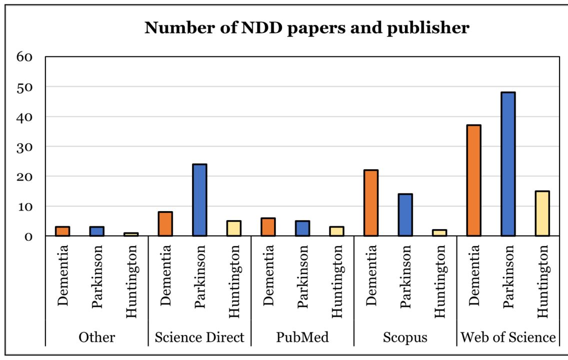
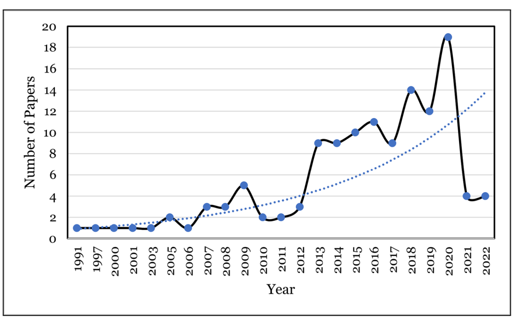
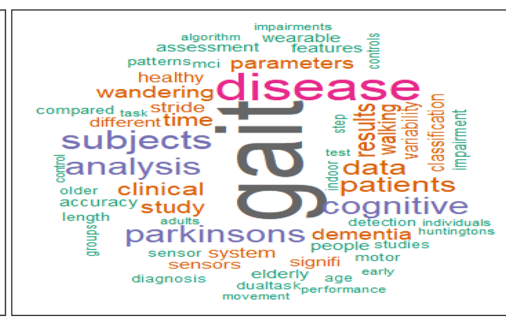


Fig. 3. Number of papers based on considered NDD categories and publisher.

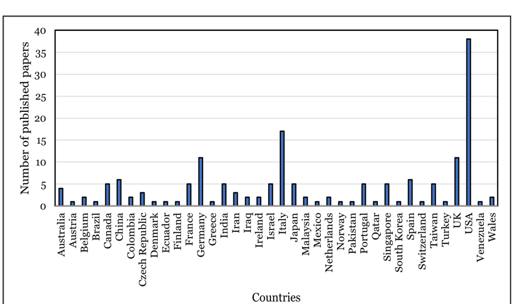


(a) Number of published papers according to the different years

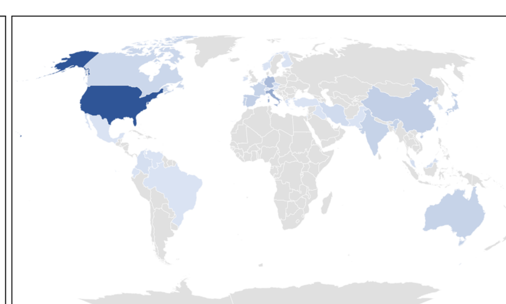


(b) Most frequent words

Fig. 4. Selected papers.



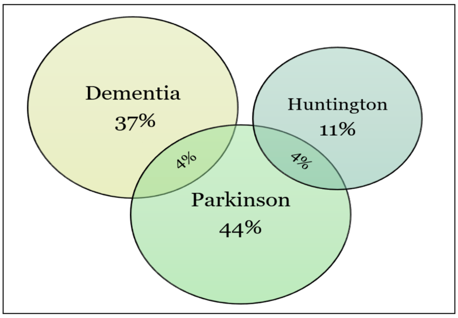
(a) Country-specific production



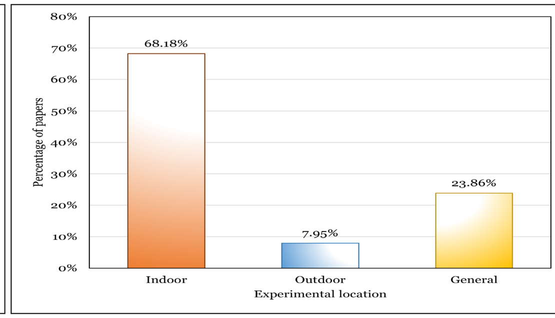
(b) Country distribution production

Fig. 5. Selected papers.

3.2.3 Country-Specific Production. Figure 5 shows that the research papers included in this survey came from 38 countries that include case studies conducted in these countries. As shown in the figure, the countries that produced the most papers considering locomotion anomaly detection and NDDs in sensory environments are the United States, Italy, Germany, and the United Kingdom. In terms of country-specific production, the highest percentage was achieved by the United States (22.75%), followed by Italy (10.17%), and then Germany (6.58%) and the United Kingdom (6.58%).



(a) Percentage of papers according to the considered diseases



(b) Percentage of papers according to observation locations

Fig. 6. Selected papers.

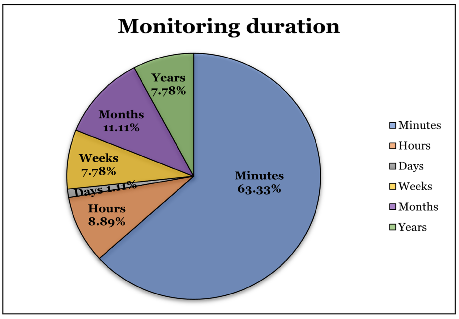
3.2.4 Scientific Production Based on Disorders and Observation Location. Considering the kind of disease, Figure 6(a) shows that PD essentially gained more attention among the researchers compared to dementia, whereas fewer works are related to HD. Considering that some papers address more than one disease, around 52% of papers address PD, about 41% of papers address dementia, and 15% address HD. We further analyzed the scenario in which the individual's locomotion is observed to provide the diagnosis. We considered two observation scenarios: *indoor* and *outdoor*. Among the selected papers, as illustrated in Figure 6(b), statistics show that there are 68.18% of papers that rely on locomotion observation indoors, particularly in private residences, retirement/nursing homes, or hospitals. Most methods relying on indoor observation assume that the individual performs predefined instructions in the presence of one or more observers. A few other papers rely on the observation of unsupervised locomotion during everyday activities in real-world environments.

Papers that rely on the observation of outdoor locomotion are fewer (i.e., approximately 7.95% of the papers). They assume the use of sensors embedded in wearable/portable devices (mainly smartphones, watches, or shoes) or outdoor localization technologies such as GPS readers. Around 23.86% of the selected papers do not rely on the assumption that the locomotion is observed either indoors or outdoors. The category of those papers is named *General* in Figure 6(b).

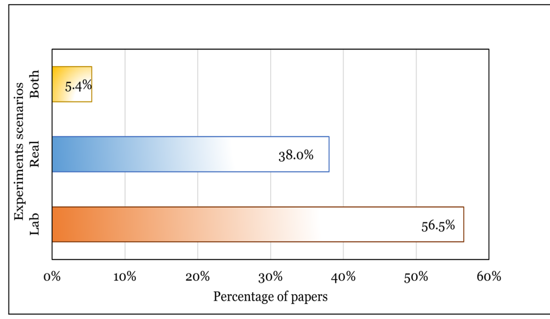
3.2.5 Scientific Production Based on Experiment Scenarios and Monitoring Duration. Figure 7(a) shows the distribution of papers according to the duration of locomotion monitoring. We found out that among those works that explicitly mentioned their observation duration (around 90 papers), many of them (around 63.3% of papers) monitored locomotion for less than 1 hour, around 8.9% of them did so for less than 24 hours, around 1% for less than a week, around 7.8% for weeks, around 11.1% for months, and around 7.8% for 1 year or more. Furthermore, as shown in Figure 7(b), 56.5% of research works carried out their experiments in a laboratory environment, 38% in a naturalistic environment such as the individual's home, and 5.4% in both a laboratory and naturalistic environments.

4 CLINICAL LOCOMOTION INDICATORS OF NDDS

We concentrate on clinical indicators of NDDs related to locomotion. Indeed, several works identified variations of gait patterns and locomotion anomalies typically observed in cognitively impaired subjects [66, 85, 125]. Different research studies consider *wandering*, a concept defined by Algase et al. [5] as a "syndrome of dementia-related locomotion behavior having a frequent, repetitive, temporally disordered, and/or spatially disoriented nature that is manifested in lapping,



(a) Percentage of papers according to monitoring duration



(b) Percentage of papers based on different experiments scenarios

Fig. 7. Selected papers.

random, and/or pacing patterns." Moreover, recent sensor technologies provide the possibility to develop methods for gait analysis to characterize NDDs based on the observation of subtle anomalies in gait patterns. In a normal gait cycle, each stride contains eight phases with functional patterns and objectives defined as follows:

(1) *Heel strike*: Initial contact of the foot touching the floor with the heel.
(2) *Loading*: When the knee flexes and the body weight is moved onto the limb while the other foot is lifted.
(3) *Mid-stance*: When the opposite leg is lifted and advanced.
(4) *Terminal stance*: When the limb advances and the phase ends with the heel striking the ground.
(5) *Pre-swing phase*: When the opposite foot starts touching the ground and the other one is lifted.
(6) *Toe-off*: Initial swing when the foot is lifted from the floor.
(7) *Mid-swing*: When the anterior limb advances.
(8) *Terminal swing*: When the leg moves ahead of the thigh, the foot strikes the floor, and the advancement is completed with the flexion of the knee.

Gait disorders can be related to two main categories: neurological and non-neurological disorders [85]. For the sake of this work, we concentrate on the former category. The instruments used to analyze human gait can be classified into two major categories: ambient/portable wireless sensors (e.g., see [24, 59, 125]) and wearable sensors (e.g., see [57]). For example, smart shoe wearable sensor systems can measure the change in gait over time, and they have been used in neurological exams to diagnose dementia and other neurological disorders. Center of mass movement during walking can be easily tracked using a small **Inertial Measurement Units (IMUs)** attached to the lower back, and it was used for neurological assessment considering the sinusoidal waveform produced by trunk movements during the gait cycle [31].

4.1 General Indicators Based on Gait Analysis

Different low-level motion indicators have been proposed in the literature to detect NDDs [59, 128]. We classify these motion indicators into three categories: simple gait parameters, complex gait parameters, and **Nonlinear Dynamics (NLD)** theory based features, presented next:

- *Simple gait parameters*: These indicators regard fine-grained characteristics of gait, mostly considered in isolation, such as stride-to-stride fluctuations in walking (both in terms of magnitude and dynamics), stride time, stride velocity, and stride length [92]. In this regard,

Table 4. Simple Gait Parameters

Parameter Classification	Parameter	Definition	Ref.
Spatial	Stride length	Distance traveled by the same foot by two consecutive heel contacts.	[12, 23, 26, 31, 42, 47, 92, 95, 112]
	Step length	Traveled distance from one heel footprint to the heel of the opposite footprint.	[14, 23, 26, 27, 63, 74, 92]
	Step width	Distance between the line of progression of the left heel footprint and the line of progression of the right heel footprint.	[50]
	Distance	The cumulative traveled distance.	[47, 57, 67]
Temporal	Stance/swing time	Duration of the stance/swing phase.	[7, 74, 114, 125]
	Stride time interval	The time interval starts when one foot makes contact with the ground and ends when that same foot contacts the ground again. It displays fractal dynamics and reflects the rhythm of the locomotion.	[7, 12, 27, 47, 53, 63, 112, 114]
	Stride time variability	This is related to the control of the rhythmic stepping mechanism and calculated by the mean and standard deviation of stride time.	[47]
	Step time	The time between two consecutive heel strikes.	[14, 23, 31, 63, 71, 74, 92, 93, 114]
	Step rate	The rate of steps per minute, also called *cadence*.	[12, 23, 26, 31, 50, 63, 93, 95]
	Single support time	'Single support' happens when only one foot is in contact with the ground. Single support time is the duration of single support.	[50, 93, 95]
	Double support time	'Double support' happens when both feet are in contact with the ground. Double support time is the duration of double support.	[26, 27, 79, 93–95, 112]
Spatiotemporal	Stride velocity	The stride length divided by the stride time.	[27, 41, 63, 71, 92, 126]
	Stride/step frequency	Number of foot contacts per second.	[12, 41, 42]
	Stride/step symmetry	Duration amplitude similarity of the shape of acceleration curves comparing right and left strides/steps.	[12, 23, 42, 71, 122]
	Step time asymmetry	Defined as the difference between the mean step time of each leg and the combined mean step time of both legs.	[23]
	Stride/step regularity	A measure of stride/step to stride/step consistency.	[12, 23, 42, 53, 71, 122]
	Gait speed	The distance walked divided by the ambulation time.	[12, 23, 27, 31, 42, 47, 53, 74, 92, 95, 112, 114, 128] [12, 12, 23, 27, 31, 47, 53, 74, 92, 95, 112, 114, 128]

gait abnormalities mostly include decreased walking speed, step frequency, step length, and increased gait variability [53]. In Table 4, we extend and refine the classification proposed by Hollman et al. [50] to define the low-level indicators that we use in the rest of the article.

- *Complex gait parameters*: These parameters consider different temporal aspects of locomotion, and structural or geometrical complexity of walked trajectories. We classify them into three groups: variability, postural control, and frequential parameters. Parameters related to variability are based on temporal characteristics of movement pattern, acceleration, speed, duration, and distance. Postural control parameters such as the **Timed Up & Go Test (TUGT)**, **Berg Balance Scale (BBS)**, **Romberg Balance (RB)**, **Short Physical Performance Battery (SPPB)** tests, and so forth include different kinds of postural and balance assessment such as regularity of movements, angles of movement, and trajectory consistency. Frequential parameters consider gait symmetry and are usually derived from Fourier analysis of trunk accelerations. In Table 5, we provide a classification and description of complex gait parameters.
- *NLD theory based features*: Gait assessment is considered as a beneficial tool to help with the diagnosis process and to assess the neurological state of the people with NDD. It is the assessment of a person's walking pattern. Walking is a compounded process that can be evaluated through the application of nonlinear analysis of human gait signals. NLD theory has been introduced to the analysis of biological data. There are also NLD features [15, 83] available such as the correlation dimension, the largest Lyapunov exponent, the **Lempel-Ziv Complexity (LZC)**, the Hurst exponent, **Detrended Fluctuation Analysis (DFA)**, and many others to assess gait impairments of NDD patients. These features are used to

Table 5. Complex Gait Parameters

Parameter Classification	Parameter	Definition	Ref.
Variability	Approximate entropy	Measure regularity of a trajectory under the assumption that a sequence is regular when it contains repetitive patterns and how its structural complexity varies over time.	[71]
	Jerk	The rate at which a subject acceleration changes with respect to time. Jerk is the first time derivative of acceleration. It quantifies the smoothness of a trajectory.	[12, 128]
	Ambulation fraction	The ratio between total time of ambulation and trajectory duration.	[64]
	Straightness	The ratio of the distance between two consecutive trajectory segments and the distance between the start and endpoint of these segments.	[60, 128]
	Path efficiency	The ratio between the distance from the start to the end of a trajectory and the trajectory length.	[64, 128]
Postural control	Turning angle	The sum of the absolute angles between any two subsequent lines in a trajectory.	[12, 64, 128]
	Sharp angles	Vector angles in a trajectory being equal to or more than 90 degrees.	[25, 60, 67, 128]
	Foot clearance	Toe and heel height during the swing phase.	[34]
	TUGT	Time taken for transition from sit to stand, walk, turning, and transition from stand to sit.	[12, 79, 94, 121, 122]
	Fall	Any unintentional event that leads to the landing of individuals on a horizontal plane.	[47, 94]
	BBS/RB/SPPB tests	Balance and postural control assessment to diagnose gait disturbance caused by abnormal perception or awareness of the position and movement of the body during predetermined tasks (i.e., Eyes Open Feet Together, Eyes Closed Feet Together, Eyes Open Feet Apart, Eyes Closed Feet Apart).	[23, 94, 108, 109, 122]
Frequential	Harmonic ratio	Step-to-step (a)symmetry within a stride.	[41, 71]
	Total harmonic distortion	Evaluates the complexity of the human motion by calculating the ratio between the fundamental waves and the harmonic waves.	[71]
	Z-method/S-method/M-method	Gait events based on anteroposterior acceleration, acceleration norm, and vertical acceleration. Both the Z-method and M-method define the gait cycle from the initial contact timing. Additionally, the M-method provides final foot contact timing estimates, swing, and stance duration. Conversely, the S-method considers the zero-crossing instants of the acceleration norm.	[114]

discriminate between NDD patients and healthy subjects and to classify patients in several stages of the disease. In some works [7, 48, 62], DFA is used for the gait assessments of patients with PD and HD. In the work of Sejdić et al. [103], the authors performed a combined analysis of spectral and NLD features to assess gait signals of 14 healthy persons, 10 PD patients, and 11 patients with peripheral neuropathy. These features were compared using the Kruskal-Wallis and Mann-Whitney tests. There are notable differences observed in features such as LZC and cross entropy, which allow to discriminate between healthy persons and PD patients. In the work of Prabhu et al. [86], the authors classified 13 PD patients, 13 amyotrophic lateral sclerosis patients, 13 HD patients, and 13 healthy subjects using data obtained from force-sensitive resistors. The authors computed NLD features such as Shannon entropy, the correlation dimension, the recurrence rate, and recurrence quantification analysis. The classification was performed with SVM and a probabilistic neural network to distinguish between patients with different NDDs and healthy persons. In Table 6, we provide the general NLD theory-based features used to assess the neurological state of patients.

4.2 Indicators of Dementia

As mentioned before, dementia causes a decline in thinking skills, severe enough to impair daily life and independent living. In particular, it affects behavior, locomotion, feelings, and relationships. Different high-level indicators have been presented in the literature to characterize the locomotion behavior of people suffering from dementia [66]. We classify those indicators into four categories: trajectory based, permission based, purpose based, and performance based. In Table 7, we define the specific indicators according to our categorization and the most relevant research works in which they are considered. In the following, we briefly discuss the three classes:

Table 6. NLD Features

Feature	Definition	Ref.
DFA	Observes the degree of correlation of one stride interval with previous and subsequent ones	[7, 48, 62]
Largest Lyapunov exponent	Provides information about the stability properties of the time series as it calculates the sensitivity to initial conditions of the signal according to the rate at which the nearby trajectories of the phase space converge	[15, 83]
Hurst exponent	Assesses the long-term dependency of the time series	[15, 83]
LZC	Relates to the number of different patterns lies along a sequence which reflects the order that is retained in a 1D temporal pattern	[15, 56, 83, 103]

(1) *Trajectory-based indicators:* Trajectory-based indicators are well known for categorizing the patterns of abnormal locomotion behaviors by PwD. A popular model in this regard was proposed by Martino-Saltzman et al. [72]. That model categorizes the trajectories into one of four distinctive patterns of movement: direct, random, lapping, or pacing, illustrated in Figure 8. The direct path is walked by cognitively healthy people, whereas random, pacing, and lapping patterns are typical indicators of dementia. In particular, scientific studies have demonstrated that severely demented individuals perform trajectory-based anomalies all day long, whereas in those who are moderately demented, the percentage of those anomalies increases in the evening and mostly at night [72].

    In a different research study conducted by Kearns et al. [57], it was shown that the tortuosity of a walked trajectory is significantly correlated with cognitive status. A high value of the *fractal* mathematical index of path tortuosity (Fractal D) indicates abnormal trajectories that are typically observed in wandering behaviors [57]. Fractal D is a compact and effective measure to characterize wandering behaviors.

(2) *Permission-based indicators:* Another class of indicators considers anomalous locomotion patterns of people living in constrained environments, which violate the permissions of the caregivers. We name this class of dementia-related locomotion anomalies *permission-based indicators*. As shown in Table 7, these indicators are further classified into abscond/elopement (leaving a safe environment without the caregiver's consent), exit seeking (trying to open locked doors without consent), and invasion/trespassing (invading the private environment of other people without consent) [5].

(3) *Purpose-based indicators:* Most of the studies about wandering behavior consider it as an aimless, directionless movement. Only a few research studies support the theory of wandering as a goal-seeking behavior. According to the latter theory, some wandering behaviors have a specific purpose, such as to satisfy a need or to communicate a need. Accordingly, we classify those behaviors as *purpose-based clinical indicators*. Most of these indicators have been identified by Algase et al. [5] and are described in Table 7.

(4) *Performance-based indicators*: These are based on the performance of certain tasks that evaluate cognitive dysfunction and memory impairment. The **Mini-Mental State Examination (MMSE)**, **Montreal Cognitive Assessment (MoCA)**, and **Canadian Consortium on Neurodegeneration in Aging (CCNA)** are widely used measures and protocols to evaluate cognitive dysfunction based on gait analysis [20, 21, 63, 122]. The score range of MMSE and MoCA is from 0 to 30. In these tests, if the final score is lower than 24 in MMSE, or less than 20 in MoCA, the subject will be regarded as cognitively impaired. However, the CCNA classifies gait disturbance into different categories such as normal gait, ataxic gait, antalgic gait, cautious gait, frontal gait, and hemiparetic gait, among others.

Although trajectory-based indicators are mostly used for diagnosis only, permission-, purpose-, and performance-based indicators are also used for ensuring the safety of the elderly suffering from NDDs by monitoring his or her locomotion behavior and prompting caregivers accordingly.

Table 7. Dementia Locomotion Indicators

Indicator Classification	Indicator	Definition	Ref.
Trajectory based	Direct	Defined as moving straight from one location to another one without relevant diversion.	[65, 119]
	Pacing	At least three consecutive back-and-forth movements between two locations.	[4, 59, 65, 67, 119]
	Lapping	Repeated circular movements around a small area.	[4, 59, 65, 67, 119]
	Random	Inefficient or aimlessly movement across different locations, generally passing through more than four locations.	[4, 65, 119]
	Fractal D	A statistical value extracted from a trajectory, which measures the geometric complexity and tortuosity. It ranges from a value of 1 when the movement path is entirely straight to a value of 2 when the movement path is random.	[57]
Permission based	Abscond (or Elopement)	This situation is referred to when a patient leaves the hospital or the ward with intent, leaving the safe environment's boundaries, or forays into the community without the caregiver's consent, causing severe concerns.	[5, 17, 77]
	Exit seeking	In this situation, the patient attempts to leave a safe environment, pressing panic bars or trying to open locked exit doors, and sometimes includes pulling, pushing, kicking, and knocking or pounding on the door.	[5, 119]
	Invasion and trespassing	This situation occurs when the patient enters other people's rooms without permission, or when the patient walks into unauthorized spaces.	[5]
Performance based	MMSE	Widely used set of question answering tests for screening cognitive function. It indicates the presence of cognitive impairment in PwD. It has the measures of orientation, registration (immediate memory), short-term memory, and language functioning.	[122]
	MoCA	Considered as a clinician-reported measure that takes about 10 minutes to analyze cognitive impairment. It measures cognition in various domains such as visual-spatial skills, executive functions, attention, concentration, calculation, language, abstraction, memory, and orientation.	[20, 27, 63]
	CCNA	Considered as a protocol on how to assess gait in the elderly, including preferred and fast pace gait, and dual-task gait.	[21]
Purpose based	Inappropriate to circumstance	This term is used when the patient constantly searches for something that is unattainable, shows aggression, repetitive behaviors, and inappropriate behavior by social standards.	[5]
	Aimless and disoriented	This type of wandering behavior is characterized by a lack of focus or no apparent direction for reasons such as fear, memory loss, and feelings of discomfort (e.g., hungriness, boredom, pain). In this situation, the patient has difficulties in finding the way and he or she is getting lost in familiar and unfamiliar places.	[5, 77, 113]
	Escapist	In this situation, the patient attempts to get somewhere beyond the view and control of the caregiver.	[5]
	Persistent	This situation occurs when the patient searches for 'missing' people or places without rest for a long time.	[5]
	Modeling (or Shadowing/ Tagging/Trailing)	In this condition, the patient follows other people around.	[5]
	Nocturnal	This situation occurs when the patient walks around inappropriately at night.	[5]
	Pottering	Pottering refers to partial attempts to carry out household tasks that, with the progress of cognitive decline, become less and less meaningful.	[5]
	Repetitive	This situation occurs when the patient walks toward a purpose, or carries out tasks, inappropriately often, repeatedly, and with abnormal frequency.	[5]

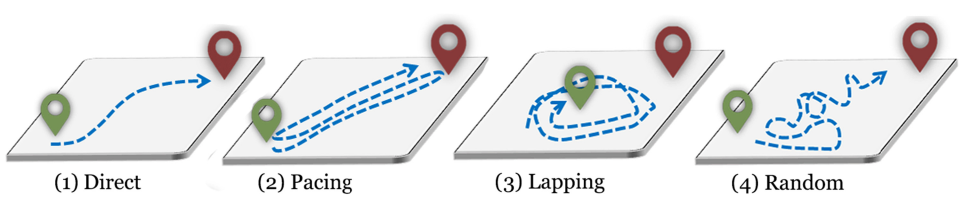


Fig. 8. Travel patterns according to the Martino-Saltzman model [60].

4.3 Indicators of PD

As anticipated, PD severely affects the human motor system. Gait impairment such as bradykinesia is one of the most common disabling symptoms for PwPD. It refers to the slowness of movement observed in patients. Locomotor dysfunction, shortened stride length, increased variability of stride, and shuffling gait are cardinal features of PD. Therefore, different indicators were proposed to characterize the pathological gait in PD. Gait analysis on the walking behavior of PwPD

Table 8. PD Movement Indicators

Indicator Classification	Indicator	Definition	Ref.
Single-task assessment	FRT	This test evaluates the stability of individuals by measuring the maximum distance they can reach forward while standing in a fixed position.	[94]
Multitask assessment	UPDRS	Employed as a tool to calculate the intensity of PD, formed as a gold standard to observe the response of medications in Parkinson's patients. It is scored on a 0 to 4 rating scale and is established on a few segments, such as motor impairment, behavior, and daily life activities.	[28, 76, 89]
	UDRS	Used to estimate involuntary movements in PD patients due to medication assumption. The scale has measurements for 'on-dyskinesias' (jerking or turning movements) and 'off-dyskinesias' (cramps).	[91]
	MDS-UPDRS	This is a revised version of UPDRS, formed in 2007, utilized to measure different aspects of PD, including nonmotor and motor functions in activities of daily living and motor complications.	[43]
	H&Y	Used to assess the progress Parkinson advancement and the level of disability, formed in 1967.	[14]
	FOG Questionnaire (FOG-Q)	Employed to measure FOG advancement for PD patients, FOG frequency, disorders in gait, and connection to clinical features associated with gait and motor aspects.	[80]
	NFOG-Q	A renowned tool to estimate the progression of FOG. It is a self-reportable questionnaire with nine items to assess FOG.	[80]

is usually performed by monitoring several low-level parameters, mentioned in Table 4, over extended periods, including stride length, step length, stride velocity, and swing time. There are also a few common complex gait parameters and NLD features used to detect gait abnormality in PD, mentioned in Tables 5 and 6.

Generally, gait disorders in PwPD are evaluated by observing the gait in a laboratory with the help of one or more other clinical assessment scales. Several clinical indicators have been introduced in the literature. We categorized them as multitask assessment indicators, which are illustrated in Table 8. The **Unified Parkinson's Disease Rating Scale (UPDRS)**, the updated version of UPDRS, and the **Movement Disorders Society Modified Unified Parkinson's Disease Rating Scale (MDS-UPDRS)** are the most common assessment scales to evaluate the severity of PD. They are focused on estimating the intensity of PD. The UPDRS was developed in 1987 as a gold standard for observing the reaction to medications employed to reduce the signs of PD [6]. These tools are scored on a 0 to 4 rating scale, where higher scores denote risen severity. Traditionally, these scales include three sections used to estimate critical areas of disability. They are based on motor function, including getting up from a chair and postural stability. The **Hoehn and Yahr (H&Y)** scale, formed in 1967 [49], is another most commonly used tool to evaluate Parkinson's symptoms and the level of disability established on motor function. It is ranked in stages from 1 to 5 and describes complex patterns of advanced motor impairment.

Advancement in H&Y stages is connected to motor decline, the decline in quality of life, and neuroimaging studies of dopaminergic loss. Table 8 summarizes the leading clinical indicators for PD related to locomotion analysis.

4.4 Indicators of HD

PwHD experience locomotion impairments that can lead to fall, reduce the quality of daily living activities, and increase hospital admission and mortality. There are two main approaches to assess mobility and balance impairments for HD diagnosis: semi-quantitative clinical observational tests and laboratory-based assessment. The former approach is based on observation by a clinical expert and regards the assessment of locomotion impairments such as bradykinesia and decreased velocity, dynamic balance loss, and increased base of support [94]. The latter approach is expensive, as there is a need for extensive training, and it is not available in most clinical settings. Hence, there is increasing interest in innovative tools for supporting the diagnosis of HD by utilizing sensor instruments. Different clinical indicators have been proposed in the literature. We classify them in two categories: single-task assessment and multitask assessment indicators, which are

Table 9. HD Clinical Indicators

Indicator Classification	Indicator	Definition	Ref.
Single-task assessment	FRT	This test evaluates the stability of individuals by measuring the maximum distance they can reach forward while standing in a fixed position.	[94]
Performance-oriented assessment	UHDRS	It includes four components: Total Motor Score, Functional Assessment Scale, Total Functional Capacity scale, and IS. It evaluates motor impairment considering a range of voluntary and involuntary movements, including retropulsion pull test for postural stability, bradykinesia, coordination, balance, and gait.	[19, 23, 26, 70, 90, 93, 94]
	HD-ADL	A scoring-based scale which is including adaptive functioning assessment based on daily living life activities and family relationships and it is validated for PwHD.	[94]

illustrated in Table 9. Most of the gait indicators used for HD diagnosis are general gait indicators (presented in Section 4.1). Here, we classified the locomotion indicators that are combined and presented as clinical tests for recognizing anomalous gait related to PwHD. Aside from those indicators, other research studies investigated the use of general gait indicators (including swing and stance intervals, stride interval time series, gait velocity, the TUGT, and BBS and RB tests) for HD diagnosis [7, 95, 114, 125]:

(1) *Single-task assessment*: Single-task assessment indicators rely on examination of gait or stability during the execution of a given locomotion task. The **Functional Reach Test (FRT)** evaluates stability by measuring the maximum distance that an individual can reach forward while standing. This measure has proved to be highly correlated with HD severity [94]. This indicator is performed during a single session and is led by a therapist.
(2) *Performance-oriented assessment*: Performance-oriented indicators evaluate different abilities, including stability and locomotion, during the execution of complex tasks. The **Unified Huntington's Disease Rating Scale (UHDRS)** considers motor impairment due to different voluntary and involuntary movements, together with the ability of independently executing daily living activities [26, 93]. The **Huntington's Disease Activities of Daily Living (HD-ADL)** scale assesses balance, postural control, and adaptive functioning during certain tasks, which may be impaired by abnormal perception of the body's position and movement in PwHD [23, 94].

5 TOOLS AND TECHNOLOGIES

It is possible to use a wide range of low-cost sensors to track the position of users and their movements, detect cognitive problems, and ensure their safety. Therefore, all locomotion analysis methods have as a first step the collecting of movement data by utilizing sensory instruments. In this section, we explain the most common sensors, either wearable/unwearable, for healthcare solutions, and discuss their pros and cons regarding locomotion anomalies and NDDs. Moreover, we refer to *device-based technologies* as those tools that require the user wearing a device/tag, or even a device needs to be carried, whereas *device-free technologies* do not require user intervention and mostly they are embedded in objects/environment [11, 81]. However, most of these devices could be invasive and obtrusive, especially the ones that need to be worn all the time by the user. Most importantly, the indoor localization technologies raise some serious privacy risks, as the position of the user is always known and that may not be desirable for the user [100].

5.1 Device-Based Localization Sensors

Device-based location identification consists of wearable/mobile devices, such as watches, bands, pendants, earphones, and collars, that help in locating the user:

- Magnetic-based technology utilizes a mobile magnetic sensor, usually a mobile phone, to measure the magnetic fields in different positions of an indoor environment. These measurements are used to construct a map of the location, which represents a reference for user localization [68].
- In mechanical-based devices, the user's location is estimated with an IMU. The IMU uses a combination of accelerometers, gyroscopes, and even magnetometers to calculate a target's current position from a known starting point, with previously determined speed and direction [4, 24].
- Location-based **Radio-Frequency Identification (RFID)** utilizes electromagnetic fields to specify tags connected to things. An RFID system has a radio transponder, receiver, and transmitter. It transmits data to a reader device when triggered by an electromagnetic interrogation pulse from the reader device [101].
- **Ultra-Wideband (UWB)** systems [57, 64] transmit information over a large bandwidth and use measures such as time of arrival and time difference of arrival to locate the distance between two entities. UWB systems provide high accuracy. The UWB signal can penetrate walls and many other additional materials.
- Force sensing technologies are those sensors used to detect physical pressure, squeezing, and weight. They could be simple resistors that are embedded in shoes and change their resistive value based on how much it is pressed, which are low cost [69] or mat-shaped step sensors to detect contact of the feet on the floor where a footswitch is installed next to the patient's bed [66].
- A wristband, watch, or smartphone is incorporated with IMU technologies or different types of sensors that are used as a combination of accelerometers, gyroscopes, touch screens, and even magnetometers. A smartphone, as an example of an IMU, makes remote patient monitoring possible and give faster access to providers and care, and such technology is widely adopted for NDD monitoring [24, 45, 89, 100, 104, 120, 127]. It also leads to improved communication, fewer hospital visits, and reduced patient costs. Furthermore, these wearable wristbands and watches can be used in healthcare solutions because of their simple design, common on-body placement, and connectivity with mobile phones [4, 48, 73].

5.2 Device-Free Localization Sensors

Device-free technologies allow gathering the user's position without needing him or her to carry any device. They are mainly based on motion detection and provide data in real time [37, 100]. There are different sensor technologies that can be used for this purpose, which are briefly explained next:

- Infrared-based technologies are utilized in passive infrared sensors and active infrared sensors [51, 59, 63, 65]. The former measure infrared light radiations from people, as they emit heat energy in the form of radiation. The latter require a transmitter to continuously send beams of infrared light and a receiver detecting when the beam stream gets interrupted by a mobile object moving across the scan area.
- **Microelectromechanical Systems (MEMS)** pressure sensors detect falls and wandering patterns based on the number and pattern of activation on a gait mat or on the floor and measure foot strike [106, 107].
- Ultrasonic transmitters emit an ultrasonic wave that gets reflected by objects in the scan area, and they detect Doppler shift at low audio frequencies, similarly to microwave devices [61].
- Computer vision based sensors such as utilizing cameras or visual sensor networks are promising in an ambient sensing approach to pervasive healthcare delivery. By utilizing these kinds of technologies, it is possible to compare sequential images from captured video

streams, monitoring 3D spaces, and detect movements when there are enough changes between the frames by scene analysis and proximity techniques even by compact on-node image processing and computer vision algorithms [63, 72, 88, 116].

- Radio signals and their reflections can be used to detect individuals' movement and position over time. Furthermore, by utilizing microwave signals, the movement of an object causes a phase shift in the emitted radiation, creating a signal at low frequency. Thanks to this technology, ultra-low-power radio signals in tomographic motion detectors [11] and wall-mounted sensors [57] can sense radio waves at frequencies that penetrate most obstacles and walls, detecting the user's position over large areas.
- Ambient light communication technologies are based on light sensors that receive the signals of light-emitting diode emitters with different flicker encoding so that they can be compared to measure direction and position, as well as provide localization [11].

5.3 Strengths and Weaknesses of Localization Sensors

All device-free and device-based technologies, as shown in Table 10, have their own strengths and weaknesses.

Mechanical-based systems are cheap and effective. They have high mean time between failure and consume less power, but they are vulnerable to cumulative error. Acoustic systems can provide high accuracy even between rooms, but the signal detection should be low power to not be heard and to not cause sound pollution. They are also sensitive to temperature changes and noise. Magnetic-based systems offer high accuracy, but they are sensitive to conductive and ferromagnetic materials. Optical-based systems provide high accuracy and are not affected by a multipath effect, but they require line of sight and consume higher power, and range is affected by obstacles [11, 100]. WiFi-based systems are relatively cheap and widely available without needing complex hardware. Bluetooth is supported by most modern devices, such as smartphones and smartwatches. It is low cost and has very low power consumption, but the signal is quite attenuated from obstacles. UWB systems provide high accuracy. They are less sensitive to multipath effects and are immune to interference, but they have shorter range and their cost is high. RFID systems consume low power and have wide range and low cost, but they require proximity and the localization accuracy is low. MEMS pressure sensors are small in size, have lower cost and power consumption, and provide high consistency.

In terms of accuracy, both mechanical-based systems and ultrasound systems offer higher accuracy. The latter can reach accuracy from 0.01 to 1 m. Magnetic-based systems provide high accuracy on the order of few centimeters. WiFi has an accuracy between 1 and 5 m; Bluetooth, instead, has an accuracy from 2 to 5 m. A beacon can determine three ranges of proximity: immediate (less than 50 cm), near (between 50 cm and 2 to 5 m), and far (between 5 and 30 mm). The accuracy depends on interference from physical obstacles. UWB offers an accuracy of up to 10 cm, whereas RFID accuracy is relatively low and is from 1 to 5 m.

In terms of obtrusiveness and privacy, ambient light systems, as audible sound, could be annoying to the user, but they could be resolved by reusing an already available light infrastructure to be not intrusive or, in the case of audible systems, using digital watermarking of audio signals. In computer vision sensors, however, they can do real-time monitoring but there remain privacy concerns and scalability problems. Additionally, there is a difficulty in detail deduction or subtle changes in movement patterns, and they are unable to detect physiological parameters, which may lead to hindering their application for ambient sensing frameworks [100].

Infrared sensors offer 1 to 2 m accuracy, whereas light-emitting diode implementations using fixed lamps report an accuracy below 20 cm. Utilizing infrared technology also has some limitations, such as moderate accuracy, the need for more receivers to improve accuracy, and interference

Table 10. Comparison of Tools and Technologies Related to Movement Detection

Tool	Sensor	Accuracy	Installation Cost	Complexity	Scalability	PowerConsumption	Advantages	Disadvantages
Device based	Magnetic	High	Low	Moderate	Moderate	Low	Real time, Easier to assess physical activity	Unethical as it decreases a person's autonomy
	Mechanical	High	High	Moderate	Moderate	Relatively high	Real time, Easier to assess physical activity	–
	UWB-IR sensors	Low	Low	Moderate	Low	Relatively high	Cheap, Nonintrusive	–
	RFID	High	High	Moderate	Moderate	Low	Real time, Easier to transmit information over a large bandwidth, Variety of activities can be detected, High accuracy	Initial cost, Array of tags is needed, Adjustment is needed in different environments, Computationally complex, Feature extraction needed, Reduced performance in complex environments
	Force sensing	Moderate	Low	Moderate	Low	–	Cheap, Nonintrusive, Easy to extract data, Detection computationally simple	Arrangement of sensors is important for higher accuracy, Impractical for some activities due to vibration
	IMUs	High	Low	Moderate	Low	Moderate	High sampling rate, Triaxial data measurement enables 3D analysis, Sensors are small, light weight, and cost-effective, Monitoring of gait properties during daily activities, Active role of patient can be monitored	Suffers from drift, Uncomfortable since sometimes needs to attach to the body, Interruption in actual data measurement due to skin movement artifacts, Different positions of sensor attachments show variations in acceleration sensing, Limited battery duration, Complex strategy to estimate gait parameters
Device free	Infrared	Moderate	High	Low-Moderate	Moderate	Low	Cheap for end user, Easy to use, Detection in darkness, Preserves privacy (low resolution)	Sunlight inference, Needs more receivers, Noise sensitive, Low range of detection
	MEMS pressure sensors	Moderate	Moderate	Low	High	Low	Extremely high sensitivity and consistency, Nonintrusive, Low power consumption, Extremely scalable, Can be readily integrated with microelectronics	Expensive, Fabrication, assembly unit costs, Testing equipment to characterize the quality and performance can be very high for low quantities
	Ultrasonic/ Ultrasound	Moderate	High	Moderate	Moderate	Low-Moderate	Good precision, Nonintrusive	Cost, Multipath effects and line of sight
	Computer vision	High	High	High	Low	Moderate	Real time, Good accuracy	Sensitive to light conditions, Privacy concerns, Unable to detect subtle changes in motion patterns and deducing details
	Radio signal	Low-Moderate	Low-Moderate	Moderate	Moderate	Low	Cheap, Penetrates most obstacles and walls and covers a large area, Nonintrusive, Cost-efficient, High accuracy, Acceptable performance in complex environments	Requires proximity, Computationally complex, Feature extraction needed, Sensitive to noise interference, Adjustment needed in different environments
	Ambient light	Low	Low	Moderate	Low	Relatively high	Cheap, Nonintrusive	Sensitive to light conditions, Could be annoying for the user

of infrared waves in the presence of fluorescent light and sunlight, leading to a reduction in system usability. They also are invisible to the human eyes, whereas ultrasound is undetectable to the human ear, so they are not intrusive at all [100]. However, they are useful for movement detection, but still there is a general limitation, which is low accuracy due to multipath effects and line of sight.

In summary, in practical applications, both device-based and device-free technologies provide complementary information, and successful systems are only feasible by integrating the two sensing modalities.

6 ALGORITHMS AND APPLICATIONS

In this section, we classified sensor-based algorithms and applications for recognizing NDDs according to the locomotion indicators reported in Section 4. This classification is presented in Figure 9. We also illustrate AmI techniques to recognize challenging behaviors.

6.1 Detection of Dementia

To categorize the existing solutions for recognizing symptoms of dementia, we propose the classification shown in Figure 9.

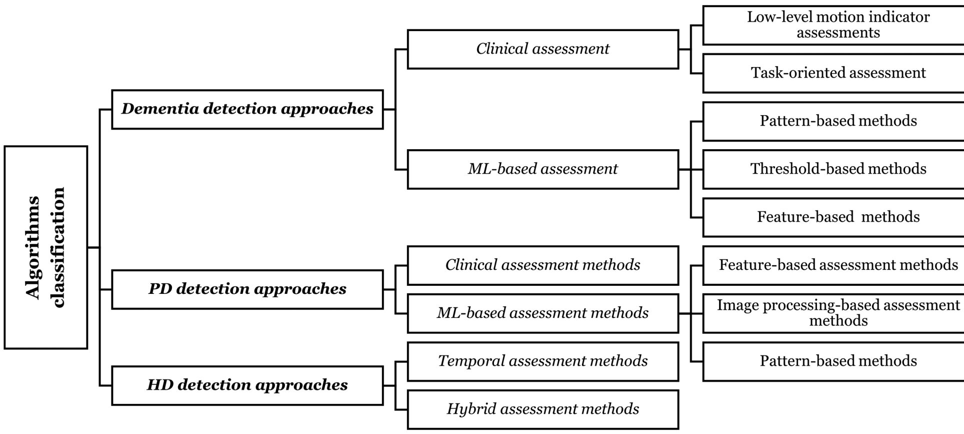


Fig. 9. The proposed framework for dementia detection approaches.

In the following, we present the most prominent methods according to our classification, namely clinical assessment and ML-based assessment. Those methods are summarized in Table 11.

6.1.1 Clinical Assessment. In this group of approaches, detection is based on prior knowledge, results of clinical tests, and statistical analysis of locomotion data by supervision of operators and medical experts. Therefore, these kinds of approaches strongly rely on human resources and experts to evaluate the cognitive status of an individual. We further classify the clinical assessment methods into *low-level motion indicator assessment* and *task-oriented assessment* methods, both of which rely on general gait indicators. The former methods consider specific low-level motion indicators, which in some cases allow distinguishing among the different dementia disease subtypes, such as AD and dementia with Lewy bodies [74, 92]. Hence, the choice of the specific indicators has an important impact on the diagnosis. In addition to motion indicators, the latter methods consider executive and memory functions, adopting an approach called *dual tasking*. In both approaches, the patient evaluation is supervised by clinicians and executed during predefined, short, structured testing sessions. The fact that tests are not performed in naturalistic conditions can obviously have an impact on the effectiveness of the evaluation [12, 74]. The methods are described as follows:

(1) *Low-level motion indicator assessment*: The evaluation of different gait features, including simple and complex gait parameters, is commonly considered an important part of dementia assessment, and their locomotion patterns are considered good predictors of diverse adverse health outcomes and mobility "bio-markers" [114]. Different studies have shown that by sensor-based gait cycle analysis of PwD vs cognitively healthy seniors, it is possible to find a correlation between variability in different gait parameters and cognitive decline progression [12, 74]. As an example, the experiments conducted by Kearns et al. [57] revealed that there is a correlation between higher tortuosity of the path with lower MMSE scores, which is assessed by clinicians.
(2) *Task-oriented assessment*: Task-oriented methods are based on single-task and dual-task (sometimes called *Talking While,Walking* [122]) walking assessment, which consider the concurrent performance of a motor-motor or motor-cognitive task. The evaluation relies on measuring the interference of the different tasks on each other. Indeed, while the individuals divide their attention to multiple tasks, they have difficulty in regulating the stride-to-stride variations of locomotion, and this difficulty is stronger for cognitively impaired

Table 11. Classification of Dementia Detection Methods

Locomotion Anomaly Detection Approach		Main Idea	Characteristics	Challenges	Algorithms
Clinical assessments	Low-level motion indicator assessment	Methods rely solely on different low-level gait indicators including simple and complex gait parameters	–Possibility to find correlation between gait parameters and cognitive status –Detecting early and longitudinal cognitive changes –Possibility of real-time assessment –Useful to help in differentiating between PwD and cognitively healthy seniors	–Relevant clinicians' effort for the evaluation of cognitive status –Clinical indicators and assessment algorithms must be carefully chosen –Experiments are supervised and they are based on predefined, short, structured testing sessions	Statistical analysis [12, 57, 74, 79]
	Task-oriented assessment	Based on single- or dual-task assessment, and the latter consists of evaluating gait parameters together with executive and memory functions	–Ability to assess the concurrent performance of a motor-cognitive or motor-motor task independently –More naturalistic gait assessment –Useful to support the diagnosis of cognitive impairment symptoms in the early stage	–Need for clinical experts for evaluating the test outcomes –Algorithms, tests, and indicators must be carefully chosen –Complex execution and evaluation of tests	Statistical analysis [27, 42, 47, 53, 71, 92, 126]
ML-based assessment	Pattern-based methods	Consider locomotion data as a temporal sequence of locations (trajectories)	–They rely on unobtrusive environmental positioning infrastructures –Based on wandering models such as the Martino-Saltzman model –Location data represented by sequences or images –Possible to add extra features and data sources –Suitable for long-term analysis	–Need large volume of data –Trajectory segmentation is challenging –Execution of daily living activities may interfere with the walked trajectories	Shallow ML algorithms [59, 60], Multilayer deep neural network [128], *K*-repeating sub-strings features [65], Recurrent neural network [16]
	Threshold-based methods	They rely on data-driven thresholds to recognize gait and locomotion phases	–Adaptive thresholds for the different classes of individuals –Low computational complexity and latency	–Thresholds definition is challenging and subject to contextual factors –They need model calibration for the different subjects	Gait phase detection method [75], Proposed algorithm based on degree of movement and orientation [119], Low-pass filtering and threshold-based peaks and valleys identification [121]
	Feature-based methods	Based on supervised ML and feature extraction methods to capture multidomain characteristics of dementia	–Inclusion of multiple factors for the recognition of dementia –Integrated analysis of locomotion, gait, and postural features –Use of feature selection to improve performance and reduce execution time	–Classification performance depends heavily on feature engineering –Need large volumes of data	Shallow ML algorithms [20, 41, 46], Convolutional neural networks [63], Trend analysis [64], Multiple logistic regression [112], probabilistic neural network [122]

people [27, 112]. Impairment in executive functions (e.g., verbal fluency [71], visual-spatial skills [47], counting aloud backward from 100 to zero [71]) is one of the earliest indicators of cognitive decline. As an example, different experiments have proved that PwD have a more variable within-bout and irregular trunk acceleration pattern, higher step duration and gait complexity, and less variable across-bout walking pattern on single- and dual-task walking (e.g., words enumeration) compared to healthy persons [47, 53, 92]. The execution and evaluation of task-oriented assessment methods is more complex than the one of low-level motion indicator methods but allows the recognition of early-stage cognitive decline.

6.1.2 ML-Based Assessment. Another group of approaches rely on ML algorithms to distinguish between cognitively healthy subjects and PwD based on the observation of movement and behavior. Compared to the clinical assessment approach, ML-based assessment enables the evaluation of the cognitive status in more naturalistic settings. Indeed, the observation is usually carried out in the inhabitant smart home or in instrumented retirement homes. Moreover, ML-based assessment can be carried out unobtrusively for long time periods and requires less clinical effort compared to the clinical assessment method, enabling both long-term and short-term monitoring [59]. We classified the different ML-based methods into three categories (see Figure 9): pattern based, threshold based, and feature based. Pattern-based methods consider movement as a temporal sequence of locations, which describe the trajectories walked by an individual, and directly process that sequence to provide a hypothesis of diagnosis. Threshold-based methods use thresholds inferred from the data to detect dementia based on locomotion signals collected by ambient or wearable sensors. Feature-based methods apply ML algorithms to feature vectors extracted from locomotion data for recognizing dementia. The underlying clinical indicators used by these methods are reported in Section 4. The methods are as follows:

(1) *Pattern-based methods*: These methods process trajectory data to recognize abnormal patterns that may indicate dementia according to specific indicators, such as the Martino-Saltzman model [72]. Since ambulation episodes are composed of locomotion and nonlocomotion phases, a key step is to segment locomotion traces to recognize significant trajectories. A wrong segmentation of trajectories may disrupt the effectiveness of the pattern recognition algorithms. Moreover, the execution of daily living activities, especially in indoor environments, may impact the individual's movements, increasing the complexity of trajectories and incorrect detection [59]. Some pattern-based methods are nonsupervised. For example, in the work of Khodabandehloo and Riboni [59], the authors detect loops (i.e., pacing and lapping episodes) building a buffer on the trajectory segments and considering the percentage of intersection among the buffered segments composing the same trajectory. Other works represent the trajectory as a string of locations, and detect abnormal patterns using the longest repeated substring algorithm [65]. Other authors propose the use of supervised ML algorithms to recognize abnormal trajectories. Zolfaghari et al. [128] represent trajectories as colored pictures to encode features such as speed and sharp points, and they use a multilayer deep neural network for determining whether the trajectory is by PwD, by a person with mild cognitive impairment, or by a cognitively healthy senior. Since pattern-based methods rely on data acquired in naturalistic environments, they are prone to misclassification errors due to noise in sensor data acquisition and interference of external factors (e.g., activities, interaction with other people, obstacles in the home). Hence, these approaches tend to be effective mostly for long-term monitoring [59]. Other methods include the application of low-pass filters to location data for noise reduction especially for data collected from inertial sensors, or the addition of extra features such as statistics extracted from trajectory data [59, 65], activities, and abnormal behaviors [60]. Furthermore, Chaudhary et al. [16] tried to implement an early dementia detection system in an indoor environment using travel patterns of the inhabitant and a recurrent neural network, which automatically extracts the high-level features.
(2) *Threshold-based methods:* This category of methods detects gait phases by mining thresholds from the data for segmenting events, recognizing gait cycles, and locomotion phases. Meng et al. [75] used accelerometer data and adaptive thresholds to recognize the gait phases of PwD and cognitively healthy seniors. In the work of Vuong et al. [119] the authors presented a solution for detecting locomotion anomalies in dementia patients using a wearable Opal monitor that includes an accelerometer, a gyroscope, and a magnetometer. To recognize direct, pacing, lapping, and random movement patterns, they considered translational acceleration threshold to detect a walk event, then they tracked the movement orientation until the algorithm would detect that the subject has made a complete stop. The classification is done by considering a different range of orientation degrees for different locomotion patterns. Wang et al. [121] proposed a threshold-based method to automatize the TUGT. Event segmentation is based on thresholds to identify peaks and valleys during forward motion, swing points, and stance point. Experimental results showed that PwD need more time for TUGT tasks such as sitting and standing up compared to cognitively healthy subjects. Of course, in such methods, a key factor is the threshold definition. Since different subjects may walk with high variation in cadence and step length, those works need adaptive thresholds

for different classes of subjects and specific model calibration for the different individuals. An advantage of threshold-based approaches is the low computational complexity and feasibility for real-time applications at the edge.

(3) *Feature-based methods*: As explained before, dementia is a complex impairment that impacts several domains. Hence, it is natural to consider different features for its detection. Feature-based methods rely on feature extraction techniques to represent the different characteristics of locomotion data, and on supervised ML algorithms to classify the feature vectors according to the cognitive status of the subject. In feature-based methods, locomotion features used for recognizing dementia include kinematic characteristics of postural control such as displacement on the transverse plane and dispersion radius [20], accelerometer-based gait parameters (e.g., walking speed, step frequency, compensation movements, acceleration variance) [41], gait symmetry and regularity [122], and other gait variables including step counts, step duration, speed, and accelerometer and gyroscope statistical measures [46].

Toosizadeh et al. [112] extracted different features from accelerometers worn by patients on the upper arm, on the wrist, and on the shins, during the execution of dual tasking. Those features considered both upper-extremity function parameters (e.g., elbow angular velocity, acceleration) and gait parameters (e.g., speed, time interval, distance). Analysis of variance tests showed significant correlation between upper-extremity features acquired during the dual task and the MoCA cognitive assessment result of the patient. Kumar et al. [64] used trend analysis on different navigational features, including speed, path efficiency, angle turn, and ambulation fraction, to distinguish PwD from cognitively healthy seniors considering UWB location data acquired in an assisted living facility. Together with feature extraction, some of these methods apply feature selection techniques to increase recognition rates, reduce computational effort, and avoid overfitting [41, 46, 122].

Kondragunta et al. [63] used data acquired from depth cameras during both single and dual tasking, and extracted several features including step length, step time, stride time, and cadence, by applying 3D human pose estimation techniques. They proposed using dynamic time warping on those features to recognize PwD, individuals with mild cognitive impairment, and cognitively healthy seniors. Compared to wearable sensor systems, techniques based on cameras are less obtrusive, but they are prone to detection errors in low-light conditions and are generally more computationally expensive. Moreover, the use of cameras pose serious privacy issues, especially when they are deployed in private homes [9]. A shortcoming of feature-based methods is that the accuracy of recognition strongly depends on feature engineering. Moreover, being based on supervised learning, those methods have a need for large volumes of training data that are expensive to capture in real-world settings.

6.2 Detection of HD

As explained in Section 4.4, HD determines impairment in motor control characterized by chorea and dystonia. Several studies have shown that HD symptoms based on locomotion are observable in premanifest individuals well before the actual diagnosis [23, 93]. Therefore, recognizing temporal changes in gait parameters is important for early diagnosis and to help in delaying disease progression. Different studies used pressure-sensitive walkway instruments capable of recording spatiotemporal gait data with high precision [23, 90, 93–95]. Other works are based on wearable sensors, such as force-sensitive switches embedded in shoes [7, 48], an accelerometer and gyroscope positioned on a waist belt [114], or IMUs attached to the shank [70]. Experimental results have shown that PwHD experience a decrease in velocity, stride length, and cadence, and an increase in parameters related to dynamic balance impairment, including increased time in double support and gait asymmetry [90]. Furthermore, as presented in the state of the art, there are facts

Table 12. Classification of HD Detection Methods

Approach	Main Idea	Characteristics	Challenges	Algorithms
Temporal assessment methods	Use IMUs mounted on waist or embedded in shoes to monitor temporal gait parameters such as stride interval	–Applicable indoors and outdoors –Data can be acquired in naturalistic conditions –Minimally obtrusive	–Limited to certain locomotion data –External events and noise can impact the recognition performance –Need for extensive training datasets acquired in variegated conditions	Statistical analysis [48], Gait event detection methods [114], Threshold-dependent symbolic entropy [7]
Hybrid assessment methods	Use wearable sensors or sensorized pressure-sensitive walkways to investigate different aspect of mobility and balance by considering different types of clinical gait indicators	–Accurate acquisition of motor data alongside clinical walking measures –The use of different types of indicators increases accuracy –Good correlation with fluctuation limitation and quantitative gait measures and gait patterns, dynamic balance, and fall risk	–Results may reflect general gait deterioration rather than HD specifically –Some of them need specific laboratory equipment	Intraclass correlation coefficient and coefficient of variation [95], HMM [70], Statistical analysis [23, 26, 90, 93, 94], Radial basis function neural networks [125], Long short-term memory network [82]

that the ability to preserve steady locomotion (i.e., low stride-to-stride variability of gait cycle interval and its subphases) would be reduced in persons with NDDs [125]. Therefore, abnormal timing of steps in NDDs leads to a distraction in gait and locomotor activity generation, and fortunately these category of clinical tests are highly correlated with functional limitation and quantitative gait measures related to gait speed [94, 125].

We classified the techniques for detecting HD locomotion anomalies into two categories: temporal assessment methods and hybrid assessment methods. The main characteristics of these approaches are summarized in Table 12.

6.2.1 Temporal Assessment Methods. These methods use different strategies to examine gait cycles and their correlations with HD by the analysis of complexity and uncertainty measures. In particular, the stride interval in human locomotion reflects the rhythm of the locomotor system, and its analysis provides a noninvasive approach for quantifying gait dynamics [7]. Since there is a correlation between fluctuation in stride interval and HD, stride analysis allows detecting locomotion impairment in PwHD at an early stage. Furthermore, the correlation degree in this indicator is inversely associated with the degree of functional impairments in PwHD [48]. Different research studies were able to differentiate PwHD from cognitively healthy subjects relying on accelerometer-based gait event detection [114] and Shannon entropy [7]. However, these temporal assessment methods need large volumes of training data acquired in variegated conditions, and noise or data perturbation due to external events can affect their accuracy and reliability.

6.2.2 Hybrid Assessment Methods. To detect locomotion changes and quantify motor symptoms of HD in premanifest and early stages, it is useful to consider further markers in addition to temporal indicators. Hybrid assessment methods investigate the progression of gait disorders through the different HD stages according to a heterogeneous set of locomotion indicators. In particular, the estimation of gait events related to stance and swing [70], as well as gait cycle variability, proved to be effective in recognizing early and longitudinal gait changes in PwHD [23]. Other works consider gait indicators to measure balance and symmetry in locomotion, which are correlated to walking impairment progression in PwD [23, 94]. Those methods apply quantitative phase plot analysis on the sinusoidal consecutive waveforms produced by trunk movement and statistical assessment methods. However, those systems are subject to possible recognition errors due to gait deterioration not specifically related to HD. Particular instruments such as sensorized pressure-based pathways in controlled environments are useful to reduce noise in locomotion data acquisition and to reduce the impact of external factors. Those methods do not support the data

Table 13. Classification of PD Detection Methods

Approach		Main Idea	Characteristics	Challenges	Algorithms
Clinical assessment		–Methods are based on prior knowledge, results of clinical tests, and statistical analysis of locomotion data by the supervision of medical experts –Based on single or dual-task assessment such as free walking, opening and closing doors, climbing stairs	–Detecting long-term changes in stride length –Demonstrate the effectiveness of gait in natural environment –Provides clinical validity of the algorithm derived from sensor to detect dyskinesias in PD patients –Possibility of real-time assessment	–Challenging to monitor accurately stride length over an extended period to characterize pathological gait	Statistical analysis [13, 34, 35, 78, 91, 97, 106, 107, 116, 118]
ML assessments	Feature-based assessment methods	These methods rely on various feature extraction methods, data collected from wearable sensors, and use ML-based algorithms to distinguish between PD patients and HCS	–Investigate the effect of gait and tremor features for early detection of PD –Based on postural analysis such as step distance, walking speed, stance, and swing phase –Apply in real-life conditions	–Difficult to determine significant features –Need extensive data for the feature classification task	LDA [84], SVM [14, 22, 54, 84], Naive Bayes classifier [14, 22, 115], RF [22, 115], MLP [115], DT [14], *K*-nearest neighbor [115], Deep 1D-Convnet [29], Deep MLP (DMLP) [120], Convolutional neural networks [117]
	Image processing based assessment methods	These methods rely on the camera used for gait analysis to classify normal or PD's gaits; based on processing images and videos from walking sessions of the PD patients and a classifier, it can detect abnormal gait pattern using a computer vision based algorithm	–Process images and videos from the patient's activity, identify every stride of the patients –Employ ML-based classifier –Identify PwPD in the early stage and diagnose Parkinson's ailment with the support of a clustering method that detects abnormal gait patterns	–Difficult to determine significant features from the image –Need extensive data for the classification task	Principal component analysis [18], LDA [18], Regional convolutional neural network [44], Canny operator and Gaussian filter [127], SVM [44, 58]
	Pattern-based methods	–Processed data to recognize abnormal patterns that may identify Parkinson –Based on shifted 1D-LBP, abnormal gait patterns, and ML methods using the dataset on gait signal	–Considers 1D-LBP from the LBP for extracting features from sensor signals –Employ in real-time application by detecting local changes in gait signal	–Difficult to determine significant patterns –Need extensive data for the classification task	Naive Bayes [30], Logistic regression [30], RF [30, 96], SVM [96], DT [96], ZUPT algorithm and Kalman filter [33], Bayes classifier [88], Bag-of-words method [96]

acquisition in fully naturalistic conditions, and their cost makes them unsuitable for continuous and large-scale deployments [94].

6.3 Detection of PD

As explained in Section 4.3, our human motor system is affected by PD. The most significant indicators of PD are locomotor dysfunction, shortened stride length, increased variability of stride, and shuffling gait. Therefore, it is essential to identify these parameters for diagnosing PD. Generally, gait disorders of PD are assessed by UPDRS. Gait freezing deteriorates the quality of life by reducing mobility and increasing falls. Patients with freezing episodes also have problems with lack of steady gait. Some research has recognized the gait disorders of PD based on wearable sensors [106, 109] placed on the patient's back or wearable devices such as smartwatches [73]. Several studies were also conducted to measure spatiotemporal gait parameters using pressure-sensitive mats such as GAITRite [13]. Emerging wrist bands or smartwatches integrated with an IMU are pledging into wearable healthcare solutions. Experiments also showed that upper body variables need to be computed together with the consideration of spatiotemporal characteristics to gain a more holistic inspection of PD for use in clinical or nonclinical environments [13, 73]. Wearable inertial sensors were used to monitor and measure head and pelvis accelerations. Pearson's product-moment correlations were computed from upper body accelerations, including magnitude, smoothness, regularity, symmetry, attenuation, and spatiotemporal characteristics such as postural control [13]. Therefore, detection methods of PD are mentioned in the following in two ways: clinical assessment methods and ML-based assessment methods. Table 13 summarizes the characteristics of existing techniques, classified into clinical or ML-based assessment methods.

6.3.1 Clinical Assessment Methods. In the clinical assessment method, PD is detected based on prior knowledge, results of clinical tests, and statistical analysis of locomotion data by the supervision of medical experts. Hence, these approaches intensely depend on expert evaluation to assess an individual's cognitive status. Patient evaluation is supervised by clinicians and executed during predefined, short, structured testing sessions. Generally, the severity of PD is measured with the UPDRS [32] score and the H&Y stage [10], as well as the **New Freeze of Gaiting Questionnaire (NFOG-Q)** [52]. Clinical evaluation can be done based on the performance of simple motor task such as walking a short distance and getting up out of a chair and the standing or walking turns [35]. The short stride length characteristic of Parkinsonian gait can be noticed from long-term changes in stride length. Locomotor impairment is one of the leading characteristics of PD. However, many other symptoms of PD, such as rigidity, difficulty swallowing, upper body tremor, and dyskinesias, cannot be noticed with a stride monitor [78]. Clinical evaluation was conducted employing the leg dyskinesia item of the UPDRS [91]. Generally, dyskinesias in PD patients are associated with motor dysfunctions, including gait and balance deficits.

6.3.2 ML-Based Assessment Methods. Currently, PD is not curable. An earlier diagnosis is necessary to enhance the patient's treatment. Gait analysis is an essential step in PD diagnosis, as gait abnormalities have been reported to appear at earlier stages. Since changes in gait are among the foremost symptoms of this disease, a gait classifier would be beneficial for physicians. Therefore, ML assessment methods can classify abnormal and normal gait. There are different approaches available to detect PD using ML, and here we divide ML assessment methods into three categories: feature based, image processing based, and pattern based:

(1) *Feature-based assessment methods*: The diagnosis of PD can be challenging in its earlier stages, and Parkinsonian gait is characterized by small steps, a slower gait cycle, smaller swing phase, and lengthier stance phase. Physicians evaluate these features in their diagnosis process to confirm the presence of PD. Gait evaluation can be difficult since it can be influenced by several aspects, such as age and health condition. Despite the considerable interest in Parkinsonian gait analysis, there is no accurate tool to help physicians with gait evaluation. To detect the characteristics of gait, feature extraction methods and ML have been used. However, gait is a physiological characteristic that differs for each person according to age, health, and other intrinsic factors. Therefore, manual preprocessing and feature extraction will always be limited in their capacity. Generally, the feature-based assessment method is used to extract significant features that will help diagnose PD. Various features such as step distance, stride length, stride velocity, stance and swing phases, heel and normalized heel forces, swing time of Parkinsonian patients, and walking speed were extracted from the data collected from wearable sensors and after that examined using an ML-based algorithm to select the most influential features that would help differentiate between the two groups: subjects with PD and healthy people. Generally, supervised learning methods such as **Linear Discriminant Analysis (LDA)** [84], SVM [14, 22, 54, 84], the naive Bayes classifier [14, 22, 115], RF [22, 115], **Multilayer Perceptron (MLP)** [115], **Decision Tree (DT)** [14], K-nearest neighbor [115], and Deep 1D-Convnet [29] are used for distinguishing between PD patients and HCSs. Furthermore, recently novel ML and deep learning based multimodal technologies have been used to identify severity in PD patients' actions by analyzing speech, movement patterns, and evaluation of motor capabilities [117, 120]. The rationale of this approach is that they may effectively capture discriminative features from time-series data or other IMU sensors collected data without the need of sophisticated feature engineering efforts.

(2) *Image processing based assessment methods:* Image processing technologies have been employed widely for PD diagnosis. PD patients show large gait variability and slower walking speeds than normal people. Cho et al. [18] introduced a gait analysis system based on a computer vision based technique for the detection of gait patterns of PD. They captured a few videos of both normal subjects and patients with PD. They processed the images from the videos to characterize the subjects. Principal component analysis and LDA were employed to extract features, and the minimum distance classifier was used as the classifier. Seven PwPD and seven healthy people from Buddhist Tzu Chi General Hospital in Taiwan participated in this study. It used the image sequences of human silhouettes during walking and extracted the intrinsic features by LDA. It can identify healthy people and PD patients by their gaits with high reliability, and it is considered a promising aid in the diagnosis of PD. Khan et al. [58] also presented a computer vision based marker-free method to detect abnormal gait in PwPD. In this study, subjects are videotaped with several gait cycles for the gait analysis of PwPD. To develop a silhouette, the subject's body is segmented through a color segmentation process. A skeleton is formed by computing the medial points of each body segment. Motion cues such as the cyclic motion of legs and the posture lean of the subject during the gait are extracted from the skeleton. Then the comparison study was compared between these two cues with the cues of the probable perfect gait pattern to assess gait impairment. Generally, a computer vision based technique is introduced for gait analysis to classify normal or PD gaits using a camera. In the work of Gong et al. [44], a masked regional convolutional neural network is applied for extracting human silhouettes from video frames based on recorded videos of normal gaits. After that, the gait energy images are constructed based on extracted human silhouettes as features, which are applied to develop an SVM model for classifying healthy and PD gaits in video clips.
(3) *Pattern-based assessment methods*: These approaches process trajectory data to recognize abnormal patterns identifying PD. Walking is a part of human movement monitored by the human brain. Gait deficits and abnormal walking patterns may appear if the brain fails to control this movement. Walking patterns can be monitored continuously and remotely over time by wearable sensors. The bag-of-words approach [96] was introduced where each individual's walking time series is defined as a bag of words. The ratio of the words together with ML techniques such as linear SVM, DT, RF, and K-nearest neighbor were employed to distinguish between patients with PD and healthy individuals. Although the bag-of-words method is used to distinguish between PD and healthy age-matched individuals, this method is also applicable to other health conditions. Each individual's walking time series is converted into signal subsequences using an overlapping sliding window. Then, each subsequence is characterized using a few statistical descriptors and similar subsequences are assigned the same word. Therefore, each person's data is converted into a bag of words and then evaluated using accelerometers' data collected from the ankles. The proposed approach illustrates a vital step toward providing healthcare through continuous monitoring and advanced analysis of movement patterns [96]. Another method was introduced to diagnose PD based on a shifted 1D **Local Binary Pattern (LBP)** using an ML algorithm [30]. The *gaitpdb* dataset was used for the evaluation task, consisting of three gait datasets based on gait signals from different circumstances. Statistical features were extracted from histograms of gait signals changed by shifted 1D-LBP. ML methods such as naive Bayes, logistic regression, MLP, were employed to extract and classify features that can be successfully used in PD detection from gait [30]. This approach may also be utilized to diagnose other symptoms such as speech. It can also be applied in any real-time application by detecting local changes in a signal.

Table 14. Challenging Behaviors

Approach Classification	Disease	Behaviors	Application Environment	Experiment Environment	Sensor Technologies	Algorithms
Single modality	Dementia (+ Parkinson)	Gait disturbance, Wandering, Ambulatory gait behavior	Indoor/Outdoor	Lab/Real world	Computer vision [17], GPS [67, 123], Accelerometer [124], QR codes [113]	Statistical analysis [113], Density-based spatial clustering of applications with noise [123], Loop detection method called Θ_WD [67], Analytical algorithm for analyzing acceleration data + K-means clustering to classify the gait variables [124], HMM [17]
Multi modality	Dementia (+ Parkinson)	Wandering, Disorientation, Limping, Fall detection, Agitation, Localization	Indoor/Outdoor/ General	LabReal world/Both	GPS [25, 72, 102], Accelerometer [25, 51, 102], Computer vision [72], Accelerometer, Metal plate, Infrared [51], Electronic patch, RFID [72], Actillume, StepWatch, Step Sensor, and TriTrac-R3D [4], Optical and video cameras [36]	Proposed algorithm [25], Different ML methods [102], Markov chain model [51], Pedestrian dead reckoning, Statistical analysis [4, 72], Multistage spatial-temporal graph convolutional network [36]

Nevertheless, it is hard to define significant features or patterns that can help in diagnosing PD. Moreover, ML-based assessment methods require large volumes of expensive training data to employ in the classification task.

6.4 Challenging Behavior Recognition

In people who suffer from NDDs, disorientation and wandering behaviors can cause potential harm, such as accidents, injuries, and sometimes death, which can occur during either the day or night [123]. These kinds of behaviors are a main concern for care personnel, as patients require continuous surveillance. This is a stressful task, which leads to confinement feelings and immense stress for caregivers. However, it is possible to use AmI and assistive technologies to recognize those *challenging behaviors* that may lead to accidents and injuries in patients with neurocognitive diseases [66, 123]. Generally, when a challenging behavior is recognized, those systems promptly inform the caregiver by issuing an alert, or they automatically trigger procedures to avoid the occurrence of accidents. For instance, the system may automatically lock doors or use wireless technologies to activate an alarm through the emission of sound or light.

To perform accurate motion analysis, those systems use techniques similar to the ones used to recognize symptoms of neurocognitive diseases [51, 123]. Human locomotion data in an indoor environment can be collected by using both device-free and device-based sensing modalities, whereas in outdoor environments the systems rely on mobile devices. Advanced systems use sensor data fusion methods to improve the accuracy and significance of acquired data. Whereas single-modality methods consist of one or multiple sensors of the same technology, multimodality methods use different kinds of sensors to acquire multimodal data. In the following, we present existing challenging behavior detection approaches according to the preceding categories, and the main methods are summarized in Table 14:

(1) *Single-modality methods*: In different works (e.g., [67, 123]), the authors use GPS data to detect wandering behaviors, whereas other works (e.g., [124]) use accelerometers for the same objective. Regarding data analysis, the techniques proposed in the work of Lin et al. [67] and Wojtusiak and Nia [123] rely on clustering, whereas in one of the works [67], the authors detect loop-like locomotion traces based on the Martino-Saltzman model. In particular, the work presented by Wojtusiak and Nia [123] is specifically based on detecting wandering by means of iterative clustering followed by ML. Other approaches monitor patients with cognitive impairment to alert caregivers when they leave the bed or exit the door. In the work of

Chen et al. [17], the authors use cameras and background subtraction technologies to model the scene background, together with the **Hidden Markov Model (HMM)** to automatically detect elopements and alert caregivers. A tool named *AssisT-In* for indoor wayfinding and wandering detection is presented in the work of Torrado et al. [113]. It is based on tagging the environment with QR codes, which need to be scanned by the user through a smartphone so that he or she can be located and can receive directions to get to the destination. That method is simple, inexpensive, and easily deployable. However, the used data localization technology is not well suited especially for people with cognitive impairment, since QR codes must be scanned frequently. An obvious advantage of single-modality approaches is simplicity; however, noise and heterogeneous environmental conditions can affect the robustness, feasibility, and stability of those approaches.

(2) *Multimodality methods*: The recognition of more complex challenging behaviors such as persistent, shadowing, pottering, or repetitive behaviors, poses additional issues. Those behaviors are not only based on the patient's trajectory but also consider environmental conditions, such as the presence or movement of other people. For this reason, some systems, including that in the work of Martino-Saltzman [72], integrate different technologies such as RFID and GPS. In the work of Homdee et al. [51], the authors use door sensors and wearable devices to detect doorway crossing events and location tracking errors with walking directions by a Markov model method, and provide correct location information using the most likelihood method. In another work [25], the authors use a smartwatch provided with GPS and an accelerometer to detect wandering and alert the patient's relatives when needed. Moreover, the development of novel treatments for objectively assessing FOG, which is a debilitating gait impairment in PD, is severely limited by its difficulty. Therefore, Filtjens et al. [36] used the Vicon 3D motion analysis system, which is combination of optical and video cameras for FOG assessment. They formulated it as an action segmentation problem where temporal models are tasked to recognize and temporally localize the FOG segments. It applies spatial graph convolutions on the human skeleton graph at each timestep that connects the same markers across consecutive timesteps.

7 DISCUSSION ON OPEN CHALLENGES

In this work, we explored different methods and technologies for detecting the symptoms of NDDs based on locomotion data. However, given the sensibility of the task, particular care should be taken before introducing these technologies in medical practice. A first fundamental challenge in sensor-based healthcare systems is the protection of privacy. Indeed, it is well known that the release of location data determines serious privacy issues [99]. Of course, the continuous observation of movements and locomotion patterns may reveal not only medical conditions but also personal routines, activities, and preferences. This problem is particularly evident in systems based on outdoor locations. For instance, recurring presence in specific locations may reveal sensitive data such as political opinions or religious beliefs, whereas frequent co-occurrence with other people may expose private contacts. The continuous observation of indoor locomotion traces at home may also challenge the individual's privacy, revealing the presence of other people or the execution of private activities of daily living. For this reason, a privacy-by-design technology must be adopted when designing and implementing locomotion-based healthcare systems [9]. Together with privacy, it is important to adopt effective cyber-security mechanisms to protect sensitive data regarding the individual. This requirement is particularly important in IoT systems, which are prone to different kinds of attacks [111]. Moreover, the use of sensor data and AI methods for neurocognitive disease assessment raises serious ethical and legal concerns, including informed consent acquisition, safety, transparency, data ownership, algorithmic fairness, and biases [40].

From a technological point of view, the need for continuous data acquisition and processing challenges the power requirements of portable or wearable systems. Novel edge computing solutions optimized for the execution of ML algorithms and supported by privacy and security mechanisms need to be introduced [1]. There is also the need for optimized, energy-efficient, and effective noise suppression algorithms for accurate localization and location data processing [81].

Finally, the accurate evaluation of proposed tools and methods necessarily relies on extensive experiments in naturalistic conditions. However, in this domain, the setup of experimental testbeds and experimentation with a large set of participants, including both people with NDD and HCSs, is particularly complex and expensive. Moreover, acquired data contain sensitive information. For these reasons, there is a lack of large datasets acquired for long time periods on a significant number of individuals that are publicly available. This fact limits the possibility of experimentally comparing different solutions for AI-based neurocognitive disease assessment using common testbed datasets. A potential solution for this could be the option to integrate external evaluation pipelines into the computation infrastructure of the institution holding the dataset, allowing external researchers to evaluate their hypotheses without the risk of data privacy violation.

8 CONCLUSION

Since the average age of the population is projected to increase significantly in the near future, early diagnosis of cognitive decline among elderly people is becoming a key objective of healthcare systems worldwide [98]. This survey explored different technologies and methods that have been demonstrated to be successful in detecting symptoms of NDDs based on locomotion sensor data and AI algorithms. We investigated 128 peer-reviewed papers discussing the detection of dementia (37%), HD (11%), and PD (44%), as well as some discussing both dementia and PD (4%) and PD and HD (4%). The experimental results presented in these papers have shown that these new technologies may provide effective support for practitioners and caregivers to improve the diagnosis and simplify patient management. In that sense, this work provided a detailed overview of different technologies and AI methods for detecting symptoms of NDDs based on locomotion sensor data. Furthermore, it discussed the open challenges and potential solutions to making the detection of NDD symptoms with AI methods more accessible and beneficial for the research community and for the practice.

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