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Applicability of Technology Outcomes Measures to Assess Gait in Dementia

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Este projeto não possui qualquer conflito de interesses de ordem pessoal, comercial, académico, político e financeiro nem qualquer apoio financeiro para o desenvolvimento da pesquisa que resultou na sua elaboração.

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RESUMO

A demência provoca alterações cognitivas e motoras que reduzem a autonomia dos doentes. A avaliação motora é desafiante, pois os métodos clínicos tradicionais dependem frequentemente da colaboração e compreensão dos doentes. A tecnologia, como sensores *wearables* e não *wearables*, surge como solução promissora e não invasiva, oferecendo uma avaliação mais objetiva dos parâmetros cinemáticos da marcha.

Este projeto explora o tema através de duas abordagens complementares. Uma revisão sistemática da literatura sobre o uso de tecnologia na avaliação e monitorização de pessoas com demência. Os sistemas *wearables* e não *wearables* mostraram-se eficazes na identificação de alterações na marcha em pessoas com demência, quando comparadas com controlos saudáveis, observando-se marcha mais lenta, com menor comprimento de passo e maior tempo de passada.

Posteriormente foi realizado um estudo clínico retrospetivo para avaliar a aplicabilidade da análise cinemática como ferramenta de avaliação da marcha em pessoas com defeito cognitivo ligeiro (MCI) e demência. Conclui-se que indivíduos com MCI apresentam passos mais longos, maior velocidade de passo e passada, e maior velocidade de marcha. O grupo com doença de Alzheimer mostrou métricas semelhantes ao grupo com MCI. Apenas a variabilidade no comprimento do passo demonstrou significância estatística entre os grupos.

Os resultados visam contribuir para a implementação de ferramentas tecnológicas na avaliação de pessoas com demência, permitindo avaliações mais rigorosas e informativas que melhorem a gestão da doença. Estudos futuros deverão focar-se na validação clínica dos parâmetros cinemáticos da marcha e na padronização de protocolos, para avaliações supervisionadas e não supervisionadas.

PALAVRAS-CHAVE

Demência, Tecnologia, Marcha, Sensores, Avaliação.

ABSTRACT

Dementia causes cognitive and motor changes that reduce patients' autonomy. Motor assessment is challenging in these patients since conventional clinical procedures frequently depend on the participation and comprehension of the patients. A viable and non-invasive approach is presented by technology, such as wearable and non-wearable sensors, which provide a more objective assessment of gait kinematic characteristics.

The present study uses two complimentary methods to investigate the topic. The first is a systematic review on the application of technology to the diagnosis, treatment, and follow-up of dementia patients. When comparing dementia patients to healthy controls, wearable and non-wearable systems were found to be successful in detecting changes in their gait, such as a slower gait, shorter steps, and longer steps.

The second phase involved a retrospective clinical study aimed at evaluating the applicability of kinematic analysis as a gait assessment tool for individuals with mild cognitive impairment (MCI) and dementia. It was found that those with MCI have longer steps, higher step and stride velocities, and faster gait speeds. The gait metrics of the MCI group and the Alzheimer's disease group were similar. Only step length variability showed statistical significance between groups.

These results are intended to encourage the use of technology for assessing dementia patients, as this could lead to more precise and informative assessments and better disease treatment. Future research must focus on standardizing methodologies for both supervised and unsupervised assessments, as well as clinical validation of gait kinematic characteristics.

KEYWORDS

Dementia, Technology, Gait, Sensors, Assessment.

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LIST OF ABBREVIATIONS

10 MWT – 10 Meters Walk Test

AD – Alzheimer's Disease

BMI – Body Mass Index

DLB – Dementia with Lewy Bodies

FTD – Fronto Temporal Dementia

HC – Healthy Controls

IMUs – Inertial Measurement Units

MCI – Mild Cognitive Impairment

MMSE – Mini Mental State Examination

NA – Not applicable

NWS – Non-wearable Systems

PWD – People with Dementia

SD – Standard Deviation

TOMs – Technology Objective Measures

Unk - Unknown

VD – Vascular Dementia

WS – Wearable Sensors

1. Introduction

1.1 Mild Cognitive Impairment

Different stages of cognitive decline affect elderly people: mild cognitive impairment (MCI), dementia, subjective cognitive impairment, and normal age-related changes. MCI is a distinct clinical disorder characterized by cognitive impairment that is greater than what would be anticipated with normal aging but has little to no effect on daily activities. It stands for a transitional phase between dementia and normal age-related cognitive deterioration (1).

MCI it is also a major early indicator of future cognitive problems, particularly Alzheimer's disease (AD). Early detection and prevention of MCI remain critical for slowing the progression of the disease, even though current treatments are only able to delay the onset of some forms of dementia. A precise diagnosis is crucial because it enables healthcare professionals to provide patients and their families with important advice regarding care requirements, living arrangements, and long-term planning (2).

The management of gait disorders and falls in older adults with MCI or dementia begins by their identification with the use of specific screening tools, such as measuring gait speed, use of dual-task gait tests, or diagnosing motoric cognitive risk syndrome, a newly described pre-dementia syndrome (1,3).

1.2 Dementia and Dementia Subtypes

Dementia mainly represents an irreversible neurological illness characterized by an impairment in cognitive abilities that makes it difficult for a person to independently carry out daily tasks. It has an impact on one or more cognitive domains, including language, executive function, and memory (1,4).

There are several causes of dementia, and each one reflects unique modifications in the brain. With 60–80% of cases of dementia being caused by AD, it is the most frequent cause of dementia. Neurons degenerate and abnormal proteins, such as phosphorylated tau and beta-amyloid, accumulate in the brain during AD. Early signs include sadness and apathy, as well as trouble remembering names, conversations, or events. Communication problems, disorientation, bad judgment, and behavioural abnormalities could appear as the illness worsens. Difficulties with walking, speaking, and swallowing is prevalent in the later stages. Notably, MCI is the initial symptom seen by anyone with AD (1,4,5).

Dementia with Lewy Bodies (DLB) is characterized by intracellular α-synuclein aggregates, or "Lewy bodies," which impair brain neural connections. Parkinsonism, recurring visual hallucinations, and fluctuating cognition are the main diagnostic characteristics of DLB (6). Visuospatial impairment, sleep difficulties, and well-formed visual hallucinations are early signs. Throughout the day or from day to day, these symptoms may drastically fluctuate. Motor function issues, similar to Parkinson's disease, are frequent. Memory loss might occur at any stage of the illness (4).

Vascular dementia (VD) patients may experience decreased emotional reactivity as well as physical impairments, including slower gait and poor balance. In addition to memory problems, early symptoms may include slow thinking or difficulty with planning, organizing, and making decisions (4). The development of vascular dementia and cognitive impairment may be explained by the brain injury caused by cerebrovascular illness, which is fuelled by vascular risk factors. Dementia and cognitive decline are the results of this damage, which affects cognitive networks (7,8).

A macroscopic pathological name for the deterioration of cortical and subcortical structures in the brain's frontal and temporal regions is Fronto Temporal Dementia (FTD). The front insular cortices, anterior temporal poles, basal ganglia, brainstem, thalamus, and, in some hereditary variants of the condition, the cerebellum are among the affected regions. With memory and visuospatial functions mostly unaffected, neural networks supporting personality, behaviour, executive processes, language, and motor abilities gradually become disturbed. Early signs are often characterized by pronounced behavioural and temperamental changes as well as challenges with language production and comprehension. In contrast to Alzheimer's, the early stages of the disease usually preserve memory (4).

1.3 Gait

Walking is a daily activity that requires a high degree of coordination between the trunk and limbs, making it one of the most complex yet common actions we perform. The central nervous system, which regulates limb motion and posture while the body is in motion, is largely dependent upon this movement. Monitoring our gait can therefore reveal important information about our general health. In addition to being necessary for preserving one's independence over time, a secure and effective gait is also useful as a worldwide health indicator. Key health outcomes, including survival, quality of life, fall risk, and cognitive decline, can be predicted by gait performance. Even though it can appear simple, walking is harder as we get older. Changes in gait in elderly individuals

without dementia may actually help anticipate the possibility of dementia or cognitive decline in the future (9–11).

Dementia and cognitive impairment in the elderly increase the risk of falls and difficulties with walking. Patients with dementia and cognitive impairment have a 2-3 times higher probability of falling than those without the disease. Moreover they also have less mobility and walk slowly (3,12).

1.4 Kinematic assessments

The semi-subjective conventional measures for analysing gait metrics in clinical settings are used by experts who examine a patient walk in order to evaluate the patient's gait quality. Occasionally, the patient is requested to complete a survey to provide a subjective assessment of the quality of the gait. These approaches have the disadvantage of providing subjective assessments, especially with regard to accuracy and precision, which can be detrimental to the diseases' diagnosis, course of care, and therapy (13). On the other hand an essential part of a physical examination is the kinematic and kinetic analysis of gait, offers vital information on functional ability and can be helpful in the assessment of disabilities (14).

More specifically, 3D kinematic analysis is essential when assessing movement quality. In order to better comprehend gait and movement limitations, machine learning algorithms have shown to be helpful in collecting and analysing 3D movement data (15,16).

Quantitative gait and balance assessments can be performed using biomechanical analysis devices, including non-wearable systems (NWS) such as motion capture systems, force platforms, and sensor-embedded walkways, as well as wearable sensors (WS) like pressure and inertial sensors (17). The NWS require more robust and expensive equipment, but they are highly accurate, reliable, and provide detailed results. While WS offer less detail, they can be used in community settings, providing healthcare professionals and patients with real-time feedback (17).

1.5 Non-wearable systems

We can divide the NWS in floor sensor systems and image processing systems. The floor sensor systems employ ground reaction force and pressure sensors placed in the floor (force platforms) to measure the forces applied by the feet during walking and obtain information on gait. The image processing systems collect gait data using optical sensors such as cameras, time-of-flight cameras, laser range scanners, and infrared sensors and they can work with markers placed on the subject or work without markers

by analysing movement using digital picture processing (13). In order to guarantee the effective functioning of these systems, controlled research facilities are needed. In these facilities, sensors are installed to record an individual's gait while they walk a specifically defined walkway (13,17).

Since non-wearable techniques offer the most comprehensive and accurate evaluations of gait kinematics, they are highly reliable for detecting early pathological changes. However, they are expensive and not really useful for everyday use (17).

1.6 Wearable sensors

Gait monitoring outside of conventional labs is now possible thanks to new advances in inertial sensors, such as inertial measurement units (IMUs). Technologies that are accessible and inexpensive, such as sensor fabrics and smartphones, are currently being studied for the purpose of capturing daily activities. The tracking of gait abnormalities is a promising application for wearable sensors and they also make possible to analyse data outside the laboratory and allow real-time monitoring (17–19).

Electronic devices called inertial sensors, such as gyroscopes and accelerometers, monitor gravitational forces, velocity, acceleration, and orientation. Using integration, accelerometers can calculate an object's acceleration, velocity, and position based on Newton's Laws of Motion. Gyroscopes use rotational inertia measurements to identify direction changes. The placement of these can vary according on what exact measurement is required, such as the foot, lower back or waist (13).

1.7 DataPark

The DataPark platform is a web platform developed by the CNS Clinical Team and the LASIGE Research Group of the Faculty of Science of the University of Lisbon (FCUL), to obtain a record of the patient's evolution over time and to help understand the impact of therapeutic interventions in inpatient or outpatient settings. It stores all data from the assessments, both objective and subjective (20).

2. Chapter 1 - Gait kinematic parameters in Dementia: a systematic review

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Abstract

Background: Over 55 million people globally have dementia. Besides cognitive symptoms, dementia often leads to motor problems like gait impairment, limiting patients' functionality and autonomy. Cognitive decline also interferes with the use of traditional clinical tests for assessing gait in people with dementia.

Objective: To summarize and critically appraise the characteristics of technology-based gait analysis in dementia and to establish reference values for spatiotemporal gait parameters.

Methods: A systematic review was conducted using the databases CENTRAL, PEDro and SciELO from their inception to September 2023 to identify all observational and experimental studies conducted in dementia that included a technology-based gait assessment. Two reviewers independently screened citations and extracted data.

Results: Forty studies were included, encompassing 1678 people with dementia (PWD) and 643 healthy controls (HC). Of these studies, 57.5% (n=23) reported supervised gait assessments and 53.3% (n=8) used wearable sensors (WS). The most frequently reported parameters were gait velocity, stride length, cadence, step length, stride time, and step width. Differences were observed for step length, stance time, and swing time, with only non-wearable systems (NWS) able to detect a difference between PWD and healthy controls.

Conclusion: Our results offer valuable data for technology-based gait assessment in dementia, including mean values for better interpretation. Further studies should explore the clinical significance of each parameter and their behaviour in non-supervised assessments and over disease progression.

Key words: Dementia, Alzheimer disease, Gait, Sensor, Technology

Background

Currently, an estimated 55 million people worldwide are living with dementia (PWD), a number that is expected to rise as average life expectancy continues to increase (1). While cognitive decline is the primary hallmark of dementia, motor symptoms such as impaired gait often emerge as the disease progresses (2). Notably, a decline in gait speed, indicating motor deterioration, can begin up to 12 years before the onset of mild cognitive impairment (3).

Standardized outcome measures are essential for monitoring disease progression, evaluating treatment effects, and improving communication among health professionals, particularly in clinical trials. However, in complex diseases like dementia, selecting the most appropriate outcome measures is challenging due to the disease's heterogeneity and varied symptoms (4). Traditional clinical scales, while validated and commonly used, have limitations: they offer only brief snapshots of a patient's condition, are susceptible to intra- and inter-rater variability, require in-person assessments, and can be time-consuming (4). These issues are particularly pronounced in PWD, who may struggle to understand and follow the instructions necessary for these assessments (4).

To overcome these challenges, there is a growing interest in integrating technology-based objective measures (TOMs) into clinical practice. TOMs provide a more objective and comprehensive assessment of symptoms, including gait, with less reliance on patient cooperation, thus reducing variability in clinical evaluations (5). These technologies can capture the complexity and diversity of symptoms with greater accuracy, offering a more realistic portrayal of patients' functionality, and enabling closer monitoring of treatment responses. TOMs also support remote assessments, benefiting patients in geographically remote areas. (6,7).

In movement analysis, inertial measurement units (IMUs) are widely used due to their compact size and cost-effectiveness. However, to ensure reliable results, it is crucial to establish consensus on the optimal number, placement, and positioning of sensors on the body, as well as the specific gait parameters to be measured (6,7).

This systematic review aims to summarize and critically evaluate the characteristics of technology-based gait analysis in dementia, while also establishing reference values for spatiotemporal gait parameters.

Methods

Literature search

We searched CENTRAL, PEDro and SciELO from their inception to September 2023 using “Dementia”, “Alzheimer”, “Frontotemporal Dementia”, “Vascular Dementia”, “Mixed Dementia”, “Lewy-body Dementia”, “Gait”, “Mobility”, “Walking”, “Sensor”, “Technology”, “Device”, “Wearable”, “Accelerometer”, “Algorithm”, “Kinematic” and “Technology Objective Measure” as key words. Reference lists from the identified articles were cross-checked to identify any further potentially eligible studies.

Study selection

We included all observational and experimental studies conducted in people with all types of dementia, that included a technology-based gait analysis focused on continuous gait disturbances and that specified which parameters had been studied. There were no restrictions regarding the type of intervention in the active and control arms.

We excluded reviews and studies written in languages other than English, French, Spanish, and Portuguese. All retrieved abstracts were independently screened by two authors. The full texts of potentially relevant articles were retrieved for further assessment. Disagreements were resolved by consensus.

Data extraction

General information (year and journal of publication, study aim, study design, population, time point assessments, technology development phase), gait assessment supplies (equipment, type of sensor, type of assessment), gait assessment procedures (protocol and other outcome tools), and gait parameter values were among the five pre-defined domains of items that were extracted.

We categorized research based on the three stages of technology development, following Maetzler's classification (8): There are three main areas of study in the field of gait analysis: preclinical development and testing, which involves developing and testing algorithms or validating new gait assessment systems; clinical development and testing phase, which involves developing and testing clinically relevant parameters; and clinical validation, which involves experimental and observational studies that use gait analysis as an outcome.

In order to present and examine the gait parameters provided in the included research, we also modified Del Din's (2016) conceptual model of gait (9). The "other parameters" section contained the parameters that did not fit the model. Two separate authors extracted the data. Arguments were used to settle disagreements.

Data analysis

We used frequencies and percentages to provide a summary of the publication characteristics. Pooled mean difference (MD) and 95% confidence interval (CI) were calculated using Review Manager software (v 5.3; Cochrane Collaboration). With the I^2 statistic and Q test, heterogeneity was evaluated. A low level of heterogeneity was determined by an I^2 value of less than 25% and a high level of heterogeneity by an I^2 value more than 75%. To combine all the results, a random-effects model was employed. When a p-value was less than 0.05, it was considered statistically significant.

Results

The electronic and manual searches identified 1215 citations. Full-text assessment for eligibility resulted in 40 studies being included. Overall, the main reasons for exclusion were inadequately defined outcome (n = 527) and inappropriate study population (n = 421).

General data

The most common study designs used were cross-sectional studies (25%, n=10), clinical controlled study (20%, n=8), and randomized controlled trials (18%, n=7). Forty-five percent (n=18) of the studies used a control group of healthy subjects. Of the 40 included studies, 57.5% (n=23 studies) NWS, 37.5% (n=15 studies) used WS, and 5% (n=2 studies) both types of devices.

Reported gait parameters

Supervised assessments

The most frequently reported parameters (≥ 25% of studies) with NWS were gait velocity (75%, n=18 studies, PWD mean = 0.89 ± 0.28 m/s), stride length (45.8%, n=11 studies,

PWD mean = 86.49 ± 22.85 cm), cadence (33.3%, n=8 studies, PWD mean = 103.92 ± 19.47 steps/min), step length (29.2%, n=7 studies, PWD mean = 0.51 ± 0.12 m), stride time (25%, n=6 studies, PWD mean = 1 ± 0.43 s), and step width (25%, n=6 studies, PWD mean = 11 ± 2.41 cm) (Table 2.1).

The most frequently reported parameters (≥ 25% of the studies) with WS were gait velocity (42.9%, n=6 studies, PWD mean value = 0.72 ± 0,18 m/sec), stride length (42.9%, n=6 studies, PWD mean value = 0.89 ± 0,35 m), step length (42.9%, n=6 studies, PWD mean value = 0.45 ± 0,13 m), cadence (35.7%, n=5 studies, PWD mean value = 100.14 ± 30.66 steps/min), swing time (35.7%, n=5 studies, PWD mean value = 0.31 ± 0.19 seconds) and stride velocity (28.6%, n=4 studies, PWD mean value = 0.92 ± 0.32 m/s (Table 2.2).

Unsupervised assessment

The most frequently reported parameters (≥ 25% of the studies) were swing time (83.3 n=5 studies, PWD mean value = 0.31 ± 0.22 seconds), step count (50%, n=3 studies, PWD mean value = 6109.67 ± 2761.94 step/day), step length (33.3%, n=2 studies, PWD mean value = 0.59 ± 0.03 m), step velocity (33.3%, n=2 studies, PWD mean value 1.02 ± 0.03), stance time (33.3%, n=2 studies, PWD mean value 0.48 ± 0.40 seconds), step length variability (33.3%, n=2 studies, PWD mean value 0.15 ± 0.002) and step velocity variability (33.3%, n=2 studies, PWD mean value 0.36 ± 0.005) (Table 2.3).

Type of assessment

Thirty-three studies (82.5%) reported supervised gait assessments, 10% (n=4) used unsupervised assessments, and 7.5% (n=3) conducted assessments in both contexts.

Supervised assessments were performed in clinic and included 23 studies with NWS and 15 studies with WS and 2 studies with both. A total of 1524 PWD and 553 healthy controls (HC) were assessed.

Unsupervised assessments were performed at patients' environment and included 6 studies with WS. In one study, a kinematic sensor system was placed on the ceiling of a specialized dementia unit for 20 days as part of a research employing in an unsupervised context. A total of 154 PWD and 90 HC were assessed.

Analysis by Groups

The analyses by group were conducted using forest plot analysis. The detailed results can be found in Appendix 2.1.

PWD vs. Healthy Controls

The available data allowed for the comparison of the following gait parameters between PWD and HC: gait velocity (m/s), stride length (meters), step length (meters), stance time (seconds), and swing time (seconds). Significant differences were observed between the groups for all parameters except swing time. High heterogeneity ($I^2 > 75\%$) was noted in all parameters except for stride length.

Supervised vs. Unsupervised Assessments

The available data allow for the comparison of stride length and step length between supervised and unsupervised assessments. On the stride length no significant differences were found between the groups, with low heterogeneity ($I^2 = 0\%$). When we see the step length demonstrates increased data variability in the in supervised assessment with WS.

Non-Wearable vs. Wearable Sensors

The available data allow for the comparison of gait velocity, step length, stance time, and swing time between non-wearable systems (NWS) and wearable sensors (WS). No significant differences were found for gait velocity, with low heterogeneity ($I^2 = 0\%$). However, differences were observed for step length, stance time, and swing time, with only NWS able to detect a difference between PWD and healthy controls. The heterogeneity in these subgroup analyses was high ($I^2 > 75\%$).

Type of Sensor

The available data allow for the comparison of gait velocity between pressure sensors, triaxial accelerometers, and accelerometers. Differences were found between the groups, with only pressure sensors able to detect a difference between PWD and healthy controls. The level of heterogeneity in these subgroup analyses was low ($I^2 = 0\%$).

Sensor Location

The available data allow for the comparison of stride length between sensors located on the lower back and feet. No significant differences were found between the groups, with low heterogeneity ($I^2 = 0\%$).

Assessment protocol

Table 2.5 shows the characteristics of the gait assessment protocol.

Supervised assessment

The most commonly used distance in supervised assessments was 10 meters 21.21% (n=7, range: 3 to 40 meters). The average number of trials conducted was 4.75 ± 7.02, with a minimum of 1 trial, a maximum of 40 trials, and a median of 2 trials. In 72.5% of the studies (n=29), gait assessments were performed at a self-selected comfortable speed.

Among the supervised assessments, 64% (n=23) used NWS and 36% (n=15) used WS, of these the most common location of the sensor was the lower back 47% (n=7).

Unsupervised assessment

In an unsupervised assessment using WS, the duration of data collection was 3 days (43%, n=3) and 7 days (43%, n=3). The most common location of the sensor was the lower back (71%, n=5). In one study, a kinematic sensor system was placed on the ceiling of a specialized dementia unit for 20 days as part of a research employing in an unsupervised context.

Sample characteristics

Supervised assessments with non-wearable systems

A total of 1372 participants was assessed in the included studies, 1173 PWD people with dementia and 199 HC. The mean age of dementia patients was 78.8 ± 4.7 years (n= 24 studies) and of 74.9 ± 4.7 years (n= 7 studies) in HC. The mean percentage of female patients was 58 ± 0.18% for dementia (n= 24 studies) and of 51 ± 0.15% for HC (n=7 studies). The mean MMSE score for dementia was 21.3 ± 2.38 (n=20 studies) and for

HC was 28.25 ± 1.9 (n=5). The mean of MOCA score for dementia was 20.2 ± 0.62 (n=3) and for HC was 27.53 ± 0.6 (n=3). None of the studies reported the duration of the disease.

Supervised assessments with wearable sensors

A total of 705 participants was assessed in the included studies, 351 people with dementia and 354 HC. The mean age of dementia patients was 76.32 ± 7.95 years (n= 14 studies) and of 71.03 ± 5.72 years (n= 8 studies) in HC. The mean percentage of female patients was 44 ± 0.19% for dementia (n= 14 studies) and of 47 ± 0.19% for HC (n= 8 studies). The mean MMSE for dementia was 21.52 ± 2.79 (n=11 studies) and for HC was 28 ± 0.95 (n=7). Only one study had the MOCA values for dementia was 20.4 and for HC was 28.1. None of the studies reported the duration of the disease.

Unsupervised assessment

A total of 244 participants was assessed in the included studies, 154 people with dementia and 90 HC. Three studies used a healthy control group. The mean age of dementia patients was 77.94 ± 5.56 years (n= 6 studies) and of 77.6 ± 5.1 years (n= 3 studies) in HC. The mean percentage of female patients was 45 ± 0.07% for dementia (n= 6 studies) and of 49 ± 0.1% for HC (n= 3 studies). The mean MMSE for dementia was 21.42 ± 1.45 (n= 5 studies) and for HC was 29 (n= 1). Only one study had the MOCA values for dementia was 16 and for HC was 26. None of the studies reported the duration of the disease.

Technological development overview

Among the 40 included studies, 15% (n=6) were in the preclinical development and testing phase, 30% (n=12) in the clinical development and testing phase, and 55% (n=22) in the clinical validation phase, as categorized by the technological development phases (Table 2.4).

Preclinical Development and Testing Phase

In the preclinical development and testing phase, WS was utilized in 50% of the studies (n=3). Cameras were the most commonly used sensors, also in 50% of the studies (n=3), followed by triaxial accelerometers (16.7%, n=1), accelerometers (16.7%, n=1), and an optical potentiometer (16.7%, n=1). The majority of the studies (83.3%, n=5) involved

supervised assessments, with the most common sensor placement being on the feet, reported in 50% of the studies (n=3).

Clinical Development and Testing Phase

In the clinical development and testing phase, WS was employed in 58.3% of the studies (n=7), while NWS was used in 41.7% (n=5). The most frequently used sensors were triaxial accelerometers (25%, n=3), followed by accelerometers, gyroscopes, and magnetometers (16.7%, n=2 each), and cameras (16.7%, n=2). Supervised assessments were conducted in 83.3% of the studies (n=10), while 25% (n=3) were conducted in an unsupervised context. The most common sensor placement was on the lower back, between the third and fifth lumbar vertebrae (41.6%, n=5).

Clinical Validation Phase

In the clinical validation phase, WS was used in 22.7% of the studies (n=5), NWS in 68.2% (n=15), and both types of devices were used in 9.1% (n=2). The most frequently used sensors were pressure sensors, employed in 63.6% of the studies (n=14), followed by triaxial accelerometers in 18.2% (n=4) and accelerometers in 13.6% (n=3). Additionally, 86.4% of the studies (n=19) involved supervised assessments, while 13.6% (n=3) were conducted in both supervised and unsupervised contexts. The most common sensor placement was on the lower back (between L3 and L5 vertebrae) and on the sternum, though the exact percentages are unspecified.

Discussion

Of the 40 included studies, the majority used NWS (60%, n = 24) and conducted a supervised assessment (75%, n = 33). The most popular WS (53.3%, n = 8) was a triaxial accelerometer, while the most frequent location for the WS (80%, n = 12) was the lower back.

What should be measured?

The most frequently reported metrics in the studies reviewed were gait velocity, stride length, step length, cadence, and swing time. Among these, step length was consistently reported across all types of assessments: supervised assessments with NWS, supervised assessments with WS and unsupervised assessments. In addition to its importance in assessing overall gait performance, step length has demonstrated itself to be a sensitive indicator for distinguishing individuals with and without cognitive impairment, including those with dementia and mild cognitive impairment (MCI). It is also

an essential metric for evaluating gait quality and stability because it has shown to be very relevant as a long-term predictor of fall risk. Furthermore, it is sensitive in both single-task and dual-task scenarios (10,11).

Compared to age-matched controls, PWD demonstrated a gait velocity, reduced stride and step length, and increased stride time. These findings align with the existing literature, which characterizes the gait of PWD as slower, with a reduced rhythm and greater variability compared to healthy aging individuals (11-14).

From a clinical point of view, not every parameter that can be measured should be measured. The collection and interpretation of the data must lead to justified outcomes, i.e., meaningful to clinicians and patients. For this, gait parameters should be correlated with robust measures of clinical meaningfulness, be able to detect a difference between patients and age-matched controls and be sensitive to disease progression and to responses to therapeutic interventions (15).

According to the literature, gait speed appears to be the most commonly employed parameter for detecting cognitive decline (16-18) and according to our analysis, both NWS and WS are sensitive to variations in gait speed; however, NWS seem to be more sensitive (see forest plot 6).

Which devices should be used?

The observation that the gait velocity revealed no significant changes may suggest that the WS algorithms are more exact and accurate for this measure. It indicates that better algorithms are probably needed. However, there was a significant difference between the four parameters: swing time, stance length, and stride length. It is important to use precaution when interpreting these results considering there's a high level of heterogeneity ($I^2 \geq 77,9\%$) and a small number of studies. We believe that this outcome may have been influenced by variations in the methods of assessment and device types used in the included trials. However, in forest plot 1 we can see that no statistically significant difference was found in the gait velocity – $p = 0.37$ when using the different NWS and WS. Considering the low heterogeneity value ($I^2 = 0\%$), wearable sensors may be a viable alternative to NWS, the gold standard for gait analysis. only NWS were able to detect the differences between PWD and HC.

WS can be made up of one or more sensors, such as accelerometers, which detect motion and velocity, and inertial measurement units, which are multi-sensor devices that measure the body's position, orientation, force, and angular rate. These sensors are

usually seen as user-friendly, safe, and problem-free by patients. Devices can be integrated into clothing or accessories or attached to the body (19,20). Considering they can be used in a variety of environments, including the clinic and the real world, WS are therefore even more interesting from a scientific standpoint (19-21). However, algorithms and metrics must account for changes in context if real-world gait assessment is to be developed as a therapeutic tool (21).

Only the influence of the WS type on gait velocity could be explored. This was achieved by comparing the use of accelerometer and pressure sensors with the triaxial accelerometer, which is utilized in 53.3% of the WS.

Depending on the activity to be measured, WS can often sample or gather movement up to 100 data points per second (100-Hertz, Hz). If an extensive assessment is required at 100 Hz for seven days in a row, one wearable with a tri-axial accelerometer will collect more than 181 million data points [(100 data points per second * 60 (seconds) * 60 (minutes) * 24 (hours) * 7 (days) * 3 (axis)] (21). A tri-axial accelerometer is a device that measures acceleration in three directions that are orthogonal to one another (22,23).

The findings indicate that pressure sensors are the only tools capable of distinguishing between people with dementia (PWD) and healthy controls (HC). However, due to their dependence on specific sensor placement conditions, pressure sensors are not the most used in clinical practice. In contrast, tri-axial accelerometers offer several advantages, such as the ability to monitor movement in three dimensions, which allows for a more comprehensive analysis of physical activity and gait. They are less invasive and can be utilized in a broader range of settings, making them a versatile tool for tracking gait patterns (24,25).

Research in various fields has explored the benefits of using smartphones for assessments (26,27). However, employing smartphones for motor assessments poses challenges, particularly for individuals with dementia. They may struggle to consistently carry the device or remember the purpose of doing so. Additionally, PWDs will need help from others to operate the smartphone, which can be another reason that contributes to the burden on caregivers (20,28).

Where to place the sensor?

Our findings revealed that in 80% (n=12) of the studies employing WS, the placement of the sensor was consistently observed at lower back, specifically between the third and fifth lumbar vertebrae.

For the stride length it was possible to conduct an analysis of the data collected with the low back position and with the feet. We can see that there is no significant difference between both locations ($p = 0.58$), and we have low heterogeneity in the data ($I^2 = 0\%$). However, we should be careful when we analyse this due to the small number of studies.

Commonly used wearable systems for this purpose are IMUs, which integrate multiple 3-axis sensors, predominantly accelerometers and gyroscopes and acquire data from them. This data includes linear acceleration and angular velocity, within their respective three-dimensional local coordinate systems. IMUs can be placed at various locations on the body to acquire motion data that can be further analysed and interpreted (23,29).

While most studies locate the sensors close to the center of the body (waist, lower back, etc.) to measure postural transition, posture, and body orientation (tilt), other proposed sensor locations included the foot, leg, wrist, chest, and head to measure other important parameters like gait stability, symmetry, acceleration, and velocity during locomotion (23).

Nevertheless the reliable estimates of gait characteristics in research involving everyday life are made possible by the robustness of assessments of gait characteristics obtained from tri-axial accelerometer data against location variations within the lumbar region and Research indicates that a low-cost accelerometer-based sensor with a combination of algorithms for calculating the gait parameters of step time, stride time, step length, and step velocity has test validity and reliability (29,30).

Standardizing the positioning of sensors and the variables examined in upcoming studies can make comparisons and analyses more significant and practically applicable.

Which gait assessment protocol?

A high heterogeneity was found on the assessment protocols used in the different studies included. Eighty-two point five percent (n=33) of the studies used a supervised assessment, 10% (n=4) used an unsupervised assessment and 7.5% (n=3) used both.

The included studies' distances walked during gait analysis differed.

Most of the examined studies (69%, n = 29) applied a self-selected comfortable pace. When it comes to the distance the mode was 10 meters (21.21%, n=7) and describe the 10-meter walk test. However, we know that modifications, like reduced gait speed, rhythm, sway, instability, or stopping, often occur during dual-task activities, particularly in individuals with cognitive decline and recent studies indicate that attention-demanding

tasks alter walking patterns in all subjects to some extent, with changes in executive function and particularly attention. Also, patients with cognitive impairments may struggle with comprehending test instructions, including the requirement to walk 10 meters at a comfortable pace. This highlights the importance of assessing gait in different conditions (11,31). Although we are unable to formulate any conclusions on this subject from the data from the included research. To fully comprehend the effects of gait protocol length on PWD gait characteristics, more research is required.

The studies refer to an unsupervised evaluation of 3 and 7 days. Mc Ardle et al. (2021) suggest that the data obtained from wearable devices may be biased due to participant modifications to walking habits. Nevertheless, this bias may be mitigated by the fact that the participants wore the device consistently for seven days (21). The value of real-world gait assessments for dementia differential diagnosis deserves further investigation. Furthermore, real-world gait assessments have a few limitations that should be addressed before incorporating them into clinical practice. Less invasive sensors and strong algorithms are required to minimize the discomfort produced by present sensors, which, despite their small dimensions, can be intrusive and uncomfortable when put, for example, on the lower back. Since many of these algorithms are currently designed for controlled lab settings, they should not rely on additional data sources like questionnaires and need to be validated for use in real-world gait analysis. Furthermore, there is a disagreement about which spatiotemporal or frequency-based measures work best for characterizing gait in real-world situations (19,26).

Standard methods to assess gait, such as instrumented walkways, frequently record spatiotemporal gait characteristics including pace (e.g. gait speed and step length), variability (e.g. changes in spatiotemporal gait characteristics, as step length variations between steps), rhythm (such as temporal gait characteristics, including step time), asymmetry (like variations between left and right steps), and postural control. These characteristics provide us a more comprehensive understanding of gait and help us to identify distinct gait signatures in dementia (19). Real-world gait patterns show good discriminatory accuracy to distinguish healthy older adults from PWD, according to pilot studies. However, as variations in gait impairment markers are only detected in very brief ambulatory bouts in the real world, lab-based gait assessment may be more effective at differentiating across dementia subtypes (19). These include the need for additional validation of algorithms for identifying gait in the real world because the majority have been developed for lab-based controlled environments, and the lack of agreement on which metrics (such as spatiotemporal or frequency-based metrics) best describe gait in the real world (19,26).

It should be mentioned in this section that the studies were carried out on subjects with dementia who showed relatively high MMSE and MoCA scores. People who are in the early stages of dementia are more likely to follow the instructions. Further research is required to determine whether it is still relevant to evaluate gait in individuals with more advanced stages of dementia and how these patients respond.

Conclusion

According to our results, technological devices were able to detect that PWD gait is decreased in gait velocity, reduced stride and step length, and increased stride time when compared with age-matched controls, which is consistent with previous published description of PWD gait. Supervised assessment with NWS still the most common used type of assessment. The most common protocol of assessment includes the use of pressure sensor, located on the floor and asking for the patients to walk 10 meters at a self-selected comfortable speed. The protocol was the same for the WS, but the patients used triaxial sensors placed on their lower back.

Future studies must be conducted to evaluate the reported gait parameters against validated, clinically meaningful outcome measures in PWD to identify the most suitable metrics for assessing and monitoring disease progression and treatment response. Additionally, further research is needed to establish a standardized assessment protocol for supervised assessments and to explore the behaviour of gait parameters, as well as the most effective methods for assessing these parameters in unsupervised settings.

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Demographic and clinical characteristics | Non-wearable systems (n=24)		
	PWD	**HC**
Age (Mean, SD (n))	78.83 ± 4.66 (24)	74.9 ± 4.7 (7)
Average % Female (Mean, SD (n))	58 ± 0.18 (24)	51 ± 0.15 (7)
BMI (Mean, SD (n))	26.3 ± 1.88 (5)	25.4 (1)
MMSE (Mean, SD (n))	21.3 ± 2.38 (20)	28.25 ± 1.9 (5)
MOCA (Mean, SD (n))	20.2 ± 0.62 (3)	27.53 ± 0.60 (3)
Alzheimer Disease (%, (n))	29.17 (7)	NA
Mild to moderate dementia (%, (n))	20.83 (5)	NA
Dementia (%, (n))	16.67 (4)	NA
Mild to moderate AD (%, (n))	8.33 (2)	NA
Moderate to severe dementia (%, (n))	8.33 (2)	NA
DCL (%, (n))	8.33 (2)	NA
VD (%, (n))	8.33 (2)	NA
Mixed dementia (%, (n))	8.33 (2)	NA

Gait Parameters Mean Values						
Domain	**Variable**	**Studies (n)**	**Units**	**Most frequent unit (n, %)**	**PWD mean value (mean, SD (n))**	**HC mean value (mean, SD (n))**
Ambulatory activity	Gait Velocity	18	m/s, cm/s	m/s (10, 55.56%)	0.88 ± 0.28 (18)	1.1 ± 0.34 (5)
	Cadence	8	steps/min, m/s, strides/s	steps/min (6, 75%)	103.92 ± 19.47 (6)	NA
Pace	Stride length	11	cm, m	cm (10, 90.91%)	86.49 ± 22.85 (11)	82.04 ± 2.27 (2)
	Stride velocity	1	cm/s	cm/s (1, 100%)	33.89 (1)	49.98 (1)
	Step length	7	m/cm	m (4, 57.14%)	0.51 ± 0.12 (7)	0.64 ± 0.21 (3)
	Step velocity	2	m/s, cm/s	cm/s (1, 50%)	35.19 (1)	52.52 (1)
	Stance phase	1	% of gait cycle	% of gait cycle (1, 100%)	68.9 (1)	NA
	Double support phase	4	% of gait cycle, sec	% of gait cycle (3, 75%)	30.43 ± 6.56 (3)	NA

Rhythm	Stride time	6	seconds	seconds (6, 100%)	1 ± 0.43 (6)	1 ± 0.43 (2)
	Step time	3	seconds, msec	seconds (2, 66.67%)	0.57 ± 0.5 (3)	0.85 (1)
	Stance time	3	seconds, msec	seconds (2, 66.67%)	1.05 ± 0.47 (2)	0.74 ± 0.31 (2)
	Swing time	2	msec, seconds	NA	NA	NA
	Double support time	2	seconds	seconds (2, 100%)	0.43 ± 0.09 (2)	0.24 (1)
Variability	Stride time variability	1	%	% (1, 100%)	23 (1)	21 (1)
	Step length variability	3	%, m	% (2, 66.67%)	17.54 ± 9.14 (2)	29 (1)
	Step time variability	2	%	% (2, 100%)	21.93 ± 17.06 (2)	32 (1)
	Step velocity variability	2	m/s, %	NA	NA	NA
	Stance time variability	2	msec, %	NA	NA	NA
	Swing time variability	2	msec, %	NA	NA	NA
	Double support variability	1	%	% (2, 100%)	100	106
Asymmetry	Step time asymmetry	2	msec	NA	NA	NA
	Stance time asymmetry	1	msec	msec (1, 100%)	11	NA
	Swing time asymmetry	1	msec	Ms (1, 100%)	10,2	NA
Postural control	Step length asymmetry	1	unk	NA	NA	NA
	Step width	6	cm, m	cm (4, 66.67%)	11 ± 2.41 (6)	12 ± 1.58 (2)
Other parameters						
	Step height (m)					

Table 2.1 - Demographic data, clinical data and mean values of gait parameters assessed with non-wearable systems. Unk – Unknown, NA – Not applicable, SD – Standard Deviation.

Demographic and clinical characteristics | Wearable sensors in a supervised assessment (n=14)		
	PWD	**HC**
Age (Mean, SD (n))	76.32 ± 7.95 (14)	71.03 ± 5.72 (8)
Average % Female (Mean, SD (n))	44 ± 0.19 (14)	47 ± 0.19 (8)
BMI (Mean, SD (n))	25.2 ± 1.36 (8)	24.95 ± 2 (5)
MMSE (Mean, SD (n))	21.52 ± 2.79 (11)	28 ± 0.95 (7)
MOCA (Mean, SD (n))	20.4 (1)	28.1 (1)
Alzheimer Disease (%, (n))	37.5 (6)	NA
AD, DCL, VD, mixed (%, (n))	31.25 (3)	NA
Mild dementia (%, (n))	18.75 (3)	NA
Mild to moderate dementia (%, (n))	12.5 (2)	NA

Gait Parameters Mean Values						
Domain	**Variable**	**Studies (n)**	**Units**	**Most frequent unit (n, %)**	**PWD mean value (mean, SD (n))**	**HC mean value (mean, SD (n))**
Ambulatory activity	Gait Velocity	6	m/s, cm/s	m/s (5, 83.33%)	0.72 ± 0.18 (5)	1.06 ± 0.22 (3)
	Cadence	5	steps/min, strides/s	steps/min (4, 80%)	100.14 ± 30.66 (4)	103.38 ± 5.87 (2)
Pace	Stride length	6	m	m (6, 100%)	0.89 ± 0.35 (6)	1.33 ± 0.11 (3)
	Stride velocity	4	m/s, m/min	m/s (3, 75%)	0.92 ± 0.32 (3)	1.15 ± 0.33 (2)
	Step length	6	m/cm	m (5, 83.33%)	0.45 ± 0.13 (6)	0.58 ± 0.19 (4)
	Step velocity	3	m/s	m/s (3, 100%)	0.93 ± 0.04 (3)	1.21 ± 0.26 (2)
	Stance phase	1	% of gait cycle	% of gait cycle (1, 100%)	63.9 (1)	NA
	Swing phase	1	% of gait cycle	% of gait cycle (1, 100%)	36.14	NA
	Double support phase	1	% of gait cycle	% of gait cycle (1, 100%)	27.72	NA
Rhythm	Stride time	3	sec, msec	sec (2, 66.67 %)	1.18 ± 0.18 (2)	NA
	Step time	3	seconds, msec	seconds (2, 66.67%)	0.23 ± 0.31 (3)	0.28 ± 0.35 (2)
	Stance time	4	seconds, msec	seconds (3, 75%)	0.46 ± 0.36 (3)	0.35 ± 0.35 (3)
	Swing time	5	msec, seconds	seconds (4, 80%)	0.31 ±0.19 (4)	0.28 ± 0.23 (3)
	Double support time	1	seconds	seconds (1, 100%)	0.2	NA

	Step length variability	3	m	m (3, 100%)	0.06 ± 0.01 (3)	0.04 ± 0.007 (2)
	Step time variability	1	s	s (1, 100%)	0.05 (1)	0.07 (1)
	Step velocity variability	3	m/s	m/s (3, 100%)	0.11 ± 0.02	0.08 ± 0.008
	Stance time variability	2	msec, sec	NA	NA	NA
	Swing time variability	2	msec, s	NA	NA	NA
Asymmetry	Step time asymmetry	2	msec/s	NA	NA	NA
	Stance time asymmetry	1	sec	msec (1, 100%)	0.02	0.007
	Swing time asymmetry	2	msec/s	NA	NA	NA
Postural control	Step length asymmetry	1	m	M (1, 100%)	0.333	0.007
Other parameters						
			stride frequency (HZ)			
			cycle duration (%, coefficient of variation)			
			stride frequency (strides/sec)			

Table 2.2 - Demographic data, clinical data and mean values of gait parameters with wearable sensors in a supervised assessment. Unk – Unknown, NA – Not applicable, SD – Standard Deviation.

Demographic and clinical characteristics | Wearable sensors in an unsupervised assessment (n=6)		
	PWD	**HC**
Age (Mean, SD (n))	77.94 ± 5.56 (6)	77.6 ± 5.09 (3)
Average % Female (Mean, SD (n))	45 ± 0.07 (6)	49 ± 0.1 (3)
BMI (Mean, SD (n))	26.08 ± 0.52 (3)	26.83 (1)
MMSE (Mean, SD (n))	21.42 ± 1.45 (5)	29 (1)
MOCA (Mean, SD (n))	16 (1)	26 (1)
AD, VD, Dementia, mixed, DCL (%, (n))	33 (2)	NA
Mild to moderate dementia (%, (n))	33 (2)	NA
AD, DCL (%, (n))	16.67 (1)	NA
Mild AD (%, (n))	16.67 (1)	NA

Gait Parameters Mean Values						
Domain	**Variable**	**Studies (n)**	**Units**	**Most frequent unit (n, %)**	**PWD mean value (mean, SD (n))**	**HC mean value (mean, SD (n))**
Ambulatory activity	Step count	3	steps/per day	steps/per day (3, 50%)	6109.67 ± 2761.94 (3)	5526 (1)
	Gait Velocity	1	m//s	m/s (1, 100%)	0.72 (1)	0.83 (1)
	Cadence	1	steps/min	steps/min (1, 100%)	97.9 (1)	101.7 (1)
Pace	Stride length	1	m	m (1, 100%)	1.04 (1)	1.15 (1)
	Step length	2	m	m (2, 100%)	0.59 ± 0.03 (2)	0.61 ± 0.006 (2)
	Step velocity	2	m/s	m/s (2, 100%)	1.02 ± 0.03 (2)	1.09 ± 0.01 (2)
	Stance time	2	seconds	seconds (2, 100%)	0.48 ± 0.40 (2)	0.18 ± 0.40 (2)
	Swing time	5	msec, seconds	seconds (4, 80%)	0.31 ±0.22 (2)	0.29 ± 0.22 (2)
	Double support time	1	seconds	seconds (1, 100%)	0.2	NA
	Step length variability	2	m	m (2, 100%)	0.15 ± 0.002 (2)	0.15 ± 0.001 (2)
	Step time variability	1	sec	s (1, 100%)	1.17 (1)	0.18 (1)
	Step velocity variability	2	m/s	m/s (2, 100%)	0.36 ± 0.005 (2)	0.37 ± 0.008
	Stance time variability	1	sec	sec (1, 100%)	0.18 (1)	0.19 (1)
	Swing time variability	1	sec	sec (1, 100%)	0.15 (1)	1.15 (1)

Asymmetry	Step time asymmetry	1	sec	s (1, 100%)	0.095 (1)	0.093 (1)
	Stance time asymmetry	1	sec	msec (1, 100%)	0.1 (1)	0.1 (1)
	Swing time asymmetry	1	sec	s (1,100%)	0.145 (1)	0.147 (1)
Postural control	Step length asymmetry	1	m	m (1, 100%)	0.083 (1)	0.081 (1)
Other parameters						
			gait h/day			

Table 2.3 - Demographic data, clinical data and mean values of gait parameters with wearable sensors in an unsupervised assessment. Unk – Unknown, NA – Not applicable, SD – Standard Deviation.

	Preclinical development and testing	Clinical development and testing	Clinical validation	Total
N	6	12	22	40
Type of assessment				
Lab (supervised assessment)	5	9	19	33
FL (unsupervised assessment)	1	3	0	4
Both	0	0	3	3
Type of device				
Wearable	3	6	5	14
Non wearable	3	6	15	24
Both	0	0	2	2
Type of sensor				
Triaxial accelerometer	1	3	4	8
Accelerometer	1	1	3	5
Accelerometer and gyroscope	0	1	0	1
Force-sensitive insoles	0	0	0	0
Accelerometer, gyroscope and magnetometer	0	2	0	2
Gyroscopes	0	0	1	1
Smartphone - Accelerometer and gyroscope	0	0	0	0
Pressure sensor	0	2	16	18
Magnetometers	0	0	0	0
Optical potentiometer	1	0	0	0
Infrared light beams	0	1	0	1
Cameras	3	2	1	6
Location of the sensor				
Lower back (L3-L5)	1	5	5	12
Feet	3	2	1	5
Lower back and ankles/feet	0	1	0	1
7 sensors	0	1	0	1
Thigh	1	0	0	1
Shank	1	0	0	1
Upper and lower limbs	0	1	0	1
Sternum	0	0	1	1
Unknown	0	1	0	1

Table 2.4 - General characteristics of technology-based gait analysis in PWD

Protocol details		
Supervised assessment		
Distance		
	Median [Min, Max in meters]	11.10 [3,40]
	Mode (n, %)	10 (7, 21.21%)
Trials		
	Median [Min, Max]	2 [1,40]
	Mean, SD	4.75 ± 7.02
Protocol		
	Self-selected comfortable speed	29
	Self-selected comfortable and dual task	4
	Self-selected comfortable and cueing	1
	Fast speed	4
	Fast, normal, and slow speed	1
	Unknown	3
Unsupervised assessment		
Duration		
	3 days (WS)	3
	7 days (WS)	3
	20 days (NWS)	1

Table 2.5 - Protocol details of supervised and unsupervised assessments

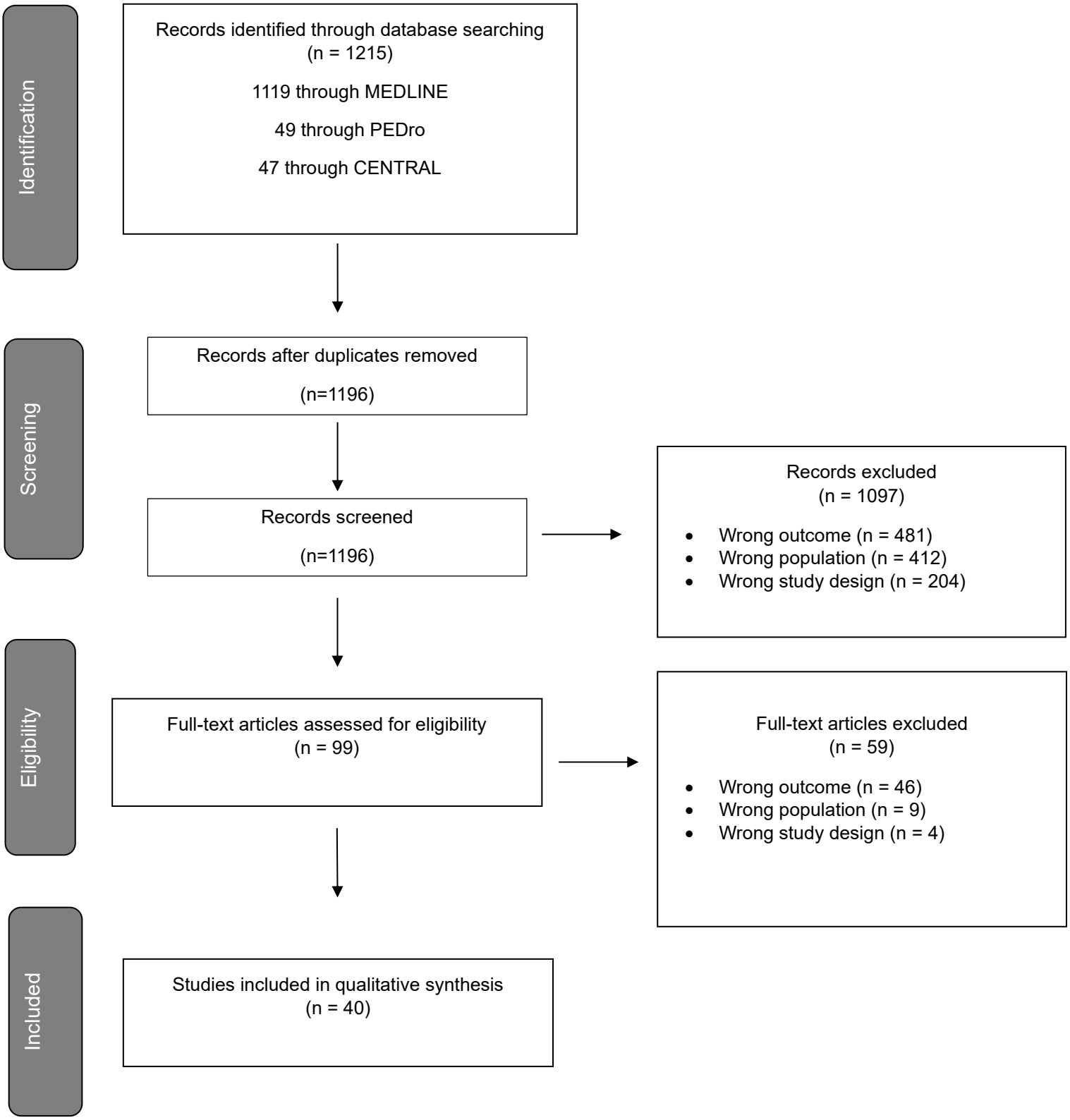
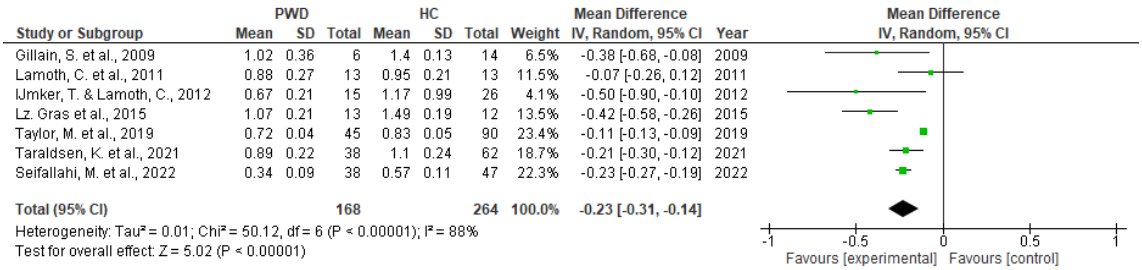


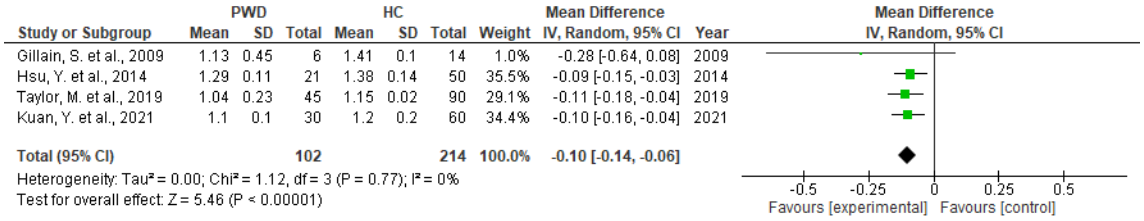
Figure 2.1 - Flow diagram of study selection process

Appendix 2.1 - Forest plot analysis for the different gait parameters

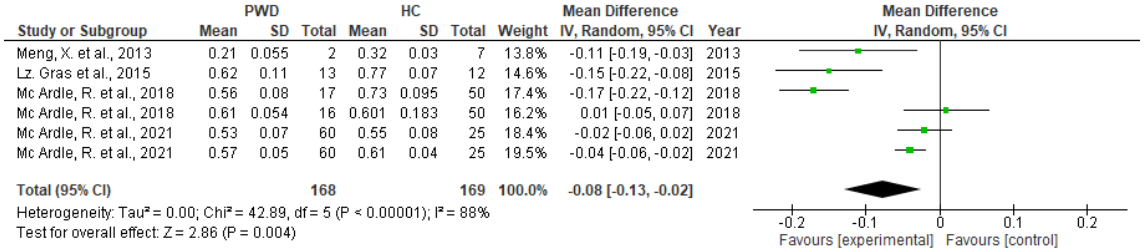
1. PWD vs Healthy controls



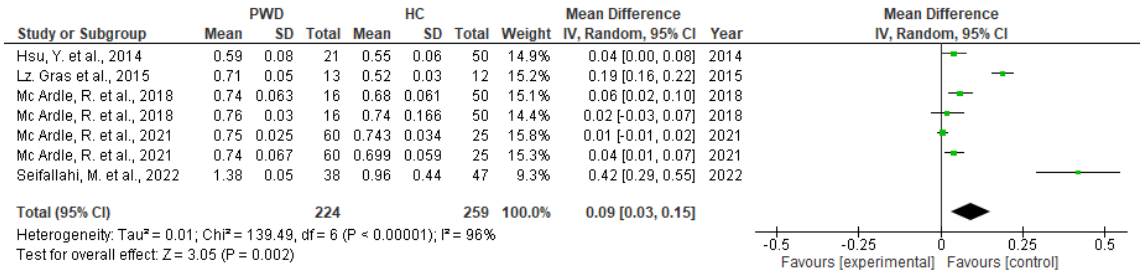
Forest Plot 1 - Gait velocity (m/s): comparison between PWD and HC



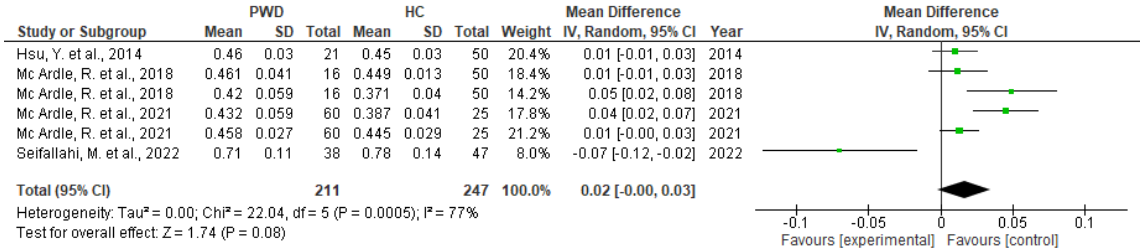
Forest Plot 2 - Stride length (meters): comparison between PWD and HC



Forest Plot 3 - Step length (meters): comparison between PWD and HC

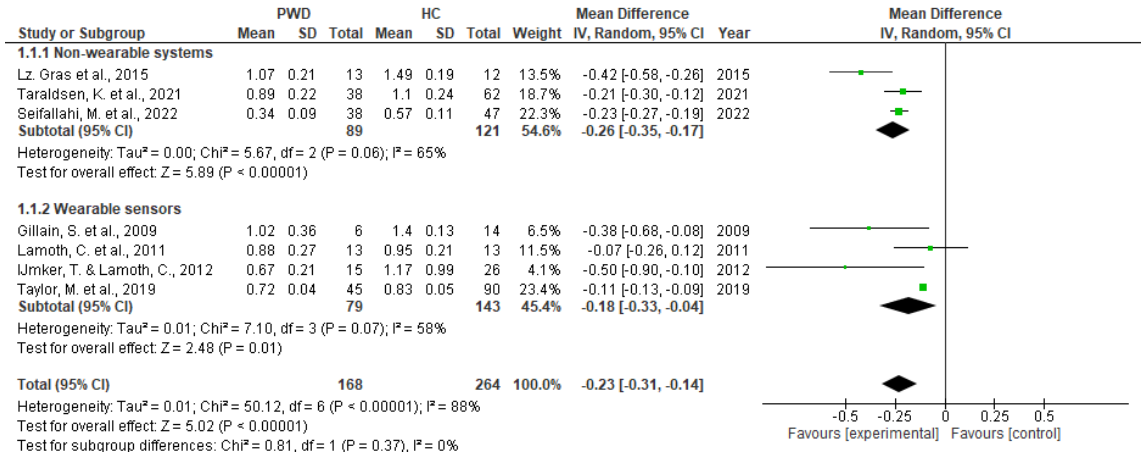


Forest Plot 4 - Stance time (seconds): comparison between PWD and HC

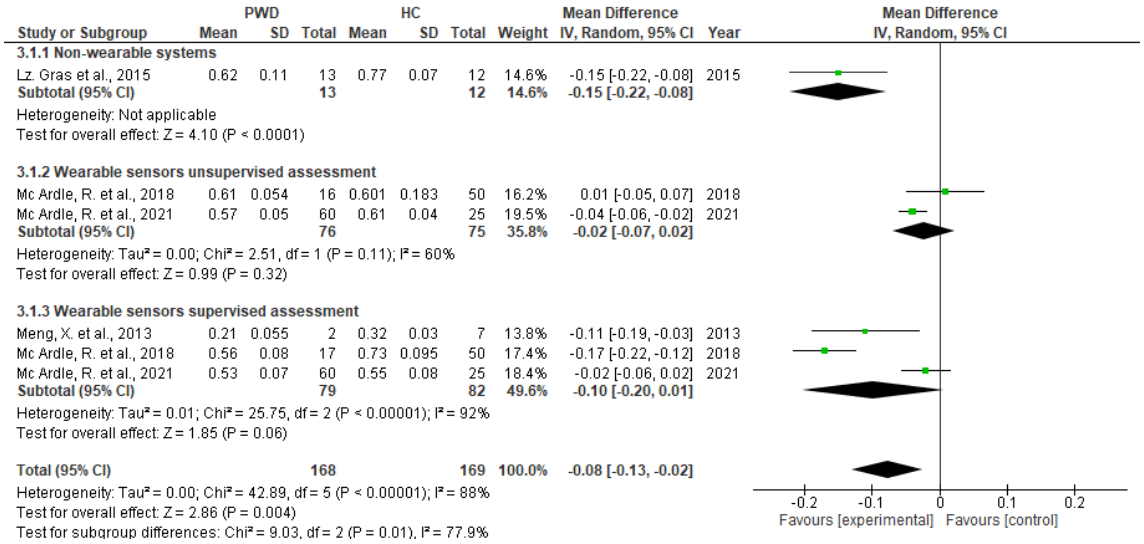


Forest Plot 5 - Swing time (seconds): comparison between PWD and HC

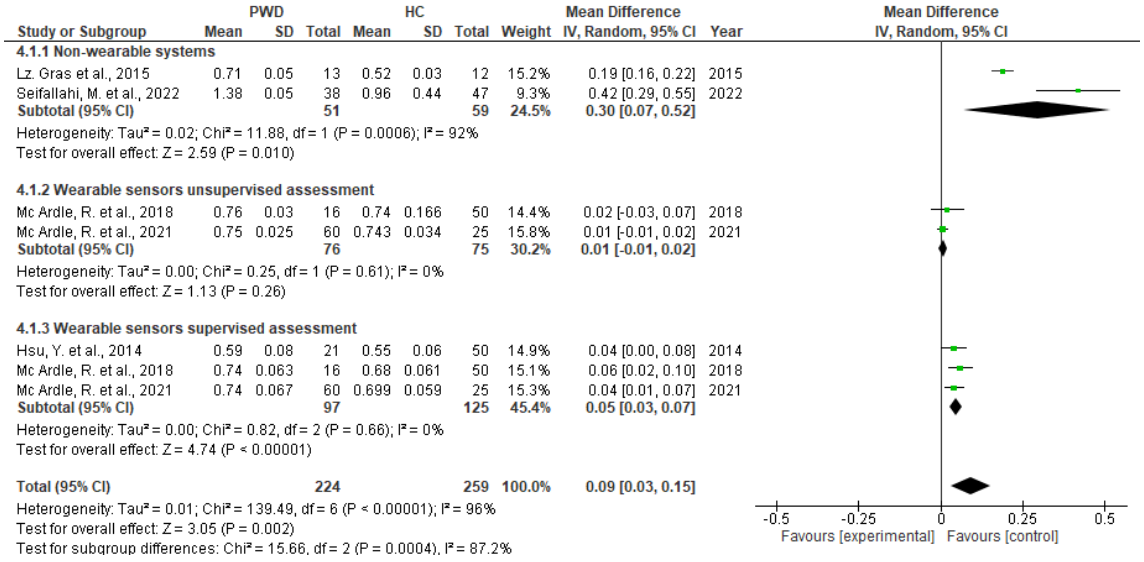
2. Non-wearable vs Wearable devices



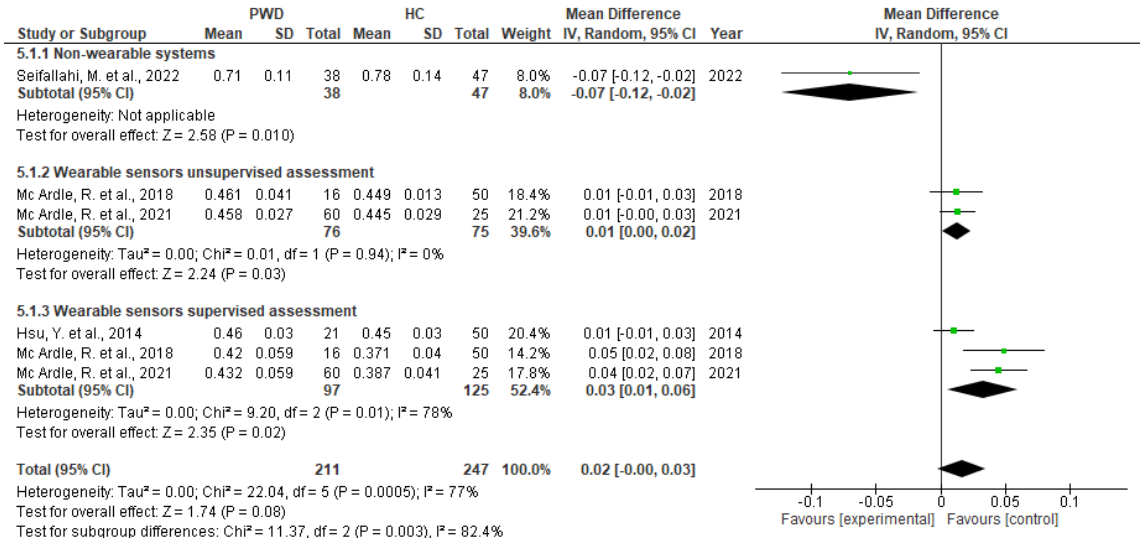
Forest Plot 6 - Gait velocity (m/s): comparison between NWS and WS



Forest Plot 7 - Step length (meters): comparison between NWS and WS

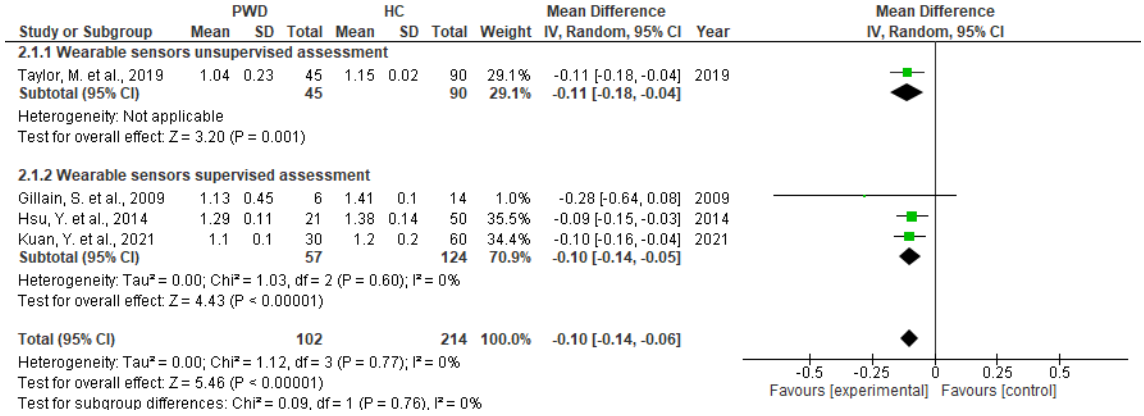


Forest Plot 8 - Stance time (seconds): comparison between NWS and WS

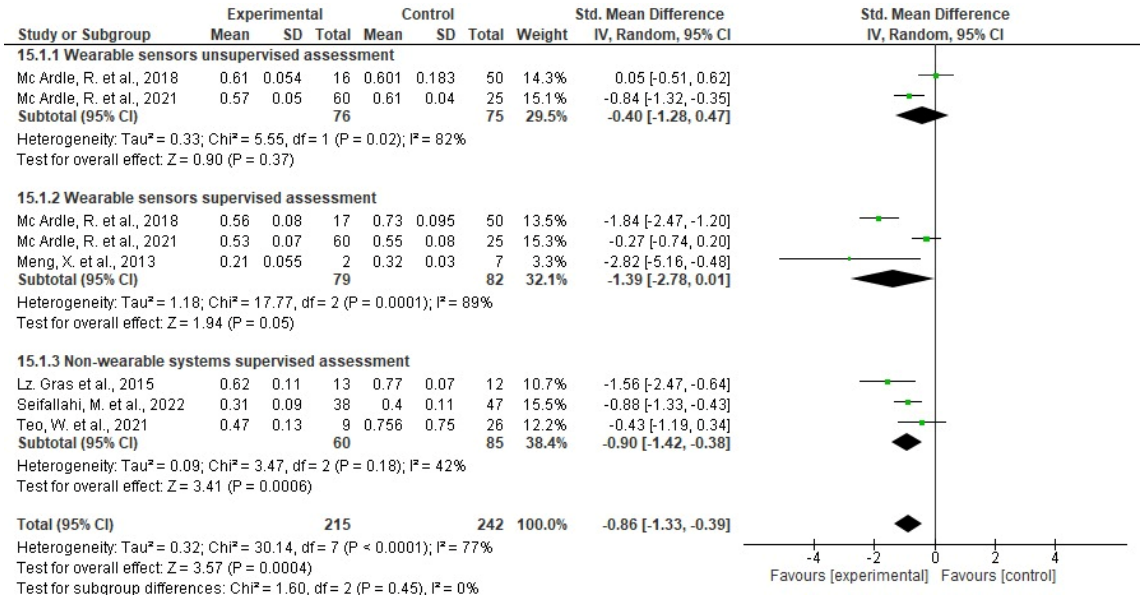


Forest Plot 9 - Swing time (seconds): comparison between NWS and WS

3. Supervised vs Unsupervised assessment

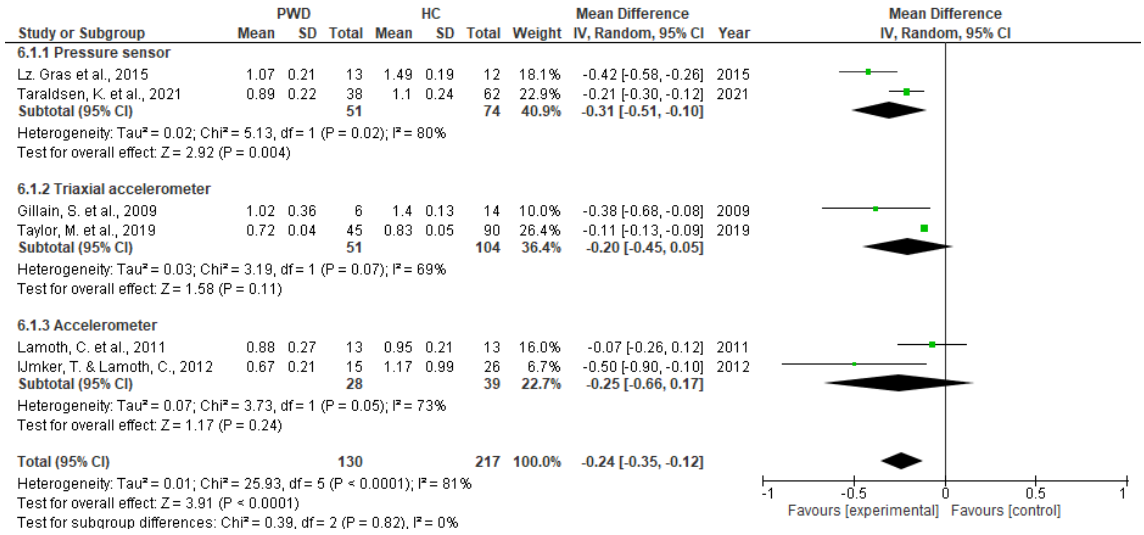


Forest Plot 10 - Stride length (meters): comparison between supervised and unsupervised assessments



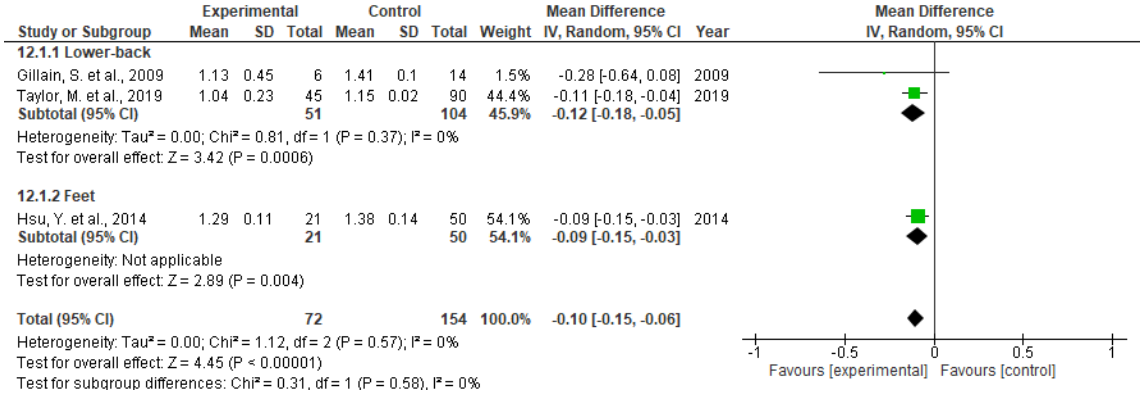
Forest Plot 11 - Step length (meters): comparison between supervised and unsupervised assessments

4. Different type of sensors



Forest Plot 12 - Gait velocity (m/s): comparison between different type of sensors

5. Different sensor's location



Forest Plot 13 - Stride length: comparison between different sensor locations

3. Chapter 2 - Applicability of technology outcomes measures to assess gait in dementia

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Abstract

Background: Increased longevity has led to a rise in dementia prevalence, with projections indicating a significant increase in cases by 2050. Dementia, characterized by cognitive decline beyond normal aging, affects gait due to impaired motor, sensory, and cognitive functions. Traditional motor assessments are limited in dementia due to their reliance on patient comprehension, attention and cooperation. Recent studies suggest that kinematic gait assessments offer a less invasive and more precise alternative, though optimal parameters for evaluating gait in dementia remain underexplored

Objective: This study aims to determine the applicability of using kinematic analysis as a tool to assess gait in people with mild cognitive impairment and dementia.

Methods: This retrospective clinical study, conducted from October 15, 2023, to March 1, 2024, evaluates the use of kinematic analysis for assessing gait in individuals with mild cognitive impairment (MCI) and various types of dementia. Participants, recruited from CNS - Campus Neurológico, were assessed using the 10-meter walk test (10MWT) and a tri-axial accelerometer. Data were extracted and analysed for spatiotemporal gait parameters.

Results: Gait parameters were analysed in 57 patients with dementia and MCI. Among the gait metrics, only step length variability showed statistical significance across groups. MCI patients had longer steps, higher step and stride velocities, and faster gait speeds. Alzheimer Disease (AD) patients had similar gait metrics to MCI, while Fronto Temporal Dementia (FTD) showed the lowest step length variability and highest bout steps. Vascular dementia (VD) and FTD patients had longer stride, stance, swing, and double support times. Dementia with Lewy Bodies (DLB) had similar cadence to MCI and AD. All groups had low asymmetry values.

Conclusion: This study shows the potential of wearable sensors in differentiating between distinct forms of dementia, despite the small sample size. The only kinematic parameter that showed significant variations was step length variability, highlighting the potential of wearable technology to improve clinical evaluations. Gait analysis exhibits potential as a non-invasive technique for the early identification and categorization of dementia and MCI.

Key words: Dementia, Mild Cognitive Impairment, Gait Assessment, Kinematic analysis, Sensor, Technology

Background

Increased longevity has led to a significant rise in the prevalence and consequent effect of aging-related disorders like dementia (1). Currently, there are more than 55 million people worldwide who have this diagnosis (2,3), being expected to double in Europe by 2050 and triple globally (2). Dementia is characterized by a decline in cognitive performance that goes above what may be predicted as a result of biological aging (2).

Cognitive deterioration and neurodegenerative conditions that interfere with top-down regulation mechanisms have been associated to gait impairment because the ability to walk depends on the complex and simultaneous interaction of the motor system, sensory control, and cognitive function, making it one of the most frequently performed sensorimotor activities in daily life (4,5). As cognition deteriorates, gait variability increases and performing other tasks while walking becomes harder (4). To evaluate walking abilities, supervised motor assessments are typically used (6). However, its use among people with dementia is limited not only because the majority of the tests lack sufficient psychometric evidence to support their use in this population, but also because its performance requires the ability to understand and follow instructions and maintain concentration during the test, which is usually challenging for those with mild to moderate dementia (7,8).

As a way to circumvent these limitations, recently published studies suggest the use of supervised kinematic gait assessments to evaluate walking ability in people with dementia (4,9). These are less invasive and require less involvement from the patient, which allow for more precise quantification of movement, as well as how it changes over time due to disease progression and in response to pharmacological or non-pharmacological therapeutic interventions (10,11).

Despite these benefits, it has not yet been determined how to evaluate or what gait parameters should we take into consideration when evaluating gait in dementia, whereby kinematic gait analysis continues to be understudied and underused in clinical routine. In this regard, the aim of this study is to examine the gait kinematic parameters in people with Mild Cognitive Impairment (MCI) and dementia such as Alzheimer's Disease (AD), Frontotemporal Dementia (FTD), Lewy Bodies Dementia (LBD) and Vascular Dementia (VD) in order to gather data for the development of this promising gait assessment technique in this population.

METHODS

Study design

A retrospective clinical study was conducted between October 15, 2023, to March 1, 2024

Objective

This study aims to determine the applicability of using kinematic analysis as a tool to assess gait in people with mild cognitive impairment and dementia.

Participants

Study participants were recruited from CNS - Campus Neurológico (CNS), a tertiary specialized movement disorders centre in Portugal. All inpatients and outpatients assessed between September 2017 and September 2023 were considered if they fulfilled the following eligibility criteria:

Inclusion criteria:

- People with a clinical diagnosis of mild cognitive impairment (MCI) and dementia (Alzheimer's, frontotemporal dementia, Lewy body dementia, vascular dementia, or mixed dementia) according to CNS medical charts;

- Have been submitted to a clinical and kinematic motor assessment by the CNS Physiotherapy Team;

- Capacity to understand and give written informed consent for the use of demographic and clinical data for research purposes.

Exclusion criteria:

- Presence of cardiovascular, pulmonary or musculoskeletal condition that according to the clinician's judgment affect patients' ability to participate in the study.

Study Procedures

All data needed to characterize the sample and to answer the outcomes, was extracted from DataPark (12), in a pseudo-anonymized format.

DataPark is a web platform to obtain a record of the patient's evolution over time and to help understand the impact of therapeutic interventions in inpatient or outpatient settings (12).

At admission in the CNS in and out-patient clinic, all patients were asked to sign the informed consent form allowing researchers to use their data in a pseudo-anonymous format.

The study protocol was approved by the Ethics Committee of the CNS – Campus Neurológico and the Ethics Committee of Escola Superior de Tecnologia da Saúde de Lisboa – Instituto Politécnico de Lisboa.

Clinical and kinematic assessment

A multidisciplinary assessment was performed. Firstly, demographic and clinical data was collected, giving information on age, sex, Body Mass Index (BMI) (13), and the Mini-Mental State Examination (MMSE) score to characterize the participants. Then, the 10-meter walk test (10MWT) (14) was used to analyse the gait parameter.

The 10MWT is an easy test to perform as it is only asked for participants to walk 10 meters in a straight line at their self-selected speed. It was developed to assess walking speed (14). During the test, in order to assess gait kinematic parameters, patients use, a tri-axial accelerometer (Axivity AX3), placed in their lower back (L5), programmed to capture raw data at 100Hz with a dynamic range of +-8g. Each subject performs three trials of each assessment. The start and end of each trial are noted on the DataPark mobile application by the physiotherapist responsible for the assessment and synced with the AX3 internal clock.

Data from multiple assessment periods can be analysed using the DataPark platform, however in this study we only focused on each patient's initial assessment. This approach ensures that the data remains unbiased by subsequent sessions the patients may have undergone. In cases where previous baseline assessments were conducted in previous years, we took into account the most recent one.

Kinematic data analysis

Departing from the segmentation of test trials that will be provided by the application, we manually adjusted the start and end of each test to match the exact start and end of the movement and remove reported periods of pause. To extract meaningful data from the raw accelerometer signal, we used Sci-Digital-Health (15). We used the pre-processing module to resample data to 100 Hz using linear interpolation, to mitigate known fluctuations of the sample rate. Afterwards, the offset was removed as well as machine

noise using a 4th order Butterworth low pass filter of 20 Hz. We focused the kinematic gait analysis in the study of spatiotemporal gait parameters. To extract gait parameters, we used the gait module that employed a wavelet-based algorithm to detect Initial Contact (IC) / Final Contact (FC) points, from which gait parameters were calculated. A concurrent validity analysis of the reported number of steps (by the physiotherapist observing the trial) and the automatic detection revealed an intra-class correlation above 0.85.

Data analysis

The primary outcome is to characterize gait in the different diagnosis, based on the kinematic gait parameters during the performance of the 10 meters walk test, in the admission assessment. The secondary outcomes are the comparison of the kinematic gait parameters among MCI and the different types of dementia.

Descriptive statistics was used for demographic and clinical variables. To compare gait parameters between MCI and the different types of dementia, we started by studying normality, using the Kolmogorov-Smirnov and the Shapiro-Wilk tests, and then use the one-way ANOVA factor test for each parameter. A significance level of 0.05 was used to set statistical significance. The statistical analysis was performed using RStudio 2024.04.2 Build 764© 2009-2024 Posit Software, PBC.

RESULTS

Out of the 2193 patients on the DataPark platform, a total of 319 with PWD and 64 with MCI were identified. From these, 57 participants were included in this study (52 PWD and 5 with MCI) – see appendix 2.1. The reasons for exclusion were the absence of kinematic gait assessment (80%, n = 310) and being reassessments after an intervention program (2.35%, n = 9). The mean age of the PWD was 76.7 ± 5.93 years, and 61.5% (n = 32) were men. The mean age of participants with MCI was 85.2 ± 6.42 years, and 1.8% (n=1) were men. The MMSE score could only be consulted for 41 patients and the mean was 22.07. Since the remaining patients were not receiving cognitive training, they were not evaluated using this scale. Table 3.1 provides a summary of the clinical and demographic information for the patients, while Table 3.2 presents a comprehensive analysis of gait metrics for each diagnostic category.

Among the gait parameters, only step length variability demonstrates statistical significance across groups. Despite the limited sample size, individuals with MCI exhibit longer step and stride lengths, higher step and stride velocities, and increased gait speed. The Alzheimer's Disease group shows gait metrics most similar to those of MCI patients, whereas the FTD group displays the most pronounced differences.

Notably, individuals with FTD are the most consistent walkers, as indicated by their lowest step length variability. Furthermore, the FTD group has the highest number of bout steps, in contrast to the AD group, which has the lowest.

In terms of variability, FTD patients have the lowest scores across all parameters except for stride time variability, where the AD group shows equivalent values.

Regarding gait rhythm, patients with VD and FTD have longer stride time, stance time, swing time, and double support time compared to other groups. Dementia with Lewy Bodies showed similar cadence results to those of MCI and AD.

Overall, all groups exhibit very similar results with low asymmetry values across the measured parameters.

DISCUSSION

The present work provides evidence that the application of kinematic gait analysis can successfully distinguish between gait patterns exhibited by persons with MCI and various forms of dementia. These findings indicate that although most gait metrics were similar among the groups, the variability in step length was a significant distinguishing characteristic, being lower in individuals with FTD and higher in those with AD and MCI. Patients diagnosed with FTD shown more uniform walking patterns, as seen by their reduced variability in step length. Conversely, those with MCI and AD demonstrated traits of higher gait speed, longer step and stride lengths.

The walking patterns of patients diagnosed with AD had a greater resemblance to those with MCI, indicating the presence of shared motor characteristics despite distinct cognitive profiles. A common underlying pathology affecting both groups may be suggested by this discovery. Furthermore, the consistent low gait asymmetry across all groups indicates that symmetry alone may not be an adequate indicator for distinct forms of cognitive impairment.

These findings emphasise the capacity of gait analysis as a non-intrusive method for the early identification and distinction of different forms of dementia and MCI, identifying

certain gait metrics such as step length variability and gait rhythm as significant indicators.

Findings' Implications for the Diagnosis and Assessment of MCI and Dementia

Given the incurability of dementia, early detection is necessary to avoid or at least decelerate the advancement of the disease. Diagnosing MCI, a significant precursor to AD, is of utmost importance. Nevertheless, the timely identification of dementia and its different forms remains a significant challenge in therapy. Traditional methods for detecting MCI include blood tests, brain imaging, EEG, and neuropsychological testing. These methods are often costly, time-consuming, and limited to practitioners with expertise in the field (16).

Significantly, previous research has revealed that stride length, step length, and gait speed are very valuable in distinguishing between distinct cognitive states. Therefore, it is highly recommended to monitor gait speed in order to promptly detect cognitive issues, so improving diagnostic precision and underscoring the utmost need of early intervention (4,16,17), Moreover, wearable technology has the potential to outperform conventional methods and offers fascinating prospects for accurately categorising dementia. The affordability and versatility of this technology enable its employment in a wider range of therapeutic applications, therefore expanding its potential utility beyond the classification of subtypes. Certain clinical applications of this technology include monitoring the progression of a disease and detecting persons who are susceptible to it (18).

Comparison of Gait Parameters Across MCI and Different Types of Dementia

When compared to normal aging, the gait impairment associated with dementia is characterized by slower speed, reduced rhythm, and higher variability. Results show that compared to people with non-AD dementias, AD group has less impairment in terms of speed, rhythm, and variability. This implies that gait analysis may be used as a clinical diagnostic to distinguish between different forms of dementia. More extensive research that includes a wide range of gait traits and more precisely defined dementia subtypes is required (19).

While gait speed is a useful measure of mobility and cognitive function, focusing just on this element of the equation may be restrictive (20). Our results showed that step length variability was the only gait metric that differed significantly between the groups (figure

2). Step length variability, which measures the consistency of step lengths, increases with age and is higher in neurological patients. It is associated with falls and predicts dementia (21).

In our results, we observed that patients with MCI (0.94 ± 0.3 m/s) and AD (0.89 ± 0.22 m/s) had higher gait speeds compared to those with DLB (0.83 ± 0.25 m/s) and VD (0.8 ± 0.23 m/s), while FTD patients (0.76 ± 0.22 m/s) had the slowest gait speed (figure 2).

Compared to elderly people with normal cognition, older adults with MCI perform worse regarding their walk, but better than those with dementia (22). Additionally, compared to healthy controls, the research shows that people with AD, LBD, and VD walk more slowly, have shorter strides, and have higher stride time variability. These gait impairments, tend to worsen as the disease progresses (17).

Advantages of Kinematic Analysis in Evaluating Patients with Dementia

Notably, significant progress has been made in hospital and residential environments by employing body-worn sensors to monitor the walking patterns of individuals with dementia. Research has shown that individuals with dementia find these sensors to be both bearable and beneficial. When analysed in their native habitats, they facilitate the identification of patterns that enable the differentiation of persons with dementia from those without (16,23,24). Such patterns are characterised by a reduced speed and increased variation in walking patterns. This development emphasises the applications of gait monitoring in identifying first indications of dementia and accurately monitoring the course of the disease. Contemporary research indicates that the use of sequential gait speed measurements in dementia risk evaluations may improve the early identification and therapy of dementia (24,25). Standard evaluations employed for diagnosing these illnesses frequently encounter subjectivity concerns and may lack the necessary sensitivity to identify minor early deficits or accurately monitor the course of the disease (19). To overcome these limitations, it is essential to integrate these conventional measures with quantitative, objective assessments of walking skill and posture control. Practical implementation of this combination has the potential to enhance both patient monitoring and diagnostic precision.

Clinical Relevance and Practical Applications

Considering that gait irregularities can be detected before the onset of cognitive deterioration, early gait analysis is a useful method for promptly detecting dementia. Technological progress has led to increased accessibility, compactness, and portability of quantitative gait analysis methods, which may enhance their value in therapeutic contexts (19,24).

The advantages and disadvantages of quantitative gait analysis should be elucidated to healthcare professionals to enable them to select appropriate tools, techniques, and assessment criteria. Continual validation of appropriate methodologies and outcome measures is necessary to effectively guide clinical management and facilitate research. For the purpose of improving diagnosis and disease monitoring, it is necessary to employ a condition-specific approach and explore deep learning and machine learning techniques (25). The establishment of normative values across a range of standardised outcomes will facilitate the interpretation of gait and postural control data, integration of their clinical use, and enable personalised patient care. Further investigation is needed to definitively establish gait and postural control as approved markers for disease diagnosis and monitoring of disease development (19,23).

Study Limitations and Areas for Future Research

One significant limitation of this study is the limited sample size, which highlights the challenges in evaluating persons who often struggle to comprehend instructions during assessments. The result's robustness may have been affected by this constraint, as well as our inability to consistently gather data on the length and severity of the diseases. To improve the reliability and validity of the results, it is crucial to standardise the evaluation procedures and characterise the samples as comprehensively as feasible.

CONCLUSION

Our results demonstrate the significant potential of wearable sensors as a useful tool for differentiating between various types of dementia, despite the small sample size. The only kinematic metric that showed significant variations across groups was step length variability, but even so, this shows how wearable technology can improve clinical examinations. Furthermore, compared to those with MCI, a significantly larger percentage of those with dementia are being monitored in physiotherapy, according to our data. This discrepancy highlights how urgent it is to improve dementia diagnosis and

treatment strategies. In the end, gait analysis shows promise for the early diagnosis and separation of MCI and dementia subtypes as a useful and non-invasive approach.

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Demographic features							
	DLB (n=21) 36.84%	AD (n=16) 28.07%	VD (n=8) 14.04%	FTD (n=7) 12.28%	All dementias (n=52) 91.23%	MCI (n=5) 8.77%	Total (n=57) 100%
Age (Mean, SD)	76.7 ± 5.91	76.6 ± 6.72	80.4 ± 3.74	72.4 ± 3.78	76.7 ± 5.93	85.2 ± 6.42	77.4 ± 6.3
Male Sex [%(n)]	86% (n=18)	38% (n=6)	63% (n=5)	43% (n=3)	62% (n=32)	20% (n=1)	58% (n=33)
BMI (Mean, SD)	24 ± 4.6	25 ± 3.44	26 ± 3.67	25 ± 3.59	25 ± 4	27 ± 2.8	25,2 ± 4

Clinical data [Mean (SD)]							
	n=14	n=14	n=5	n=6	n=39	n=2	n=41
MMSE	23 ± 5.2	20 ± 6.58	22 ± 7.9	25 ± 3.59	22±6.03	26 ± 1	22.07 ± 6
	n=21	n=16	n=8	n=7	n=52	n=5	n=57
10 MWT time (seconds)	15 ± 5.58	12 ± 4.73	15 ± 5.7	15 ± 5.22	14 ± 5.57	12 ± 2.21	13.69 ± 5.3
10MWT steps	24 ± 8.08	20 ± 5.79	23 ± 7.41	24 ± 7.44	23 ± 7.57	21 ± 2.61	22.4 ± 7.2

Table 3.1: Demographical and clinical characteristics of the sample - mean ± sd values

	DLB (n=21) 36.84%	AD (n=16) 28.07%	VD (n=8) 14.04%	FTD (n=7) 12.28%	MCI (n=5) 8.77%	*p-value*
Bout steps	67.81 ± 23.93	54.63 ± 16.96	69.38 ± 15.5	71 ± 25	57.4 ± 9.9	0.214
Pace						
Step length (meters)	0.48 ± 0.1	0.52 ± 0.09	0.49 ± 0.08	0.46 ± 0.09	0.53 ± 0.11	0.546
Stride length (meters)	0.95 ± 0.19	1.03 ± 0.18	0.97 ± 0.16	0.93 ± 0.18	1.07 ± 0.27	0.526
Step velocity (m/s)	0.82 ± 0.25	0.88 ± 0.22	0.79 ± 0.23	0.75 ± 0.22	0.92 ± 0.29	0.667
Stride velocity (m/s)	0.82 ± 0.25	0.89 ± 0.22	0.8 ± 0.22	0.76 ± 0.23	0.93 ± 0.3	0.643
Gait speed (m/s)	0.83 ± 0.25	0.89 ± 0.22	0.8 ± 0.23	0.76 ± 0.22	0.94 ± 0.3	0.628
Variability						
Step time variability (seconds)	0.068 ± 0.05	0.076 ± 0.06	0.102 ± 0.07	0.06 ± 0.03	0.076 ± 0.05	0.574
Step length variability (meters)	0.07 ± 0.02	0.088 ± 0.03	0.084 ± 0.03	0.054 ± 0.01	0.092 ± 0.04	0.0248
Stance time variability (seconds)	0.066 ± 0.05	0.077 ± 0.05	0.104 ± 0.07	0.06 ± 0.03	0.088 ± 0.05	0.376
Swing time variability (seconds)	0.062 ± 0.05	0.065 ± 0.06	0.08 ± 0.05	0.057 ± 0.03	0.068 ± 0.05	0.896
Stride time variability (seconds)	0.09 ± 0.06	0.09 ± 0.08	0.102 ± 0.07	0.09 ± 0.05	0.106 ± 0.08	0.964
Double support variability (seconds)	0.03 ± 0.02	0.024 ± 0.01	0.024 ± 0.009	0.02 ± 0.01	0.03 ± 0.009	0.767
Rhythm						
Cadence (steps/min)	103.32 ± 13.33	103.29 ± 14.11	97.83 ± 12.25	97.31 ± 16.73	103.32 ± 14.87	0.763
Stride time (seconds)	1.19 ± 0.16	1.2 ± 0.18	1.25 ± 0.15	1.28 ± 0.24	1.19 ± 0.17	0.546
Stance time (seconds)	0.76 ± 0.11	0.76 ± 0.12	0.81 ± 0.11	0.81 ± 0.15	0.76 ± 0.11	0.751
Swing time (seconds)	0.44 ± 0.05	0.44 ± 0.07	0.45 ± 0.05	0.47 ± 0.09	0.44 ± 0.06	0.815
Step time (seconds)	0.599 ± 0.08	0.601 ± 0.09	0.637 ± 0.09	0.639 ± 0.12	0.6 ± 0.09	0.726
Swing phase (% of gait cycle)	0.37 ± 0.01	0.37 ± 0.01	0.36 ± 0.01	0.36 ± 0.005	0.38 ± 0.009	0.754
Double support time (seconds)	0.32 ± 0.05	0.32 ± 0.06	0.34 ± 0.05	0.35 ± 0.06	0.31 ± 0.05	0.66
Double support phase (% of gait cycle)	0.27 ± 0.02	0.27 ± 0.02	0.27 ± 0.02	0.27 ± 0.01	0.26 ± 0.02	0.777
Asymmetry						
Stride time asymmetry seconds	0.003 ± 0.005	0.004 ± 0.009	0.002 ± 0.005	0.003 ± 0.005	0.004 ± 0.006	0.989
Step time asymmetry seconds	0.002 ± 0.004	0.002 ± 0.004	0.002 ± 0.007	0	0.004 ± 0.006	0.644
Stance time asymmetry seconds	0.002 ± 0.004	0.002 ± 0.006	0.002 ± 0.007	0.001 ± 0.004	0.004 ± 0.006	0.95
Swing time asymmetry seconds	0.003 ± 0.005	0.004 ± 0.01	0.005 ± 0.008	0.001 ± 0.004	0.004 ± 0.006	0.886
Step length asymmetry meters	0.002 ± 0.005	0.004 ± 0.008	0.004 ± 0.005	0	0.004 ± 0.006	0.657
Stride length asymmetry meters	0.004 ± 0.008	0.002 ± 0.005	0.002 ± 0.005	0	0	0.964

Table 3.2: Gait parameters of the different diagnosis - mean ± sd values

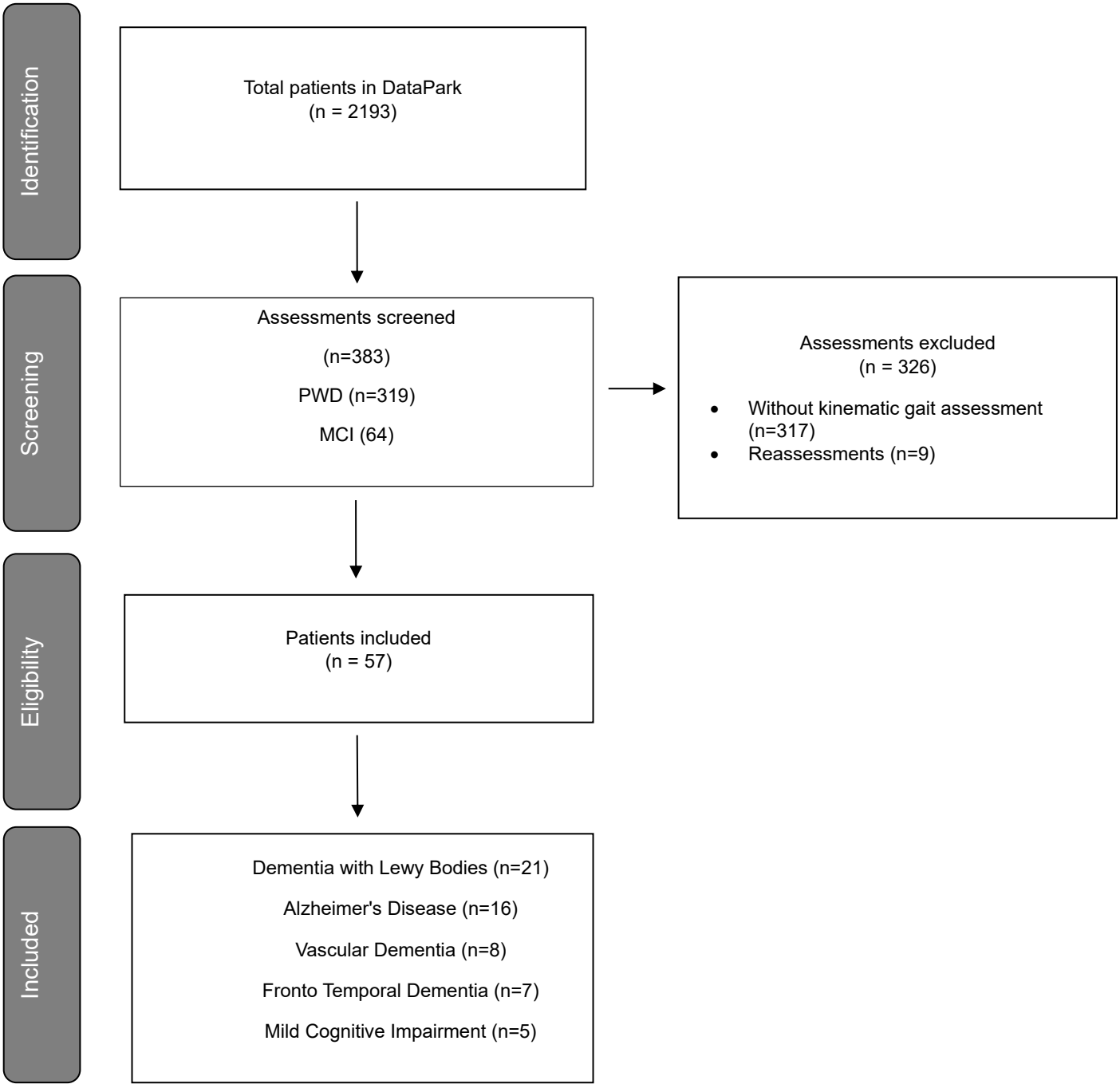

Figure 3.1 - Flow diagram of patient selection process

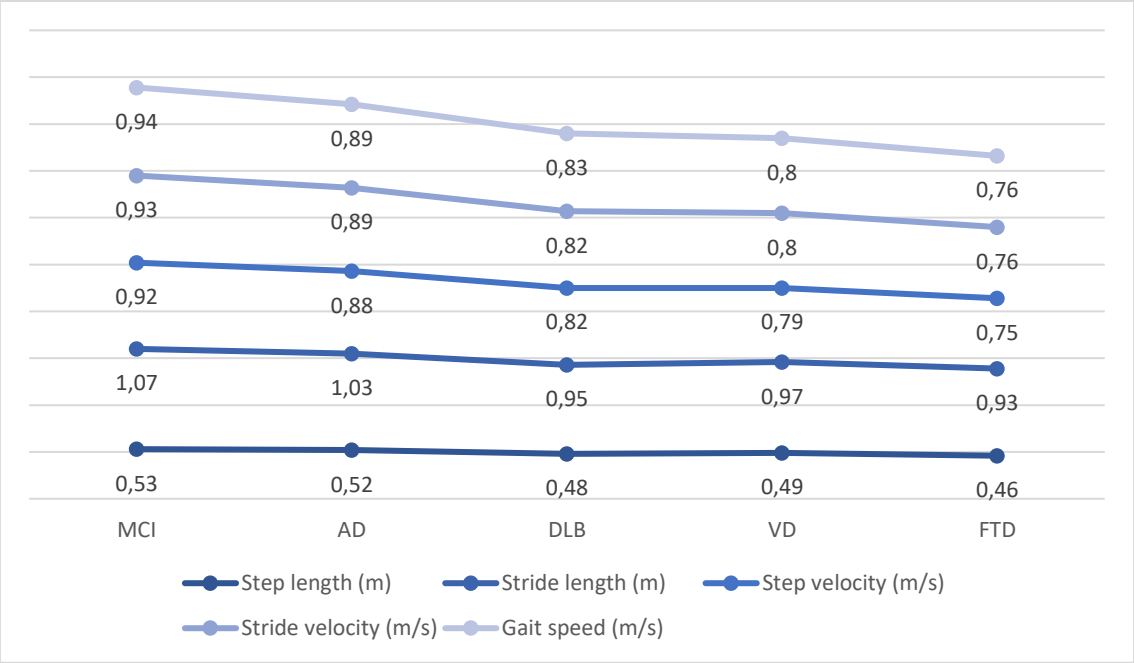

Figure 3.2 – Differences between groups – Pace

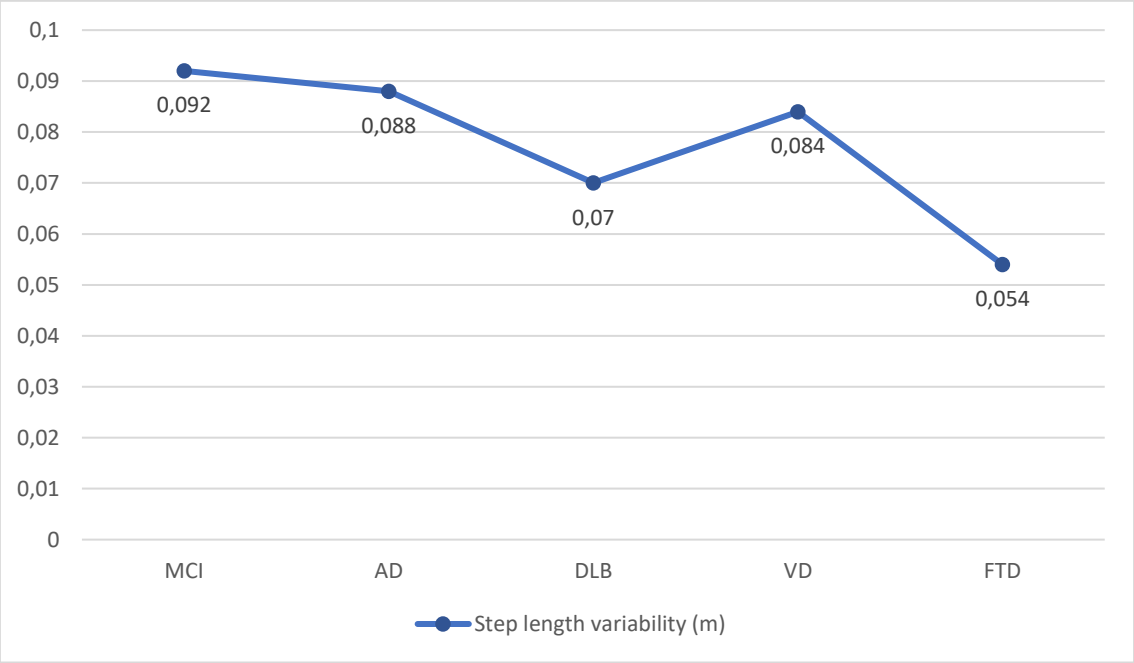

Figure 3.3 – Differences between groups – Step length variability (meters)

4. Discussion

Analysing gait patterns, particularly the spatiotemporal, kinematic, kinetic, and balancing aspects of gait, can provide insight into how well a person walks in relation to their general health and functional capacity. Artificial intelligence, including machine learning and deep learning techniques, and smart technology are becoming increasingly popular in the field of gait research. These methods have the potential to significantly change the way gait is quantified by collecting, storing, and analysing multifactorial complex gait data, as well as capturing its variability and non-linear dynamic properties, despite their limited application in clinical settings (16). However, only a select few patients at some tertiary hospitals can have complete gait analysis. Many experts have suggested that gait analysis needs to be performed for all patients suffering from degenerative illnesses and those requiring extended therapy (19).

Gait metrics, such as gait velocity, stride length, step length, cadence, and swing time, were often documented in the forty included studies, according to the systematic review. Step length was found to be very responsive and consistent among the different assessment types (supervised assessment with WS and with NWS and unsupervised assessments). In the retrospective clinical study, the only kinematic characteristic that significantly changed between groups was step length variability.

The review show that WS, particularly triaxial accelerometers, are widely used and that the lower back is frequently where the sensors are located. Although WS appear promising because of their reduced intrusiveness and adaptability, NWS are still the gold standard (36, 37). Although algorithms require improvement, WS showed promise for gait analysis in a variety of scenarios despite variations in sensor performance (38).

The retrospective clinical study examined the kinematic gait of MCI and dementia. We observe that a measure that has proven crucial for distinguishing between the different types of dementia is step length variability. Furthermore, despite having different cognitive profiles, people with AD and MCI showed similar gait patterns, indicating a shared set of motor features. Both groups demonstrated longer step lengths and higher gait speeds. Moreover, it was noted that step length variability was lower in those with FTD. It was not possible to differentiate between different kinds of dementia using just gait symmetry.

5. Conclusion

The use of sensors enables the detection of gait changes in PWD in comparison to HC, according to the findings of published studies. This experiment found that PWD have slower gaits, shorter steps and strides, and longer stride times, which is consistent with previous research. Considering their capacity to distinguish between various forms of dementia, step length and step length variability appear to be the most intriguing metrics.

While supervised assessments using NWS are the most common form of assessment, WS seem promising because of their ability to distinguish between different forms of dementia as well as their early detection and subtype classification capabilities.

It is essential that we recognize the limitations of these research studies, specifically the small sample size and heterogeneity of the data.

More investigation is required to determine a uniform evaluation process for supervised evaluations, examine the behaviour of gait metrics, and determine the best techniques for evaluating these parameters in unsupervised environments.

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