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Vision-based motion capture for the gait analysis of neurodegenerative diseases: A review

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ABSTRACT

Background: Developments in vision-based systems and human pose estimation algorithms have the potential to detect, monitor and intervene early on neurodegenerative diseases through gait analysis. However, the gap between the technology available and actual clinical practice is evident as most clinicians still rely on subjective observational gait analysis or objective marker-based analysis that is time-consuming.
Research question: This paper aims to examine the main developments of vision-based motion capture and how such advances may be integrated into clinical practice.
Methods: The literature review was conducted in six online databases using Boolean search terms. A commercial system search was also included. A predetermined methodological criterion was then used to assess the quality of the selected articles.
Results: A total of seventeen studies were evaluated, with thirteen studies focusing on gait classification systems and four studies on gait measurement systems. Of the gait classification systems, nine studies utilized artificial intelligence-assisted techniques, while four studies employed statistical techniques. The results revealed high correlations of gait features identified by classifier models with existing clinical rating scales. These systems demonstrated generally high classification accuracies and were effective in diagnosing disease severity levels. Gait measurement systems that extract spatiotemporal and kinematic joint information from video data generally found accurate measurements of gait parameters with low mean absolute errors, high intra- and inter-rater reliability.
Significance: Low cost, portable vision-based systems can provide proof of concept for the quantification of gait, expansion of gait assessment tools, remote gait analysis of neurodegenerative diseases and a point of care system for orthotic evaluation. However, certain challenges, including small sample sizes, occlusion risks, and selection bias in training models, need to be addressed. Nevertheless, these systems can serve as complementary tools, equipping clinicians with essential gait information to objectively assess disease severity and tailor personalized treatment for enhanced patient care.

1. Introduction

1.1. Background

With a rapidly ageing world population, the incidence of neurodegenerative diseases has increased, with diseases such as dementia affecting over 55 million people [1] and Parkinson's disease affecting over 9.4 million people [2] globally in 2020. Neurodegenerative diseases—mainly consisting of Alzheimer's disease, Parkinson's disease, Multiple Sclerosis, Amyotrophic Lateral Sclerosis, Huntington's disease, and dementia—share characteristics of progressive cognitive decline, limited functional ability to conduct activities of daily living, and motor deficits affecting gait and balance. Gait impairments which are common among patients with neurodegenerative disease are known to adversely affect mobility performance and quality of life [3–5].

In the clinical setting, the quantitative study of human gait characteristics can provide key information for patient-centered diagnosis, monitoring, and treatment of neurodegenerative diseases. The regular monitoring of mobility performance in patients can help facilitate timely diagnosis and allow for pre-emptive intervention before severe complications arise. As the disease progresses, gait analysis can help inform fall risk assessments and monitor variations in mobility performance,

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such as decreased gait speed and decreased cadence, to deliver effective patient-centered care [6,7]. Several reviews on quantitative gait analysis [8–11] have been published in the past, demonstrating significant interest in the field. These reviews have highlighted an increasing trend towards portable gait analysis systems as indicated by the increasing evidence of greater precision, conformability, usability, and transportability. However, most existing reviews have studied research methodologies using wearable sensors [8,11] or hybrid sensor systems [9]. Further research is required to establish a consensus on the use of vision-based systems for quantitative gait analysis in patients with neurodegenerative diseases.

1.2. Observational gait analysis and gait scores

There is a clear gap between the technology available and current practices as many clinicians still use subjective observational gait analysis and semi-subjective gait scores [12]. These methods are often reported to be unreliable due to the difficulty in assessing the position of multiple body segments simultaneously, leading to the high probability of human error [13,14]. Furthermore, while gait scores have been reported to have good intra-rater reliability, there may be poor inter-clinician reliability as there may be different interpretations of the same scores between clinicians [15]. In addition, many gait scoring systems often require specialized technical knowledge and equipment that is too time consuming to be applied in the clinical setting.

In the context of neurodegenerative diseases, clinician rating using reference scoring systems remain the standard practice for clinical diagnosis [16]. Common examples of clinical reference tests include the Movement Disorder Society - Unified Parkinson's disease Rating Scale (MDS-UPDRS) for Parkinson's disease [17] and Expanded Disability Status Scale (EDSS) for Multiple Sclerosis assessment [18]. While many of these scales are quantitative, these scoring systems are still considered to be semi-subjective, and ratings may differ based on clinician experience [19,20].

1.3. Key gait parameters of neurodegenerative diseases

The most prevalent neurodegenerative diseases include Alzheimer's disease, Parkinson's disease, Multiple sclerosis, Amyotrophic lateral sclerosis, and Huntington's disease [10,21–24]. The quantitative gait analysis of neurodegenerative diseases has been widely studied, providing invaluable spatiotemporal and kinematic joint analysis. The clinical presentation and key gait parameters of the common neurodegenerative diseases have been summarized below:

(1) Alzheimer's disease (AD)
- Clinical Presentation: Alzheimer's disease is characterized by hyperkinesia, apraxia, and abnormalities in walking and trunk movements.
- Key Gait Parameters: Patients with Alzheimer's disease typically exhibit decreased gait speed, decreased stride length, decreased stride frequency, increased support time, increased stride-to-stride variability, and decreased cadence in their walking patterns [25].

(2) Parkinson's disease (PD)

- Clinical Presentation: Parkinson's disease is associated with hypokinetic movement, bradykinesia, hypotonia, tremor, flexed posture, gait festination, loss of postural reflexes, and freezing of gait (FOG).
- Key Gait Parameters: Individuals with Parkinson's disease often demonstrate decreased gait speed, increased cadence, decreased stride length, decreased swing time, and increased double support time while walking [26].

(3) Multiple Sclerosis (MS)

- Clinical Presentation: Multiple Sclerosis presents with motor weakness, spasticity, ataxia, and sensory disturbances.
- Key Gait Parameters: People with Multiple Sclerosis typically exhibit decreased gait speed, decreased step length, decreased cadence, and increased double support time in their gait patterns [27].

(4) Amyotrophic Lateral Sclerosis (ALS)

- Clinical Presentation: ALS is characterized by perturbations in fluctuation dynamics, altered gait rhythm, and muscle weaknesses in the legs, feet, or ankles.
- Key Gait Parameters: ALS patients often display decreased gait speed, increased stride time variability, and increased stride time while walking [28].

(5) Huntington's disease (HD)

- Clinical Presentation: Huntington's disease is marked by uncontrolled movements, emotional problems, psychiatric disorders, and loss of cognitive abilities.
- Key Gait Parameters: Individuals with Huntington's disease commonly show decreased gait speed, decreased step and stride length, increased stance and swing phase, and decreased single support time during walking [29].

1.4. Development of vision-based motion capture

Currently, marker-based optoelectronic systems, such as the VICON system, often represent the "gold standard" for quantitative gait analysis due to their validated accuracy and precision [30]. However, such systems require a large laboratory space, expensive equipment, and significant technical knowledge to operate [31]. In addition, marker-based systems are susceptible to soft tissue artifacts where soft tissue movement between reflective skin markers and underlying bone induces errors in gait analysis [32]. Recently, the development of inexpensive, and portable marker-less systems, such as Red Green Blue (RGB) cameras in smartphones and Microsoft Kinect® devices, provide a promising alternative and are gaining interest in gait analysis. Many systems now use depth measurement techniques to calculate the spatial position of key body segments in the 3D space and form a visual representation of a subject's gait [9]. This may include a graphical or video depiction of the spatial temporal and kinematic characteristics of gait, facilitating a comprehensive analysis of gait features. Different types of optical scanners, such as RGB cameras, time-of-flight cameras, structured light, and infrared sensors are now commonplace.

In addition, advances in computer vision and human pose estimation algorithms, such as OpenPose[1] and Kinect Tracker application,[2] allow the tracking of specific body points and the visualization of estimated skeleton models. A skeleton model is defined as a set of joints and bones with the skeleton parameterized based on the length of bones and rotation of each joint. Effectively, these algorithms convert videos into sequential body point coordinates, which can be used for further mathematical and computational analysis to calculate length of body segments and joint angles.

There are 3 different approaches in marker-less vision-based motion capture [33]:

[1] OpenPose is an open-source software library for real-time multi-person key point detection and multi-threading written in C++ using the OpenCV and Caffe deep learning libraries. It allows the tracking of the human body and its limbs, as well as detection of facial landmarks, hand gestures, and poses using 2D video.

[2] Kinect Tracker is an application in Microsoft Kinect that uses the depth and RGB data captured by the Kinect sensor to detect and track the position and movement of human body parts, such as the head, torso, arms, and legs

1) Chroma keying: where the background of the scene is painted a single specific color, allowing the silhouette of the person to be easily segmented [34,35]. One common example of chroma keying is the use of a green screen background with the subject dressed in suitably distinct colors, allowing for silhouette extraction. In environments where chroma keying is not suitable, background subtraction algorithms [36] may be applied to extract image silhouettes.
2) Discriminatory algorithms: by mapping directly from image features to a description of pose, a machine learning algorithm is "taught" how to determine the pose of a simple skeleton model using only image data [37,38]. Most common examples are OpenPose and Kinect Tracker V.2 application. Alternatively, a database of poses can be created then searched to discover the most similar pose.
3) Generative Algorithms: pose and shape of person is determined by fitting the body model to information extracted from the image [39,40]. Using cost functions, algorithms can minimize the distances between the 3D vertices of the body model to the points of the 3D reconstruction, allowing for optimal projection to an image.

Furthermore, developments in machine learning techniques, such as Support Vector Machine (SVM) and Convolutional Neural Networks (CNN), allow for the training of machine learning models to recognize and classify human gait patterns [41]. This has become increasingly important for neurodegenerative diseases as machine learning algorithms can facilitate effective diagnosis and classification of severity levels [42].

Vision-based motion capture systems use one or more optic sensors to record data of an individual's gait pattern, and through digital image processing or computer vision algorithms, obtain objective measurements of gait parameters [33]. Generally, vision-based gait analysis methodologies can be categorized into 1) Gait measurement systems and 2) Gait classification systems. Gait measurement systems utilize video data to extract objective measurements of spatiotemporal and kinematic features from human gait. This would aim to facilitate analysis of gait features such as walking speed and cadence, enabling a quantitative analysis of gait. Gait classification systems share the same processes of data collection and gait feature extraction, with the added use of extracted gait features to classify the gait patterns of subjects based on the onset and progression of the neurodegenerative disease. Gait classification systems can be further subdivided into systems using artificial intelligence assisted techniques and systems using statistical techniques.

Overall, these developments in vision-based systems can make objective gait analysis more accessible to clinicians due to the lower cost, increased portability, and less technical know-how as many of these systems can be automated.

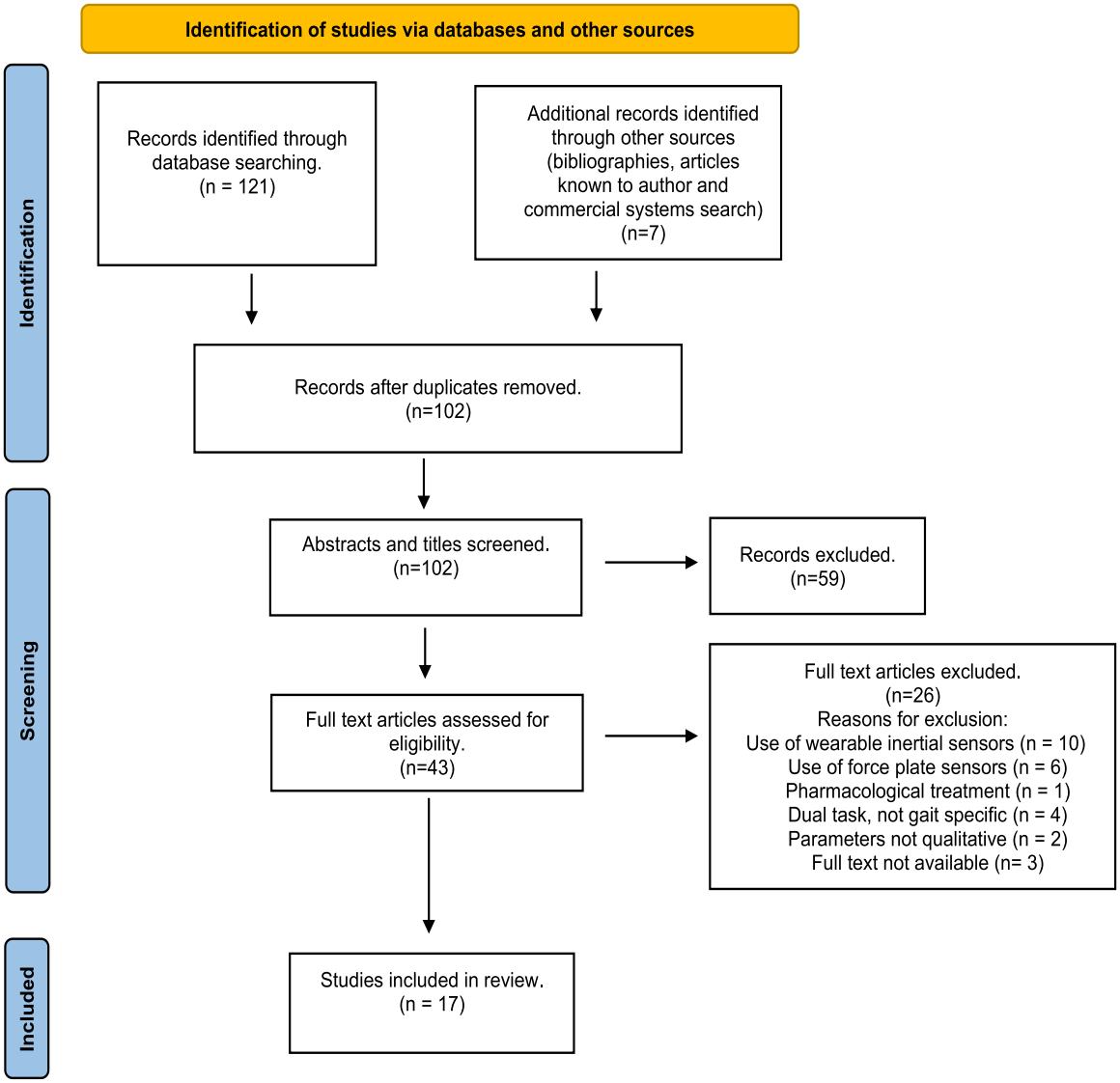

Fig. 1. PRISMA flow diagram of the methodology.

1.5. Objective

This paper aims to review the main developments of vision-based motion capture and how such advances may be integrated into clinical practice. This paper would examine how these technologies may be used to identify key gait parameters in neurodegenerative diseases, classify gait patterns based on disease severity level and provide practical advice for clinicians to utilize these technologies effectively. Contributing to the existing evidence base, this review seeks to inform the current state of vision-based motion capture, bridging the gap between technological research and the clinical field.

2. Methodology

2.1. Protocol

The methodology of this review was documented according to the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) statement [43], as shown in Fig. 1. Studies were graded according to the Critical Appraisal Skills Program (CASP) guidelines for diagnostic studies [44]. A second questionnaire, developed by Wen et al. [45], was used to quantitatively evaluate AI-assisted technologies.

2.2. Search strategy

Relevant research studies were obtained using Boolean searching applied to six online databases, namely SCOPUS, PUBMED/MEDLINE, Embase (Ovid), CINAHL, SPORTDiscus and the Cochrane Library. The database search included key search terms and synonyms related to the research aim, such as "gait analysis", "vision" and "neurodegenerative", joined with AND/OR connectives. As this review focuses on the current advances of vision-based motion capture, the search was limited to studies published in the last decade, including studies published in 2013. The end of the search date was March 2023. Peer-reviewed articles, clinical trials and observational studies were considered. Methodologies using video cameras, machine learning for gait classification and quantitative outcome measures were included. Non-English/abstract papers, studies involving animal subjects, children/adolescents (<18 years) and pharmacological/robotic treatments were excluded. Methodologies that involved wearable sensors, included running trials and qualitative methods of gait assessment were excluded. As this review focuses on gait analysis, methodologies focusing primarily on dual task assessments for the comparison of cognitive and motor abilities were also excluded. A commercial system search of vision-based motion capture technologies, such as DeepMotion [46] and Rokoko Video [47], was also taken into consideration. However, most of the research using these commercial systems did not have methodologies focused on the gait analysis of neurodegenerative diseases and, thus, did not meet the selection criteria.

2.3. Quality assessment

The methodological quality of papers was assessed using the Critical Appraisal Skills Program (CASP) for Diagnostic Test Studies [44]. This typically involves 12 questions in 3 sections: 1) Are the results of the study valid? 2) What are the results? 3) Will the results help locally? However, the third section was deemed as irrelevant as the objective of this study is not to apply the findings to a local population. As such, each paper was evaluated based on 8 questions from the first 2 sections. Secondarily, a questionnaire developed by Wen et al. [45] was used to assess the quality of AI-assisted technologies. This questionnaire consists of 10 questions that quantitatively evaluate the methodological quality of the AI algorithms used. For both quality appraisal tools, the questions included have 3 optional answers, "Yes", "No" and "Partly". These answers scored as follows: "Yes" = 1.0, "Partly" = 0.5 and "No" = 0. The total score for each paper was computed by summing the scores for each question. Studies with a score of >75 % were rated as high evidence, studies with a score of 60–75 % were rated as medium evidence and studies with a score of <60 % were rated as low evidence [48]. (CASP Scores: <5 = low, 5–6 = medium, >6 =high) (AI questionnaire: <6 = low, 6–7.5 = medium, >7.5 =high)

3. Results

3.1. Overview of selected studies

The review process yielded seventeen applicable studies. The included studies were all published between 2014 [49] and 2022 [50–52]. These were quality assessed and important study characteristics were extracted. Each article was categorized into three main approaches: 1) Gait classification systems using artificial intelligence assisted techniques 2) Gait classification systems using statistical techniques 3) Gait measurement systems that obtain objective spatiotemporal and kinematic joint parameters. Tables 1 and 2 show the results of the CASP (diagnostic test studies) and AI quality assessments respectively. Tables 3, 4, and 5 show the study characteristics, the main clinical findings and limitations for gait classification systems using AI-assisted techniques, gait classification systems using statistical techniques and gait measurement systems respectively.

Overall, there were twelve studies [49,51–61] that investigated subjects with Parkinson's disease, two studies [57,62] investigating subjects with Dementia, one study [63] investigating subjects with Alzheimer's disease, one study [64] investigating subjects with Multiple Sclerosis and one study [50] investigating both Parkinson's disease and Multiple Sclerosis subjects. These studies included subjects with an age range from 49 to 85 years old and generally had a higher participation of male subjects, except for four studies [58,62–64]. Two studies [52,65] did not specify gender participation rates. As these studies investigated different conditions, studies report using a wide range of reference tests, such as clinician rating using MDS-UPDRS and EDSS. Two studies [52,63] mention that patients were identified through clinician diagnosis; however, they did not mention what reference system was used in diagnosis. Different types of motion capture sensors used: three studies used Kinect V.1 sensors [49,54,64], four studies used Kinect V.2 sensors [57,61–63], eight studies used Standard RGB Camera [50,52,53,55,56,58,59,65], one study used Stereoscopic cameras [51] and one study used a VICON® System [60] (only video data was used to build classification model).

3.2. Quality assessment

As shown in Table 1, two studies [59,62] were rated as high evidence, eleven studies [49–51,53–56,58,61,63,64] were rated as medium evidence and four studies [52,57,60,65] were rated as low evidence. All included studies were found to have an inherent lack of evaluation blinding when designing vision-based systems and most studies suffered from small sample sizes, limiting the generalizability of findings.

3.3. AI quality assessment

A second questionnaire was used to quantitatively evaluate the methodological quality of AI-assisted technologies used in nine studies [50,52,54–56,59–61,63]. As shown in Table 2, four studies [50,56,59,63] were rated as high evidence and five studies [52,54,55,60,61] were rated as medium evidence. Most studies provided adequate descriptions of the estimation context and all studies had clear reporting of classification accuracy. However, differences in study characteristics, patient condition, reference tests used, and classification labels used make inter-study comparison of accuracy difficult. Moreover, there was a lack of consistency in reporting machine learning performance evaluation metrics with studies often missing key metrics. Three studies [55,61,63] did not compare their results to any other algorithm. While most studies

Table 1
CASP (diagnostic test studies) quality assessment.

Bibliographic Citation	1. Was there a clear question for the study to address?	2. Was there a comparison with an appropriate reference standard?	3. Did all patients get the diagnostic test and reference standard?	4. Could the results of the test have been influenced by the results of the reference standard?	5. Is the disease status of the tested population clearly described?	6. Were the methods for performing the test described in sufficient detail?	7. Were the results clearly presented?	8. How sure are we about the results?	Total Score	CASP Quality
Zhu et al., 2016 [65]	1	1	1	0	0	0.5	1	0	4.5	Low
Buongiorno et al., 2019 [61]	1	1	1	0	0	1	0.5	1	5.5	Medium
Gholami et al., 2017 [64]	1	1	1	0	1	1	1	0	6	Medium
Khan et al., 2021 [55]	1	1	1	0	0	1	1	0	5	Medium
Kaur et al., 2022 [50]	1	1	1	0	1	1	1	0	6	Medium
Seifallahi et al., 2020 [63]	1	1	0.5	0	0	1	1	1	5.5	Medium
Sabo et al., 2020 [57]	1	1	1	0	0	0.5	0.5	0	4	Low
Delval et al., 2021 [60]	1	1	1	0	1	0.5	0	0	4.5	Low
Rocha et al., 2014 [49]	1	1	1	0	0.5	1	1	0	5.5	Medium
Sato et al., 2019 [58]	1	1	1	0	0	1	0.5	1	5.5	Medium
Lu et al., 2021 [59]	1	1	1	0	1	1	1	1	7	High
Stricker et al., 2021 [53]	1	1	1	0	0	1	1	0	5	Medium
Dolatabadi et al., 2019 [62]	1	1	1	0	1	0.5	1	1	6.5	High
Zanela et al., 2022 [51]	1	1	1	0	1	1	1	0	6	Medium
Dranca et al., 2018 [54]	1	1	1	0	1	0.5	0.5	0	5	Medium
Bama and Jinila, 2022 [52]	1	1	1	0	0	1	0	0	4	Low
Guayacan, Martinez, 2021 [56]	1	1	1	0	0	1	1	0.5	5.5	Medium

reported using sizeable datasets of gait videos, these datasets often contained multiple recordings of a small sample of patients, adversely affecting the generalizability of findings.

3.4. Gait classification systems using AI-assisted technologies

Nine studies [50,52,54–56,59–61,63] utilized gait classification systems using AI-assisted technologies. Two studies [52,55] used the tracking of image silhouettes, one study [59] used generative algorithms (where the human pose was determined by fitting a 3D body model to the gait video), and six studies [50,54,56,60,61,63] used Kinect or OpenPose pose estimation algorithms to extract spatiotemporal and kinematic gait parameters. Overall, a wide range of machine learning techniques was used for gait classification; examples include Support Vector Machines (SVM), Bayesian Networks and Convolutional Neural Networks (CNN). SVM was the most popular technique with its use cited in six studies [50,54,55,60,61,63].

As presented in Table 3, most studies generally report high gait classification accuracies, ranging from 62.1 % to 97.0 %, and high correlations of key gait features identified with clinical reference tests. However, differences in study characteristics, patient condition, reference tests used, and classification labels make inter-study comparison of accuracy difficult. In addition, four studies [50,54,59,61] reported the discovery of novel gait features with high discriminatory power, facilitating a better diagnosis of disease severity levels. These developments were attributed to the use of machine learning techniques. By mapping multiple gait features into a higher dimensionality space, classification systems were reported to recognize non-linear relationships between gait features to achieve a better classification of gait between disease severity levels.

Notably, Lu et.al [59] developed a gait classification neural network, with the training of network was regularized by using a rater confusion estimation (RCE) to avoid bias in training models with subjective scores of a single clinician. The proposed method outperformed human raters by showing higher levels of agreement with the majority vote of raters compared to inter-rater agreement. This was shown by the model's average pairwise value[3] being higher (0.49) than that of all human rater pairs which are 0.38, 0.39, and 0.30.

Furthermore, saliency mapping was reported in two studies [56,59] showing the identified body joints with the highest discriminating power, such as feet and arm features, to differentiate severity levels in gait pathology. These saliency maps, in the form of images or visualized

[3] Average pairwise values quantify the consistency or concordance between different assessments or predictions, providing a measure of average agreement levels across all possible pairs of raters or classifiers

Table 2
AI methodological quality assessment of studies.

Bibliographic Citation	1. Are the aims of the research clearly defined?	2. Is the estimation context adequately described?	3. Are the estimation methods well defined and deliberate?	4. Is the experimental design appropriate and justifiable?	5. Is the experiment applied on sufficient project data sets?	6. Is the estimation accuracy measured and reported?	7. Is the proposed estimation method compared to other methods?	8. Are the findings of the study clearly stated and supported by reporting results?	9. Are the limitations of the study analyzed explicitly?	10. Does the study add value to academia or clinical community?	Total Score	AI Quality
Buongiorno et al., 2019 [61]	1	1	1	1	0	1	0	1	0	0.5	6.5	Medium
Khan et al., 2021 [55]	1	1	1	0	1	1	0	0	0	1	6	Medium
Kaur et al., 2022 [50]	1	1	1	1	0.5	1	1	1	0.5	0.5	8.5	High
Seifallahi et al., 2020 [63]	1	1	1	1	0	1	0	1	1	1	8	High
Delval et al., 2021 [60]	1	1	0	0.5	1	1	0.5	0	1	1	7	Medium
Lu et al., 2021 [59]	1	1	1	1	0	1	0.5	1	1	1	8.5	High
Dranca et al., 2018 [54]	1	1	1	1	0	1	1	0	1	0.5	7.5	Medium
Bama and Jinila, 2022 [52]	1	1	0	0.5	0	1	1	0	1	0.5	6	Medium
Guayacan, Martinez, 2021 [56]	1	1	1	1	0	1	1	1	1	0.5	8.5	High

skeletons, highlighted the key body joints that contributed the most to classification model predictions. For instance, the saliency map used by Lu et al. [59] highlighted the heel and ankle region in green, indicating that joint angles of heel and ankle were important in classifying between Parkinson's disease MDS-UPDRS stages 1 and 2. This provides a visual representation for the clinician to understand the gait features most important in gait classification, without any prior technical knowledge.

3.5. Gait classification systems using statistical techniques

Four studies [49,57,62,64] investigated gait classification systems that used statistical techniques. As presented in Table 4, all four studies extracted spatiotemporal and kinematic data from Kinect skeleton data for gait classification. Using the gait data of Multiple Sclerosis subjects, Gholami et al. [64] assessed the reliability of eight gait indices obtained from the proposed method and found seven out of the eight indices to be reliable with intraclass correlation coefficients ranging from 0.61 to 0.99. This includes the novel dynamic-time warping (DTW) distance index which quantifies the degree of dissimilarity between a patient's joint angle pattern compared to a set of control subjects. Seven out of eight Multiple Sclerosis gait indices correlated with the clinical reference tests used with a Pearson correlation coefficient of more than 0.40. Rocha et. al [49] evaluated 34 spatiotemporal and kinematic gait parameters of 3 Parkinson's disease patients treated with deep brain stimulation. Using the Kruskal-Wallis statistical test, the study found that the variance of center shoulder velocity presented with the highest discriminative power to distinguish non-PD, PD ON and PD OFF states ($p = 0.004$). In a longitudinal study, Sabo et.al [57] used multivariate ordinal logistic regression models that incorporated 2D and 3D gait features of dementia patients. The study concluded that vision-based systems have the potential to be used as a tool for longitudinal monitoring of parkinsonism in residential settings.

In a longitudinal study, Dolatabadi et.al [62] recorded the natural walks that occurred in dementia patient's daily routine and the cued walks with a research assistant present. A total of 3843 gait bouts were recorded over 6 months in an inpatient setting. However, approximately 50 % of recordings were unsuccessful primarily because the subject was walking away from the camera and the gait could not be tracked from behind. Furthermore, the system required a minimum of 2 gait cycles to reliably extract spatiotemporal gait features. Out of 3843 gait bouts, 1171 gait bouts could be used to extract spatiotemporal gait features reliably for fall risk classification. Suggesting improvements to the system, such as installing cameras facing both sagittal and coronal planes, the study hypothesized that this might make the long-term monitoring of Dementia patient's gait in an inpatient environment more feasible.

3.6. Gait measurement systems

Four studies [51,53,58,65] proposed quantitative measurement systems for the feature extraction of gait. Three studies [53,58,65] used 2D video of Parkinson's disease patients from standard RGB cameras to extract parameters of step length [53], stride length [65] and cadence [58]. One study [51] used stereoscopic vision cameras integrated with computer vision algorithms to analyze multiple gait parameters of Parkinson's disease patients. As presented in Table 5, these studies generally found accurate measurements of gait parameters, with low mean absolute errors [65] and high intra- and inter-reliability [53].

Using a smartphone and a printed PVC walking mat, Zhu et. al [66] developed a computer vision algorithm that was shown to obtain stride length measurements of Parkinson's disease patients with a mean absolute error of 0.62 cm. This was found to be robust despite variations in environmental lighting conditions, gait abnormalities and with differences in clothing. However, the study also cited challenges, such as parallax errors between the shoe and the marker mat, and suggested improvements to the algorithm (mapping function) to overcome these limitations.

Table 3
A summary of gait classification systems using AI-assisted technologies.

Bibliographic Citation	Study Type	Population Characteristics	Motion Analysis System	AI-assisted technique	Procedure	Reference Test
Buongiorno et al., 2019 [61]	Cross-sectional observational study	16 PD patients and 14 healthy controls Gender:13 M, 3 F. Age:63–87	One Microsoft Kinect v2 camera in coronal plane	Classifiers tested: Support Vector Machine and Artificial Neural Networks	3 motor exercises examined: 1) gait - patients walk towards Kinect 2) finger tapping 3) foot tapping	MDS-UPDRS
Khan et al., 2021 [55]	Retrospective study	19 PD patients (456 videos) Gender: 19 M, 5 F. Age: 50–75	One RGB camera, 352×288p at 25 fps, in coronal plane	Support Vector Machine used for classification	Patient asked to rise from chair, walk straight to camera, turn, and walk back to the chair	UPDRS
Kaur et al., 2022 [50]	Cross-sectional observational study	10 MS patients, 9 PD and 14 healthy controls. Gender: 12 M, 21 F. Age: 61–77	Two 800 ×448 resolution RGB cameras at 30 fps, in coronal and sagittal planes	4 convolutional Deep Learning (DL) models tested for feature extraction and 3 recurrent DL models were tested for gait classification	2 self-paced walking tasks on an treadmill: 1) single task walking trial and 2) walking while talking trial	EDSS and Hoehn and Yahr Scale
Seifallahi et al., 2020 [63]	Cross-sectional observational study	30 AD patients, 30 healthy controls. Gender: 0 M, 60 F. Age: 65–85	One Microsoft Kinect v.2 camera, subject's elliptical walking path captures both sagittal and coronal planes	Support Vector Machine to build classification model based on 7 gait features	10 m single task walking trial designed in an elliptical shape	Clinician rating. Rating scale not specified
Delval et al., 2021 [60]	Retrospective study	174 PD patients Gender: 106 M, 68 F. Age: 49–73	VICON® system, at 100 Hz (only video motion system used), videos were processed with MATLAB® script	Support Vector Machine used for classification: a) clinical data only b) both clinical data and gait parameters	10 m indoor walking trial at self-regulated pace. Clinical data, such as MDS-UPDRS scores, age, Levodopa equivalent dose taken.	Fall history and clinical data
Lu et al., 2021 [59]	Cross-sectional observational study	55 participants (PD patients and healthy controls) Gender: 27F, 28M. Age: 47-75	MDS-UPDRS videos using RGB camera (gait and finger tapping videos), in coronal plane	Ordinal focal neural network for classification. Rater confusion estimation regularize network	MDS-UPDRS videos scored by 3 neurologists. 3D skeleton extraction and motor score estimation.	MDS-UPDRS
Dranca et al., 2018 [54]	Cross-sectional observational study	30 PD: 8 early stages, 11 mid stages and 11 severe stages. Gender: 25 M, 5 F. Age: 64–76	Two Microsoft Kinect v.1, in coronal and sagittal planes	10 AI classification methods tested. 3 Feature filter methods tested	Patients walk 4.5–5.5 m in both directions (with spins) 4 times for gait recording.	MDS-UPDRS
Bama and Jinila, 2022 [52]	Retrospective study	14 subjects (PD and hemiplegia patients, controls) Numbers for each gender not specified. Age: 50–85	Rasbery Pi-3 and camera module. VPIDS cloud computing layer (plane not specified)	3 AI classification methods tested. 3 feature selection methods tested	Walking frames transformed into binary silhouettes for feature extraction and gait classification	Clinician rating. Rating scale not specified
Guayacan and Martinez, 2021 [56]	Retrospective study	11 PD patients and 11 controls. Gender: 9 M, 2 F. Age: 65–79	One RGB camera, Nikon D3200 at 60 Fps, in sagittal plane	3D convolutional neural network for feature selection. CNN applied to raw videos and optical flow fields for comparison	Walking at a self-regulated pace, 4 times to the left and 4 times to the right.	Hoeh and Yarh Scale

Author	Classlabels	Accuracy[1] (%)	Precision[2] (%)	Recall[3] (%)	Specificity[4] (%)	Area Under Curve[5]	Key gait features	Main Clinical Benefits	Limitations
Buongiorno et al., 2019 [61]	1) PD vs non-PD 2) Mild PD vs moderate PD	89.4 % (using 9 features)	-	87.0 %	91.8 %	-	Postural features (e.g., Trunk and neck flexion angles)	Identification of novel postural features useful for distinguishing between PD severity levels. Able to identify subtle gait differences difficult to observe by clinician	Small sample sizes. Lack of integrated analysis for the 3 exercises.
Khan et al., 2021 [55]	UPDRS integer scores from 0 to 2	70.8 %	-	-	-	0.81	Step shuffling and gait festination	Key gait features identified as most significant for classification have high correlations with clinical rating scale	Small sample size
Kaur et al., 2022 [50]	MS, PD vs healthy controls	78.1 %	79.0 %	76.7 %	-	0.87	Stride length, feet, and knee features	Feet and knee features are found to be important in distinguishing between MS, PD, and healthy controlsStride wise classification allows single stride trial for easier procedure	Small sample size Gender imbalances between groups
Seifallahi et al., 2020 [63]	AD vs non-AD	92.3 %	88.6 %	96.3 %	90.8 %	-	Walking speed, step length, stride length and mean stride velocity	Key gait features identified as most significant for classification matched the features identified by previous validated studiesEarly detection of AD using skeleton data from Kinect camera	Small sample size Study conducted on an all women population.
Delval et al., 2021 [60]	Fallers vs non-fallers	97.0 %	-	94.0 %	70.0 %	0.97	Walking speed, stride length, stride time,	Foot clearance height during swing phase useful for distinguishing between fallers	Risk of selection bias as most patients recruited

(continued on next page)

Table 3 (*continued*)

Author	Classlabels	Accuracy[1] (%)	Precision[2] (%)	Recall[3] (%)	Specificity[4] (%)	Area Under Curve[5]	Key gait features	Main Clinical Benefits	Limitations
							minimum foot clearance height	and non-fallersIncorporating kinematic gait data into prediction models can improve fall risk assessment- 97 % accuracy compared to 94 % accuracy using clinical data only	were not demented. Self-reporting of falls may not be accurate
Lu et al., 2021 [59]	MDS-UPDRS integer scores from 0–3	72.0 %	50.0 %	52.0 %	-	0.82	Joint angles of heels, ankles, and toes	Saliency mapping highlighted key gait features most significant in diagnosing PD severity RCE reduced inter-rater variabilities, improved classification performance	Lack of objective "ground-truth" scores Small sample size
Dranca et al., 2018 [54]	1) PD vs non-PD 2) MDS-UPDRS integer scores from 1–3	93.4 % (using 7 features)	-	-	-	-	Movement and position of left arm, trunk posture and left shin angles	Identification of novel gait features that were shown to improve accuracy of diagnosing PD severity Feature discretization has been shown to improve classification performance	Small sample size. Sample consisted of mostly right-handed patients
Bama and Jinila, 2022 [52]	PD, Hemi-plegia vs control	93.6 %	-	-	-	-	Spatial variance between joints (e.g., variance between hip center and shoulder center)	Model that incorporates patient history, real-time gait videos and AI assisted techniques shown to diagnose PD severity Improvements in prediction time (10.69 %) and accuracy (7.83 %) compared to statistical techniques Remote gait analysis in real time	Small sample size Risk of occlusions Low resolution and frame rate of camera
Guayacan and Martinez, 2021 [56]	PD vs non-PD	94.9 %	91.0 %	100.0 %	-	0.95	Step length and gait speed. Head and trunk posture.	Saliency mapping highlighted key gait features most significant in diagnosing PD severity Fully automated feature extraction and classification allows ease of use and efficient diagnosis	Lack of baseline comparison

[1] Accuracy measures the percentage of correctly classified instances out of all instances
[2] Precision measures the percentage of correctly labelled positive instances out of all positively labelled instances
[3] Recall measures the percentage of correctly labelled positive instances out of all instances
[4] Specificity measures the percentage of correctly labelled negative instances out of all negatively labelled instances
[5] Area under curve provides an aggregate measure of performance across all possible classification thresholds

Stricker et. al [53]conducted a study evaluating the reliability of step length measurements from two-dimensional (2D) video in individuals with Parkinson's disease, comparing the step lengths of individuals with and without a recent history of falls. Intra- and inter-rater reliability of step length measurements were reported to be high, with mean intra-class correlation coefficient (ICC) of 0.988 (range: 0.986–0.991) and 0.987 (0.985–0.990) respectively, demonstrating excellent reliability. Stricker et. al [53] hypothesized that this system would be useful in fall risk classification of Parkinson's disease patient, citing that shorter step length is associated with increased fall risk in Parkinson's disease.

In a retrospective study, Sato et.al [58] proposed an unsupervised method of analyzing frontal gait videos recorded in clinical practice for estimation of cadence in Parkinson disease patients. Using a statistical distance-based approach, the system was shown to identify the timing of gait steps that were distinguishable between FOG steps and involuntary leg oscillations, allowing a more accurate estimation of cadence.

4. Discussion

The purpose of this literature review was to report on the main developments of vision-based motion capture and how such advances can be integrated into clinical practice. This section aims to cover how these technologies may be used to identify key gait parameters in neurodegenerative diseases, classify gait patterns based on disease severity level and provide practical advice for clinicians to utilize these technologies effectively. In addition, this paper seeks to elucidate how these advances can inform the further development and optimization of orthotic management strategies as a point-of-care system.

Improvements in vision-based motion capture technology have increased the potential for data-driven objective quantification of the gait analysis in neurodegenerative diseases. Previously, quantification of gait was limited to expensive optoelectronic systems that required the use of specialized equipment and a large laboratory space. Currently, gait measurement systems that use low-cost vision technology have been shown to effectively extract spatiotemporal gait features [51,53,58,65]. For instance, using a smartphone camera and printed PVC walking mat, Zhu et.al [65] was able to extract stride length measurements of Parkinson's disease patients with low mean absolute errors, comparable to the validated walking mat GAITRite system. Furthermore, the advancement of human pose estimation algorithms, such as OpenPose and Kinect Tracker applications, allows the tracking of 3D body segments, which can be used for the spatiotemporal and kinematic joint analysis of gait. The gait features identified with the most discriminative power for classification were shown to have high levels of agreement

Table 4
A summary of the gait classification systems using statistical methods.

Author	Study Type	Population Characteristics	Motion Analysis System	Statistical Technique	Procedure	Key gait features	Main Clinical Findings	Limitations
Gholami et al., 2017 [64]	Cross-sectional study	10 MS patients and 10 healthy controls. Gender: 9 F, 1 M. Age: 41–79.	A Microsoft Kinect sensor, facing coronal plane.	a) Reliability and validity assessment of 8 gait indices b) Principal component analysis and Linear discriminant analysis to classify MS severity levels.	Patients walk facing Kinect camera for 5–10 trials	Gait velocity, stride length, double support percentage, knee, and hip range of motion	7 out of 8 gait indices were found to be reliable, valid and have high correlations with clinical reference tests Novel DTW gait index allows optimal comparison of complete sequences of subject's gait compared to a healthy control	Small sample size. Lack of validation using marker-based capture system. Limited range of view
Rocha et al., 2014 [49]	Cross-sectional study	3 PD patients with deep brain stimulator implants and 3 healthy controls. Gender: 2 M, 1 F Age:47–59	Microsoft Kinect sensor facing coronal plane view of subject	Kruskal-Wallis statistical test to identify statistically significant gait features between groups	Walking trial with turn at the end: with the stimulator on (ON) and with the stimulator off (OFF).	Center shoulder velocity	The variance of center shoulder velocity had the highest discriminatory power and was statistically significant in distinguishing PD groups Depth images and skeleton data based on infrared light allows less controlled environment	Small sample size. Lack of validation using marker-based capture system
Dolatabadi et al., 2019 [62]	Long-itudinal study	20 Dementia patients. Gender: 10 M, 10 F. Age: 70–83	AMBIENT set-up: Microsoft Kinect for Windows version 2, facing sagittal plane of patient	Descriptive statistics, including mean, median, standard deviation, and variability measures, to compare gait features between fallers and non-fallers	1) Natural walks detected during day and night in inpatient settings. 2) Cued walking trials with assistant	Step length, step time, cadence, step length symmetry, step time symmetry and gait velocity	Potential for the long-term monitoring of Dementia patient's gait in an inpatient environment Despite the high rate of unsuccessful recordings, half of the gait bouts provided valuable data for fall risk classification. Improvements to the sensor positioning and the motion analysis system may make system more feasible	Approximately 50 % unsuccessful recordings, primarily due to poor positioning of subject relative to sensors Requires manual processing prior to data extraction.
Sabo et al., 2020 [57]	Long-itudinal study	14 Dementia patients with varying PD severity. Gender: 8 M 6 F Age: 67–85	Microsoft Kinect v2 sensor in coronal plane	Multivariate ordinal logistical regression model to classify PD severity levels	Single task walking, recordings collected over the course of several weeks	Stride length, gait velocity and bilateral asymmetry	Spatiotemporal, variability and symmetry measures of gait extracted from 2D, and 3D videos had high correlations with clinical reference test measures Potential for longitudinal and remote gait analysis	Regression models not well suited for predictions as they could only identify linear relationships between the gait features

with the features used in clinical rating scales. This is important for neurodegenerative diseases as the objective quantification of gait could be used to develop useful clinical predictors, such as disease severity classification, prognosis and fall risk assessment. In the context of orthotic management, this can allow clinicians to evaluate the effectiveness of the orthotic prescription and make fine-tuning adjustments to optimize fit and function. Overall, vision-based motion capture may thus provide clinicians with objective gait data to inform timely clinical diagnosis and tailor personalized treatment for patients with neurodegenerative diseases.

However, while vision-based systems can quantify gait features of neurodegenerative diseases, this review does not support the complete replacement of existing clinical tests with these technologies. In fact, the included studies cite existing challenges, such as parallax error [65], occlusions [51,52] and small sample sizes, that affect the accuracy and generalizability of measurements. As cited by Zhu et.al [65], parallax errors occur when the camera or sensor used to capture the motion is not positioned correctly or there is a shift in perspective between the camera and the object being tracked. This can result in inaccurate measurements of the movement and position of the object. Two studies [51,52] mentioned that the risk of occlusion, which occurs when a body segment is blocked from view of the camera results in the missing gait data, adversely affects accurate motion analysis. Furthermore, most of the included studies reported having relatively small sample sizes of patients, ranging from 3 [49] to 174 [60] patients, affecting the generalizability of clinical findings on the patient population. Despite small sample sizes, these vision-based systems often generated large datasets of videos (due to multiple views and frequency of walks), presenting challenges with scaling up such technologies. The increased volume of video data would require substantial storage facilities and computational resources, which would be important cost considerations for widespread clinical implementation. Therefore, the developments of vision-based motion capture should be viewed with cautious optimism and serve as a complementary observational tool to be integrated with

Table 5
A summary of gait measurement systems.

Author	Study Type	Population Characteristics	Motion Analysis System	Procedure	Key gait features	Main Clinical Benefits	Limitations
Zhu et al., 2016 [65]	Cross-sectional study	44 PD patients and 11 healthy controls. Gender: not specified. Age: 50–75	A smartphone camera, at 1080p and 30fps, facing sagittal plane and a printed PVC walking mat	Walks from left to right with turns at end and walking back over the PVC matt	Stride length	Stride length measurement having a mean absolute error of 0.62 cm, comparable to the validated GAITRite system. Supports various environmental conditions	Limited field of view of the camera and refresh rate of camera. Parallax error between shoe and markers. Limited use of ground truth measurements
Sato et al., 2019 [58]	Retro-spective study	2 PD patients and 117 healthy controls. Gender: 2 F. Age: 60–70	Home video cameras, at 320×240 at 25 fps. Coronal and sagittal plane videos.	Gait sequences of 2–4 gait cycles recorded. Feature extraction, calculation of cadence.	Cadence	Extract sequential gait features to calculate cadence. Quantify gait steps periodicity to improve reliability of calculated cadence.	Lack of ground truth measurements. The sample size of PD patients was very small. Technical limitations of system.
Stricker et al., 2021 [53]	Retro-spective study	24 PD patients. Gender: 17 M and 7 F. Age: 58–80	HDR-CX 240 Sony Corp camera (RGB) at 30 Hz, facing sagittal plane	3 walking trials of a 10 m. Patient's history of falls was recorded.	Step length	Quantify step length with minimal measurement error, good intra- and inter-rater reliability. Aids fall risk assessment	Lack of comparison to "gold standard" optoelectronic system. Sample size consisted mostly of early PD patients. Self-reporting of falls may not be accurate
Zanela et al., 2022 [51]	Cross-sectional study	5 PD patients and 5 healthy controls. Gender: 3 M, 2 F. Age:49–75	A Stereolabs ZED2 stereoscopic cameras, facing coronal and sagittal planes at 2560×720 and 60 fps.	1) standing position to walk with turn at end 2) walking with obstacles to avoid and turn at end.	Stride speed, stride length, height of feet clearance, turning time and time avoiding obstacles	3D reconstruction of gait. High level of agreement with MDS-UPDRS features. Quantification of gait corrects human error and increasing degree of objectivity	Risk of occlusion and non-univocal correspondence with image pixels, result in missing video data.

existing clinical diagnostics tests for effective patient care.

Besides the quantification of gait, vision-based motion capture technologies have the potential to expand current gait assessment tools for neurodegenerative diseases in a clinician interpretable manner. Advances in vision-based systems have been shown to identify newly discovered discriminating gait features between different severity levels of neurodegenerative diseases. The reasons for this are two-fold: a) computer vision algorithms can simultaneously process multiple gait indices, such as spatiotemporal, kinematic joint parameters and even the novel DTW index. This allows optimal comparison of complete phases of a subject gait cycle compared to a healthy control. b) with greater pattern recognition and learning capabilities, gait classification systems can train machine learning models to identify patterns to classify gait using multiple gait dimensions. For instance, using AI-assisted classification techniques, such as Support Vector Machine (SVM), classification models can plot and achieve an optimal classification of gait data on a higher dimensionality feature space. Importantly, these discriminating features can extend beyond the linear relationships that humans observe and factor in multiple gait parameters simultaneously to capture the nuances of gait. Two studies [56,59] advocate the use of saliency mapping to make results more clinically interpretable. Saliency mapping can help clinicians visually understand which body joints contributed the most to model predictions for the classification of disease severity levels, without any prior technical knowledge. Overall, the studies in this review can provide proof of concept for the expansion of gait assessment tools for neurodegenerative diseases in a clinician interpretable manner.

Another challenge of integrating semi-subjective clinical rating systems into machine learning models, as mentioned by Lu et.al [59], is the handling of inter-rater variabilities in training data. By training machine learning algorithms based on the scores of a single rater, classification models may become biased toward the subjective opinions of the rater, reducing the generalizability of findings. To solve this issue, Lu et.al concluded that the use of a RCE can help account for inter-rater variabilities, avoid bias in training models and even outperform human raters when compared to a majority-vote ground truth score. In future work, classification systems using AI-assisted technologies should consider using the scores of multiple raters for the training of machine learning models to avoid bias.

Lower cost, lower technical barriers, and increased portability of vision-based motion capture also opens opportunities for real-time remote gait monitoring of neurodegenerative disease. This is important as it allows continuous and objective monitoring of disease progression over time, without the need for frequent visits to the clinic or hospital. Most of the studies used low-cost vision systems, such as smartphones, home video cameras and Kinect sensors, which are much less expensive, easier to set up and more portable than existing gait laboratory systems. Bama and Jinila [52] proposed a cloud-based vision-system that integrates clinical patient data with a remote vision-based system capable of providing real-time remote gait analysis insights to clinicians. In a longitudinal study, Dolatabadi et.al [62] hypothesized with future improvements to the sensor positioning, that vision-based systems have the potential to be used as a tool for the long-term monitoring of fall risk for Dementia patients in an inpatient setting. These studies, thus, support real-time remote gait analysis which can provide useful insights to clinicians, such as fall risk assessments and gait data. Ultimately, these insights may be used for the early detection of gait changes and to tailor personalized treatment for effective care for neurodegenerative diseases.

5. Limitations

It should be noted that differences in study characteristics, patient condition and reference tests used make objective meta-analysis of accuracy, reliability, and validity of these systems challenging. Moreover, a lack of consistency in reporting classification performance metrics was found, making inter-study comparisons difficult.

This literature search and review was done by only one author, only considering studies that were written in English. This may have resulted in possible oversight of other studies written in another language. While the included studies involved patients with Parkinson's disease, Alzheimer's disease, dementia and Multiple Sclerosis, no studies involving Huntington's disease and Amyotrophic Lateral Sclerosis were found. Most of the studies included also cited small sample sizes of patients as limitations. Hence, the findings from this review may not be fully representative of the patient population with neurodegenerative

diseases. Attempts at organizing the studies into subgroups for the context of this review may also have discounted some details that each vision-based motion capture approach presents.

6. Recommendations for future work

In the context of orthotic rehabilitation, future research can be focused on implementing vision-based motion capture as a point-of-care system to evaluate the effectiveness of orthotic treatment. Vision-based systems could be installed in the walkways of a clinic or over telecommunication platforms, providing clinicians with real-time objective gait parameters of the patient even before the appointment. As a standard point-of-care system, this may ease the burden of clinicians having to react to patient needs through observational gait analysis, and instead provide real-time objective gait parameters to proactively address patient needs. This is supported by the recommendations of existing literature for gait scoring systems [67]. At the same time, patients can monitor their own progress over time, providing a sense of engagement and empowerment in rehabilitation. Moving forward, further real-world testing and validation of these vision-based systems would be essential in ensuring their accuracy and reliability in diverse clinical settings. Overall, future implementation of vision-based motion capture as a point-of-care system has the potential to improve the gait assessment of orthotic rehabilitation, while also empowering patients to monitor their own progress over time.

Future work may also consider integrating vision-based motion capture with wearable inertial sensor technologies to improve the accuracy of these systems. This can help resolve challenges that vision-based methodologies face, such as occlusion and parallax errors, as these sensors do not rely on the field of view or resolution of the camera. At the same time, it can address current challenges that wearable inertial sensors face, such as motion artefacts and sensor placement variabilities [68], as the broader field of view (video data) can provide context for better spatial tracking of sensor location. Future studies may also include larger sample sizes of patients to increase the generalizability of findings. At the same time, future studies should seek to address the scalability challenges associated with increased video data volume, enabling widespread clinical adoption. Finally, this review recommends that future studies can adopt a more standardized approach to report key machine learning evaluation performance metrics, such as accuracy, precision, specificity, recall and area under the curve. This can enable better inter-study comparison of gait classification performance.

7. Conclusion

This review examined the available scientific evidence for the developments in vision-based motion capture systems for the gait analysis of neurodegenerative diseases and its relevance to the clinical setting. Limited evidence with vision-based methodologies was found, with few studies providing high quality evidence. The greatest challenges with these studies are the use of small sample sizes and the inherent lack of evaluation blinding when designing computer vision algorithms. Nevertheless, this review contributes to the evidence base and aims to bridge the gap between clinical practice and the technology available. This review found that vision-based motion capture technology has the potential to provide quantification of gait, allow the expansion of gait assessment tools, remote gait monitoring and implementation as a point of care system. However, challenges, such as parallax errors, occlusion and small sample sizes affect the accuracy and validity of these studies. Moreover, a lack of consistency in reporting classification performance was found, making inter-study comparisons difficult. Moving forward, future studies using vision-based systems can consider using larger sample sizes and further real-world testing in clinical settings to improve the quality and generalizability of findings on the patient population. A standardized means of reporting classification performance metrics would also be a step in the right direction. Ultimately, vision-based motion can serve as a complementary tool to effectively provide key gait information and appropriate gait classification. This allows clinicians to make informed decisions about the disease severity and tailor personalized treatment for effective care\

CRediT authorship contribution statement

David Sing Yee Vun: Conceptualization, Methodology, Formal analysis, Investigation, Data curation, Writing – original draft Preparation, Writing – review & editing, Visualization. **Robert Bowers**: Supervision, Writing – review & editing, Project administration, Resources. **Anthony McGarry**: Supervision, Writing – review & editing, Conceptualization, Methodology, Project administration.

Declaration of Generative AI and AI-assisted technologies in the writing process

The authors did not use AI when writing this paper.

Declaration of Competing Interest

The authors declare that they do not have any conflict of interests in this project.

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