Comparability of methods for remote assessment of gait quality:

An example from people with Parkinson's Disease (PD)

Natasha Hassija *B.Sc. (Physical Therapy)*

School of Physical and Occupational Therapy

Faculty of Medicine and Health Sciences

McGill University

Montreal, Quebec, Canada

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Abstract

Background: Advancements in technologies for the analysis of gait enable efficient, costeffective, and remote gait analysis that allows personalized, real-time assessments within the comfort of a person's home. However, in clinical practice, gait analysis remains anchored to traditional observational methods that focus on performance in a controlled environment, failing to accurately assess a person's true motor competence. For instance, a person with PD at an early stage may be able to cover an optimal distance while walking when assessed in a clinic but may not necessarily exhibit an efficient gait pattern, increasing the risk of falls. It is thus important to assess gait capacity and gait quality parameters in daily life. Although digital technologies are poised to fill this gap, their limited integration into clinical practice is due to uncertainties related to their comparability and reliability with methods used in clinical practice.

Objective: The overall aim is to contribute evidence as to the comparability of 3 methods of remote gait assessment in individuals with Parkinson's Disease. Specifically, the purpose is to estimate the extent to which values on gait metrics are similar/different among 3 different methods of assessing gait quality (1) Observational analysis by physiotherapists; (2) Wearable sensor - Heel2Toe™ sensor; (3) Pose estimation – MediaPipe Pose. Secondarily, the aim is to identify challenges encountered with each of these methods.

Methods: A cross-sectional, multiple case series study was conducted remotely recruiting adult members of Parkinson Quebec with mild to moderate gait deficits. After screening for eligibility, 20 participants submitted videos of them performing a modified TUG test at home/in their neighbourhood with the Heel2Toe™ sensor. A checklist for observational analysis of gait specific to PD was developed for this study. Each video was subsequently analyzed by six raters using the checklist who were allotted videos at random. The same videos were then analyzed using a customized program with the MediaPipe Pose library.

Results: Crude agreement over individual items on the checklist ranged between 71-100%. Scores created by summing the item scores (maximum 35) given by the raters yielded an ICC of 0.78 indicating reliability sufficient to compare groups of people but not sufficient for within-individual change. The quality of the videos significantly affected the overall agreement, where a video with 'excellent' quality had an estimated association of 13.7 (0.0013) points higher than a video of poor quality. Agreement on 'excellent' quality videos was 96%. The values from the wearable sensor and observational ratings were compared pairwise to the inter-rater agreement results. The observational ratings agreed with the wearable sensor on

accurately detecting the heel strike 64% of the time and 28.5% of the time on detecting the push-off. Agreed 35.7% of the time on detecting foot clearance and 85% of the time on detecting cadence. A Spearman's rank correlation of 0.32 ($p = 0.260$) for heel strike and -0.22 ($p = 0.386$) for push-off was calculated from the comparison between pose estimation and wearable sensor; a correlation coefficient of -0.28 ($p = 0.225$) for heel strike and 0.15 ($p = 0.514$) for push-off was calculated from the comparison between pose estimation and observational ratings. Thus, values for heel strike and push-off obtained from pose estimation had a weak correlation with both the wearable sensor and observational ratings.

Conclusion: A combination of digital technologies for remote gait analysis, such as wearable sensors and pose estimation, can detect subtle nuances in gait impairments that may be overlooked by the human eye, offering greater accuracy and reducing variability among raters.

Résumé

Contexte: Les progrès des technologies d'analyse de la marche, permettent une analyse efficace, rentable et à distance de celle-ci ce qui permet des évaluations personnalisées en temps réel dans le confort du domicile d'une personne. Cependant, dans la pratique clinique, l'analyse de la marche reste ancrée dans les méthodes d'observation traditionnelles qui se concentrent sur la performance dans un environnement contrôlé, ce qui ne permet pas d'évaluer avec précision la véritable compétence motrice d'une personne. Par exemple, une personne atteinte de la maladie de Parkinson (MP) à un stade précoce peut être capable de parcourir une distance optimale en marchant lorsqu'elle est évaluée en clinique, mais ne présente pas nécessairement un schéma de marche efficace, ce qui augmente le risque de chutes. Il est donc important d'évaluer la capacité de marche et les paramètres de qualité de la marche dans la vie quotidienne. Bien que les technologies numériques visent à combler cette lacune, leur intégration limitée dans la pratique clinique est due aux incertitudes liées à leur comparabilité et fiabilité avec les méthodes de la pratique clinique.

Objectif: L'objectif général est d'apporter des preuves de la comparabilité de 3 différentes méthodes d'évaluation à distance de la marche chez les personnes atteintes de la MP. Il s'agit d'estimer dans quelle mesure les valeurs des paramètres de la marche sont similaires/différentes entre ces méthodes (1) analyse observationnelle par des physiothérapeutes; (2) capteur - Heel2Toe™; (3) estimation de pose (EP) - MediaPipe Pose. Le second objectif est d'identifier les difficultés rencontrées avec chacune de ces méthodes.

Méthodes: Une étude transversale de séries de cas multiples a été menée à distance pour recruter des membres adultes de Parkinson Québec présentant des déficits de marche légers à modérés. Après vérification de l'admissibilité, 20 participants ont soumis des vidéos d'eux effectuant un test TUG modifié à la maison ou dans leur quartier équipé du capteur portable (CP). Une liste pour l'analyse observationnelle de la marche (AOM) spécifique à la MP a été élaborée pour cette étude. Chaque vidéo a ensuite été analysée par 6 évaluateurs à l'aide de ladite liste, qui se sont vu attribuer des vidéos au hasard. Ces vidéos ont ensuite été analysées par l'EP.

Résultats: L'accord brut sur les éléments individuels de liste de l'AOM se situait entre 71 et 100 %. Les scores créés en additionnant ceux des éléments donnés par les évaluateurs ont donné un ICC de 0,78 indiquant une fiabilité suffisante pour comparer des groupes de personnes mais insuffisante pour un changement intra-individuel. La qualité des vidéos a eu une incidence significative sur l'accord global, une vidéo d’excellente qualité ayant un score

estimé de 13,7 (0,0013) points de plus qu'une de mauvaise qualité. L'accord sur les vidéos d'excellente qualité était de 96%. Les valeurs du CP et de l'AOM ont été comparées deux à deux pour obtenir les résultats de l'accord inter-évaluateur. Les AOM étaient en accord avec le CP pour détecter avec précision la frappe du talon (FT) dans 64% des cas et dans 28,5% des cas pour la détection de la poussée. Elles ont concordé dans 35,7% des cas pour la détection du dégagement du pied et dans 85% des cas pour la détection de la cadence. Une corrélation de rang de Spearman de 0,32 ($p = 0,260$) pour la FT et de -0,22 ($p = 0,386$) pour la poussée a été calculée à partir de la comparaison entre l'EP et le CP, un coefficient de corrélation de -0,28 ($p = 0,225$) pour la FT et de 0,15 ($p = 0,514$) pour la poussée a été calculé à partir de la comparaison entre l'EP et l'AOM.

Conclusion: Une combinaison de technologies numériques pour l'analyse à distance de la marche, telles que les CP et EP, peut détecter des nuances subtiles dans les déficiences de la marche qui peuvent être négligées par l'œil humain, offrant ainsi une plus grande précision et réduisant la variabilité entre les évaluateurs.

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It always seems impossible until it’s done! The journey of writing my thesis has been incredibly fulfilling, and I am indebted to everyone who made this possible. First and foremost, I express my profound gratitude to Lord *Gaṇeśa*, whose blessings have guided me from the very beginning. His presence has been a constant source of strength throughout this challenging phase, and I am thankful for the wonderful people he has placed in my life all along the way.

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I greatly appreciate the expertise and insightful feedback of my co-supervisor, Dr. Etienne DeVillers Sidani. I would further like to extend my gratitude to Dr. Helen Dawes (HD), for being part of my supervisory committee. Her expertise and experience in the field of neurorehabilitation have been of great value.

This thesis was conducted in collaboration with PhysioBiometric Inc., the McGill spin-off company behind manufacturing the Heel2Toe™ sensor integral to this study. I am thankful to their entire team for their generosity in allowing me to deploy the sensor for this research. Pose Estimation of the gait videos using the MediaPipe Pose library wouldn’t have materialized without the intellect and expertise of Dr. Edward Hill (EH), I am immensely thankful for his effort in building the program.

Data for the inter-rater agreement was collected using the REDCap® platform, many thanks to Dr. Stan Hum for setting up the platform. I would also like to express my gratitude towards Lyne Nadeau, for her guidance in using the SAS software for data analysis and her expertise in the field. I am extremely thankful to all the raters Dr. Kedar Mate, Dr. Ahmed Abou-Sharkh, Dr. Lois Finch, Dr. Ayse Kuspinar, Jennifer Wai, Adriana Venturini, Ezinne Ekediegwu, Eren Timurtaş, HD and NM who took time off their busy schedules to analyze multiple videos very patiently and provided insightful feedback that helped me iterate the observational checklist specific to gait analysis in PD. I have been very fortunate to have the support of my colleagues in the lab – Ana Moga, Henry Michael, and Alessandra Granata – who encouraged me throughout the process. I would further like to thank every participant in the study and their caregivers who stepped out of their comfort zone to record and upload the walking videos and navigated their way around using the sensor and application despite all the challenges. I would also like to thank Parkinson Quebec for their collaboration.

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Preface

The purpose of this master's program is to acquire the skills necessary for conducting research and to effectively apply both established and emerging methods and tools in the field of rehabilitation.

Evolution and Development of Research Project

Analysis of gait forms an integral part of understanding human locomotion, diagnosis of conditions with gait impairments and designing rehabilitation interventions. With the availability of newer technology, it is now possible to obtain very precise measures of a person's motor activity during everyday tasks such as walking. However, in clinical practice, gait analysis continues to remain anchored to methods of broad classification based on observations by clinicians. A systematic review published by Ridao-Fernandez et al in 2019 on measures for observational gait assessment brought to light the variability among measures such as on parameters assessed and the lack of standardized protocol to assess gait in a clinical setting. This led me to question the limited integration of existing techniques into clinical practice, which was also the motive that drove this thesis. Leveraging my experience as a physiotherapist, I aimed to explore possible obstacles that contributed to this limitation. This journey of exploring obstacles and limitations was filled with engaging challenges primarily the uncertainty of comparing parameters from three distinct methods based on different measuring scales, which was made possible solely through the expertise of Dr. Mayo. Many lessons were learned during this process and experiences ranged from embracing mistakes made and learning from feedback to triumphant moments of obtaining results that resonated with theory and clinical experience.

The process of designing this study commenced with an investigation of the available literature under the guidance of my supervisor on various methods and tools available for gait assessment. The methods were then grouped based on the setting they were utilized. Technology in the field of remote assessment was confined to the research setting except those available commercially used in the sports sector or by the general population.

The reason for choosing PD as an example for this study was gait impairment is a distinguishing feature of PD, yet no standardized method is available for a comprehensive analysis of all relevant gait parameters. This challenge was dealt with by developing a checklist based on the existing literature and then comparing the results of this approach to the common parameters recorded using the wearable sensor (Heel2Toe^{TM}) and the method of pose estimation (MediaPipe Pose).

Contribution of Authors

This thesis was embedded in the larger ongoing trial on implementing the wearable sensor – Heel2Toe^{TM} among people with PD to change gait patterns, walking behaviours, and motivational, functional and quality of life indicators over 3 months (PI: Nancy Mayo, Etienne De-Villers Sidani). As supervisor, Dr. Mayo oversaw all aspects of this thesis. As there was no specific measure consisting of all gait quality parameters essential for being assessed in PD, a bespoken checklist was developed as part of the first component of this study which required an investigation of the literature, performed by the master's student (NH) under the thorough supervision of Dr. Mayo. All raters Kedar Mate, Jennifer Wai, Ezinne Ekediegwu, Eren Timurtas, Adriana Venturi, Ayse Kuspinar, Lois Finch, Ahmed Abou-Sharkh, Helen Dawes and Nancy Mayo analyzed 8-10 gait videos and provided insights and feedback on the checklist that led to 5 iterations of the checklist. The analysis of agreement and reliability was performed by NH under the thorough supervision of Dr. Mayo and Lyne Nadeau. The program for pose estimation using MediaPipe Pose was developed by Dr Edward Hill. He ran multiple experiments using the program to tailor it to extract gait parameters similar to the ones listed in the checklist. Finally, a comparison across the three methods was performed by NH under the guidance of Dr. Mayo.

Organization of the thesis

This thesis comprises seven chapters in total, which is in line with the Graduate and Post Doctoral Studies (GPS) regulations for a chapter-based traditional thesis. It begins with an introduction and ends with an overall discussion and conclusion. A brief outline of the thesis is as follows.

Chapter 1 consists of an overview of normal gait and covers in detail the various methods of gait analysis followed by its relevance and importance in PD

Chapter 2 covers the rationale which drove this thesis and lists the objectives specific to the study

Chapter 3 details the overall methodology used for testing the three methods for remote gait analysis (observation, wearable sensor and pose estimation) and the sample size estimate.

Chapter 4 provides details of the development and iterations of the observational checklist specific to PD along with the analysis for agreement and reliability. This chapter concludes with a final recommendation for an observational checklist after five iterations.

Chapter 5 details an overview of the wearable sensor used in the second component of this study. It describes in detail the gait parameters analyzed using the sensor and concludes with pairwise comparison between the common gait parameters recorded using the sensor and the ratings given by raters.

Chapter 6 provides details of the technology used for pose estimation, and development of the tailored program using the MediaPipe Pose library. It further describes the gait parameters that were possible to estimate using this method and concludes with the challenges and comparison between the common gait parameters across all three methods of remote gait analysis.

Chapter 7 is the overall discussion and conclusion based on the previous chapters included in this thesis. It also highlights the implications of this work

Corresponding tables and figures are presented at the end of each chapter. The references for all chapters have been provided at the end.

Conflict of Interest

As a graduate student under Dr. Nancy E Mayo's supervision, I acknowledge our research study's potential conflict of interest. The study employs the Heel2Toe™ sensor developed by PhysioBiometric Inc., a McGill spin-off company founded and led by Dr. Mayo. While recognizing this affiliation, I am committed to maintaining research integrity by adhering to rigorous methodology and transparent reporting practices.

Chapter 1: Background

The restrictions placed on in-person contacts, even for health-related reasons, during the COVID-19 pandemic amplified the need for remote assessments and telerehabilitation (Nguyen et al., 2023; Arntz et al., 2023). In physical rehabilitation, there is a strong focus on gait and mobility traditionally assessed only in person. (Zanin et al., 2022; Bernhardsson et al., 2023). Gait is the manner of walking (Ali et al., 2012). Normal gait is described as a systematic, cyclical and rhythmic pattern with coordinated movement of the limbs and the trunk that enables locomotion (Perry & Burnfield., 2010). The extent to which this pattern occurs would indicate gait quality (Hulleck et al., 2022). Walking is a rhythmic dynamic activity involving large muscles (Morris & Hardman, 1997). Walking can be further classified according to capacity and performance using the ICF (Okochi et al., 2013). Capacity can be measured by testing in a clinical setting usually quantified as walking speed (Hendriks et al., 2022). At the same time, performance in the real-world setting is often quantified as steps per day and walking bouts (Ainsworth et al., 2011; Mate & Mayo, 2020). Capacity and performance quantify walking (Brandes et al., 2008).

Good gait quality is the foundation for both walking capacity and performance, making gait assessment and gait training the primary activities of physical rehabilitation (Mate et al., 2019; Hausdorff et al., 2018; Keren et al., 2021). Methods for remote gait assessment became increasingly important during the pandemic period as illustrated by the number of publications in the area, especially those using digital technology (Micó-Amigo et al., 2023). Figure 1.1 shows results from a PubMed search revealing a 77.3% surge in articles published in the field starting after 2019. This digital revolution stems from the need to provide assessment and monitoring that is closely equivalent to that when done in person (Abernethy et al., 2022). In addition, rehabilitation interventions can often be moved out of the clinic to the person’s home making them much more personalized and cost-effective (Gurchiek et al., 2019; Mayo, 2016) necessitating technology to keep pace. Specifically, the opportunity afforded by the increased interest in real-time remote monitoring and telerehabilitation has stimulated digital technologies specifically for gait analysis (Arntz et al., 2023).

1.1 Gait Analysis

The analysis of gait originates from the earliest studies of bipedal gait (Lovejoy et al., 1973;

Winter et al., 1990). Gait analysis can be defined as a set of procedures to observe, record, analyze and interpret movement patterns performed while walking (Baker et al., 2016). Different applications of gait analysis are illustrated in Figure 1.2.

A wide array of methods are available for analyzing gait, and one method will not fit all purposes. It is crucial for diagnostic purposes, guiding treatment, and understanding mechanisms of optimal and pathological gait (Kyriazis., 2001). At one end of the spectrum are simple, inexpensive, and commonly used methods involving direct observation by an expert. At the other end are complex, costly, technologically aided methods, some of which require extensive infrastructure and specialized personnel. In addition, these measures are based on different measurement properties affecting the measurement scale and the quantification of various gait parameters (Rudisch et al., 2021). This section presents various gait analysis methods, including the specific gait-related parameters assessed. The section begins with the description of gait as it forms the basis of understanding deviations from the standard pattern. This section is followed by methods of assessment that require no equipment and progresses to more elaborate techniques.

1.1.1 Normal Gait

Gait is a term used to describe the pattern of walking which is a fundamental component of mobility (Webber & Raichlen, 2016; Ataullah & De Jesus, 2024). Gait has been studied extensively by many researchers over the past 100 years (Braune & Fischer, 1987; Burnfield, 2010; Isman & Inman, 1969; Marey, 1894). Normal gait is a generalized pattern considered optimal for walking (Morris & Hardman, 1997). Gait consists of multiple repetitions of sequential patterns, each forming a cycle (Kirtley., 2006). Each cycle begins when the foot contacts the ground also known as the heel strike and continues until the heel strike of the same foot in preparation for the next stride (Pirker & Katzenschlager., 2017) shown in Figure 1.3. The core variables that describe a cycle and are essential for gait analysis such as step length, stride length and step width are also illustrated in Figure 1.3. The gait cycle is divided into stance (60%-62% of the cycle) and swing phase. The stance phase comprises five phases: initial contact (heel strike), loading response (foot-flat), midstance, terminal stance (heel-off) and preswing (toe-off). The swing is divided into the initial swing (acceleration), midswing and terminal swing (deceleration) (Burnfield, 2010; Coutts, 1999; Pirker & Katzenschlager, 2017) explained in Figure 1.4.

Some of the features of normal gait include alternating movement of the limbs, clear heel to toe pattern to avoid scuffing, proper pre-positioning, sufficient step length and natural anteroposterior sway of the trunk (Akl, 2014). The core elements of gait assessment: temporo-spatial, kinematic, and kinetic parameters, are described in Table 1.1.

1.1.2 Gait - An indicator of motor competency

Independent bipedal walking is a major milestone of motor development, occurring during the early stages of childhood. Motor development is one of the concepts encompassed within the broader umbrella of motor competency (Bardid et al., 2019). Walking is a complex motor task (Verghese et al., 2009), hence an indicator of motor competency as it requires a synchronized interplay of the musculoskeletal, cardiorespiratory, central (CNS) and peripheral nervous systems (PNS) (Pirker & Katzenschlager., 2017). The number and complexity of the events needed to master this basic capacity are shown in Figure 1.5.

Motor competency signifies performance and participation in daily activities and is categorized into locomotor (e.g., walking), object control (e.g., control of body movements and coordination) and stability (e.g., balance). Thus, motor competency refers to an individual's proficiency while performing a motor task underpinning their ability and quality of movement (Cattuzzo et al., 2016; Hulteen et al., 2018). Gait is one of the most frequently assessed indicators of motor competency and gait assessment guides rehabilitation interventions (Pohl et al., 1996; Dasgupta et al., 2021). Proficient gait comprises covering an adequate distance essential for daily activities with an optimal number of steps at an optimal pace but also the ability to produce good quality steps. The link between gait quality and walking quantity is well known (Kaneko et al., 1991; Mate et al., 2019; Mayo et al., 2023). The ability to competently and safely navigate the community is called walking competency. Walking speed and walking distance are some of the elements that explain walking competency (Salbach et al., 2004) while the extent of heel strike, swing at the hip and toe push-off are some of the elements that describe the quality of steps (Ginis et al., 2017; Mayo et al., 2023).

1.1.3 Methods of Gait Analysis

The diverse methods available for gait analysis are distinguished by the parameters assessed and the settings in which they are applied, whether in-person or remotely. Methods specific to different settings are listed in Table 1.2.

In a clinical setting, the direct observation method by a clinician is most widely used. In measurement terminology, this falls under the rubric Clinical Outcome Assessment (COA).
COA can rely on different sources of information: Clinician Reported Outcomes (ClinRO) and Performance Outcomes (PerFOs) (Mayo et al., 2017; McLeod et al., 2011; Berg et al., 2024). ClinROs typically include a structured checklist (Powers et al., 2017). The checklists list various gait parameters, including those related to movements of the trunk, pelvis, hip, knee, and ankle, the quality of which is rated by an expert clinician (Rancho Los Amigos Medical Center Professional Staff et al., 1989). PerfOs on the other hand rate a person's performance on a standardized test such as the 10-meter walking test (10MWT), Timed-Up and Go (TUG), or the 6-min walking test (6MWT). The results are interpreted as an individual's capacity to walk or move (Mate & Mayo, 2020).

Another rapidly advancing and evolving stream of outcome measures is those assessed using technology (TechO) (Mayo et al., 2017) such as instrumented gait analysis which can be done using non-wearable or wearable technologies (Muro-De-La-Herran et al., 2014). Wearable technologies can be used both clinically (or research) and for remote monitoring (Liao et al., 2019). However, the non-wearable systems are not optimized for remote monitoring. These systems comprise marker-based motion capture systems, instrumented walkways (GAITRite), and force plates. Both wearable and non-wearable technologies can measure spatial, temporal, kinematic, and kinetic parameters. Non-wearable technologies are highly accurate and have been considered as the research gold standard (Shanahan et al., 2018). The drawback of using these technologies is that they are fixed, expensive, and need extensive infrastructure, including trained personnel to operate and manage data from these systems. A newer technology based on markerless motion capture (e.g. pose estimation using digital software) arose from the animation industry (Ferrari et al., 2009) and is suitable for remote monitoring as it takes advantage of video recording. This system detects movements by tracking anatomical landmarks such as those when a person is walking which can be used to calculate temporal, spatial and kinematic parameters that underpin gait analysis.

Since this thesis focuses on comparing different methods of remote gait assessment, the following sections will describe in greater detail the observational, wearable, and pose-estimation methods.

1.1.3.1 Observational Methods (ClinROs/PerfOs)

Observational or visual gait analysis is the simplest method of analysis made by the unaided human eye the results of which are documented using a checklist. The checklists used for observational analysis in various settings are inspired by the one developed by (Rancho Los Amigos Medical Center Professional Staff et al., 1989). The structured method for observational analysis that is most relevant today is attributed to Dr J Perry (Perry, 1992). The ratings used in these checklists can be binary (e.g., present or absent) or graded using ICF qualifiers (e.g., no problem, mild problem, moderate problem, severe problem, complete problem, not specified or not applicable) (Organization, 2007; Stucki et al., 2002). In addition to the checklist, certain observation-based performance tests listed above (PerfOs) are also widely used. This assessment can be conducted in a clinical setting or remotely via video.

All observational methods are limited by expertise and by the eye that cannot observe subtle nuances in movement that occur at a rapid pace. The reliability of measures of observational gait analysis has been summarized in Table 1.3. Of the 12 measures listed in the table, eight measures included the kinematics of the leg, only four scales included arm swing, only five scales included both spatial and temporal parameters and only one scale included the evaluation of symmetry of spatial and temporal parameters (Ridao-Fernández et al., 2019).

Observational methods are best suited for judging spatial gait parameters including posture. However, the observer has the benefit of a three-dimensional view of the client when in person. Research has shown variability in the ratings across observers indicating moderate inter-rater reliability of observational method of analysis (Brunnekreef et al., 2005). Despite limitations, this is the most widely used method in a clinical setting (Anwary et al., 2020)

Remotely, the observational method is used to analyze videotaped gait. The idea of videotaping originated in the 1990s; however, now images are produced through direct digital recording devices. The advancements in digital recording have now made monitoring gait in daily life (outside a clinic or lab) possible. The person need not repeat trials to aid in the evaluation, and the image can provide valuable feedback to the client. To overcome the limitations of high-speed movements, the video can be slowed down, but the sophistication of the recording device, the technical skill of the person making the recording, and the two-dimensional view of the client remain limitations (Hulleck et al., 2022).

One component of the research in this thesis uses a combination of a ClinRO and a PerfO. The ClinRo is a structured observational checklist completed while viewing a video of a person with PD performing the 'Timed Up and Go' (TUG) test with a modification to extend the walking distance. This test times how long it takes the participant to stand up from sitting, walk 3 meters (approximately 10 meters for the video recording), turn and return to the chair and sit down. The TUG is widely used in clinical and research settings as it integrates, in a functional task, changing position against gravity, balance, gait speed, and turning (Okumiya et al., 1998).

1.1.3.2 Wearable Technologies (TechO)

As the name suggests, wearable technologies are designed to be worn. Wearable technologies burst onto the health and fitness industries (Tao et al., 2012) owing to the availability and miniaturization of internal measurement units (IMUs) that report raw inertial body movements using three-axis accelerometers (for linear acceleration), three-axis gyroscopes (for rotational velocities), and magnetometers (for magnetic field strength concerning the earth's axes). The history of wearables can be traced back to the 19th century when a wearable camera was developed in 1907 and used on pigeons to capture aerial images (Ometov et al., 2021). One of the earliest wearable sensors was the Galvanic Skin Response (GSR) invented before World War II to detect lying using pulse rate and blood pressure (Vicianova, 2015).

Today, most wearable sensors available in the market are lightweight, cheap, and can be used to collect data without disturbing daily life activities. New generation wearables connect to smartphone devices and IMUs are also part of every smartphone now that track steps, stairs climbed, movement time, and even some aspects of gait such as stride length, unsteadiness, and asymmetry, making smartphone-based human motion assessment feasible (Guk et al., 2019). Some examples of wearable sensors include pedometers, smart watches, posture meters, attachable sensors for any part of the body, insoles, flexible goniometers, electromagnetic tracking systems, and sensing fabric (Tao et al., 2012).

Wearable sensors can be attached anywhere on the body but for gait analysis, they are placed at the waist, hip, knee, ankle, and/or foot or worn as a sock or an insole. Chizeck deployed a flexible goniometer and attached it to the hip, knee, and ankle joints to record joint angles (kinematic parameter) during different phases of the gait cycle (Chizeck, 1997) and Slavelberg and Lange used foot pressure insoles with sensors embedded in the insole of the footwear to estimate ground reaction forces (Savelberg & De Lange, 1999).

With increasing sophistication, the data generated from IMUs can be stored in the device for long periods. They provide post-performance information on the quantity of movement, for example, steps taken when walking, as well as on some temporal, spatial, kinematic, and kinetic parameters, depending on where the sensor is worn. Recent wearables available in the market not only help detect movement related to gait but are also capable of providing realtime feedback on gait parameters (Hulleck et al., 2022; Muro-De-La-Herran et al., 2014).

Mate et al. (2023) conducted a review of these wearable technologies that have feedback capability and are aimed at promoting a safer and more normal gait pattern. The wearables chosen for review were those commercially available to the public and not just for use in a clinical or research setting, indicating emerging evidence of their effectiveness (Mate et al., 2023).

Another component of this study makes use of a wearable sensor, Heel2Toe™, that comprises a 3-axial linear accelerometer, gyroscope, and magnetometer designed to detect the angular velocity of the ankle joint during walking. It is a smart wearable as it was developed to provide real-time auditory feedback for a "good" step, one in which the step is initiated with a strong heel strike. The Heel2Toe™ sensor has been shown to detect these "good" steps with a high degree of accuracy (Vadnerkar et al., 2014). In clinical populations, the angular velocities generated during walking are associated with cadence and falls (Mayo et al., 2023). In healthy participants, Tomita et al. showed a single bout of training with the Heel2Toe™ on the right leg produced changes to the gait pattern on the trained and untrained leg (Tomita et al., 2024).

1.1.3.3 Pose Estimation / Markerless Motion Capture (TechO)

Pose estimation is a markerless method of gait analysis that uses advanced computer vision techniques and algorithms to detect anatomical landmarks from an image or video frame, that can then be tracked during movements of joints and limbs during a series of "poses" that make up a functional activity like walking. This method can analyze 2D images or videos recorded using a smartphone camera or a professionally mounted camera. It can also analyze 3D representations captured using precise yet cumbersome and expensive systems like monochrome CMOS sensor and infrared projector; DARI motion system (uses eight highspeed cameras placed around the subject and a computer vision engine); and 4DBODY System (uses a single frame structured light illumination) (Connie et al., 2022; Hii et al., 2023). Detection of movement patterns facilitates the analysis of different gait parameters like step length, gait speed and joint angles. This avoids the time-consuming process of placing markers and sensors over the body and using a series of cameras to detect motion (Vun et al., 2024).

Like wearable sensors, pose estimation provides an opportunity for remote assessment and real-time assessment of gait in daily life (Mroz et al.). Some common libraries for pose estimation are OpenPose, AlphaPose and MediaPipe Pose. These libraries are often open source, but data processing requires an expert in coding to help extract various gait parameters increasing their accessibility and cost. Before the advent of these libraries, analyzing video data involved experts watching video playback, noting the times and locations of specific events, and converting the footage into a series of 2D images. This process was followed by separating the background from the subject in the video ultimately leading to a frame-by-frame analysis. This was a time-consuming activity, requiring expert knowledge of the motion to be analyzed, and thus was prone to analyst variability (David & Perona, 2014).

Pose estimation is used in the sports sector to detect the positions of body segments during athletic activities. The analysis of body segments provides valuable feedback for improving athlete performance (Stenum, Cherry-Allen, et al., 2021). However, recent literature highlights the use of this method in the health sector for video-based analysis of the gait pattern. For example, to analyze human gait, Stenum et al. used a 2D video-based approach deploying the OpenPose library to analyze temporal and spatial gait parameters (Stenum, Rossi, et al., 2021). Ramesh and Lemaire implemented an observational gait assessment measure (Edinburgh Visual Gait Score) using the OpenPose library on a video recorded using a handheld smartphone to make gait analysis more accessible (Ramesh et al., 2023). Tony Hii et al. compared three different markerless pose estimation libraries viz. OpenPose, MMPose, and MediaPipe Pose. Their ability to assess lower limb kinematics was compared and it was concluded that MediaPipe Pose was the optimal platform for analyzing lower limb joint kinematics with minimal error (Hii et al., 2023). The third and last component of this study deploys the MediaPipe Pose library for gait analysis.

1.2 Relevance of Gait Analysis in Parkinson's Disease (PD)

PD is a progressive, neurological, movement disorder caused by the degeneration of nerve cells in the substantia nigra situated in the basal ganglia. The loss of cells in the substantia nigra reduces the amount of dopamine available for controlling movement, and for regulating mood, judgement and decision-making. The four cardinal dopaminergic motor symptoms of PD are resting tremor, bradykinesia, postural instability and rigidity. 90% of those affected also exhibit a wide array of non-motor symptoms which include neuropsychiatric, autonomic, sleep and sensory symptoms (Grimes & Bulman, 2002). Nevertheless, one of the most serious consequences of PD is falls and fractures, most of which occur during walking (Creaby & Cole, 2018). People with PD are 2.5 times more likely than a peer group to sustain a hip fracture (Leslie et al., 2010). While most are diagnosed over the age of 60, ≈10% develop symptoms before the age of 50 (Ferguson et al., 2016). Even within 5 years of diagnosis, 60% have trouble walking and experience postural instability leading to a fall. Out of those living with PD, ≈78% experience symptoms of impaired gait, and 68% fall each year, leading to fractures that result in significant healthcare costs (Schrag et al., 2002). PD is reported to have the 3rd highest level of direct health care costs (Albarmawi et al., 2022). In 2019, the Michael J. Fox Foundation estimated the annual cost of PD in America to be $51.9 billion every year, with $25.4 billion attributable to direct medical costs (e.g., hospitalizations, medication) and $26.5 billion in nonmedical costs like missed work, lost wages, early forced retirement and family caregiver time. In Canada, estimates in today's currency would be almost $1 billion.

PD begins with subtle and gradual motor changes with a distinctive gait pattern. As PD is degenerative, those affected may exhibit asymmetric, reduced, or no arm swing, shuffling gait characterized by short steps and foot scuffing leading to trips and falls (Kim et al., 2018). There is also a forward flexion of the body including the trunk, neck and extremities. Lateral trunk flexion presenting as asymmetry of the trunk is very common and is seen in up to 80% of those affected. The rigidity of the trunk is also evident when turning. The person turns in a block due to the loss of the craniocaudal sequence while turning. Furthermore, bradykinesia is commonly manifested; for example, by trouble getting up from a chair, needing more than one attempt or their arms as support. Additionally, walking and standing occur with a narrow base of support which grows narrower as the disease progresses. This distinctive presentation of gait and postural impairments typical of PD facilitates the comparison of gait metrics (parameters) generated across different remote methods (Raccagni et al., 2020).

1.3 Epidemiological burden of Parkinson's Disease (PD)

A disease commonly diagnosed in the elderly and middle-aged, PD has become a huge public health concern (Xu et al., 2024). According to the analyses of the Global Burden of Disease study, 2016 the prevalence of PD has doubled with the rise in the aging population. It is the second most common neurodegenerative disease (Dorsey et al., 2018). According to Stats Canada, approximately four million people worldwide are living with PD, out of which 100,000 are Canadians. This is projected to increase by 65% by 2031. As the population of those living with PD grows, the demand for PD-related therapies will increase (Bennett et al., 1996; Bronstein et al., 2009).

Prevalence and risk of mortality of PD are known to be higher in men than women by a ratio of 4:1 (Cerri et al., 2019). Africa, Asia and Latin America report lower prevalence of the disease when compared to Europe and North America (Abbas et al., 2018). The EUROPARKINSON study reported that 54% of those living with PD above the age of 65 were under-diagnosed (De Rijk et al., 1997).

1.4 Physiology behind gait impairment in Parkinson's Disease (PD)

The physiology underlying gait and postural impairment in PD is complex and involves dysfunction at the cortical and subcortical levels within the locomotor network. The locomotor network comprises the spinal central pattern generators, brainstem mesencephalic and cerebellar locomotor regions, and cortico-striatal input projecting to the primary motor cortex. Execution of the complex motor task of walking is partially dependent on this network (Bohnen et al., 2022). Dopamine depletion disrupts the equilibrium between the events and systems required by the locomotor network. This disruption leads to tremors, rigidity, bradykinesia, and impaired balance and coordination resulting in impaired gait. In addition to this, people with PD also lose the ability to modulate gait due to difficulty recruiting cortical motor areas, particularly the frontoparietal and supplementary areas. Normally walking in adults is automatic and requires minimal use of attention. However, in PD due to loss of dopaminergic input in the posterior putamen that is known to be associated with automatic behavior, there is more difficulty walking without consciously paying attention (Wu et al., 2015).

1.5 Emphasis on analyzing gait impairments in Parkinson's Disease (PD)

Gait impairments are closely linked to posture and balance impairments and are the most prevalent core axial symptoms of PD. Gait impairments have a debilitating consequence on the person's quality of life and self-efficacy (Di Biase et al., 2020; Tosin et al., 2024)

In 1817, James Parkinson emphasized the need for gait evaluation by stating, “Observation of patients begins while they are walking into the office”. Thus, gait is a potential biomarker for detecting the progress of PD, calibrating appropriate medication doses, and measuring response to therapies (Goetz, 2011).

There is evidence that dopaminergic medication (L-dopa) improves both episodic symptoms like freezing and those that persist during daily activities such as short step length and increased gait speed. There is also evidence that these medications can further impair gait leading to fluctuations in motor response, gait variability, impaired rhythmic movement, and dyskinesia (Smulders et al., 2016). Hence, a person with PD might be able to cover optimal distance while walking in the earlier stages but they may not necessarily walk with a safe and efficient pattern rendering walking more tiring and less enjoyable (Lamont et al., 2012). Thus, it is essential that not only the person’s walking capacity is assessed but also that a robust assessment of the gait quality parameters that explain walking capacity is carried out. Despite this need, most clinical gait assessments for PD are restricted to measures of walking capacity and performance with measures such as the Unified Parkinson Disease Rating Scale (UPDRS), Movement Disorder Society MDS-UPDRS, Freezing of Gait Questionnaire (FOG-Q), Parkinson Disease Quality of Life Questionnaire (PDQ-39), 10 Minute Walk test, 6 Minute Walk test, Timed Up and Go test (TUG), Berg Balance Scale (BBS) and Dynamic Gait Index (DGI) focusing on capacity and performance of gait (Bloem et al., 2016; Holden et al., 2016).

The next chapter outlines the rationale and objectives for this thesis.

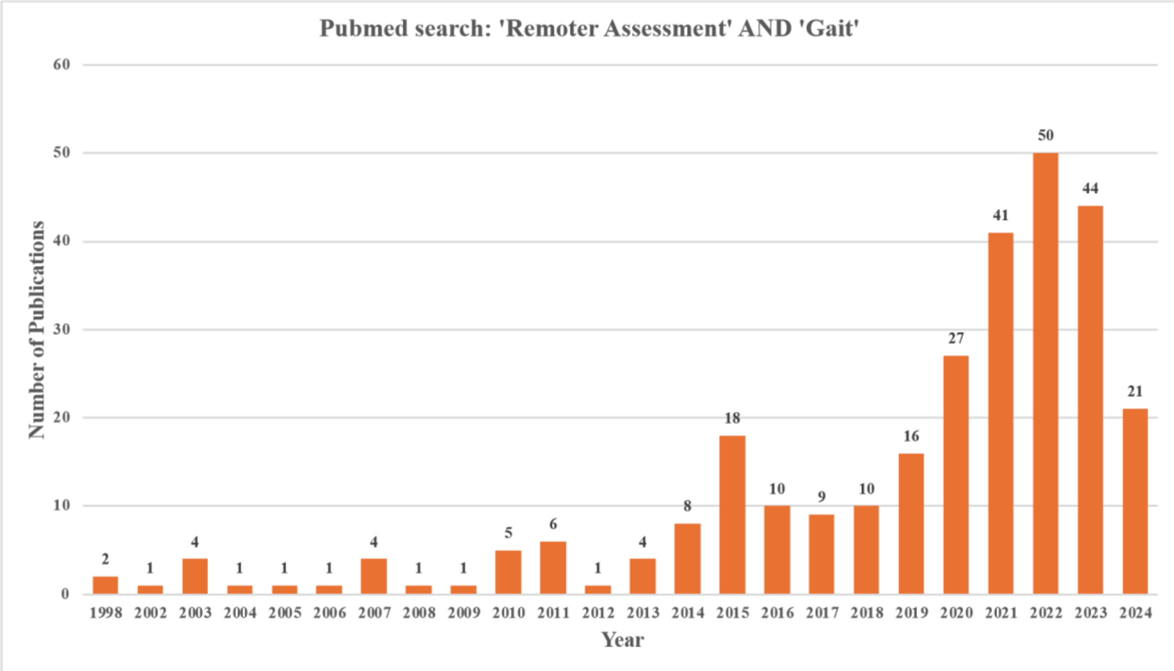

Figure 1.1 Literature search on PubMed for remote assessment of gait

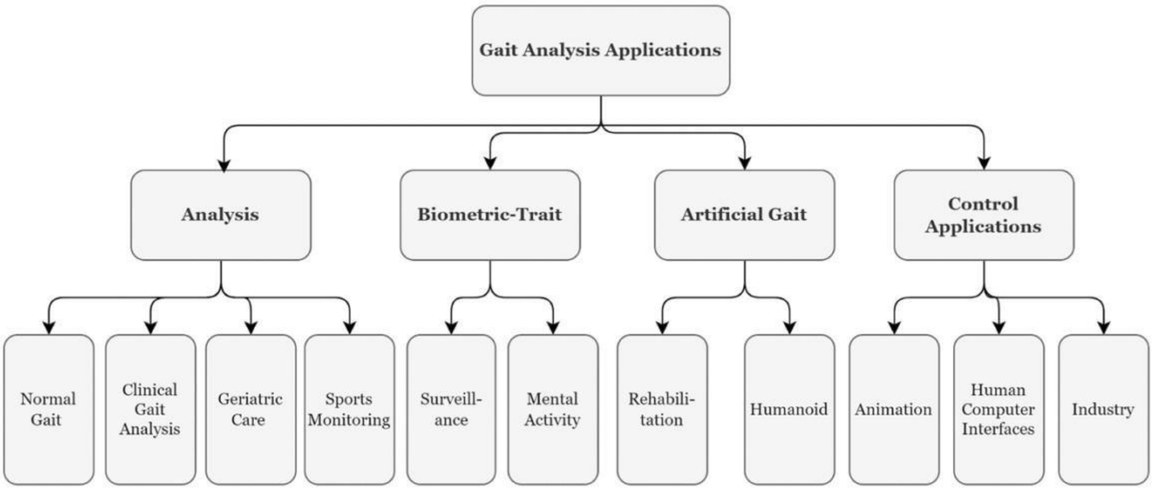

Figure 1.2 Applications of gait analysis: Reproduced from (Sethi et al., 2022)

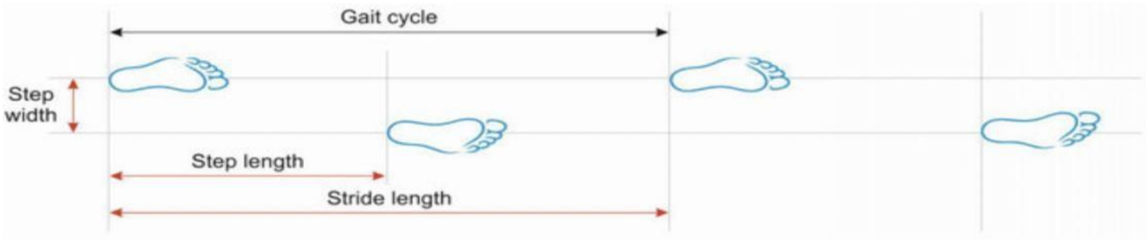

Figure 1.3 Terminology describing gait cycle: Reproduced from (Pirker & Katzenschlager, 2017)

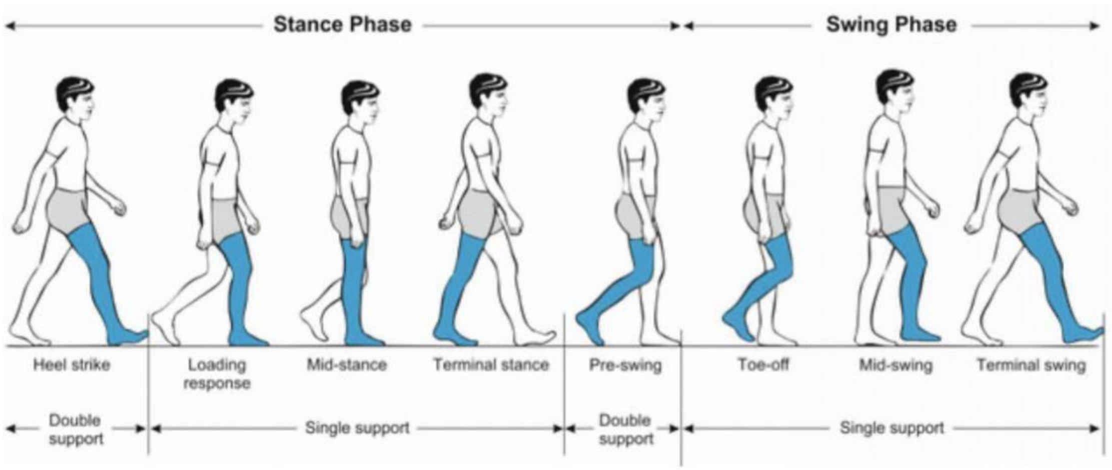

Figure 1.4 Illustrates phases of the gait cycle: Reproduced from (Pirker & Katzenschlager, 2017)

Table 1.1. Core Elements of Gait Assessment

Elements	Description	Gait parameters
Temporal and Spatial (often referred to as temporospatial)	Movement and positioning of body segments in space and time during walking	Temporal parameters are cadence, speed, step and stride time. Spatial parameters include step length, step width and stride length, while (Lohman, 2011)
Kinematic	Motion of the body segment relative to the other during different phases of gait without considering the forces acting on the body	Angular velocity, stride velocity, joint angles (Habersack, 2022)
Kinetic	Forces acting on bodies	Ground reaction force, impulse, active and passive propulsion (Habersack, 2022)

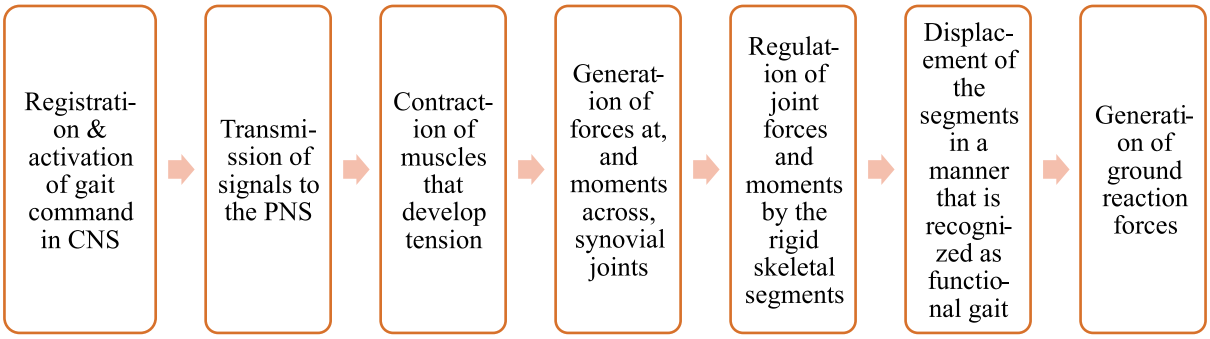

Figure 1.5 Sequence of events that occur for walking to occur

Table 1.2. Methods of Gait Assessment that are feasible in different settings. Those crossed out indicate methods that aren't feasible under the specific setting

Clinical and Research Setting	Remote Setting
Observational Analysis	Observational Analysis
Instrumented Walkways	~~Instrumented Walkways~~
Marker-based motion capture system	~~Marker-based motion capture system~~
Marker-less motion capture (e.g. Pose Estimation)	Marker-less motion capture (e.g. Pose Estimation)
Wearable Sensors	Wearable Sensors

Table 1.3. Summary of reliability of measures used for observational analysis of gait

	Measure	Reliability	Reference
1	RVGA (Rivermead Visual Gait Assessment)	Moderate	(Lord et al., 1998)
2	GAIT (Gait Assessment and Intervention Tool)	Substantial	(Daly et al., 2009)
3	OGS (Observational Gait Scale)	Moderate	(Mackey et al., 2003)
4	GABS (Gait and Balance Scale)	Moderate	(Thomas et al., 2004)
5	VGAS (Visual Gait Assessment Scale)	Moderate to perfect	(Dickens & Smith, 2006)
6	EVGS (Edinburgh Visual Gait Score)	Excellent	(Uysal et al., 2023)
7	BAWI (Bath Assessment of Walking Inventory)	Substantial	(Clarke & Eccleston, 2009)
8	VAHG (Visual Assessment of Hemiplegic Gait)	Moderate	(Hughes & Bell, 1994)
9	SGS (Standardised Gait Score)	Substantial	(Macri et al., 2012)
10	SCI-FAI (Spinal Cord Injury Functional Ambulation Inventory)	Moderate	(Field-Fote et al., 2001)
11	FGA (Functional Gait Assessment)	Moderate to Substantial	(Wrisley & Kumar, 2010)
12	CHAGS (Chamorro Assisted Gait Scale)	Substantial	(Chamorro-Moriana et al., 2016)

Chapter 2: Rationale and Objectives

2.1 Rationale

People with PD have a typical gait pattern, characterized by stooped posture and short shuffling steps with the center of mass too far forward to be safe. This pattern is disabling and dangerous and negatively impacts their quality of life, making gait impairment the leading reason for individuals with PD to seek physical rehabilitation. The recent Canadian Guideline for Parkinson's Disease states, "Physiotherapy specific to PD should be offered to people experiencing balance or motor function problems" (Grimes et al., 2019). However, there is a huge discrepancy between what should be and what currently exists. According to the Canadian Institute for Health Information (2021), only 1.5% of home care visits in Canada are attributed to PD. At best, a person may see a therapist for an assessment at a regular medical visit. According to the Global Burden of Disease study, 2016 the prevalence of PD has doubled with the rise in the aging population (Dorsey et al., 2018). Thus, the demand for individualized gait assessment and therapy will greatly exceed available resources and technology is poised to fill this gap.

Gait assessments in clinical practice primarily focus on walking competency as reported by the person themselves (or family member), measured using performance tests (such as gait speed, or TUG), or observed by the clinicians during a walking task. Rarely do clinical assessments include measures of gait quality as represented by temporal, spatial, kinematic and kinetic gait parameters.

These episodic assessments often fail to provide a comprehensive and accurate picture of a person's walking behaviours in daily activities. Technology can readily provide data for all these measurement situations and can be used outside of the clinic. The question that now emerges is the extent to which the different methods of obtaining information on how a person with PD walks are comparable across different methods of obtaining these clinically relevant data.

2.2 Specific Objectives

The overall aim is to contribute evidence as to the comparability of 3 methods of remote gait assessment in individuals with Parkinson's Disease.

Specifically, the purpose is to estimate the extent to which values on gait metrics are similar/different among 3 different methods of assessing gait quality:

(1) Observational analysis by physiotherapists

(2) Wearable sensor – Heel2Toe^{TM} sensor

(3) Pose estimation – MediaPipe Pose library

Secondarily, the aim is to identify challenges encountered with each of these methods.

Chapter 3: Methodology

The methods of analysis of gait-related data using three methods are explained in this chapter and the subsequent chapters. Data was acquired remotely and analyzed at McGill University Health Centre Research Institute (RI-MUHC), Montréal, Canada on a sample of people with PD who submitted video recordings while performing a modified Timed Up and Go Test (TUG) at home or in their neighborhood. This study is embedded in the larger ongoing study on implementing the wearable sensor – Heel2Toe™ among people with PD to change gait patterns, walking behaviors, and motivational, functional and quality of life indicators over 3 months. MedTeq, Mitacs, and Healthy Brains, Healthy Lives (HBHL) have funded this study through a partnership with PhysioBiometrics Inc. (McGill spin-off company dedicated to developing practical and accessible innovations for people with movement and posture vulnerabilities) and McGill University. Ethical approval for this study was obtained from The Institutional Review Board of McGill University.

3.1 Study Design

The study in this thesis follows a cross-sectional, multiple-case series design.

3.2 Participant Recruitment

To recruit participants Parkinson Quebec sent a newsletter announcing the study. Those interested responded by email and were sent a REDCap® link to consent and complete questionnaires for participation in the implementation trial. All communication regarding the study, including consent forms and questionnaires, were in both English and French. Videos submitted by the participants were stored on McGill's secure OneDrive portal and screened based on eligibility. Only adult members of Parkinson's Quebec with mild to moderate gait deficits equivalent to Hoen and Yahr grade 3 or less and those able to perform the TUG test independently with a minimum of 10 steps were included. In contrast, those unable to recover their balance from a perturbation during the TUG test, those unable to reinitiate movement without assistance, or those lost balance during a freezing episode while performing the TUG were excluded.

3.3 Sample Size

The sample size was estimated based on the number of probable observations in pairs or person-measures using MedCalc. For example, with 3 parameters: Heel strike, Push-off and Poor Foot clearance across two methods if there were 14 videos (participants) there would be

3*14 observations or 42 person-measures. Considering agreement on only half of these person measures, the confidence interval around this rate of 5 per 10 person-measures changed only marginally with increasing sample size. For example, N=14 95% CI 3.0 to 7.6 per 10 person measures, N=20 95% CI 3.3 to 7.1, N=30 95% CI 3.6 to 6.7. However, with 14 participants if excellent agreement (9 similarities per 10 person-measures) was presumed the 95% confidence interval was 6.4 to 12.4. Hence considering the feasibility, a sample size of 20 with 95% CI 6.7-11.7 was estimated.

3.4 Data Acquisition and Analysis

Data was collected remotely using the REDCap® platform operational on the Brain Health Outcomes Platform (bhop.mni@mcgill.ca). It was stored and analyzed using the SAS® software exclusively accessible through the RI-MUCH (McGill University Health Centre Research Institute) research network.

Three methods were compared: observational gait analysis of the video recordings, metrics of ankle angular velocity from the Heel2Toe™ sensor, and joint angle parameters obtained from pose estimation of the video recordings extracted using MediaPipe Pose. Pairwise comparisons between methods across common gait parameters were conducted, and the number of agreement pairs was counted, results for which are presented in the following chapters. Table 3.1 presents these gait parameters acquired from the three methods and illustrates the commonality of parameters across methods.

Table 3.1. Commonality of parameters assessed across the three different remote gait analysis methods

Gait Metrics assessed during modified TUG test	Observational Analysis by Physiotherapists	Data from Hee2toe™ wearable sensor	Pose Estimation using MediaPipe Pose library
Freezing	✓	✗	✗
Base of Support	✓	✗	✗
Poor foot clearance	✓	✓	✗
Unsteady while walking	✓	✗	✗
Variable Pace dynamics	✓	✗	✗
Heel Strike	✓	✓	✓
Push Off	✓	✓	✓
Cadence	✓	✓	✗
Swing at the hip	✓	✗	✓
Gait Symmetry	✓	✗	✗
Symmetry of arms while swinging	✓	✗	✗
Forward and backward arm swing	✓	✗	✓
Posture	✓	✗	✗
Tremor	✓	✗	✗
Dyskinesia	✓	✗	✗
Rotated trunk	✓	✗	✗
Ability to pivot	✓	✗	✗

Chapter 4: Inter-rater Agreement for Observational Gait Analysis

Chapter 1, section 1.1.3.1 discusses the challenges with using observational methods for gait analysis, particularly that there is variation across raters (see Table 1.3). As a bespoke checklist was developed for this study of people with PD, it was important to assess inter-rater agreement and modify as needed before proceeding further. This chapter will provide information on the development of the checklist, the video material rated, the characteristics of the raters, the results, and modifications made as a consequence of ratings.

4.1 Development of the Checklist

Sources from the literature were used to develop an initial checklist shown in Figure 4.1. (Eastlack et al., 1991; Guo et al., 2022; Krebs et al., 1985; Ridao-Fernández et al., 2019; Thomas et al., 2004). 34 gait parameters relevant to PD were identified from the literature. The structure and gradings in the checklist were inspired by the observational checklist developed at the Rancho Los Amigos Medical Center (Rancho Los Amigos Medical Center Professional Staff et al., 1989) and the ICF qualifiers (Organization, 2007). This version of the checklist was reviewed, piloted, and revised by 9 raters assessing one video. Raters entered their ratings on the REDCap® platform. Figure 4.2 presents the crude agreement across all raters where the average crude agreement was 84.9% with 13 out of 34 items having an agreement of 100%. The item related to side-of-arm symmetry had the lowest agreement (3/9 raters: 33.3%). Agreement results across items have been summarized in Table 4.1 below. Based on the consensus of this developmental assessment, items with agreement of less than 80% were reviewed and rephrased to improve clarity using a cognitive debriefing approach. (EggerRainer, 2019). Six iterations were needed until at least two members approved the final version. During the process, the items for the side of the asymmetric arm swing, movement of the trunk as a block, and hip extension were deleted (n=3) while the item for foot clearance was merged with scuffing. An additional item for co-ordination of the arms with legs was added to prevent confusion between symmetry and coordination. These amendments were based on feedback from the raters, culminating in the final checklist comprising 31 parameters illustrated in Figure 4.3.

4.2 Video Recording Material

Chapter 3 presented the methods for this thesis. Participants received a comprehensive list of instructions for recording the video with an example video recorded by the research team as reference. Participants were asked to record both lateral and frontal views performing the modified TUG test between 30 minutes to 2 hours of taking their medication (Levodopa/Carbidopa). The research team assessed the videos for walking safety as the Heel2Toe training was delivered remotely. The videos varied by setting and quality of the recording. As shown in Figure 4.4, 27 videos were screened and 7 were deemed of insufficient quality based on the extent of visibility, clarity and completeness of the test for rating gait quality parameters.

All participants were instructed to submit both frontal and side views of themselves performing the modified TUG (with a clear view of them getting up from a chair, walking a minimum of 15 steps (if possible) instead of the standard 3 meters, turning around, walking back and sitting on the chair), thereby ensuring all gait parameters are vividly visible and easy to assess. However, only 4 out of 20 participants shared both frontal and lateral views, the rest only shared a lateral view or a combination of frontal and lateral views.

4.3 Participant Characteristics

Of the 20 participants, 10 were male and 10 were female, with a mean age of 69.9 years (SD = 6.34). The participants' ages ranged from 56 to 81 years.

4.4 Raters

A diverse group of 10 raters, all experienced physiotherapists, analyzed videos using the final version of the checklist. Six raters were internationally educated, and their clinical experience varied widely, ranging from 2.5 to 30 years. Raters underwent a training session with the final checklist before commencing the process of analyzing the videos.

4.5 Process of Rating

Each of the 20 videos of adequate quality was analyzed by 6 randomly assigned raters, as shown in Table 4.2 below. Ratings were entered on the REDCap® platform. While assessing the videos, raters could pause, reduce the playback speed and replay the video multiple times. Each item on the checklist was accompanied by a short description. The checklist comprised spatial, temporal and kinematic parameters where spatial and temporal parameters were rated on a dichotomous scale and the kinematic parameters were rated on a trichotomized scale (Krebs et al., 1985). The items in the checklist encompassed both positive and negative phrasing and hence the raters were warned to be vigilant in discerning the nuances within the items. The maximum number of points available was 35 with a higher score indicating better gait quality.

4.6 Results from Inter-rater agreement

Inter-rater reliability for the checklist was calculated using the percent agreement method. Additionally, to account for agreement by chance, Fleiss' Kappa was calculated for each of the 31 items. Both methods were analyzed using the SAS® software and results have been presented in Table 4.3. The table presents a matrix of percent agreement values across 20 videos (V1-V20) and 31 items (I1-I31) with Weighted Kappa values for each item and their interpretation. The column labelled 'Avg' shows the average agreement for each item. The matrix has 2 missing values labelled as 'MCAR' (Missing Completely at Random) corresponding to video 17 for items 30 and 31 as the end of the video was not clear enough to score the two items, as reported by the raters unanimously.

Item 1 (Freezing while getting up), Item 5 (Freezing while walking) and Item 29 (Freezing while sitting down) show the highest average agreement of 100%. While Item 4 (Narrow base of Support) shows the lowest percent agreement of 71%. Items 10 (Heel strike), 11 (Push off), 13 (Hip swing), 14 (Gait Symmetry), 17 (Forward arm swing), 18 (Backward arm swing), 21 (One shoulder lower than other) and 22 (Forward lean of head) show an average agreement ranging between 71 and 80% which indicates moderate agreement. However, the general trend of average agreement is above 80 and 90%. For Kappa values, items 2 (Needs arms as support to get up), 3 (More than 1 tries to get up), 30 (Uses arms as support to sit), 31(Unable to control descent) and 6 (Looks at feet while walking) show substantial to almost perfect agreement. Items 10 (Heel strike), 16 (Coordination of arms with legs), 17 (Forward arm swing), 18 (Backward arm swing), 20 (Rounded shoulders), 24 (Dyskinesia), 25 (Rotated trunk) and 27 (Unable to pivot) show moderate agreement. Lastly, item 4 (Narrow base of support) has the lowest kappa showing slight agreement.

4.7 Reliability of scores given by raters and influence of video quality

Each item in the checklist had a binary or three-point ordinal rating scale, that when summed yielded a total score with a maximum of 35 points where a higher score indicated better gait quality. The scores given by each rater for individual videos was analyzed using the Intraclass Correlation Coefficient (ICC) to provide estimates of reliability using the random effects model, (Liljequist et al., 2019); the ICC was 0.78 indicating reliability sufficient for comparing groups of people but insufficient for estimating within-person change for which the reference value is 0.90 (Norman & Streiner, 2008).

Additionally, the effect of video quality on overall agreement and total scores was estimated. Table 4.4 shows the average crude agreement, the total score given by majority raters for individual videos, and their corresponding video quality, where video quality ratings were based on the angle of the camera, vividness, level of accuracy of the frames and details captured. V4 with 'excellent' quality showed the highest level of average crude agreement (96%). For each video, the average crude agreement was regressed on video quality using simple linear regression. A second model regressed total gait quality scores on video quality.

Table 4.5 shows the results of the first regression model with 'poor' quality videos as a reference. According to the results, the average crude agreement differed across categories of video quality. For example, agreement was higher by 13.7% (p=0.0013) among videos considered to be of 'excellent' quality, 5.6% (p=0.0120) higher. among videos of 'good' quality., and 3.25% (p=0.1123) for videos of 'fair' quality. Table 4.6 shows the results of the second regression model with 'poor' quality videos as a reference as there was only one 'excellent' quality video it was grouped with 'good' quality videos. The estimates in the output from the regression were interpreted based on the standard deviation (SD) values of the scores by raters (6) and ½ SD (3) was considered to be a clinically important difference (CID). Thus, according to the results, for every one category difference in video quality, the overall scores differed by 5 units, an amount considered clinically relevant using the ½ SD criterion.

4.8 Comparison between checklist scores assigned by raters and experts

The agreement results summarized above were reviewed item by item by the senior-most rater on the team along with the principal investigator of the study, focusing on items with disagreements. All 20 videos were re-analyzed by the two members and items with less than 100% agreement were rescored where the new score was considered as the consensus or score given by experts. Comparison of scores given by raters and experts have been illustrated using the Bland-Altman plot in Figure 4.5, the mean of scores was plotted on the x-axis and the y axis shows the difference between scores given by most raters and experts. Most points on the plot lie within the 95% CI bounds except for one outlier. The bias i.e. mean of differences between scores is -0.7 which indicates there is not much discrepancy between scores given by most raters and experts. Although the 95% CI ranges from -6.3 and 4.9, most points are clustered between ±1 SD indicating scores given by most raters and experts are almost equivalent. It was noticed that although the overall scores did not show much difference there were disagreements on individual items. Thus, cumulative differences at the item level have been shown in Figure 4.6. The graph shows the number of times expert opinion differed from the opinion of most raters and whether the scores improved or reduced. V6 exhibited the highest number of disagreements. In each of these cases, the scores were consistently lowered compared to what most raters agreed upon, which is highlighted in orange on the graph.

During the review of scores, the experts discussed probable reasons for disagreements. This collaborative effort led to the development of a modified checklist aimed at improving interrater reliability. The revised checklist recommended for the observational analysis of gait specific to PD based on the results is presented in Figure 4.7 below. Modifications and additions to the checklist have been highlighted in green and one item that was deleted is highlighted in red.

Gait Parameters	Description	Classifiers
Getting up from chair		
Freezing while getting up	Sudden inability to move despite the intention to. We are looking to see if any of the participants experience this sudden inability to move while getting up from a chair	0 Present 1 Absent
Needs arms	Does the participant use support of the armrest/ side of the chair or does the participant place their arm on their thighs of knees as support to get up from the chair	0 Yes 1 No
More than one try to get up from a chair	Does the participant try getting up more than once from the chair due to one unsuccessful try/inability to get up in one attempt?	0 Yes 1 No
Walking		
Base Of Support Narrow	Base of support is the area formed by contact points of the feet with the ground. For example, when you stand with your feet shoulder-width apart, your base of support is the area covered between the feet. Base of support changes with movement. Narrow base of support while walking can be noticed if there is crossing of feet noticed. Normal base of support is slightly less that shoulder width, the feet would be in line with the width of the hips.	0 Yes 1 No
Freezes while walking	Freezing - Sudden inability to move despite the intention to. We are looking to see if any of the participants experience this sudden inability to move while walking.	0 Present 1 Absent
Looks at feet	Does the participant look down at their feet while walking instead of looking forward.	0 Yes 1 No
Scuffs foot	Does not lift and place foot on the ground, instead drags it	0 Yes 1 No
Unsteadiness while walking	Experiences short instances of losing balance while walking without falling.	0 Yes 1 No
Pace dynamics while walking		
Variable pace while walking	Individuals may experience episodes of both bradykinesia (slowness of movement) and festination (acceleration of steps). This leads to a gait pattern where the pace of walking may fluctuate, with periods of slower movements interspersed with episodes of rapid, uncontrollable acceleration.	0 Yes 1 No
Gait parameters		
Heel strike	A heel strike is also known as initial contact. It is a phase of the gait cycle that occurs when the heel touches the ground while walking.Hint: When viewed anteriorly, a complete visual of the sole when the heel contacts theground indicates a 'strong' heel strike.	2 Strong 1 Weak 0 Absent
Push Off	The Push-off phase involves the propulsion of the body forward as the foot pushes off the ground to initiate the swing phase of walking.Hint: A complete visual of the sole during the phase indicates a 'strong' push-off when viewed posteriorly.	2 Strong 1 Weak 0 Absent
Fast Cadence	Does the individual have an abnormal increase in speed or frequency of steps, leading to a rapid and shuffling gait?	0 Present 1 Absent
Swing at hip	The swing phase is when the leg is not in contact with the ground and actively moves forward to prepare for the next step. It is characterized by a series of movements at the hip joint, including hip flexion, extension, and abduction/adduction, which facilitate leg clearance and forward progression.	1 Present 0 Absent
Hip Extension	It refers to the backward movement of the thigh relative to the pelvis, resulting in the extension of the hip joint.	2 Strong 1 Weak 0 Absent
Poor Foot Clearance	Foot clearance, also referred to as leg clearance or toe clearance, is an essential aspect of the gait cycle that ensures smooth and unobstructed forward movement during walking. It pertains to the ability of the swinging leg to clear the ground as it moves forward, avoiding contact with the supporting leg or any obstacles.	0 Yes 1 No
Symmetry		
Gait symmetry	Gait symmetry refers to the equality between the movements of the left and right limbs during walking. This will be shown through differences in step length, time of foot contact with the ground and amplitude of joint movement.	1 Present 0 Absent
Symmetry of arms while swinging	Symmetry of the arms during walking refers to the balanced and coordinated and alternating movement of the left and right arms. It	1 Present 0 Absent
If arm swing is asymmetrical	Right > Left OR Left > Right	1 Right 0 Left
Arm Swing		
Forward arm swing	The forward arm swing involves the swinging of the arm in synchronization with the opposing leg during the stride. The degree of forward arm swing can vary among individuals, but a typical range is around 60 to 90 degrees of flexion at the shoulder joint	2 Optimal 1 Reduced 0 Absent
Backward arm swing	The degree of backward arm swing is typically less than the forward arm swing, with a range of around 20 to 45 degrees of extension at the shoulder joint.	2 Optimal 1 Reduced 0 Absent
Posture		
Flexed at hip	Forward flexion of the trunk or bending at the waist. Along with the forward-leaning posture, individuals with Parkinson's may also have flexed hips. This means that the hips are bent or flexed forward, leading to a reduced range of motion in the hip joints. The flexed hip posture contributes to the overall stooped appearance.	0 Yes 1 No
Rounded shoulders	A rounded shoulder or slouched posture is a common postural issue where the shoulders are positioned forward, causing the upper back to appear rounded.	0 Yes 1 No
One shoulder lower than other	The shoulders may not be at the same level due to differences in muscle tone on either side of the body, which could lead to the asymmetrical presentation of the shoulders.	0 Yes 1 No
Forward lean of head	It is a common postural misalignment, often evident when the head is positioned forward compared to the shoulders and the ear aligns ahead of the shoulder rather than directly over it.	0 Yes 1 No
Tremor		
Tremor	Arm Tremors typically occur at rest and usually involve rhythmic shaking or oscillatory movements of the forearms/wrists/hands	0 Present 1 Absent
Dyskinesia	Dyskinesia is characterized by involuntary and uncontrolled movements that are often exaggerated or excessive. These movements can be jerky, writhing, or twisting, typically affecting the limbs, face, or trunk. Dyskinesia can manifest as chorea (rapid, jerky movements), dystonia (sustained muscle contractions causing twisting or repetitive movements), or athetosis (slow, writhing movements).	0 Present 1 Absent
Trunk while walking		
Rotated	The trunk would be twisted or rotated towards the affected side while walking due to differences in tone and muscle weakness.	0 Yes 1 No
Moves as a block	Walking with no movement of the trunk / being stiff	0 Yes 1 No
Anteroposterior movement of the trunk	Anteroposterior movement of the trunk refers to the forward and backward motion of the upper body during walking. When we walk, our trunk naturally sways back and forth in coordination with the movement of our legs.	0 Present 1 Absent
Turning		
Unable to pivot	Instead of taking small steps to execute a turn, the individual pivots on one foot while the other foot rotates to change direction.	0 Yes 1 No
Sitting on the chair		
Unable to turn and sit in one motion without support	Unable to turn and sit in one motion.Takes multiple small steps (more than 2 steps while turning to sit)	0 Yes 1 No
Freezes while trying to sit on the chair	Sudden inability to move despite the intention to. We are looking to see if any participants experience this sudden inability to move while trying to sit on the chair.	0 Yes 1 No
Uses arms as support to sit	Does the participant use the support of the armrest/ side of the chair or place their arm on their thighs or knees to sit on the chair?	0 Yes 1 No
Unable to control the descent	The participant uses the support of both arms or one arm to control the descent on the chair or drops the entire body weight instantly instead of sitting gradually in a controlled manner.	0 Yes 1 No

Figure 4.1 Initial version of the checklist for video-based observational analysis of gait

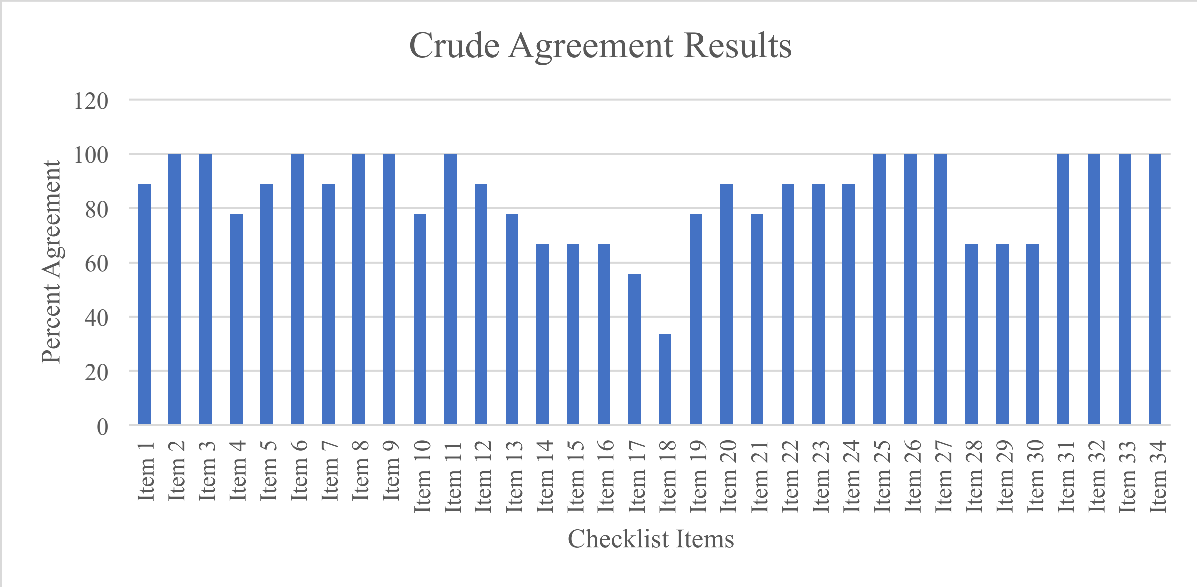

Figure 4.2 Results from Pilot review of one video showing crude agreement among 9 raters

Table 4.1. Agreement across items in the initial checklist

Agreement (High to low)	Item Number	Name of Item
100%	2	Needs arms as support while getting up from the chair
100%	3	More than one tries to get up from the chair
100%	6	Looks at feet
100%	8	Unsteadiness while walking
100%	9	Variable pace while walking
100%	11	Toe Push-Off
100%	25	Arm tremor
100%	26	Dyskinesia
100%	27	Rotated trunk
100%	31	Unable to turn and sit in one motion
100%	32	Freezes while trying to get up from the chair
100%	33	Uses arms as support to sit
100%	34	Unable to control descent
88.8%	1	Freezing while getting up from chair
88.8%	5	Freezing while walking
88.8%	7	Foot Scuffing
88.8%	12	Fast cadence
88.8%	20	Backward arm swing
88.8%	22	Rounded shoulders
88.8%	23	One shoulder lower than the other
88.8%	24	Forward lean of head
77.7%	4	Narrow Base of Support
77.7%	10	Heel Strike
77.7%	13	Swing at hip
77.7%	19	Forward arm swing
77.7%	21	Flexed at hip
66.6%	14	Hip extension
66.6%	15	Poor foot clearance
66.6%	16	Gait Symmetry
66.6%	28	Moves as a block
66.6%	29	Anteroposterior movement of the trunk
66.6%	30	Unable to pivot
55.5%	17	Symmetry of arms while swinging
33.3%	18	If arm swing is asymmetric, Right > Left or Left > Right

Gait Parameters	Description	Classifiers
Getting up from chair		
Freezing while getting up	Sudden inability to move despite the intention to. We are looking to see if any of the participants experience this sudden inability to move while getting up from a chair	0 Present 1 Absent
Needs arms	Does the participant use support of the armrest/ side of the chair or does the participant place their arm on their thighs or knees as support to get up from the chair?	0 Yes 1 No
More than one try to get up from a chair	Does the participant try getting up more than once from the chair due to one unsuccessful try/inability to get up in one attempt?	0 Yes 1 No
Walking		
Narrow Base of Support	Base of support is the area formed by contact points of the feet with the ground. For example, when you stand with your feet shoulder-width apart, your base of support is the area covered between the feet. Base of support changes with movement. Narrow base of support while walking can be noticed if there is crossing of feet noticed. Normal base of support is slightly less that shoulder width, the feet would be in line with the width of the hips.	0 Yes 1 No
Freezes while walking	Freezing - Sudden inability to move despite the intention to. We are looking to see if any of the participants experience this sudden inability to move while walking.	0 Present 1 Absent
Looks at feet	Does the participant look down at their feet while walking instead of looking forward.	0 Yes 1 No
Scuffs foot/Poor foot clearance	Does the participant drag their foot (not lift it sufficientv to place it on the ground)? Please note that you could select 'Yes' even if there is poor foot clearance only on one side	0 Yes 1 No
Unsteadiness while walking	Experiences short instances of losing balance while walking without falling.	0 Yes 1 No
Pace dynamics while walking		
Variable pace while walking	A gait pattern where the pace of walking may fluctuate, with periods or slower movements interspersed with rapid uncontrollable acceleration. Does the participant experience bradykinesia (slow movement) and festination (acceleration of steps)?	0 Yes 1 No
Gait parameters		
Heel strike	A heel strike is also known as initial contact. It is a phase of the gait cycle that occurs when the heel touches the ground while walking.Hint: When viewed anteriorly, a complete visual of the sole when the heel contacts theground indicates a 'strong' heel strike.	2 Optimal 1 Weak 0 Absent
Push Off	The Push-off phase involves the propulsion of the body forward as the foot pushes off the ground to initiate the swing phase of walking.Hint: A complete visual of the sole during the phase indicates a 'strong' push-off when viewed posteriorly.	2 Optimal 1 Weak 0 Absent
Fast Cadence	Does the individual have an abnormal increase in speed or frequency of steps, leading to a rapid and shuffling gait?	0 Present 1 Absent
Swing at hip	The swing phase is when the leg is not in contact with the ground and actively moves forward to prepare for the next step. It is characterized by a series of movements at the hip joint, including hip flexion, extension, and abduction/adduction, which facilitate leg clearance and forward progression.	1 Optimal (step is initiated with an almost straight knee) 0 Weak (Excessive movement of the knee from flexion to extension
Symmetry		
Gait symmetry	Gait symmetry refers to the equality between the movements of the left and right limbs during walking. This will be shown through differences in step length, time of foot contact with the ground and amplitude of joint movement.	1 Present 0 Absent
Symmetry of arms while swinging	The symmetry of the arms during walking refers to equality between the arm swings on the right and left sides	1 Present 0 Absent
Coordination of the arms with the legs	This refers to the balanced and alternating movement of the arms in coordination with the movement of the legs, contributing to a smooth and efficient gait pattern	1 Present 0 Absent
Arm Swing		
Forward arm swing	The forward arm swing involves rotational movement of the arms alongside the body where the arms swing forward crossing the midaxillary line. Predominantly, forward arm swing is greater than backward arm swing	2 Optimal 1 Reduced 0 Absent
Backward arm swing	The backward arm swing entails rotational movement of the arms along side the body where the arm swings backward crossing the midaxillary line.	2 Optimal 1 Reduced 0 Absent
Posture		
Flexed at hip	The forward-leaning posture predominnatly seen in people with Parkinson's is associated with flexion at the hip. This means the hips are bent or flexed forward, reducing the range of motion at the hip contributing to an overall stooped appearance.	0 Yes 1 No
Rounded shoulders	A rounded shoulder or slouched posture is a common postural issue where the shoulders are positioned forward, causing the upper back to appear rounded.	0 Yes 1 No
One shoulder lower than other	The shoulders may not be at the same level due to differences in muscle tone on either side of the body, which could lead to the asymmetrical presentation of the shoulders.	0 Yes 1 No
Forward lean of head	It is a common postural misalignment, often evident when the head is positioned forward compared to the shoulders and the ear aligns ahead of the shoulder rather than directly over it.	0 Yes 1 No
Tremor		
Tremor	Arm Tremors typically occur at rest and usually involve rhythmic shaking or oscillatory movements of the forearms/wrists/hands	0 Present 1 Absent
Dyskinesia	Dyskinesia is characterized by involuntary and uncontrolled movements that are often exaggerated or excessive. These movements can be jerky, writhing, or twisting, typically affecting the limbs, face, or trunk. Dyskinesia can manifest as chorea (rapid, jerky movements), dystonia (sustained muscle contractions causing twisting or repetitive movements), or athetosis (slow, writhing movements).	0 Present 1 Absent
Trunk while walking		
Rotated	The trunk would be twisted or rotated towards the affected side while walking due to differences in tone and muscle weakness.	0 Yes 1 No
Anteroposterior movement of the trunk	Anteroposterior movement of the trunk refers to the normal forward and backward motion of the upper body during walking. For example: when we walk, our trunk naturally sways back and forth in coordination with the movement of our legs.	0 Present 1 Absent
Turning		
Unable to pivot	Instead of pivoting on one foot (active rotation of the foot around its own vertical axis) to execute the turn, the individual may take small steps in a circle	0 Yes 1 No
Sitting on the chair		
Unable to turn and sit in one motion without support	Unable to turn and sit in one motion.Takes multiple small steps (more than 3 steps while turning to sit)	0 Yes 1 No
Freezes while trying to sit on the chair	Sudden inability to move despite the intention to. We are looking to see if any participants experience this sudden inability to move while trying to sit on the chair.	0 Yes 1 No
Uses arms as support to sit	Does the participant use the support of the armrest/ side of the chair or place their arm on their thighs or knees to sit on the chair?	0 Yes 1 No
Unable to control the descent	The participant uses the support of both arms or one arm to control the descent on the chair or drops the entire body weight instantly instead of sitting gradually in a controlled manner.	0 Yes 1 No

Figure 4.3 Final version of the checklist used for analyzing 20 videos

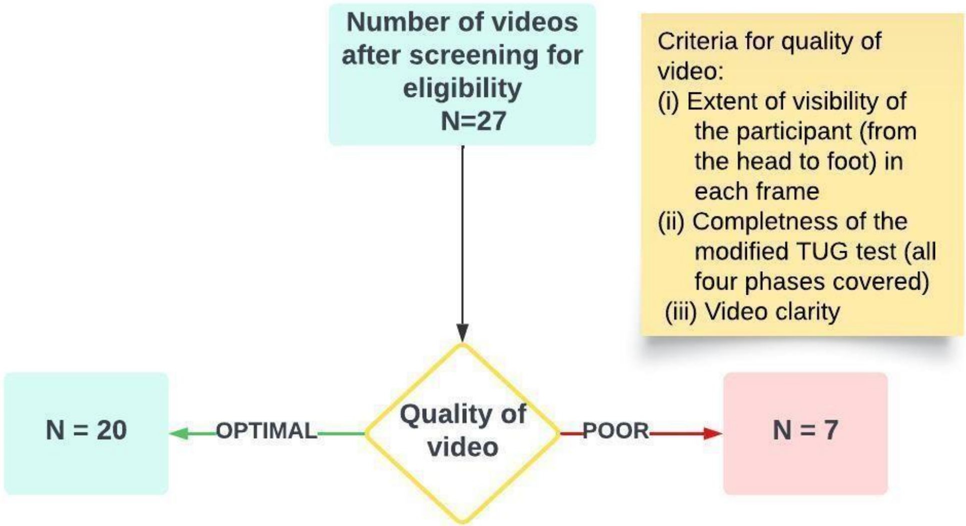

Figure 4.4 Flowchart showing the inclusion of videos based on their quality

Table 4.2. Random allotment of videos to raters

Video					**Raters**						**No of ratings per video**
V1	R1	R2	R3			R6	R7		R9		6
V2	R1	R2	R3			R6	R7		R9		6
V3	R1		R3	R4	R5			R8		R10	6
V4	R1	R2	R3	R4		R6	R7				6
V5	R1	R2			R5	R6	R7			R10	6
V6	R1			R4	R5			R8	R9	R10	6
V7	R1	R2		R4		R6	R7	R8			6
V8	R1			R4		R6	R7		R9	R10	6
V9	R1	R2		R4	R5			R8		R10	6
V10	R1	R2	R3			R6	R7		R9		6
V11	R1		R3		R5			R8	R9	R10	6
V12	R1			R4	R5	R6		R8		R10	6
V13	R1	R2			R5			R8	R9	R10	6
V14	R1			R4	R5			R8	R9	R10	6
V15	R1	R2			R5	R6	R7		R9		6
V16	R1	R2		R4			R7	R8	R9		6
V17	R1			R4	R5	R6	R7	R8			6
V18	R1		R3	R4		R6	R7			R10	6
V19	R1	R3		R5	R6	R7	R8				6
V20	R1	R3	R4		R6	R7		R9			6

Table 4.3. Crude interrater agreement results alongside Weighted Kappa for each item across 20 videos with the interpretation of Kappa scores (Landis and Koch 1977)

	V1	V2	V3	V4	V5	V6	V7	V8	V9	V10	V11	V12	V13	V14	V15	V16	V17	V18	V19	V20	Avg	Weighted Kappa	Interpretation of Kappa
I1	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	NE	NE
I2	100	83	100	100	67	100	100	50	100	100	100	100	67	100	100	100	67	50	100	100	89	0.7	Substantial
I3	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	83	100	100	100	100	99	0.77	Substantial
I4	83	50	50	67	67	67	83	83	67	100	67	100	100	67	50	67	50	67	50	83	71	0.16	Slight
I5	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	NE	NE
I6	100	100	100	100	100	83	100	67	100	100	100	100	100	67	100	100	100	100	100	100	96	0.81	Almost Perfect
I7	67	100	67	100	67	67	83	67	100	100	83	100	67	67	100	50	67	83	83	100	81	0.26	Fair
I8	100	100	100	100	67	83	100	67	100	100	100	100	67	83	100	83	100	100	100	83	92	0.39	Fair
I9	83	100	100	100	67	83	100	67	83	83	83	100	50	67	100	83	100	100	100	83	87	0.17	Slight
I10	50	67	83	100	83	83	83	67	50	100	67	100	100	67	83	67	83	67	50	100	78	0.41	Moderate
I11	83	50	67	83	83	83	100	50	50	67	50	67	67	83	100	83	83	83	67	67	73	0.34	Fair
I12	83	100	100	100	83	100	100	100	83	83	83	100	50	83	83	83	83	100	100	100	90	0.37	Fair
I13	67	83	100	83	83	83	50	100	67	67	67	83	100	100	100	83	67	83	50	67	79	0.31	Fair
I14	67	67	67	100	67	67	83	67	83	67	100	100	67	50	83	83	67	83	83	67	76	0.1	Slight
I15	67	100	83	83	50	83	100	83	100	67	83	67	100	100	83	100	100	67	50	83	82	0.35	Fair
I16	83	67	100	100	83	83	100	100	67	100	100	83	67	67	100	100	83	100	100	100	89	0.52	Moderate
I17	67	50	100	100	83	83	67	83	83	67	100	50	50	67	83	100	67	83	100	100	79	0.57	Moderate
I18	67	67	100	100	67	83	50	100	83	67	100	67	50	67	67	100	50	50	50	100	74	0.52	Moderate
I19	83	100	50	100	83	83	100	100	83	67	83	83	83	67	100	67	83	83	100	83	84	0.31	Fair
I20	67	83	83	100	83	83	100	100	83	50	83	67	83	67	83	100	83	100	83	83	83	0.35	Fair
I21	67	100	50	67	83	50	83	50	50	83	100	100	67	67	100	50	67	83	83	83	74	0.18	Slight
I22	50	50	83	100	83	83	100	100	83	67	67	83	83	100	50	83	100	67	83	67	79	0.31	Fair
I23	67	67	67	100	67	100	100	83	100	100	100	67	100	83	100	50	67	83	100	67	83	0.27	Fair
I24	100	83	83	100	100	100	100	100	100	100	100	100	100	100	100	50	100	100	100	100	96	0.57	Moderate
I25	100	100	100	100	100	83	83	50	100	100	83	100	100	83	100	67	83	100	100	100	92	0.52	Moderate
I26	83	50	100	83	100	100	50	100	67	100	67	67	100	100	100	100	83	83	67	100	85	0.39	Fair
I27	83	83	67	100	100	100	100	50	67	100	100	100	50	50	100	67	83	67	67	100	82	0.34	Fair
I28	100	100	100	100	100	83	100	67	83	100	100	100	67	67	100	67	100	100	100	83	91	0.37	Fair
I29	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	100	NE	NE
I30	100	100	100	100	83	100	100	100	100	100	83	100	83	100	100	100	MCAR	100	100	100	97	0.69	Substantial
I31	100	100	100	100	100	100	100	67	100	100	100	100	67	83	100	83	MCAR	100	50	100	92	0.74	Substantial

Where V = ‘video’, I = ‘item’, NE = ‘not estimable’, Avg = Average, MNAR = ‘Missing Not At Random’

Table 4.4. Video Quality and overall percent agreement (%)

Video_ID	Video_Quality	Avg Agreement	Total Scores
V4	Excellent	96	24
V15	Good	92	24
V7	Good	91	26
V20	Good	90	32
V10	Good	88	14
V18	Good	87	25
V2	Good	84	28
V1	Good	83	31
V12	Fair	90	30
V11	Fair	89	34
V3	Fair	87	29
V6	Fair	87	24
V5	Fair	84	23
V19	Fair	84	22
V16	Fair	82	12
V14	Fair	81	25
V8	Poor	81	22
V9	Poor	85	13
V17	Poor	83	20
V13	Poor	80	21

Table 4.5. Results from simple linear regression: Average percent agreement for each video regressed over video quality

Parameter Estimates					
	DF	**Estimate**	**Standard Error**	**T value**	**Pr > |t|**
Intercept	1	82.25	1.57	52.08	□.0001
Excellent Quality Videos (n=1)	1	13.75	3.53	3.89	0.0013
Good Quality Videos (n=7)	1	5.60	1.97	2.83	0.0120
Fair Quality Videos (n=8)	1	3.25	1.93	1.68	0.1123
Poor Quality Videos (n=4)	0	Referent			

y = average percent agreement, x = video quality; reference as ‘poor’ video quality

Table 4.6. Results from Multiple Linear Regression: Overall scores of each video regressed over video quality and average percent agreement for each video

Parameter Estimates					
Parameter	**DF**	**Estimate**	**Standard Error**	**T value**	**Pr > |t|**
Intercept	1	1.23	33.13	0.04	0.9707
Good Quality Videos (n=8)	1	5.06	4.49	1.13	0.2761
Fair Quality Videos (n=8)	1	5.17	3.85	1.34	0.1981
Poor Quality Videos (n=4)	0	Referent			
Percent Agreement (n=20)	1	0.21	0.40	0.54	0.5979

y = total scores, x = video quality, overall percent agreement; reference = ‘poor’ quality video

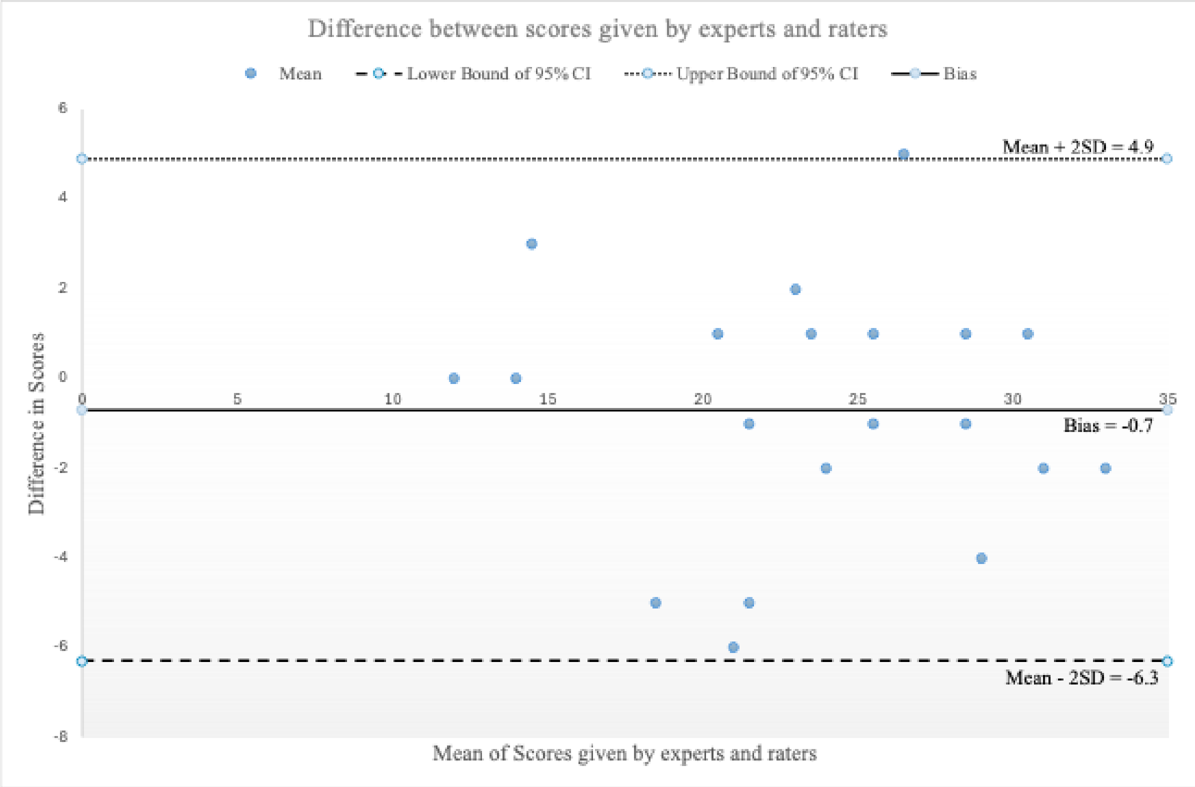

Figure 4.5 Bland-Altman Plot summarizing the difference between scores by experts and majority raters

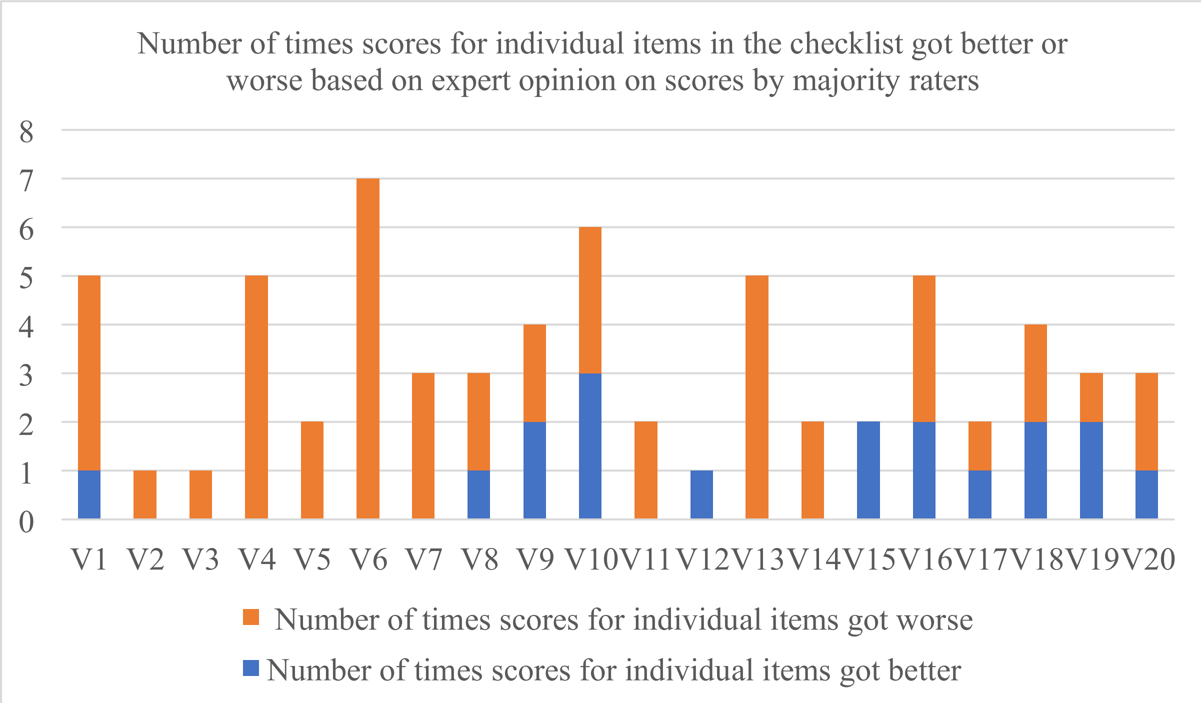

Figure 4.6 Overview of the number of items for each video where expert opinion differed from majority scores by raters

Gait Parameters	Description	Classifiers
	Getting up from chair	
Freezing while getting up	Sudden inability to move despite the intention to. We are looking to see if any of the participants experience this sudden inability to move while getting up from a chair	0 Present 1 Absent
Uses arms as support for getting up	Does the participant use support of the armrest/ side of the chair or does the participant place their arm on their thighs or knees as support to get up from the chair?	0 Yes 1 No
More than one try to get up from a chair	Does the participant try getting up more than once from the chair due to one unsuccessful try/inability to get up in one attempt?	0 Yes 1 No
	Walking	
Narrow Base of Support	Base of support is the area formed by contact points of the feet with the ground. For example, when you stand with your feet shoulder-width apart, your base of support is the area covered between the feet. Base of support changes with movement. Narrow base of support while walking can be noticed if there is crossing of feet noticed. Normal base of support is slightly less that shoulder width, the feet would be in line with the width of the hips.	0 Yes 1 No
Freezes while walking	Freezing - Sudden inability to move despite the intention to. We are looking to see if any of the participants experience this sudden inability to move while walking.	0 Present 1 Absent
Looks at feet	Does the participant look down at their feet while walking instead of looking forward.	0 Yes 1 No
Scuffs foot/Poor foot clearance	Does the participant drag their foot (not lift it sufficientv to place it on the ground)? Please note that you could select 'Yes' even if there is poor foot clearance only on one side	0 Yes 1 No
Unsteadiness while walking	Experiences short instances of losing balance while walking without falling.	0 Yes 1 No
	Pace dynamics while walking	
Variable pace while walking	A gait pattern where the pace of walking may fluctuate, with periods or slower movements interspersed with rapid uncontrollable acceleration. Does the participant experience bradykinesia (slow movement) and festination (acceleration of steps)?	0 Yes 1 No
	Gait parameters	
Heel strike	A heel strike is also known as initial contact. It is a phase of the gait cycle that occurs when the heel touches the ground while walking.Hint: When viewed anteriorly, a complete visual of the sole when the heel contacts theground indicates a 'strong' heel strike.	2 **Optimal** 1 Weak 0 Absent
Push Off	The Push-off phase involves the propulsion of the body forward as the foot pushes off the ground to initiate the swing phase of walking.Hint: A complete visual of the sole during the phase indicates a 'strong' push-off when viewed posteriorly.	2 **Optimal** 1 Weak 0 Absent
Fast Cadence	Does the individual have an abnormal increase in speed or frequency of steps, leading to a rapid and shuffling gait?	0 Present 1 Absent
Swing at hip	The swing phase is when the leg is not in contact with the ground and actively moves forward to prepare for the next step. It is characterized by a series of movements at the hip joint, including hip flexion, extension, and abduction/adduction, which facilitate leg clearance and forward progression.	1 **Optimal** (step is initiated with an almost straight knee) 0 Weak (Excessive movement of the knee from flexion to extension
	Symmetry	
Gait symmetry	Gait symmetry refers to the equality between the movements of the left and right limbs during walking. This will be shown through differences in step length, time of foot contact with the ground and amplitude of joint movement.	1 Present 0 Absent
Symmetry of arms while swinging	The symmetry of the arms during walking refers to equality between the arm swings on the right and left sides	1 Present 0 Absent
Coordination of the arms with the legs	This refers to the balanced and alternating movement of the arms in coordination with the movement of the legs, contributing to a smooth and efficient gait pattern	1 Present 0 Absent
	Arm Swing	
Forward arm swing	The forward arm swing involves rotational movement of the arms alongside the body where the arms swing forward crossing the midaxillary line. Predominantly, forward arm swing is greater than backward arm swing	2 Optimal 1 Reduced 0 Absent
	Right > Left **Left > Right** **Left = Right**	**1 Left = Right** **0 Right > Left /Left > Right**
Backward arm swing	The backward arm swing entails rotational movement of the arms along side the body where the arm swings backward crossing the midaxillary line.	2 Optimal 1 Reduced 0 Absent
	Right > Left **Left > Right** **Left = Right**	**1 Left = Right** **0 Right > Left /Left > Right**
	Posture	
Flexed at hip	The forward-leaning posture predominnatly seen in people with Parkinson's is associated with flexion at the hip. This means the hips are bent or flexed forward, reducing the range of motion at the hip contributing to an overall stooped appearance.	0 Yes 1 No
Rounded shoulders	A rounded shoulder or slouched posture is a common postural issue where the shoulders are positioned forward, causing the upper back to appear rounded.	0 Yes 1 No
One shoulder lower than other	The shoulders may not be at the same level due to differences in muscle tone on either side of the body, which could lead to the asymmetrical presentation of the shoulders.	0 Yes 1 No
Forward lean of head	It is a common postural misalignment, often evident when the head is positioned forward compared to the shoulders and the ear aligns ahead of the shoulder rather than directly over it.	0 Yes 1 No
	Tremor	
Tremor	Arm Tremors typically occur at rest and usually involve rhythmic shaking or oscillatory movements of the forearms/wrists/hands	0 Present 1 Absent
Dyskinesia	Dyskinesia is characterized by involuntary and uncontrolled movements that are often exaggerated or excessive. These movements can be jerky, writhing, or twisting, typically affecting the limbs, face, or trunk. Dyskinesia can manifest as chorea (rapid, jerky movements), dystonia (sustained muscle contractions causing twisting or repetitive movements), or athetosis (slow, writhing movements).	0 Present 1 Absent
	Trunk while walking	
Rotated	The trunk would be twisted or rotated towards the affected side while walking due to differences in tone and muscle weakness.	0 Yes 1 No
Anteroposterior movement of the trunk	Anteroposterior movement of the trunk refers to the normal forward and backward motion of the upper body during walking. For example: when we walk, our trunk naturally sways back and forth in coordination with the movement of our legs.	0 Present 1 Absent
	Turning	
Pivots	Instead of pivoting on one foot (active rotation of the foot around its own vertical axis) to execute the turn, the individual may take small steps in a circle	**0 No** **1 Yes**
	Sitting on the chair	
Turns and sits in one motion	**Sits in one motion taking 3 steps while turning**	**0 No** **1 Yes**
Freezes while trying to sit on the chair	Sudden inability to move despite the intention to. We are looking to see if any participants experience this sudden inability to move while trying to sit on the chair.	0 Yes 1 No
Uses arms as support to sit	Does the participant use the support of the armrest/ side of the chair or place their arm on their thighs or knees to sit on the chair?	0 Yes 1 No
Unable to control the descent	The participant uses the support of both arms or one arm to control the descent on the chair or drops the entire body weight instantly instead of sitting gradually in a controlled manner.	0 Yes 1 No

Figure 4.7 Recommended Checklist based on the results

Chapter 5: Comparison of Gait Parameters from Observational Checklist with the Wearable Sensor

This chapter provides greater detail about the wearable sensor and the kinematic parameters recorded using the sensor, followed by the methodology specific to this component of the study and concludes with a comparative analysis of the gait parameters recorded by the sensor to those analyzed using the observational method described in the previous chapter. As mentioned in Chapter 3, only common gait parameters can be compared. Therefore, the agreement pairs for four out of the 31 parameters discussed in Chapter 4, were counted to verify comparability between the two methods.

5.1 Overview of the wearable sensor technology used in the study

This study utilizes the Heel2Toe™, a small, wireless, inexpensive and lightweight wearable sensor that clips to the side of the shoe shown in Figure 5.1. It was developed through a collaborative effort of the research team comprising physiotherapists, software and biomedical engineers at McGill University and PhysioBiometrics Inc., under the guidance of Prof Nancy Mayo. The algorithm used in the sensor analyzes in real-time, the angular velocity at the ankle joint in the sagittal plane and provides positive feedback at the same time in the form of a beep for every good step (one that is initiated with a strong heel strike) provided the angular velocity at the ankle crosses a certain threshold. These are features that set it apart from other wearable sensors, mostly designed for assessing the gait of healthy individuals. Furthermore, the Heel2Toe™ sensor has been successfully tested among individuals with Parkinson's Disease demonstrating optimal efficacy, feasibility and potential in the population (Carvalho et al., 2020; Mayo et al., 2024)

The Heel2Toe™ can used for both assessment and training purposes, it is programmed at a sensitivity of 96.2% at an operating point of 75% specificity. The Inertial Measurement Unit (IMU) of this sensor forms the sensing module for detection of heel strike comprising a tri-axial accelerometer (Range ± 6g, sensitivity 200mV/g), gyroscope (Range ± 500deg/s, sensitivity 2mV/deg/sec), magnetometer and an eight-channel microcontroller.

To start recording gait parameters, the sensor is first calibrated using the Heel2toe Step Analyzer Android application platform shown in Figure 5.2. The sensor connects with the application using Bluetooth. Raw data is transmitted to an Android phone or computer and the feature extraction algorithm then analyzes the raw data displaying results from the recorded session shown in Figure 5.3. The development of the hardware and algorithm has been reported

(Vadnerkar et al., 2014) The Step Analyzer application includes features for personalizing the walk time and step threshold, allowing the client to adjust the intensity of the training session. When the beep is turned off, the sensor operates solely in ‘assessment mode’, which was the mode used for data collection in this study.

5.2 Gait profile and kinematic parameters recorded by the wearable sensor

The Heel2Toe™ records the angular velocity of the heel strike (initial contact), toe push-off, and power generated from heel strike to push-off along with speed and power during the swing phase of the gait cycle further described in Table 5.1. These parameters are recorded over the medial-lateral axis of the foot over the z-axis of the gyroscope. The angular velocity at heel strike is a distinguishing feature between good and bad steps. The angular velocities of heel strike, push-off, and power cycle are displayed as negative values, as they are recorded when the ankle pivots clockwise first toward the ground and then away from it. More negative values indicate larger angular velocity, better foot clearance and a ‘good’ step. Lower values (e.g., angular velocities for heel strike and push off ≤ -120°/sec) indicate a higher risk of fall. The angular velocities of the foot swing and the balance phase are displayed as positive values, as they occur in the counterclockwise direction and higher values indicate greater angular velocity, better single-leg stance and balance. Lastly, the coefficient of variation indicates regularity of the gait pattern and optimally ranges between 10-15%, a high coefficient of variation implies inconsistent gait which is fatiguing and can increase fall risk. All numeric values obtained from the analysis were categorized for ease of interpretation by the lay user. Table 5.2 presents values for only the common gait parameter recorded at the ankle and their corresponding categories and interpretations used for comparison with the items from the observational checklist. These categorizations were based on proprietary data from 83 healthy McGill students who helped test the sensor. The application also has a feature for summarizing the results over multiple sessions presented in Figure 5.4. In addition to mapping the overall gait profile, the algorithm plots the overall best and worst steps of the client in comparison to the optimal requirement illustrated in Figure 5.5.

5.3 Method used for collecting data using the wearable sensor

As described in Chapter 4, all those considered safe for the remote trial based on their submitted video performing the modified TUG test and willingness to continue the study were sent a short technology readiness survey electronically consisting of five binary questions explaining willingness and ability to use and adapt to the sensor: Wi-Fi access, an Android smartphone, use a smartphone and applications installed on it with/without aid, positive about learning new things, and last but not least able to walk outdoors on most days weather permitting. Eligibility for this component of the study was based on participants positively endorsing all 5 questions.

Out of 20 participants, six were deemed ineligible for this component of the study since they did not have a phone with an Android operating system compatible with the sensor. Thus, 14 eligible participants were mailed the Heel2Toe™ sensor with a comprehensive bilingual user manual as part of the larger implementation study on Parkinson's Disease. They received 5 online training sessions with a physiotherapist on using the sensor along with 5 basic exercises and were advised to use the sensor for a minimum of 3 months for 10 minutes twice every day, the Heel2Toe™ sensor which currently costs 150 CAD was given to the participants to keep after the trial was over.

In an idealistic scenario of comparing two different methods of gait analysis, the gait parameters must be recorded simultaneously using both methods. Hence, participants were instructed to submit a similar video of them performing a modified TUG test, however, this time with the sensor clipped on in 'assessment' mode with the session time set at two minutes. However, out of the 14 participants, 10 were unable to record a video simultaneously while using the sensor due to reasons of travel, injury, lack of interest in the study or technical difficulties with using the sensor illustrated in Figure 5.6. For participants who were not able to share videos while actively using the sensor, the session recorded with the sensor closest in date and time to the shared video was used for comparison. Given that Parkinson's disease is a chronic condition, with relatively slow progression, major changes in gait pattern were not expected in a short time frame.

5.4 Comparison of metrics from the observational checklist and the wearable sensor

As mentioned in Chapter 3, only common items from the observational checklist corresponding to heel strike and push-off, rated on a three-point ordinal scale as 'optimal/weak/absent', and those corresponding to poor foot clearance and fast cadence rated on a binary scale 'yes/no' or 'present/absent', were compared pairwise to parameters recorded using the Heel2Toe™ sensor. These comparisons were possible due to the categorization of the numerical values obtained from the sensor, shown in Table 5.2. For ease of comparison of heel strike and push-off, categories 'excellent/very good' were considered equivalent to 'optimal'; 'good' was considered equivalent to 'weak'; and 'fair/poor' was considered equivalent to 'absent'. For foot clearance categories 'excellent/very good' i.e. foot clearance greater than 400°/sec was considered equivalent to 'no – foot clearance not poor' and all values below that corresponding to 'good/fair/poor' were considered equivalent to 'yes – poor foot clearance'. Lastly, for the presence or absence of fast cadence, a step count of over 120 steps per minute recorded by the sensor was considered as 'present'. The category cut-offs for comparison were determined in consultation with the senior rater on the team, considering normative values and thresholds for fall risk.

Agreement pairs for each parameter were counted and have been presented in the contingency tables below. Majority ratings were considered for comparison. In cases where the overall ratings by most raters could not be determined i.e. in cases of a tie between responses, ratings given by experts as presented in section 4.8 were used as consensus. Ratings for heel strike and push-off were compared using a 3-way comparison while ratings from foot clearance and cadence were compared using a 2-way comparison in Table 5.3. The table shows agreement pairs for heel strike, push-off, foot clearance and cadence; where the first column of the table represents ratings from the observational checklist and the first row represents categorical equivalents from the Heel2Toe^{TM} sensor grouped into three segments. For heel strike out of 14 times, raters agreed with the sensor 9 times (64.2%). Out of the 9 times, raters were able to detect an optimal heel strike 3 times and a weak heel strike 6 times. For instance, the sensor recorded angular velocity at the heel strike as -378°/sec (excellent) and the majority rated that heel strike as optimal. In another case, the sensor recorded a heel strike of -120°/sec (fair), rated as weak. For push-off raters agreed with the sensor 4 out of 14 times (28.5%), detecting 2 optimal and 2 weak push-offs. For example, when the angular velocity at push-off recorded by the sensor was -439°/sec (very good), most raters rated that push-off as optimal. On the other hand, a push-off -320 (good) was rated as optimal by raters. However, with a push-off of -390°/sec (good), the majority rated it as weak. For foot clearance, where raters agreed with the sensor 3 times on detecting a good foot clearance and 2 times on detecting a poor foot clearance (35.7%). For example, when the sensor recorded foot clearance of -290°/sec (poor) it was rated as 'no' by the majority. However, in another case foot clearance of -495°/sec (excellent) was rated as 'no' by the majority. For agreement on cadence, raters were able to identify correctly the absence of fast cadence 12 out of 14 times (85%). However, one of the cases with a cadence of 263 steps/minute (fast cadence) was rated by the majority as an 'absent fast cadence'.

Figure 5.1 Heel2Toe^{TM} sensor clipped to the right shoe

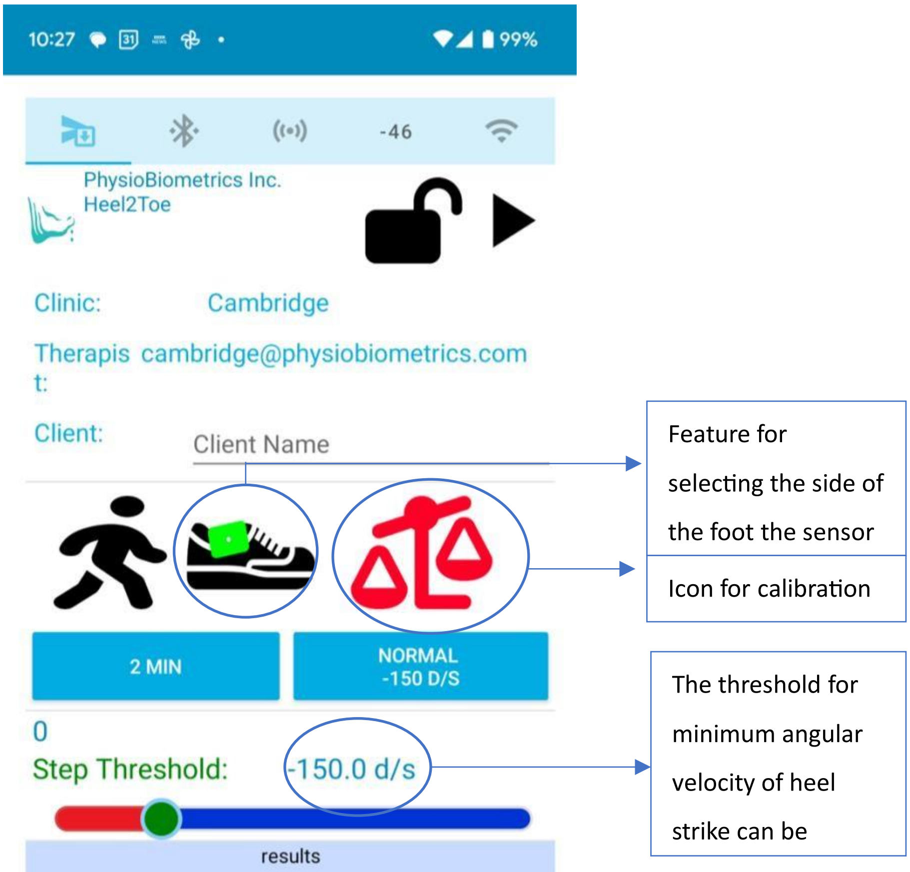

Figure 5.2 Snapshot of the application page for calibrating and personalizing the settings of the sensor

Analysis	Value	Units
sampling rate	50	Hz
Session length	6082	s
Good Step Threshold	-150	d/s
Walking time	119.42	s
Total Steps	107	count
Good Steps	99	0.93%
Bad Steps	8	0.07%
Average step	1.13	s
Cadence	106.51	step/m
Heel Strike Angular Velocity (AV)	-326.23	d/s
Heel Strike AV Standard deviation	117.91	d/s
Heel Strike Coefficient of variation	-0.36	CV
Foot Swing Angular Velocity (AV)	407.26	d/s
Foot Swing AV Standard deviation	84.97	d/s
Foot Swing Coefficient of variation	0.21	CV

GOOD STEPS:
PERCENTAGE OF GOOD VS. BAD STEPS TAKEN DURING THE WALK

CADENCE:
100 STEPS/MIN IS A SUPPORTED THRESHOLD INDICATIVE OF MODERATE INTENSITY AMBULATION

Figure 5.3 Snapshot of the results displayed on the application in real-time

Table 5.1. Gait parameters and metrics that can be recorded using the Heel2Toe™

Gait Parameter and metrics		Description
1	**Angular velocity at heel strike (HeelStrikeAV)**	The speed at which the foot moves from dorsiflexion when the heel strikes the ground to neutral when the foot is flat on the floor. It is measured in °/sec. It is the clockwise movement of the ankle at the pivot which is recorded as a negative value by the sensor.
2	**Angular velocity at pushoff (HeelOffPowerAV)**	The speed at which the heel lifts off the floor to propel the body forward. It is a clockwise movement around the pivot point of the ankle and is recorded as a negative value by the sensor.
3	**Power cycle (PowerPhaseAUCAV)**	The phase of the gait cycle from heel strike to push off that essentially generates the power to propel the body forward. It is calculated by summing the areas under the zero line on the graph. It is recorded as a negative value and is measured in $(°/sec)^2$
4	**Angular velocity of foot clearance (FootSwingAV)**	The speed at which the foot pivots around the ankle joint from plantarflexion at push-off to dorsi-flexion when the leg is preparing to position the foot to make a heel strike. A certain angular speed is needed to clear the toes from the ground, or the person can stumble and fall. As the movement is counterclockwise, the value is positive.
5	**Balance cycle (BalancePhaseAACAV)**	The swing phase of the gait cycle when one foot is in the air swinging forward and the other foot is on the ground. The height and duration of the swing creates an area measured in $(°/sec)^2$. The magnitude of this area depends on the person being able to stand on one leg, termed single leg stance.
6	**Coefficient of variation HeelStrikeAVCV HeelOffPowerAVCV FootSwingAVCV PowerPhaseAUCAVCV BalancePhaseAACAVCV**	The sensor generates gait metrics for each step. When the person takes many steps, as in a walking test, the average value is one summary metric as well as the variability (standard deviation) around the mean. The coefficient of variation is the ratio of the standard deviation of angular velocity to the average value, indicating how consistently a person walks.

Table 5.2. Categorization of the range of values of common gait parameters recorded from the Heel2Toe^{TM} sensor on a sample of 83 health professional students

Parameters /Category ratings	**Excellent**	**Very Good**	**Good**	**Fair**	**Poor**
	|Maximum|	**25th or 75th percentile**	**Median**	**25th or 75th percentile**	**|Minimum|**
Heel strike (°/sec)	-400 to < -320	-320 to < -280	-280 to < -200	-200 to < -120	< -120
CV%	10 to < 20	20 to < 25	25 to < 30	30 to < 50	≥ 50
Push-off (°/sec)	-600 to -481	-480 to -421	-420 to -301	-300 to -121	-120 to 0
CV%	5 to < 15	15 to < 25	25 to < 30	30 to < 50	≥ 50
Foot clearance (°/sec)	600	400	360	340	200
CV%	5 to < 10	10 to < 15	15 to < 20	20 to < 30	≥ 30

Note: For heel strike, and push-off the more negative the number the stronger the step; for foot clearance the more positive the number the stronger the step

Figure 5.4 Example dashboard generated for a client showing metrics for each gait parameter recorded

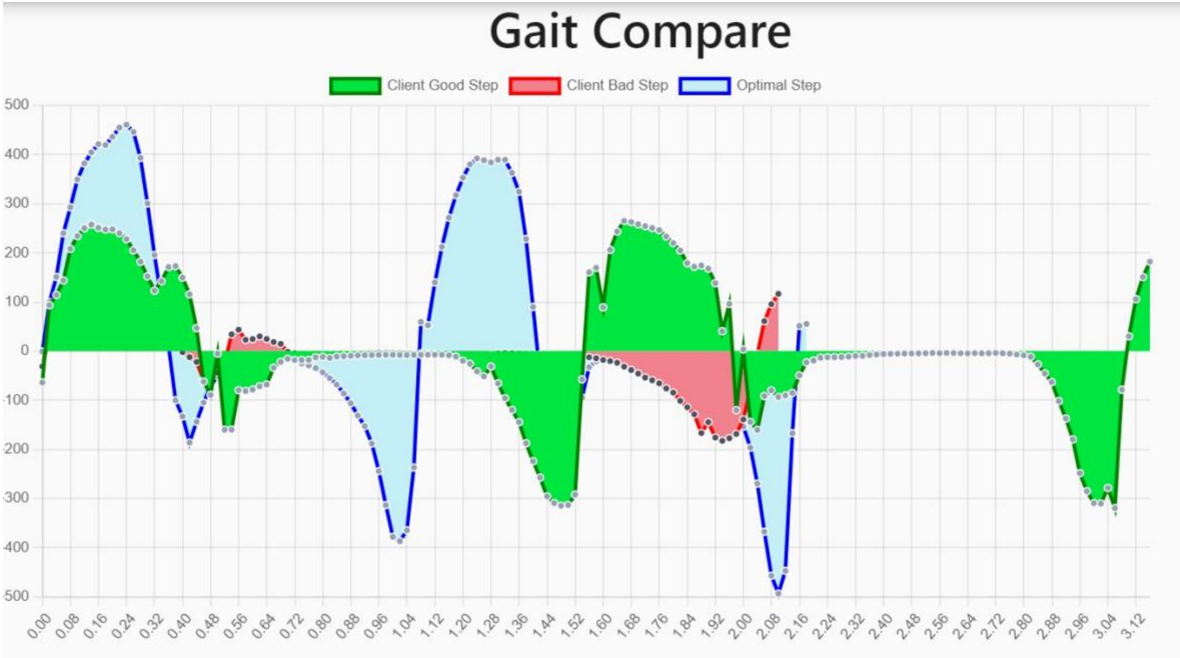

Figure 5.5 Client’s best and worst steps graphed against the optimal step requirement

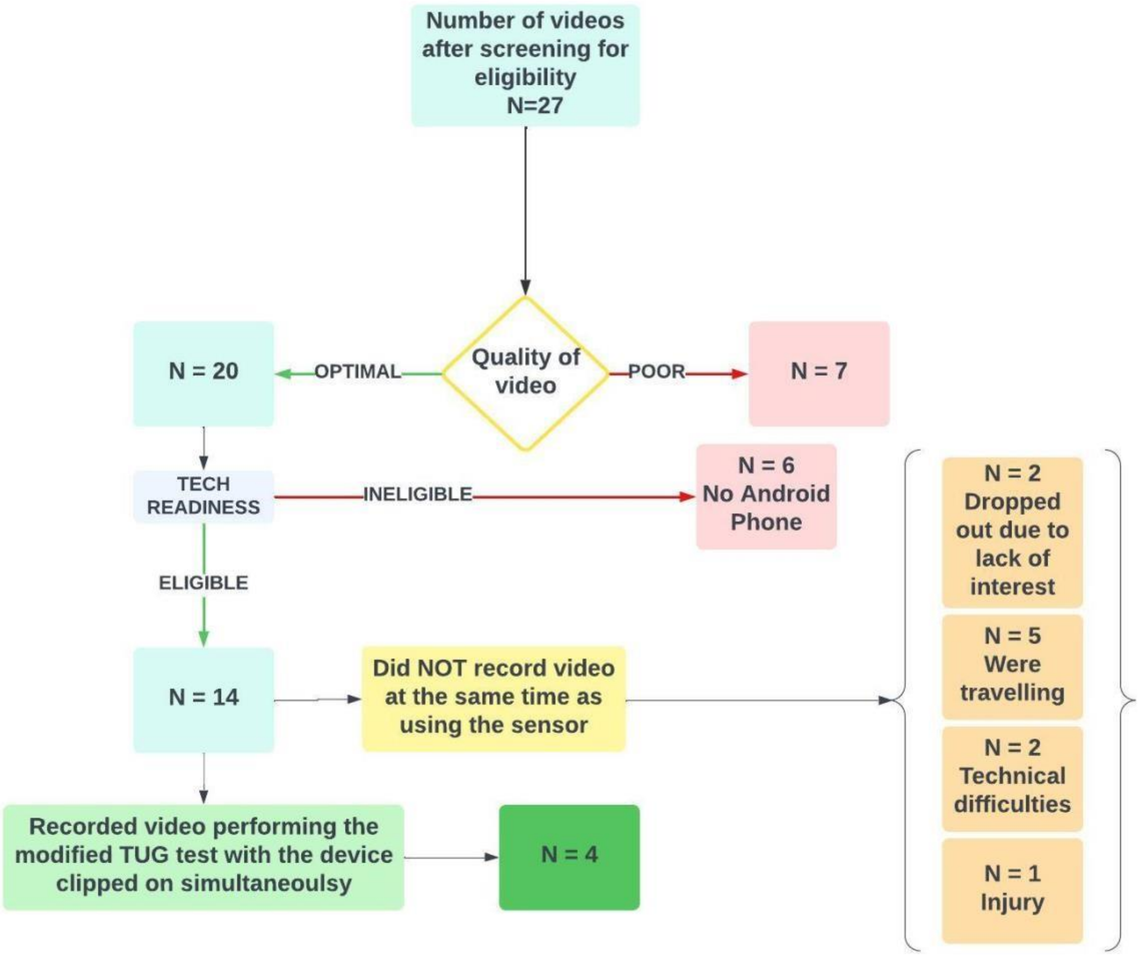

Figure 5.6 Eligible participants and drop-outs from the wearable component of the study

Table 5.3. Agreement pairs for 14 participants with common gait parameters between the observational checklist and the wearable sensor

Ratings from the observational checklist	**Categorical gradings for numeric data from the Heel2Toe™ sensor**			
Heel Strike	**Excellent/Very Good**	**Good**	**Fair/Poor**	**Total**
2 (Optimal)	3	2	0	5
1 (Weak)	2	6	1	9
0 (Poor)	0	0	0	0
Total	5	8	1	14
Crude Agreement	64.%			
Push Off	**Excellent/Very Good**	**Good**	**Fair/Poor**	**Total**
2 (Optimal)	2	2	0	4
1 (Weak)	3	2	4	9
0 (Poor)	0	1	0	1
Total	5	5	4	14
Crude Agreement	28.5%			
Foot Clearance	**Excellent/Very Good**	**Good/Fair/Poor**		**Total**
1 (Not poor)	3	8		11
0 (Yes poor)	1	2		3
Total	4	10		14
Crude Agreement	35.7%			
Fast Cadence	**Slow/Purposeful/ Moderate/Brisk**	**Fast**		**Total**
1 (Absent)	12	1		13
0 (Present)	1	0		1
Total	13	1		14
Crude Agreement	85%			

Note: Agreement pairs are highlighted in green

Chapter 6: Application of MediaPipe Pose in real-world Gait Observations: Challenges and Solutions

The third and final method tested for application for remote gait analysis in this study was the pose estimation method (section 1.1.3.3). A PubMed® search on pose estimation in gait analysis revealed 128 papers published since 1999. A large number of studies relied on the labor-intensive process of separating the background from the subject in the video and manually identifying anatomical landmarks. However, with advancements in technology, there are now more open-source libraries that streamline and automate these tasks. Nevertheless, coding is still required to extract gait parameters from the identified landmarks. This chapter provides greater details about implementing such an open-source library, MediaPipe Pose with a tailored program to estimate gait parameters. Also addressed are the challenges encountered by applying this method to videos recorded in the real world and some suggestions for estimating specific parameters. Finally, a comparison of matching gait parameters across all three methods is presented.

6.1 Overview of the technology used for pose estimation

The MediaPipe Pose Landmarker task, developed by Google, was used to analyze gait videos using the Python PyPI package. The Pose Landmarker model uses the convolutional neural network to map human pose by estimating 33 3-dimensional (x, y, z) landmarks also called anatomical landmarks in real-time, as shown in Figure 6.1. The x-coordinate represents the normalized horizontal position of the landmark, the y-coordinate represents the normalized vertical position of the landmark, and the z-coordinate represents the normalized depth of the landmark. This library can identify both anatomical landmarks and world coordinates. It processes RGB video frames i.e. frame-by-frame analysis of a video using a model that represents images in terms of red, green and blue channels with a whole-body background segmentation mask, which is a binary mask that separates the subject from the background in an image or video frame. Compared to other open-source libraries, MediaPipe is relatively fast and shows high accuracy. It has been tested for reliability in gait analysis and the detection of motor impairments in PD. Studies done so far using the MediaPipe Pose library for gait analysis have reported detecting: heel strike, push-off, step length, stance time, swing time and double support time (Latreche et al., 2023; Hii et al., 2023).

6.2 Attempt to tailor the program to suit the requirements of the study

To meet the need for detecting a broader range of temporal, spatial, and kinematic gait parameters for a comprehensive analysis best suited for clinical interpretation, a program inspired by the studies on pose estimation (Connie et al., 2022; Ramesh et al., 2023; Yang et al., 2021) was customized specifically to the observational checklist developed in this study, described in Chapter 4. The script for the program was created by the software engineer (EH) on our team in collaboration with the senior rater (NM) and principal investigator (NH). We aimed to identify as many gait parameters as possible. In the process, each gait parameter was first defined, and the relevant anatomical landmarks were listed. After running multiple experiments attempting to estimate angles and distances on the videos shared by the participants, we were limited to estimating 5 out of the 31 parameters from the checklist. This limitation was due to challenges of lack of an estimate of the ground, inconsistencies in distance covered during the modified TUG test, fluctuating angles of the camera, inconsistent resolution, and unsteady recording leading to variability in the video frames captured. The parameters thus possible to estimate were: (i) heel strike and push-off; (ii) swing at the hip; and (iii) forward and backward arm swing.

6.3 Overview of the tailored program

The libraries and modules used in the program were: the OpenCV library, SciPy library, NumPy, Pandas and the 'os' module. The parameters were estimated using the method of (i) the relative distance, (ii) the angle at the joint and angular velocity, or (iii) a combination of relative distance and angles. Where relative distances were measured in pixels, angles in degrees (°) and angular velocities in degrees/second (°/sec). An outline of the program with the initial output has been shown in Figure 6.2.

Relative distances were estimated using the Euclidean distance formula, where 'd' the distance between points,

$$\sqrt{(x2-\mathrm{x}1)^2+(y2-y1)^2}$$

x_1 and y_1 are the coordinates of the first point and x_2 and y_2 of the second, x represents the horizontal position and y represents the vertical.

The angle at the joint was estimated using the dot product formula for two vectors,

$$a\,.\,b = \| a \| \, \| b \| \cos\theta$$

where θ is the angle between a and b, ‖a‖ ‖b‖ is the magnitude of the vectors a and b.

The angular velocity was estimated using the formula,

$$\omega = \Delta\theta / \Delta t = \Delta\theta \times fps$$

Where ω is the angular velocity, $\Delta\theta$ is the change in angle calculated using,

$$\Delta\theta = \theta n + 1 - \theta n$$

Δt is the time interval between frames, $\Delta t = 1/fps$ where fps is frames per second.

All 20 videos included were analyzed at 60 frames per second resulting in an output of 600 to 900 frames per participant. Methods for data collection and inclusion of videos have been detailed in Chapters 3 and 4. All videos were converted to the MP4 format for analysis. This tailored program was first tested and validated on a video with no gait impairments. The process of extracting gait parameters was structured using this test video. An overview of the method used for estimating heel strike and push-off has been shown in Figure 6.3. A similar method was used for estimating arm swing, except instead of angular velocity, the angle at the shoulder that corresponded to the one frame of the best optimally viewed forward and backward arm swing was considered best for clinical relevance and comparison to the observational method as discussed with the senior rater. For swing at the hip, the average value of angle at the hip throughout one gait cycle with the standard deviation was suggested for comparison with the observational method. The method used has been explained in Figure 6.4.

6.4 Estimate of Heel Strike and Push-off from Participant Videos

The process of identification of gait parameters commenced by identifying the landmarks to estimate heel strike and push-off as they are the key events of a gait cycle shown in Figure 6.5. It was found that both parameters could be measured using the relative distance between the hip and the foot index (refer figure 6.1), where the distance between the hip and the foot index was expected to be the smallest at push-off and largest at heel strike. A graph plotting the relative distances showing values of heel strikes and push-offs from the video with no gait impairments is shown in Figure 6.6, where peaks represent heel strikes and troughs are push-offs. The other possible method was to measure the angle and angular velocity at the ankle, where the angle and angular velocity at the heel strike were expected to be lower when compared to the angle and angular velocity at push-off. The landmarks for relative distance used were 24, 32 and 23, 31 while those for the angle at the ankle were 26, 28, 32 and 25, 27, 31 as shown in Figure 6.1. When tested on the video with no gait impairments, the angle for the best heel strike was recorded as 103.1° with an angular velocity of -293.1°/sec and a normalized relative distance of 0.3246.

The angle for the best push-off was 116.6°, with an angular velocity of 497°/sec and a normalized relative distance of 0.2568.

6.4.1 Challenges encountered during the process and solutions

Most videos submitted by the participants had inconsistent camera angles with views fluctuating from frontal to lateral and posterior. Due to the small size of the foot, variable angles and focus of the camera lens, there was a lack of clarity and consistency in tracking the landmarks at the ankle. These errors led to ambiguity in angular velocity values, producing both negative and positive values for the same parameter. Estimating the angular velocity accurately from the calculated angles using the MediaPipe Pose library was difficult. Contrary to our hypothesis, the minimum and maximum angles at the ankle from the individual manually identified gait cycles did not correspond to a heel strike or push-off. For example, the maximum angle recorded was at the foot flat phase of the gait cycle. Additionally, the relative distances varied with the angle and distance of the camera from the person in the video. Thus, for ease of interpretation and comparative analysis, the most optimally viewed frame of the best heel strike and push-off was identified by observation by the principal investigator. The angular velocity corresponding to that frame was reported. As the above method was based on one frame only and did not capture the variability in steps, a second method was used as a proof-of-concept. Instead of analyzing only the one best frame, all frames showing an optimally viewed heel strike and push-off were identified and the values of angular velocity of heel strike and push-off averaged. The data from each of these methods was used to derive heel strike and push-off parameters as shown in Table 6.1 and Table 6.2 respectively, along with ratings given by observers using the checklist, and angular velocity measured using the Heel2Toe™ sensor and averaged over all recorded steps.

6.4.2 Results

Table 6.1 shows that for Video 14 (V14) the optimally viewed method showed an angular velocity of heel strike of -364°/sec; the observers rated this participant's heel strike as weak; the measured angular velocity from the sensor was -311°/sec which is "excellent/very good" using our normative data (see Chapter 5). For Video 20 (V20) the optimally viewed method using MediaPipe showed an angular velocity of -223°/sec which was rated as optimal by the observers and the value recorded by the sensor was -216°/sec which is "good" (see Chapter 5). Finally, in Video 6 (V6) the average angular velocity for the heel strike calculated was 20°/sec with a standard deviation of 66.2°/sec while the optimally viewed method showed an angular velocity of 139.5°/sec; observers rated the heel strike as weak and measurements from Heel2Toe™ -240°/sec indicated a rating of "good".

The Spearman's rank correlation between the angular velocity at heel strike from the optimally viewed value using pose estimation (column 2, Table 6.1) and that recorded from the sensor (column 5, Table 6.1) was 0.32 ($p = 0.260$), considered non-significant weak correlation. The difference in the paired observations between the two methods was neither consistent nor significant as shown by the Wilcoxon Signed Rank Test value of 27.5 (z-value: 0; $p = 1.0$). Additionally, the Spearman's rank correlation between the angular velocity at heel strike from the optimally viewed value using pose estimation (column 2, Table 6.1) and the ratings by raters (column 4, Table 6.1) was -0.28 ($p = 0.225$), considered non-significant weak and negative correlation. The difference in the paired observations between the two methods was significant as shown by the Wilcoxon Signed Rank Test value of 7 ($z = -3.658$, $p = 0.0002$).

Table 6.2 shows the same information for push-off. For Video 3 (V3) the optimally viewed method showed an angular velocity of push-off was 327.9°/sec which was rated optimal by the raters and the measured angular velocity recorded by the sensor was -439°/sec which is "excellent/very good" based on our normative data (see Chapter 5). Similarly, for Video 6 (V6), the average angular velocity for push-off calculated was 138.2°/sec with a standard deviation of 57.6°/sec, while the optimally viewed method showed an angular velocity of 205.8°/sec, which was rated weak by the raters, and measurements from Heel2Toe of -390°/sec indicating "good" (see Chapter 5). The Spearman's rank correlation between the angular velocity at push-off from the optimally viewed value using pose estimation (column 2, Table 6.2) and that recorded from the sensor (column 5, Table 6.2) was -0.22 ($p = 0.386$); considered nonsignificant weak and negative correlation. The mean difference of ranks between the two methods was significant as shown by the Wilcoxon Signed Rank Test value of 5 (z-value: 2.98; $p = 0.00144$). Additionally, the Spearman's rank correlation between the angular velocity at push-off from the optimally viewed value using pose estimation (column 2, Table 6.2) and the ratings by raters (column 4, Table 6.2) was 0.15 ($p = 0.514$), considered non-significant weak correlation. The difference between paired observations between the two methods was neither significant nor consistent as shown by the Wilcoxon Signed Rank Test value 86 ($z = -0.709$, $p = 0.477$).

6.5 Estimate of swing at hip

The metric of interest here is whether the participant showed movement at the hip during a gait cycle. Especially with PD, rigidity can result in very little hip movement and more knee flexion/extension to advance the foot. It was found that swing at the hip could be measured by calculating the change in angle ($\Delta\theta$) at the hip for one gait cycle as shown in Figure 6.4. The landmarks used to calculate the angle at the hip joint were 26,24,12 and 25,23,11 as shown in Figure 6.1. When tested on the video with no gait impairments as shown in Figure 6.7, the angle at the hip during a heel strike, during forward hip swing of leg (Panel A), was 156.9° and push-off during backward swing of the leg (Panel B) was 152.9°, with a difference of approximately 4°. The neutral angle is 180° and the mean angle at the hip averaged over all frames on one gait cycle including both forward and backward movements was 165.7° ± 8.89 with an average difference in angle of 0.32° degrees yielding a standard deviation of 2.8° (range -7.78° to 8.05°). As this angle is measured proximally, it indicates a much larger excursion of the foot, and it is the standard deviation that represents change of movement at the hip.

6.5.1 Challenges encountered during the process and solutions

The hip being a larger joint and typically closer to the camera, made it vivid and easier to track compared to the ankle joint. Consequently, there were fewer errors when tracking the angle at the hip. The trunk lean affected the angles at the hip demonstrating problems of using the torso instead of the pelvis to calculate the angle at the hip. Additionally, challenges due to the inconsistency of frames and variable views while recording the videos as mentioned earlier led to some ambiguities in results. Thus, frames of one complete gait cycle vividly visible and optimally recorded were identified manually and the Mean±SD of angles at the hip for that segment was reported. Table 6.3 presents the Mean±SD of the angle at the hip for all 20 videos estimated using MediaPipe, alongside their corresponding ratings by majority raters from the observational checklist. As the sensor was limited to recording parameters at the ankle, no values were available for the swing phase at the hip.

6.5.2 Results

As shown in the table the Mean±SD of the angle at the hip for one gait cycle for video 18 (V18) was 171.9°±6.5°; rated as optimal by the raters; the value for video 17 (V17) was 125.5°±1.8°; rated as poor by the raters and the value for video 3 (V3) was 177.3°±1.1°, rated as optimal by the raters. The Spearman's rank correlation between the SD of the angles at the hip recorded for one gait cycle using pose estimation (column 2, Table 6.3) and ratings from raters (column 3, Table 6.3) was 0.228 (p = 0.332), considered a non-significant weak correlation. There was a significant difference between the angles at the hip recorded using pose estimation and the ratings as shown by the Wilcoxon Signed Rank Test value of 4.5(z-value: -3.75; p = 0.0018).

6.6 Estimation of forward and backward arm swing

In individuals with no gait impairments, an alternating gait pattern is observed, the arm alternates with the foot at heel strike exhibiting maximal forward swing and exhibiting maximal backward swing when the foot is pushing off. It was found that arm swing like heel strike and push-off could be measured using relative distance, angle and angular velocity at the shoulder. The relative distance between the shoulder and the wrist was expected to be largest during the maximum forward swing of the arm and comparatively smaller for the backward arm swing in the opposite direction. The landmarks used to detect relative distance were 12,16 and 11,15 and those used to measure the angle at the shoulder were 14,12,24 and 23,11,13 as shown in Figure 6.1. Based on clinical experience the angle and angular velocity at the shoulder, for the forward arm swing was expected to be greater compared to the angle and angular velocity during the backward swing of the arm. The side of the trunk served as an axis in between the arm swings. When this method was tested on a video with no gait impairments, the angle for the manually identified, best optimally viewed forward arm swing was 58.93° with an angular velocity of 80.3°/sec with the relative distance between the shoulder and the wrist as 0.1534. Whereas the angle for the best-viewed backward arm swing was 40.98□ with an angular velocity of -23.9°/sec and a relative distance of 0.1042. Relative distances between the shoulder and the wrist indicating arm swing for both left and right side (peaks = forward arm swing, troughs = backward arm swing) recorded from the video with no gait impairments have been graphed with relative distances of heel strike and push-off for the left and right foot (peaks = heel strike, troughs = push-off), as shown in Figure 6.8

6.6.1 Challenges encountered during the process and solutions

The challenge with reporting the angular velocities for arm swing is that these vary with gait speed (Plate et al., 2015). The gait speed of participants in this study was variable as the videos were recorded in a real-world setting, making values of angular velocity unreliable for comparisons and relative distance was not clinically relevant. The shoulder joint was comparatively vivid, however, issues such as a rotated trunk, or fluctuating lateral, frontal and posterior views of the person in the video led to the aforementioned challenges. The relative distances were difficult to translate clinically. Additionally, the output generated recorded all angles at the shoulder without distinguishing the gait parameter. The lack of automation for identifying gait parameters using the program led to the tedious labor-intensive process of manually segregating, identifying and isolating frames based on individual gait events. Consequently, the angles of the best optimally viewed forward and backward arm swing were chosen to be the metric reported. Tables 6.4 and 6.5 present angles of using the optimally viewed method for forward and backward arm swing respectively alongside corresponding ratings given by raters using the observational checklist. As the wearable sensor (Heel2Toe™) was limited to recording gait parameters at the level of the foot, there were no values recorded.

6.6.2 Results

Table 6.4 shows that for video 1 (V1) the angle recorded using the optimally viewed (representative of the best angle for forward arm swing) was 39.3°, rated as optimal by the raters; for video 17 (V17) the angle recorded was 2.6°, rated as absent by the raters and for video 3 (V3) the angle recorded was 16.9°, rated as weak by the raters. The Spearman's rank correlation between the angle of the optimally viewed forward arm swing using pose estimation and corresponding ratings was 0.426 ($p = 0.06$), indicating a non-significant but moderate correlation. There was a significant difference between angles at forward arm swing estimated using pose estimation and the ratings by raters as shown by the Wilcoxon Signed Rank Test value 0 ($z = -3.919$, $p = 0.00008$).

Table 6.5 shows that for video 20 (V20) the angle for the backward arm swing recorded using the optimally viewed method was 29.1°, which was rated optimal by the raters whereas an angle of 17° for video 13 (V13) was rated absent by the raters and video 7 (V7) with an angle of 11.4° was rated weak by the raters. The Spearman's rank correlation between the angle of the optimally viewed backward arm swing using pose estimation and corresponding ratings was 0.574 ($p = 0.008$), indicating a large significant correlation. There was a significant difference between angles at backward arm swing estimated using pose estimation and the ratings by raters as shown by the Wilcoxon Signed Rank Test value 0 ($z = -3.6214$, $p = 0.0003$).

6.7 Summary of results

The correlation for parameters such as heel strike and push-off was found to be weak and not significant when angular velocity estimated using pose estimation was compared to both the wearable sensor and the ratings from the observational method. Moreover, the correlation for the parameter of swing at hip was also weak and not significant when the standard deviation of the angle at the hip during one gait cycle estimated from pose estimation was compared to the ratings from the observational analysis. Only the parameters of forward and backward arm swing showed moderate to strong correlation which was significant only in the case of backward arm swing when angles estimated using pose estimation were compared to the observational ratings by raters. Arm swing likely showed a better correlation to the other parameters due to its greater vividness in the video and the proximity of the shoulder joint to the camera. Table 6.6 presents an overview of the correlation coefficients for the five parameters estimated using the method of pose estimation when compared to the other two methods of gait analysis used in this study.

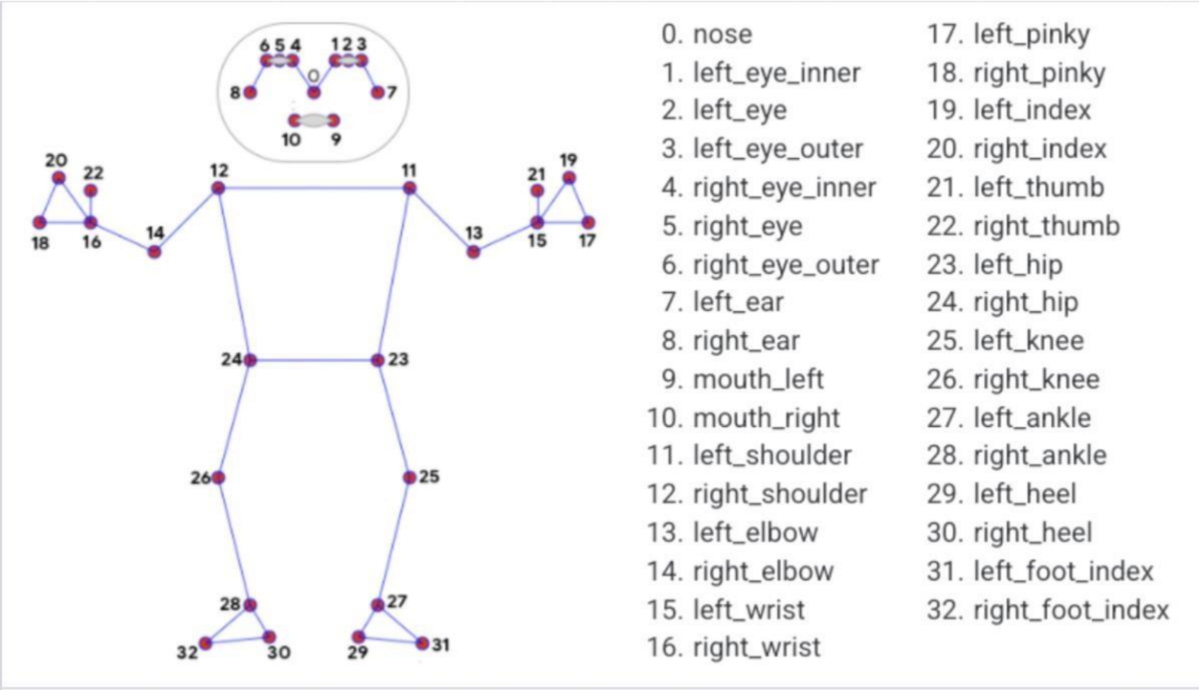

Figure 6.1 Anatomical landmarks tracked by the MediaPipe Pose Landmarker task. This image has been reproduced from (Bazarevsky et al., 2020)

Begin
Initialize MediaPipe Landmarker task
Import os
Import NumPy
Import SciPy
Import any_angle library for hip, ankle and shoulder
Import pandas
Use utilities to visualize landmarks and import holistic solutions of MediaPipe Pose
Set up class 'Pose' from MediaPipe's pose module and set minimum detection and tracking confidence level of 50%
while (current video frame ≤ last video frame) do [For each frame of the analyzed video the following operations were applied
Identify the region of interest using landmark numbers
Extract and save the positions of body key points in the region of interest
Define Euclidean distance for relative distance and the dot product formula for angles
Apply savgol filter
Calculate angles and relative distances for both sides
Save data as csv file
End

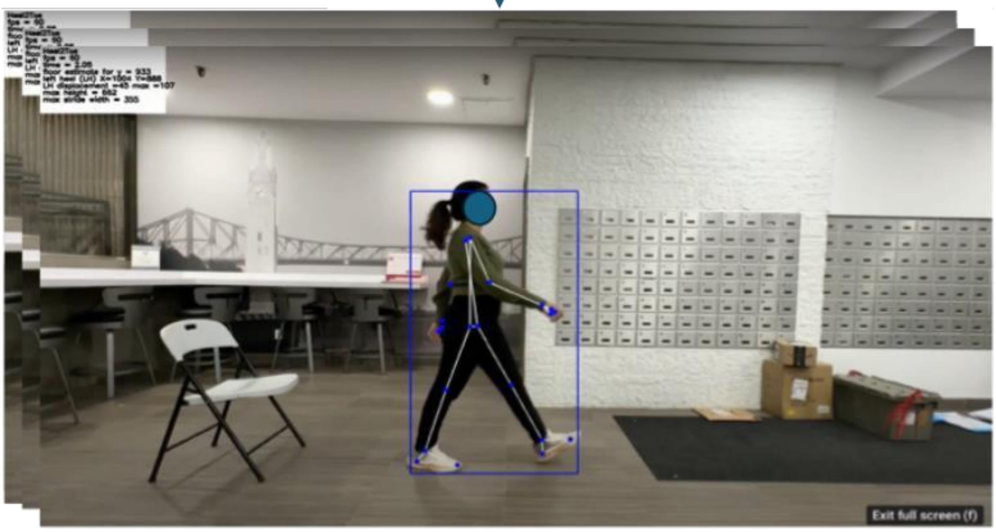

Figure 6.2 Outline of the program and initial output

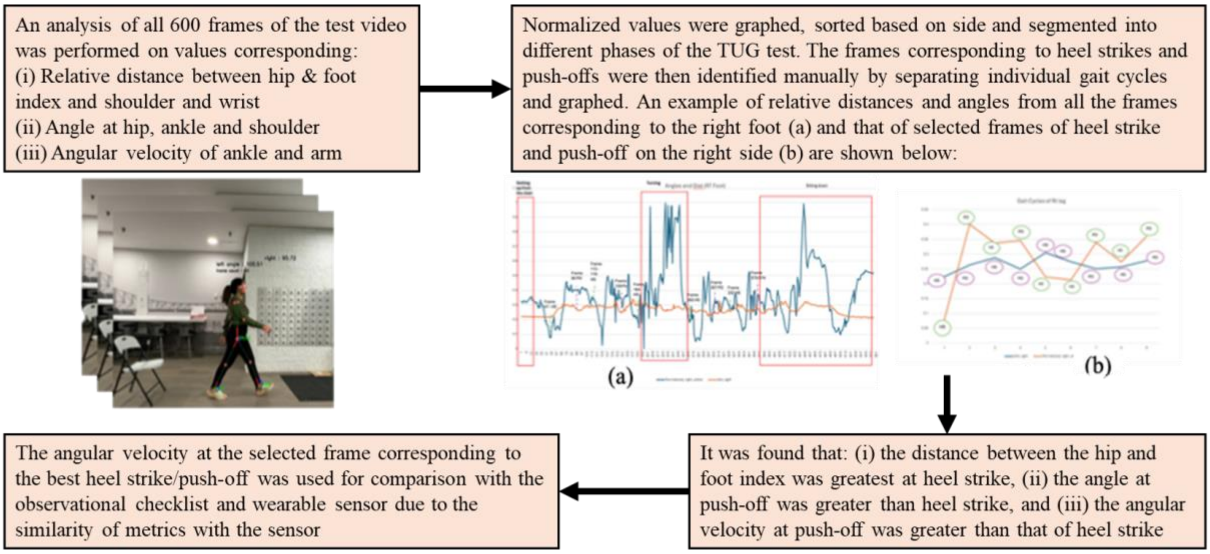

Figure 6.3 Overview of the workflow for estimating heel strike and push-off

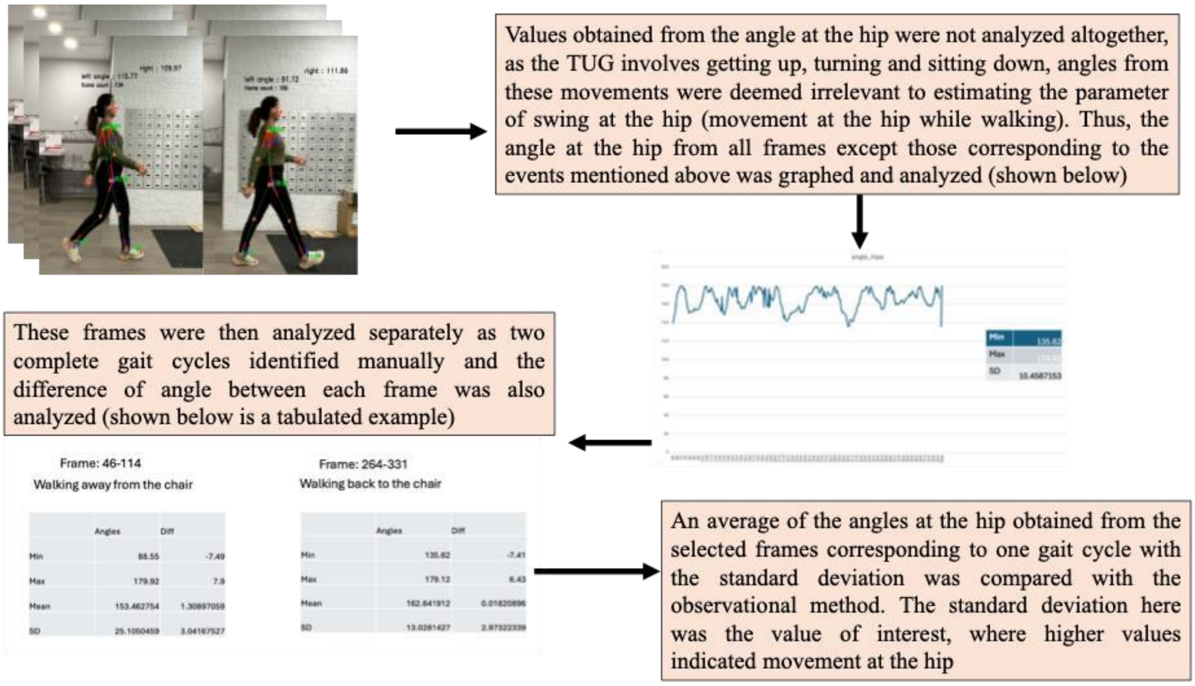

Figure 6.4 Overview of the workflow for estimating swing at the hip

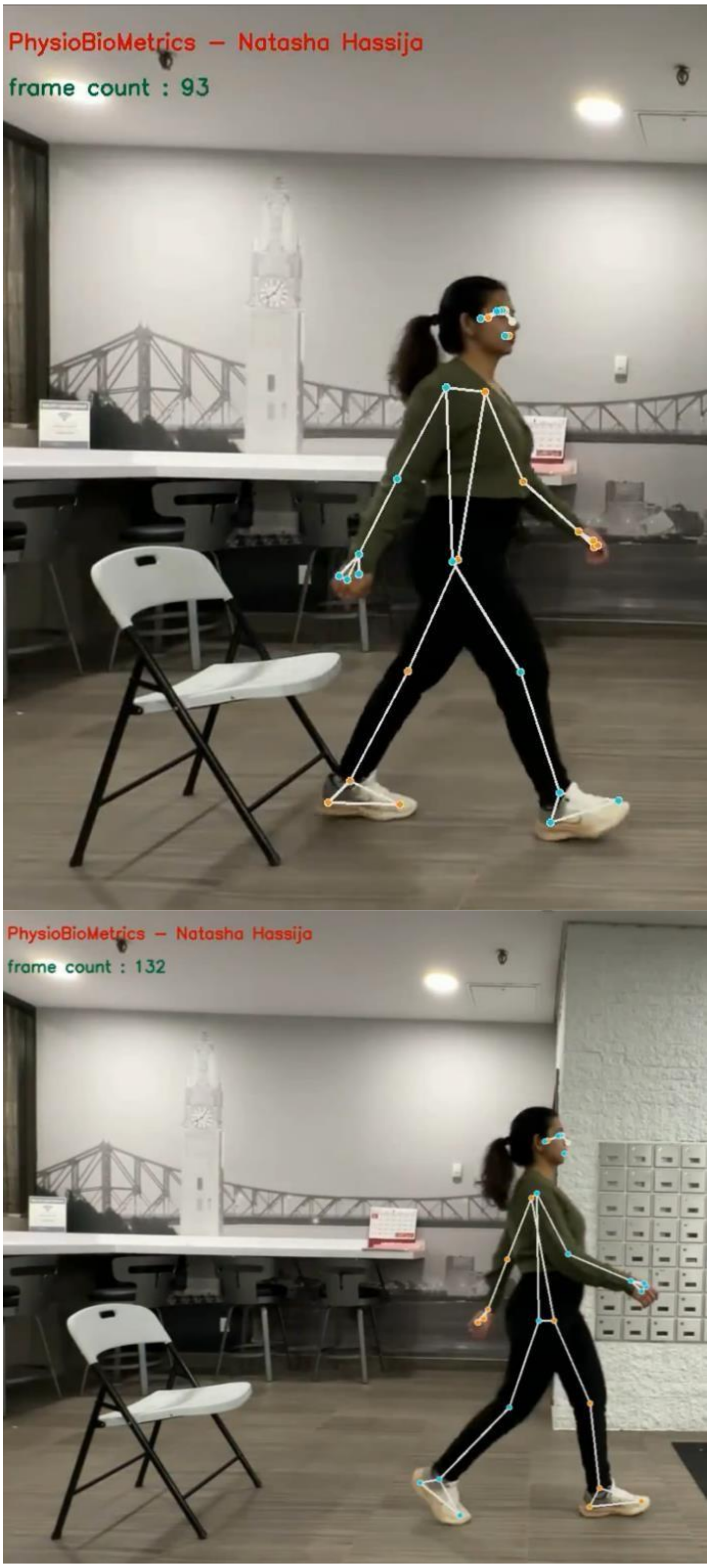

Figure 6.5 Video frames frozen at heel strike (above) and push-off (below) for the right ankle

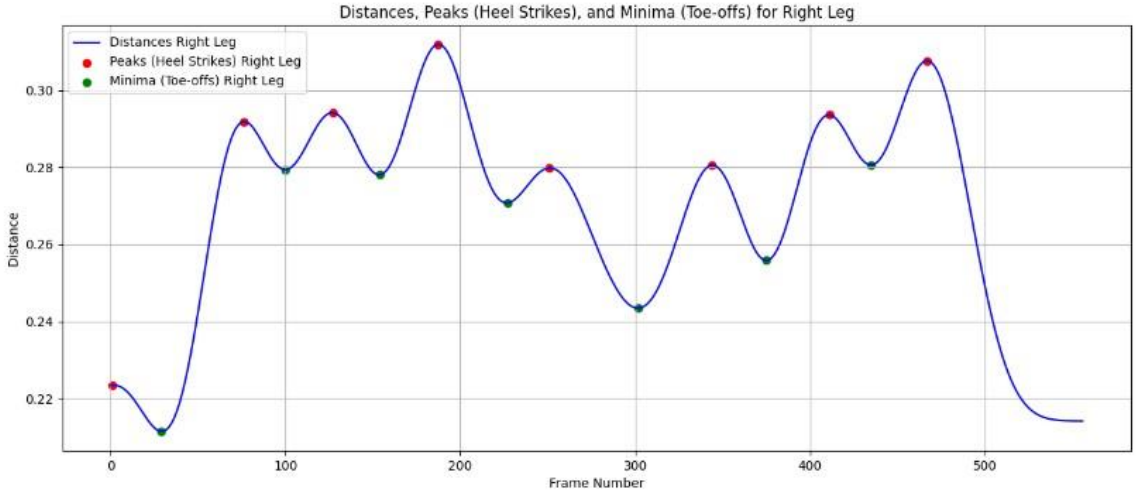

Figure 6.6 Graph showing the relative distance between hip and foot index on the right side for a modified TUG video with no gait impairments, where distance is measured in pixels

Table 6.1. Comparison of angular velocity at heel strike to observational ratings of videos of people with Parkinson's Disease

Videos	Angular Velocity of the best optimally viewed heel strike (°/sec)	Proof of concept Mean ± SD (°/sec)	Ratings given by raters using the observational checklist	Average Angular Velocity over all steps recorded during walking session Heel2Toe™ sensor (°/sec)
V14	-364.0	--	Weak	-311
V13	-339.0	--	Weak	--
V18	-289.1	--	Weak	-350
V3	-267.0	--	Optimal	-301
V11	-264.0	--	Optimal	--
V1	-239.0	--	Optimal	-212
V15	-223.5	--	Optimal	-346
V20	-223.0	--	Optimal	-216
V16	-177.6	--	Weak	-120
V8	-156.1	--	Weak	-234
V5	-140.5	--	Weak	--
V2	-120.0	--	Optimal	-378
V10	-116.4	--	Weak	-264
V12	-100.3	--	Weak	-204
V4	-83.9	--	Weak	--
V7	-55.3	--	Weak	-226
V17	-30.0	--	Weak	-227
V6	139.5	20.1 ± 66.2	Weak	-240
V9	-264.3	-136 ± 172	Weak	--
V19	-213.3	-109.4 ± 118.3	Weak	--

Table 6.2 Comparison of angular velocity at push-off to observational ratings of videos of people with Parkinson's Disease

Videos	Angular Velocity of the best optimally viewed push-off (°/sec)	Proof of concept Mean ± SD (°/sec)	Ratings given by raters using the observational checklist	Average Angular Velocity over all steps recorded during walking session Heel2Toe™ sensor (°/sec)
V3	327.9	--	Optimal	-439
V15	272.4	--	Weak	-504
V1	232	--	Optimal	-389
V10	206.1	--	Weak	-519
V2	186.6	--	Optimal	-320
V17	127.3	--	Weak	-304
V16	-100.5	--	Weak	-219
V4	-121.3	--	Weak	--
V5	-132.4	--	Weak	--
V8	-134.2	--	Absent	-416
V7	-163.8	--	Weak	-442
V12	-180.4	--	Weak	-349
V13	-188.4	--	Weak	--
V11	-222	--	Optimal	--
V20	-233.7	--	Weak	-240
V18	-270	--	Optimal	-600
V14	-388	--	Weak	-233
V6	205.8	138.2±57.6	Weak	-390
V19	-253.2	-83.4±240.1	Weak	--
V9	-100.6	-68±46.1	Weak	--

Panel A Panel B

Figure 6.7 Snapshot of the frames showing angle at the hip during heel strike and push-off recorded for a video with no gait impairments

Table 6.3 Comparison of swing at the hip to corresponding observational ratings of people with Parkinson's Disease

Videos	Mean±SD (°) (neutral = 180°) For the angle at the hip	Ratings given by raters using the observational checklist
V8	177.5±1.4	Poor
V3	177.3±1.1	Optimal
V11	175.9±3.1	Optimal
V6	175.2±2.7	Poor
V19	174.9±2.3	Poor
V5	174.6±2.3	Optimal
V4	174.4±3.8	Poor
V12	174.1±1.9	Poor
V9	173.1±2.7	Poor
V14	172.8±2.3	Poor
V13	172.5±3.7	Poor
V20	172.1±2.7	Poor
V18	171.9±6.5	Optimal
V15	169.3±4.7	Optimal
V7	168.6±7.3	Poor
V16	169.4±2.7	Poor
V10	168.5±8.2	Poor
V2	168.5±6.6	Optimal
V1	166.1±7.6	Optimal
V17	125.5±1.8	Poor

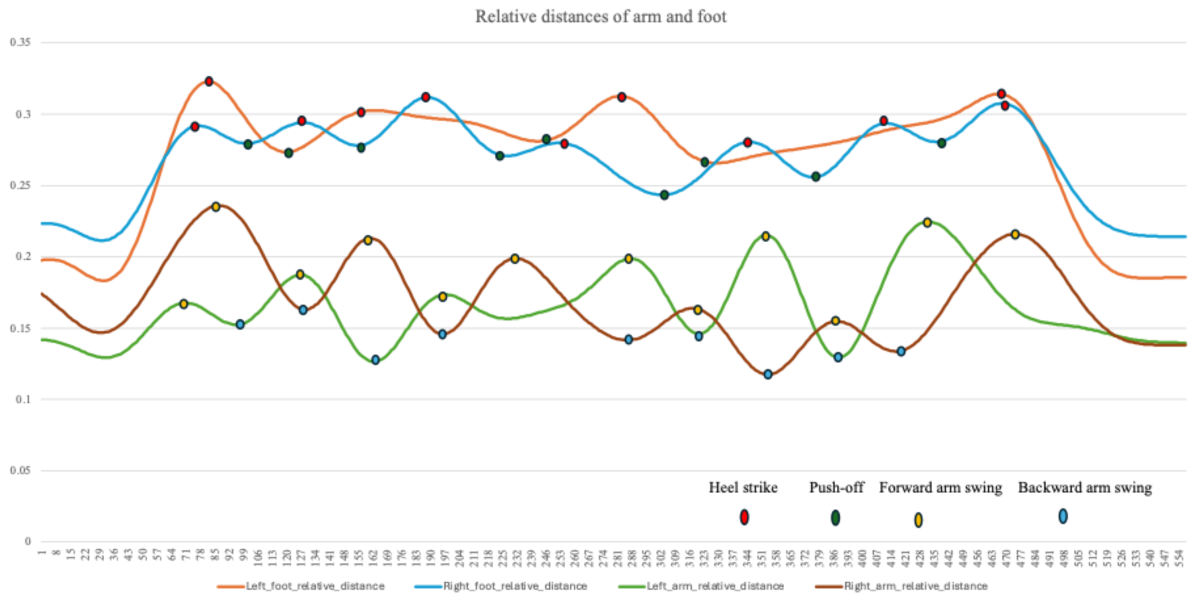

Figure 6.8 Relative distances of arm swing and foot showing forward and backward arm swings and heel strikes and push-offs on either side during the modified TUG test

Table 6.4 Comparison of the angle at forward arm swing to corresponding observational ratings of people with Parkinson's Disease

Videos	Angle at forward arm swing (°)	Ratings given by raters using the observational checklist
V1	39.3	Optimal
V15	28	Weak
V14	25.3	Weak
V18	25.1	Weak
V5	24.9	Weak
V20	23.2	Optimal
V2	23	Optimal
V13	23	Weak
V11	22.1	Optimal
V4	22	Absent
V7	21.2	Weak
V19	20	Weak
V12	19.2	Optimal
V8	18.6	Weak
V6	18.5	Optimal
V3	16.9	Weak
V16	12.8	Absent
V10	12.4	Weak
V17	2.6	Absent
V9	0.82	Absent

Table 6.5. Comparison of the angle at backward arm swing to corresponding observational ratings of people with Parkinson's Disease

Videos	Angle at backward arm swing (°)	Ratings given by raters using the observational checklist
V20	29.1	Optimal
V3	17.9	Weak
V6	17.7	Optimal
V13	17	Absent
V5	16.2	Weak
V19	16.2	Weak
V12	15.8	Optimal
V11	15.8	Optimal
V16	12.4	Absent
P41	12	Weak
V7	11.4	Weak
V18	10.5	Weak
V15	10	Absent
V10	9.5	Weak
V2	9.1	Weak
V14	8.5	Absent
V1	2.27	Weak
V4	0	Absent
V9	0	Absent
V17	0	Absent

Table 6.6. Summary of Results of correlation between Pose Estimation parameters and matching Observational Ratings and metrics from the Heel2Toe^{TM} sensor

Gait Parameter	**Pose Estimation – Observational Ratings r (p-value)**	**Pose Estimation – Wearable Sensor r (p-value)**
Heel Strike	-0.28 (p = 0.225)	0.32 (p = 0.260)
Push-Off	0.15 (p = 0.514)	-0.22 (p = 0.386)
Swing at Hip	0.228 (p = 0.332)	--
Forward Arm Swing	0.426 (p = 0.06)	--
Backward Arm Swing	0.574 (p = 0.008)	--

Chapter 7: Overall Discussion

The COVID-19 pandemic catalyzed the widespread development of affordable and easily accessible technology allowing for therapeutic activities to be conducted with patients at home. In the context of telerehabilitation, these activities included gait assessment and monitoring triggering a paradigm shift in clinical practice toward remote assessments. This chapter provides insights into challenges encountered and summarizes the lessons learned in the attempt to test available technology in comparison with the traditional method in a scenario that closely simulates real-world remote clinical practice.

The subsequent sections detail the challenges encountered by each method used in this study.

7.1 Challenges encountered with the remote observational method

The observational checklist's structure required raters to provide a single overall rating for each gait parameter, regardless of the side that was being assessed. This approach caused confusion, particularly in cases of asymmetry, a common occurrence in PD. For instance, if a participant exhibited an absent arm swing on one side but optimal on the other, they would still get a point. Additionally, the rating categories did not provide an option for raters to indicate when a parameter was not observable. The inconsistencies in the phrasing of questions in the checklist with a mix of positive and negative statements led to difficulties interpreting the questions. Although the process of observational analysis is predominantly used due to its ease of use and simple data interpretation, it is tedious, time-consuming and only moderately reliable to detect impairments. Each rater took on average 15 minutes to rate one video. A minimum of 8 videos were assigned to each rater, which made the analysis cumbersome and fatiguing for them. Finally, inconsistencies in camera resolution, angle and frequency of recording, insufficient lighting, and clutter in the environment, led to obstruction of the full view of the participant. This culminated in difficulties in observing certain gait parameters, given some parameters such as arm symmetry are best viewed frontally while swing at the hip and heel strike are best viewed laterally.

7.2 Challenges encountered while using the wearable sensor remotely

Although the inertial measurement units in the Heel2Toe™ sensor accurately detect movements, the main challenge encountered with the wearable sensor used in this study was its unreliable Bluetooth connectivity and its exclusive compatibility with the Android operating system. This led to multiple exclusions and dropouts. Additionally, connectivity issues during the test contributed to the loss of data. Furthermore, certain participants struggled to record videos while wearing the sensor which hindered simultaneous assessments using the different methods.

7.3 Challenges encountered while using the method of Pose Estimation

The pose estimation method was tested on the same videos used for observational analysis, utilizing the MediaPipe Pose library. Among the three methods, this proved to be the most challenging in terms of clinical integration, data extraction and interpretation. The challenges were encountered although this method is known to provide accurate values of most gait parameters when used under perfect conditions, especially when videos are recorded using a multiple-camera system in a controlled environment. Accurately capturing the true joint angle using this method relies on depth estimation, triangulation of joints and the combination of triangulation of multiple pairs of cameras. However, this study was performed in a 'real-world' set-up, where only one camera was used and recordings had variable camera angles as caregivers used their smartphones to record the modified TUG test. According to Dill et al., 2023, the accuracy of pose estimation using MediaPipe is highly dependent on the camera angle and the activity being evaluated. Our study confirmed these findings, revealing multiple instances of overestimation and underestimation of landmarks that were tracked using the library. Another challenge encountered was the absence of an estimate of the ground due to variable walking paths and distances walked by the participants limiting the estimation of gait parameters. However, the motive behind this study was to explore 'real-world' applications that are far from optimal scenarios. Additionally, the lack of automation of our program to identify gait events made the process labour-intensive and time-consuming. Although pose estimation libraries like MediaPipe are free, their implementation requires hiring skilled software engineers to develop tailored programs.

7.4 Recommendations and Lessons Learned

The most significant lesson learned from this journey is that the accuracy of remote gait analysis is influenced not only by the method used but also by the environment and quality of the videos. To achieve better quality videos optimal for remote analysis, a comprehensive list of instructions must be provided, comprising ways to avoid clutter while filming the video, ensuring the person is completely visible throughout, appropriate lighting, specified aperture, minimum camera resolution, distance of the camera from the person and fixed walking distance. As some videos submitted were of suboptimal quality, a reference video filmed by the research team was sent to the participants which improved the quality of videos that were received later. Additionally, timely assistance should be provided to address any technical issues participants may encounter. While technology may seem easy to use in a controlled setup, it becomes considerably challenging in real-world scenarios explaining their poor integration into a clinical setup despite being proven valid and reliable. For future practice, a combination of both methods, the wearable sensor and pose estimation would be ideal for comprehensive analysis as the sensor although highly accurate is limited to recording parameters at the level of the foot. These technological methods have the potential to detect subtle nuances missed by the human eye and overcome the challenge of variability in ratings. Further research is needed in the field of pose estimation to make the estimates obtained comparable and reliable to the gold standard and automate programs to identify gait events accurately despite variable camera angles.

7.5 Conclusion

When comparing the three methods, it seems at the moment, the wearable sensor has the most promise for regular clinical use as it was possible for patients to use themselves and the data is readily interpretable by both the patient and clinician. Newer versions of the Heel2Toe^{TM} have eliminated the need for a Bluetooth connection to an Android smartphone. It does, however, provide a limited set of gait parameters. The observational checklist is too time-consuming and unreliable for individual assessment of change. Media Pipe pose requires too much expertise for the average clinician to use on a regular basis but certainly provides rich data when used optimally. Advances in automating the program for estimating a variety of gait parameters and in image processing could change its real-world applications.

References

Abbas, aM. M., Xu, Z., & Tan, L. C. S. (2018). Epidemiology of Parkinson's Disease—East Versus West. *Movement Disorders Clinical Practice*, *5*(1), 14-28. https://doi.org/10.1002/mdc3.12568

Abernethy, A., Adams, L., Barrett, M., Bechtel, C., Brennan, P., Butte, A.,…Valdes, K. (2022). The Promise of Digital Health: Then, Now, and the Future. *NAM Perspectives*, *6*(22). https://doi.org/10.31478/202206e

Ainsworth, B. E., Haskell, W. L., Herrmann, S. D., Meckes, N., Bassett, D. R., Tudor-Locke, C., Leon, A. S. (2011). 2011 Compendium of Physical Activities. *Medicine & Science in Sports & Exercise, 43(8),* 1575-1581. https://doi.org/10.1249/mss.0b013e31821ece12

Akl, A.-R. (2014). *Biomechanics of Gait*. https://doi.org/10.13140/RG.2.1.1757.1600

Albarmawi, H., Zhou, S., Shulman, L. M., Gandhi, A. B., Johnson, A., Myers, D. E.,…Onukwugha, E. (2022). The economic burden of Parkinson disease among Medicare beneficiaries. *Journal of Managed Care & Specialty Pharmacy*, *28*(4), 405-414. https://doi.org/10.18553/jmcp.2022.28.4.405

Ali, A., Sundaraj, K., Ahmad, B., Ahamed, N., & Islam, A. (2012). Gait disorder rehabilitation using vision and non-vision based sensors: A systematic review. *Bosnian Journal of Basic Medical Sciences, 12(3), 193*. https://doi.org/10.17305/bjbms.2012.2484

Anwary, A. R., Yu, H., & Vassallo, M. (2020). Gait quantification and visualization for digital healthcare. *Health Policy and Technology*, *9*(2), 204-212. https://doi.org/10.1016/j.hlpt.2019.12.004

Arntz, A., Weber, F., Handgraaf, M., Lällä, K., Korniloff, K., Murtonen, K.-P., . . . Grüneberg, C. (2023). Technologies in Home-Based Digital Rehabilitation: Scoping Review. *JMIR Rehabilitation and Assistive Technologies, 10, e43615*. https://doi.org/10.2196/43615

Ataullah, A. H. M., & De Jesus, O. (2024). Gait Disturbances. In *StatPearls*. StatPearls Publishing Copyright © 2024, StatPearls Publishing LLC.

Aung, M. S. H., Thies, S. B., Kenney, L. P. J., Howard, D., Selles, R. W., Findlow, A. H., & Goulermas, J. Y. (2013). Automated Detection of Instantaneous Gait Events Using Time Frequency Analysis and Manifold Embedding. IEEE Transactions on Neural Systems and Rehabilitation Engineering, 21(6), 908-916. https://doi.org/10.1109/tnsre.2013.2239313

Baker, R., Esquenazi, A., Benedetti, M. G., & Desloovere, K. (2016). Gait analysis: clinical facts. *Eur J Phys Rehabil Med*, *52*(4), 560-574.

Bardid, F., Vannozzi, G., Logan, S. W., Hardy, L. L., & Barnett, L. M. (2019). A hitchhiker's guide to assessing young people's motor competence: Deciding what method to use. *Journal of Science and Medicine in Sport*, *22*(3), 311-318. https://doi.org/10.1016/j.jsams.2018.08.007

Bazarevsky, V., Grishchenko, I., Raveendran, K., Zhu, T., Zhang, F., & Grundmann, M. (2020). Blazepose: On-device real-time body pose tracking. *arXiv preprint arXiv:2006.10204*.

Bennett, D. A., Beckett, L. A., Murray, A. M., Shannon, K. M., Goetz, C. G., Pilgrim, D. M., & Evans, D. A. (1996). Prevalence of Parkinsonian Signs and Associated Mortality in a Community Population of Older People. *New England Journal of Medicine*, *334*(2), 71-76. https://doi.org/10.1056/nejm199601113340202

Berg, A. T., Ludwig, N. N., Wojnaroski, M., Chapman, C. A. T., Hommer, R., Conecker, G.,…Downs, J. (2024). FDA Patient-Focused Drug Development Guidances. *Neurology*, *102*(1). https://doi.org/10.1212/wnl.0000000000207958

Bernhardsson, S., Larsson, A., Bergenheim, A., Ho-Henriksson, C.-M., Ekhammar, A., Lange, E., . . . Bornhöft, L. (2023). Digital physiotherapy assessment vs conventional face-to-face physiotherapy assessment of patients with musculoskeletal disorders: A systematic review. PLOS ONE, 18(3), e0283013. https://doi.org/10.1371/journal.pone.0283013

Bloem, B. R., Marinus, J., Almeida, Q., Dibble, L., Nieuwboer, A., Post, B.,…Schrag, A. (2016). Measurement instruments to assess posture, gait, and balance in Parkinson's disease: Critique and recommendations. *Movement Disorders*, *31*(9), 1342-1355. https://doi.org/10.1002/mds.26572

Brandes, M., Schomaker, R., Möllenhoff, G., & Rosenbaum, D. (2008). Quantity versus quality of gait and quality of life in patients with osteoarthritis. Gait & Posture, 28(1), 74-79. https://doi.org/10.1016/j.gaitpost.2007.10.004

Braune, W., & Fischer, O. (1987). The Human Gait. https://doi.org/10.1007/978-3-642-703263

Bronstein, J., Carvey, P., Chen, H., Cory-Slechta, D., Dimonte, D., Duda, J.,…Weisskopf, M. (2009). Meeting Report: Consensus Statement—Parkinson's Disease and the Environment: Collaborative on Health and the Environment and Parkinson's Action Network (CHE PAN) Conference 26–28 June 2007. *Environmental Health Perspectives*, *117*(1), 117-121. https://doi.org/10.1289/ehp.11702

Brunnekreef, J. J., Van Uden, C. J., Van Moorsel, S., & Kooloos, J. G. (2005). Reliability of videotaped observational gait analysis in patients with orthopedic impairments. *BMC Musculoskeletal Disorders*, *6*(1). https://doi.org/10.1186/1471-2474-6-17

Burnfield, J. P. a. J. M. (2010). Gait Analysis: Normal and Pathological Function. *J Sports Sci Med*, *9*(2), 353. https://doi.org/ISBN: 978- 1556427664

Canadian Institute for Health Information. (2021). Profile of Clients in Home Care, 2019–2020. Ottawa, ON: CIHI.

Cattuzzo, M. T., Dos Santos Henrique, R., Ré, A. H. N., De Oliveira, I. S., Melo, B. M., De Sousa Moura, M.,…Stodden, D. (2016). Motor competence and health related physical fitness in youth: A systematic review. *Journal of Science and Medicine in Sport*, *19*(2), 123-129. https://doi.org/10.1016/j.jsams.2014.12.004

Carvalho, L. P., Mate, K. K. V., Cinar, E., Abou-Sharkh, A., Lafontaine, A.-L., & Mayo, N. E. (2020). A new approach toward gait training in patients with Parkinson's Disease. Gait & Posture, 81, 14-20. https://doi.org/10.1016/j.gaitpost.2020.06.031

Cerri, S., Mus, L., & Blandini, F. (2019). Parkinson's Disease in Women and Men: What's the Difference? *Journal of Parkinson's Disease*, *9*(3), 501-515. https://doi.org/10.3233/jpd-191683

Chamorro-Moriana, G., Ridao-Fernández, C., Ojeda, J., Benítez-Lugo, M., & Sevillano, J. L. (2016). Reliability and Validity Study of the Chamorro Assisted Gait Scale for People with Sprained Ankles, Walking with Forearm Crutches. *PLOS ONE*, *11*(5), e0155225. https://doi.org/10.1371/journal.pone.0155225

Chizeck, H. (1997). Fuzzy model identification for classification of gait events in paraplegics. *IEEE Transactions on Fuzzy Systems*, *5*(4), 536-544.

Clarke, J. E., & Eccleston, C. (2009). Assessing the quality of walking in adults with chronic pain: The development and preliminary psychometric evaluation of the Bath Assessment of Walking Inventory. *European Journal of Pain*, *13*(3), 305-311. https://doi.org/10.1016/j.ejpain.2008.04.009

Connie, T., Aderinola, T. B., Ong, T. S., Goh, M. K. O., Erfianto, B., & Purnama, B. (2022). Pose-Based Gait Analysis for Diagnosis of Parkinson's Disease. *Algorithms*, *15*(12), 474. https://doi.org/10.3390/a15120474

Coutts, F. (1999). Gait analysis in the therapeutic environment. *Manual Therapy*, *4*(1), 2-10. https://doi.org/https://doi.org/10.1016/S1356-689X(99)80003-4

Creaby, M. W., & Cole, M. H. (2018). Gait characteristics and falls in Parkinson's disease: A systematic review and meta-analysis. *Parkinsonism & Related Disorders*, *57*, 1-8. https://doi.org/10.1016/j.parkreldis.2018.07.008

Daly, J. J., Nethery, J., McCabe, J. P., Brenner, I., Rogers, J., Gansen, J.,…Holcomb, J. (2009). Development and testing of the Gait Assessment and Intervention Tool (G.A.I.T.): A measure of coordinated gait components. *Journal of Neuroscience Methods*, *178*(2), 334-339. https://doi.org/10.1016/j.jneumeth.2008.12.016

Dasgupta, P., Vanswearingen, J., Godfrey, A., Redfern, M., Montero-Odasso, M., & Sejdic, E. (2021). Acceleration Gait Measures as Proxies for Motor Skill of Walking: A Narrative Review. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, *29*, 249-261. https://doi.org/10.1109/tnsre.2020.3044260

David, & Perona, P. (2014). Toward a Science of Computational Ethology. *Neuron*, *84*(1), 18-31. https://doi.org/10.1016/j.neuron.2014.09.005

De Rijk, M. C., Tzourio, C., Breteler, M. M., Dartigues, J. F., Amaducci, L., Lopez-Pousa, S.,…Rocca, W. A. (1997). Prevalence of parkinsonism and Parkinson's disease in Europe: the EUROPARKINSON Collaborative Study. European Community Concerted Action on the Epidemiology of Parkinson's disease. *Journal of Neurology, Neurosurgery & Psychiatry*, *62*(1), 10-15. https://doi.org/10.1136/jnnp.62.1.10

Di Biase, L., Di Santo, A., Caminiti, M. L., De Liso, A., Shah, S. A., Ricci, L., & Di Lazzaro, V. (2020). Gait Analysis in Parkinson's Disease: An Overview of the Most Accurate Markers for Diagnosis and Symptoms Monitoring. *Sensors*, *20*(12), 3529. https://doi.org/10.3390/s20123529

Dickens, W. E., & Smith, M. F. (2006). Validation of a visual gait assessment scale for children with hemiplegic cerebral palsy. *Gait & Posture*, *23*(1), 78-82. https://doi.org/10.1016/j.gaitpost.2004.12.002

Dill, S., Rösch, A., Rohr, M., Güney, G., De Witte, L., Schwartz, E., & Hoog Antink, C. (2023). Accuracy Evaluation of 3D Pose Estimation with MediaPipe Pose for Physical Exercises. *Current Directions in Biomedical Engineering*, *9*(1), 563-566. https://doi.org/10.1515/cdbme2023-1141

Dorsey, E. R., Elbaz, A., Nichols, E., Abbasi, N., Abd-Allah, F., Abdelalim, A.,…Murray, C. J. L. (2018). Global, regional, and national burden of Parkinson's disease, 1990–2016: a systematic analysis for the Global Burden of Disease Study 2016. *The Lancet Neurology*, *17*(11), 939-953. https://doi.org/10.1016/s1474-4422(18)30295-3

Eastlack, M. E., Arvidson, J., Snyder-Mackler, L., Danoff, J. V., & McGarvey, C. L. (1991). Interrater Reliability of Videotaped Observational Gait-Analysis Assessments. Physical Therapy, 71(6), 465-472. https://doi.org/10.1093/ptj/71.6.465

Egger-Rainer, A. (2019). Enhancing validity through cognitive interviewing. A methodological example using the Epilepsy Monitoring Unit Comfort Questionnaire. *Journal of Advanced Nursing*, *75*(1), 224-233. https://doi.org/10.1111/jan.13867

Ferguson, L. W., Rajput, A. H., & Rajput, A. (2016). Early-onset vs. Late-onset Parkinson's disease: A Clinical-pathological Study. *Canadian Journal of Neurological Sciences / Journal Canadien des Sciences Neurologiques*, *43*(1), 113-119. https://doi.org/10.1017/cjn.2015.244

Ferrari, V., Marín-Jiménez, M., & Zisserman, A. (2009). 2D Human Pose Estimation in TV Shows. In (pp. 128-147). Springer Berlin Heidelberg. https://doi.org/10.1007/978-3-64203061-1_7

Field-Fote, E. C., Fluet, G. G., Schafer, S. D., Schneider, E. M., Smith, R., Downey, P. A., &

Ruhl, C. D. (2001). THE SPINAL CORD INJURY FUNCTIONAL AMBULATION INVENTORY (SCI-FAI). *Journal of Rehabilitation Medicine*, *33*(4), 177-181. https://doi.org/10.1080/165019701750300645

Foundation MJF. https://www.michaeljfox.org/publication/parkinsons-disease-economicburden-patients-families-and-federal-government-52-billion#:~:text. 2019.

Ginis, P., Pirani, R., Basaia, S., Ferrari, A., Chiari, L., Heremans, E.,…Nieuwboer, A. (2017). Focusing on heel strike improves toe clearance in people with Parkinson's disease: an observational pilot study. *Physiotherapy*, *103*(4), 485-490. https://doi.org/10.1016/j.physio.2017.05.001

Goetz, C. G. (2011). The History of Parkinson's Disease: Early Clinical Descriptions and Neurological Therapies. *Cold Spring Harbor Perspectives in Medicine*, *1*(1), a008862a008862. https://doi.org/10.1101/cshperspect.a008862

Grimes, D. A., & Bulman, D. E. (2002). Parkinson's genetics—creating exciting new insights. *Parkinsonism & Related Disorders*, *8*(6), 459-464. https://doi.org/10.1016/s1353-8020(02)00030-5

Grimes, D., Fitzpatrick, M., Gordon, J., Miyasaki, J., Fon, E. A., Schlossmacher, M.,…Hutton, B. (2019). Canadian guideline for Parkinson disease. *Canadian Medical Association Journal*, *191*(36), E989-E1004. https://doi.org/10.1503/cmaj.181504

Guk, K., Han, G., Lim, J., Jeong, K., Kang, T., Lim, E.-K., & Jung, J. (2019). Evolution of Wearable Devices with Real-Time Disease Monitoring for Personalized Healthcare. *Nanomaterials*, *9*(6), 813. https://doi.org/10.3390/nano9060813

Guo, Y., Yang, J., Liu, Y., Chen, X., & Yang, G.-Z. (2022). Detection and assessment of Parkinson's disease based on gait analysis: A survey. Frontiers in Aging Neuroscience, 14. https://doi.org/10.3389/fnagi.2022.916971

Gurchiek, R. D., Choquette, R. H., Beynnon, B. D., Slauterbeck, J. R., Tourville, T. W., Toth, M. J., & McGinnis, R. S. (2019). Open-Source Remote Gait Analysis: A Post-Surgery Patient Monitoring Application. *Scientific Reports*, *9*(1). https://doi.org/10.1038/s41598-019-54399-1

Hausdorff, J. M., Hillel, I., Shustak, S., Del Din, S., Bekkers, E. M. J., Pelosin, E.,…Mirelman,

A. (2018). Everyday Stepping Quantity and Quality Among Older Adult Fallers With and Without Mild Cognitive Impairment: Initial Evidence for New Motor Markers of Cognitive Deficits? *The Journals of Gerontology: Series A*, *73*(8), 1078-1082. https://doi.org/10.1093/gerona/glx187

Hendriks, M. M. S., Vos-Van Der Hulst, M., Weijs, R. W. J., Van Lotringen, J. H., Geurts, A. C. H., & Keijsers, N. L. W. (2022). Using Sensor Technology to Measure Gait Capacity and Gait Performance in Rehabilitation Inpatients with Neurological Disorders. Sensors, 22(21), 8387. https://doi.org/10.3390/s22218387

Hii, C. S. T., Gan, K. B., Zainal, N., Mohamed Ibrahim, N., Azmin, S., Mat Desa, S. H.,…You, H. W. (2023). Automated Gait Analysis Based on a Marker-Free Pose Estimation Model. *Sensors*, *23*(14), 6489. https://doi.org/10.3390/s23146489

Holden, S. K., Jones, W. E., Baker, K. A., Boersma, I. M., & Kluger, B. M. (2016). Outcome Measures for Parkinson's Disease Dementia: A Systematic Review. *Movement Disorders Clinical Practice*, *3*(1), 9-18. https://doi.org/10.1002/mdc3.12225

Hughes, K. A., & Bell, F. (1994). Visual assessment of hemiplegic gait following stroke: pilot study. *Archives of Physical Medicine and Rehabilitation*, *75*(10), 1100-1107. https://doi.org/10.1016/0003-9993(94)90085-x

Hulteen, R. M., Morgan, P. J., Barnett, L. M., Stodden, D. F., & Lubans, D. R. (2018). Development of Foundational Movement Skills: A Conceptual Model for Physical Activity Across the Lifespan. *Sports Medicine*, *48*(7), 1533-1540. https://doi.org/10.1007/s40279-0180892-6

Hulleck, A. A., Menoth Mohan, D., Abdallah, N., El Rich, M., & Khalaf, K. (2022). Present and future of gait assessment in clinical practice: Towards the application of novel trends and technologies [Review]. Frontiers in Medical Technology, 4. https://doi.org/10.3389/fmedt.2022.901331

Isman, R. E., & Inman, V. T. (1969). Anthropometric studies of the human foot and ankle. *Bulletin of prosthetics research*.

Kaneko, M., Morimoto, Y., Kimura, M., Fuchimoto, K., & Fuchimoto, T. (1991). A kinematic analysis of walking and physical fitness testing in elderly women. *Can J Sport Sci*, *16*(3), 223228.

Keren, K., Busse, M., Fritz, N. E., Muratori, L. M., Gazit, E., Hillel, I.,…Quinn, L. (2021). Quantification of Daily-Living Gait Quantity and Quality Using a Wrist-Worn Accelerometer in Huntington's Disease. *Frontiers in Neurology*, *12*. https://doi.org/10.3389/fneur.2021.719442

Kim, S. M., Kim, D. H., Yang, Y., Ha, S. W., & Han, J. H. (2018). Gait Patterns in Parkinson's Disease with or without Cognitive Impairment. *Dementia and Neurocognitive Disorders*, *17*(2), 57. https://doi.org/10.12779/dnd.2018.17.2.57

Kirtley, C. (2006). *Clinical gait analysis: theory and practice*. Elsevier Health Sciences.

Krebs, D. E., Edelstein, J. E., & Fishman, S. (1985). Reliability of Observational Kinematic Gait Analysis. Physical Therapy, 65(7), 1027-1033. https://doi.org/10.1093/ptj/65.7.1027

Kyriazis, V. (2001). Gait analysis techniques. *Journal of Orthopaedics and Traumatology*, *2*(1), 1-6. https://doi.org/10.1007/pl00012205

Lamont, R. M., Morris, M. E., Woollacott, M. H., & Brauer, S. G. (2012). Community Walking in People with Parkinson's Disease. *Parkinson's Disease*, *2012*, 1-8. https://doi.org/10.1155/2012/856237

Landis, J. R., & Koch, G. G. (1977). The measurement of observer agreement for categorical data. *Biometrics*, *33*(1), 159–174

Latreche, A., Kelaiaia, R., Chemori, A., & Kerboua, A. (2023). Reliability and validity analysis of MediaPipe-based measurement system for some human rehabilitation motions. *Measurement*, *214*, 112826. https://doi.org/10.1016/j.measurement.2023.112826

Leslie, W. D., O'Donnell, S., Lagacé, C., Walsh, P., Bancej, C., Jean, S.,…Jaglal, S. (2010). Population-based Canadian hip fracture rates with international comparisons. *Osteoporosis International*, *21*(8), 1317-1322. https://doi.org/10.1007/s00198-009-1080-1

Liao, Y., Thompson, C., Peterson, S., Mandrola, J., & Beg, M. S. (2019). The Future of Wearable Technologies and Remote Monitoring in Health Care. *American Society of Clinical Oncology Educational Book*(39), 115-121. https://doi.org/10.1200/edbk_238919

Liljequist, D., Elfving, B., & Skavberg Roaldsen, K. (2019). Intraclass correlation – A discussion and demonstration of basic features. PLOS ONE, 14(7), e0219854. https://doi.org/10.1371/journal.pone.0219854

Lord, S. E., Halligan, P. W., & Wade, D. T. (1998). Visual gait analysis: the development of a clinical assessment and scale. *Clinical Rehabilitation*, *12*(2), 107-119. https://doi.org/10.1191/026921598666182531

Lovejoy, C. O., Heiple, K. G., & Burstein, A. H. (1973). The gait of <i>Australopithecus</i>. *American Journal of Physical Anthropology*, *38*(3), 757-779. https://doi.org/10.1002/ajpa.1330380315

Mackey, A. H., Lobb, G. L., Walt, S. E., & Stott, N. S. (2003). Reliability and validity of the Observational Gait Scale in children with spastic diplegia. *Developmental Medicine & Child Neurology*, *45*(1), 4-11. https://doi.org/10.1111/j.1469-8749.2003.tb00852.x

Macri, F., Marques, L. F., Backer, R. C., Santos, M. J., & Belangero, W. D. (2012). Validation of a standardised gait score to predict the healing of tibial fractures. *The Journal of Bone and Joint Surgery. British volume*, *94-B*(4), 544-548. https://doi.org/10.1302/0301-620x.94b4.27927

Marey, E.-J. (1894). *Le mouvement*. G. Masson.

Mate, K. K. V., & Mayo, N. E. (2020). Clinically Assessed Walking Capacity Versus RealWorld Walking Performance in People with Multiple Sclerosis. International Journal of MS Care, 22(3), 143-150. https://doi.org/10.7224/1537-2073.2019-047

Mate, K. K., Abou-Sharkh, A., Morais, J. A., & Mayo, N. E. (2019). Real-Time Auditory Feedback–Induced Adaptation to Walking Among Seniors Using the Heel2Toe Sensor: Proofof-Concept Study. *JMIR Rehabilitation and Assistive Technologies*, *6*(2), e13889. https://doi.org/10.2196/13889

Mayo, N. E., Mate, K. K. V., Fellows, L. K., Morais, J. A., Sharp, M., Lafontaine, A.L.,…Sharkh, A.-A. (2024). Real-time Auditory Feedback for Improving Gait and Walking in People with Parkinson's Disease: A Pilot and Feasibility Trial. Cold Spring Harbor Laboratory. https://dx.doi.org/10.1101/2024.01.04.24300838

Mayo, N., Sharkh, A. A., & Mate, K. (2023). Fall risk assessment from a wearable sensor in seniors and people with neurological conditions. *Journal of the Neurological Sciences*, *455*, 122147. https://doi.org/10.1016/j.jns.2023.122147

Mayo, N. E., Figueiredo, S., Ahmed, S., & Bartlett, S. J. (2017). Montreal Accord on PatientReported Outcomes (PROs) use series – Paper 2: terminology proposed to measure what matters in health. *Journal of Clinical Epidemiology*, *89*, 119-124. https://doi.org/10.1016/j.jclinepi.2017.04.013

Mayo, N. E. (2016). Stroke Rehabilitation at Home. *Stroke*, *47*(6), 1685-1691. https://doi.org/10.1161/strokeaha.116.011309

McLeod, L. D., Coon, C. D., Martin, S. A., Fehnel, S. E., & Hays, R. D. (2011). Interpreting patient-reported outcome results: US FDA guidance and emerging methods. *Expert Review of Pharmacoeconomics & Outcomes Research*, *11*(2), 163-169. https://doi.org/10.1586/erp.11.12

Micó-Amigo, M. E., Bonci, T., Paraschiv-Ionescu, A., Ullrich, M., Kirk, C., Soltani, A.,…Del Din, S. (2023). Assessing real-world gait with digital technology? Validation, insights and recommendations from the Mobilise-D consortium. *Journal of NeuroEngineering and Rehabilitation*, *20*(1). https://doi.org/10.1186/s12984-023-01198-5

Morris, J. N., & Hardman, A. E. (1997). Walking to Health. *Sports Medicine*, *23*(5), 306-332. https://doi.org/10.2165/00007256-199723050-00004

Mroz, S., Baddour, N., McGuirk, C., Juneau, P., Tu, A., Cheung, K., & Lemaire, E. (2021). Comparing the Quality of Human Pose Estimation with BlazePose or OpenPose.

Muro-De-La-Herran, A., Garcia-Zapirain, B., & Mendez-Zorrilla, A. (2014). Gait Analysis Methods: An Overview of Wearable and Non-Wearable Systems, Highlighting Clinical Applications. *Sensors*, *14*(2), 3362-3394. https://doi.org/10.3390/s140203362

Nguyen, G., King, K., & Stirling, L. (2023). Telerehabilitation use and experiences in occupational and physical therapy through the early stages of the COVID-19 pandemic. *PLOS ONE*, *18*(11), e0291605. https://doi.org/10.1371/journal.pone.0291605

Norman, G. R., & Streiner, D. L. (2008). *Biostatistics: the bare essentials*. PMPH USA (BC Decker).

Okochi, J., Takahashi, T., Takamuku, K., & Escorpizo, R. (2013). Staging of mobility, transfer and walking functions of elderly persons based on the codes of the International Classification of Functioning, Disability and Health. *BMC Geriatrics*, *13*(1), 16. https://doi.org/10.1186/1471-2318-13-16

Okumiya, K., Matsubayashi, K., Nakamura, T., Fujisawa, M., Osaki, Y., Doi, Y., & Ozawa, T. (1998). THE TIMED "UP & GO" TEST IS A USEFUL PREDICTOR OF FALLS IN COMMUNITY-DWELLING OLDER PEOPLE. *Journal of the American Geriatrics Society*, *46*(7), 928-929. https://doi.org/10.1111/j.1532-5415.1998.tb02737.x

Ometov, A., Shubina, V., Klus, L., Skibińska, J., Saafi, S., Pascacio, P.,…Lohan, E. S. (2021). A Survey on Wearable Technology: History, State-of-the-Art and Current Challenges. *Computer Networks*, *193*, 108074. https://doi.org/10.1016/j.comnet.2021.108074

Organization, W. H. (2007). *International Classification of Functioning, Disability, and Health: Children & Youth Version: ICF-CY*. World Health Organization.

Perry, J. P., Burnfield, J. M. (2010). Gait analysis: Normal and pathological function. Journal of Sports Science and Medicine, 9(2), 353.

Perry, J. (1992). *Gait Analysis: Normal and Pathological Function*. SLACK.

Pirker, W., & Katzenschlager, R. (2017). Gait disorders in adults and the elderly. *Wiener klinische Wochenschrift*, *129*(3), 81-95. https://doi.org/10.1007/s00508-016-1096-4

Plate, A., Sedunko, D., Pelykh, O., Schlick, C., Ilmberger, J. R., & Bötzel, K. (2015). Normative data for arm swing asymmetry: How (a)symmetrical are we? *Gait & Posture*, *41*(1), 13-18. https://doi.org/10.1016/j.gaitpost.2014.07.011

Pohl, P. S., Winstein, C. J., & Fisher, B. E. (1996). The Locus of Age-Related Movement Slowing: Sensory Processing in Continuous Goal-Directed Aiming. *The Journals of Gerontology Series B: Psychological Sciences and Social Sciences*, *51B*(2), P94-P102. https://doi.org/10.1093/geronb/51b.2.p94

Powers, J. H., 3rd, Patrick, D. L., Walton, M. K., Marquis, P., Cano, S., Hobart, J.,…Burke, L. B. (2017). Clinician-Reported Outcome Assessments of Treatment Benefit: Report of the ISPOR Clinical Outcome Assessment Emerging Good Practices Task Force. *Value Health*, *20*(1), 2-14. https://doi.org/10.1016/j.jval.2016.11.005

Raccagni, C., Nonnekes, J., Bloem, B. R., Peball, M., Boehme, C., Seppi, K., & Wenning, G. K. (2020). Gait and postural disorders in parkinsonism: a clinical approach. *Journal of Neurology*, *267*(11), 3169-3176. https://doi.org/10.1007/s00415-019-09382-1

Ramesh, S. H., Lemaire, E. D., Tu, A., Cheung, K., & Baddour, N. (2023). Automated Implementation of the Edinburgh Visual Gait Score (EVGS) Using OpenPose and Handheld Smartphone Video. *Sensors*, *23*(10), 4839. https://doi.org/10.3390/s23104839

Rancho Los Amigos Medical Center Professional Staff, A., Rancho Los Amigos Medical Center Pathokinesiology, S., & Rancho Los Amigos Medical Center Physical Therapy, D. (1989). *Observational gait analysis handbook*. Professional Staff Association, Rancho Los Amigos Medical Center.

Ridao-Fernández, C., Pinero-Pinto, E., & Chamorro-Moriana, G. (2019). Observational Gait Assessment Scales in Patients with Walking Disorders: Systematic Review. *BioMed Research International*, *2019*, 1-12. https://doi.org/10.1155/2019/2085039

Rudisch, J., Jöllenbeck, T., Vogt, L., Cordes, T., Klotzbier, T. J., Vogel, O., & Wollesen, B. (2021). Agreement and consistency of five different clinical gait analysis systems in the assessment of spatiotemporal gait parameters. *Gait & Posture*, *85*, 55-64. https://doi.org/10.1016/j.gaitpost.2021.01.013

Salbach, N. M., Mayo, N. E., Wood-Dauphinee, S., Hanley, J. A., Richards, C. L., & Côté, R. (2004). A task-orientated intervention enhances walking distance and speed in the first year post stroke: a randomized controlled trial. *Clinical Rehabilitation*, *18*(5), 509-519. https://doi.org/10.1191/0269215504cr763oa

Savelberg, H., & De Lange, A. (1999). Assessment of the horizontal, fore-aft component of the ground reaction force from insole pressure patterns by using artificial neural networks. *Clinical Biomechanics*, *14*(8), 585-592.

Schrag, A., Ben-Shlomo, Y., & Quinn, N. (2002). How common are complications of Parkinson's disease? *Journal of Neurology*, *249*(4), 419-423. https://doi.org/10.1007/s004150200032

Sethi, D., Bharti, S., & Prakash, C. (2022). A comprehensive survey on gait analysis: History, parameters, approaches, pose estimation, and future work. *Artificial Intelligence in Medicine*, *129*, 102314. https://doi.org/10.1016/j.artmed.2022.102314

Shanahan, C. J., Boonstra, F. M. C., Cofré Lizama, L. E., Strik, M., Moffat, B. A., Khan, F.,…Kolbe, S. C. (2018). Technologies for Advanced Gait and Balance Assessments in People with Multiple Sclerosis. *Frontiers in Neurology*, *8*. https://doi.org/10.3389/fneur.2017.00708

Smulders, K., Dale, M. L., Carlson-Kuhta, P., Nutt, J. G., & Horak, F. B. (2016). Pharmacological treatment in Parkinson's disease: Effects on gait. *Parkinsonism & Related Disorders*, *31*, 3-13. https://doi.org/10.1016/j.parkreldis.2016.07.006

Stenum, J., Cherry-Allen, K. M., Pyles, C. O., Reetzke, R. D., Vignos, M. F., & Roemmich, R. T. (2021). Applications of Pose Estimation in Human Health and Performance across the Lifespan. *Sensors*, *21*(21), 7315. https://doi.org/10.3390/s21217315

Stenum, J., Rossi, C., & Roemmich, R. T. (2021). Two-dimensional video-based analysis of human gait using pose estimation. *PLOS Computational Biology*, *17*(4), e1008935. https://doi.org/10.1371/journal.pcbi.1008935

Stucki, G., Cieza, A., Ewert, T., Kostanjsek, N., Chatterji, S., & Üstün, T. B. (2002). Application of the International Classification of Functioning, Disability and Health (ICF) in clinical practice. *Disability and rehabilitation*, *24*(5), 281-282.

Tao, W., Liu, T., Zheng, R., & Feng, H. (2012). Gait Analysis Using Wearable Sensors. *Sensors*, *12*(2), 2255-2283. https://doi.org/10.3390/s120202255

Thomas, M., Jankovic, J., Suteerawattananon, M., Wankadia, S., Caroline, K. S., Vuong, K. D., & Protas, E. (2004). Clinical gait and balance scale (GABS): validation and utilization. *Journal of the Neurological Sciences*, *217*(1), 89-99. https://doi.org/10.1016/j.jns.2003.09.005

Tomita, Y., Sekiguchi, Y., & Mayo, N. E. (2024). Efficacy of a Single-Bout of Auditory Feedback Training on Gait Performance and Kinematics in Healthy Young Adults. *Sensors*, *24*(10), 3206. https://doi.org/10.3390/s24103206

Tosin, M. H., Goetz, C. G., & Stebbins, G. T. (2024). Patient With Parkinson Disease and Care Partner Perceptions of Key Domains Affecting Health-Related Quality of Life. *Neurology*, *102*(3). https://doi.org/10.1212/wnl.0000000000208028

Uysal, İ., Özden, F., Tuna, S., & Tümtürk, İ. (2023). Psychometric properties of the Edinburgh Visual Gait Score in children with spastic cerebral palsy. *Egyptian Pediatric Association Gazette*, *71*(1). https://doi.org/10.1186/s43054-023-00175-w

Vadnerkar, A., Figueiredo, S., Mayo, N. E., & Kearney, R. E. (2014). Classification of gait quality for biofeedback to improve heel-to-toe gait. 36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society, 3626-3629. https://doi.org/10.1109/EMBC.2014.6944408

Vadnerkar, A., Figueiredo, S., Mayo, N. E., & Kearney, R. E. (2018). Design and Validation of a Biofeedback Device to Improve Heel-to-Toe Gait in Seniors. IEEE Journal of Biomedical and Health Informatics, 22(1), 140-146. https://doi.org/10.1109/jbhi.2017.2665519

Verghese, J., Holtzer, R., Lipton, R. B., & Wang, C. (2009). Quantitative Gait Markers and Incident Fall Risk in Older Adults. *The Journals of Gerontology Series A: Biological Sciences and Medical Sciences*, *64A*(8), 896-901. https://doi.org/10.1093/gerona/glp033

Vicianova, M. (2015). Historical Techniques of Lie Detection. *Europe's Journal of Psychology*, *11*(3), 522-534. https://doi.org/10.5964/ejop.v11i3.919

Vun, D. S. Y., Bowers, R., & McGarry, A. (2024). Vision-based motion capture for the gait analysis of neurodegenerative diseases: A review. *Gait & Posture*, *112*, 95-107. https://doi.org/10.1016/j.gaitpost.2024.04.029

Webber, J. T., & Raichlen, D. A. (2016). The role of plantigrady and heel-strike in the mechanics and energetics of human walking with implications for the evolution of the human foot. *Journal of Experimental Biology*, *219*(23), 3729-3737. https://doi.org/10.1242/jeb.138610

Winter, D. A., Olney, S. J., Conrad, J., White, S. C., Ounpuu, S., & Gage, J. R. (1990). Adaptability of Motor Patterns in Pathological Gait. In J. M. Winters & S. L. Y. Woo (Eds.), *Multiple Muscle Systems: Biomechanics and Movement Organization* (pp. 680-693). Springer New York. https://doi.org/10.1007/978-1-4613-9030-5_44

Wrisley, D. M., & Kumar, N. A. (2010). Functional Gait Assessment: Concurrent, Discriminative, and Predictive Validity in Community-Dwelling Older Adults. *Physical Therapy*, *90*(5), 761-773. https://doi.org/10.2522/ptj.20090069

Wu, T., Liu, J., Zhang, H., Hallett, M., Zheng, Z., & Chan, P. (2015). Attention to Automatic Movements in Parkinson's Disease: Modified Automatic Mode in the Striatum. *Cerebral Cortex*, *25*(10), 3330-3342. https://doi.org/10.1093/cercor/bhu135

Xu, T., Dong, W., Liu, J., Yin, P., Wang, Z., Zhang, L., & Zhou, M. (2024). Disease burden of Parkinson's disease in China and its provinces from 1990 to 2021: findings from the global burden of disease study 2021. *The Lancet Regional Health - Western Pacific*, *46*, 101078. https://doi.org/10.1016/j.lanwpc.2024.101078

Yang, Y., Liu, P., Sun, Y., Yu, N., Wu, J., & Han, J. (2021). A Video-Based Method to Classify Abnormal Gait for Remote Screening of Parkinson's Disease.

Zanin, M., Olivares, F., Pulido-Valdeolivas, I., Rausell, E., & Gomez-Andres, D. (2022). Gait analysis under the lens of statistical physics. Computational and Structural Biotechnology Journal, 20, 3257-3267. https://doi.org/10.1016/j.csbj.2022.06.022