CHALLENGES AND POSSIBLE RISK FACTORS ASSOCIATED WITH USING WEARABLE DEVICES FOR ASSESSING THE MOTOR SYMPTOMS OF PEOPLE WITH PARKINSON'S DISEASE: A SCOPING REVIEW

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BY

LEE WEN KE

A Research proposal submitted to the Department of Physiotherapy, M. Kandiah Faculty of Medicine and Health Sciences, Universiti Tunku Abdul Rahman, in partial fulfilment of the requirements for the Degree of Bachelor of Physiotherapy (Honours).

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ABSTRACT

Background and Objective: The rising incidence of Parkinson's Disease (PD) underscores the need for innovative strategies to assess its symptoms, especially motor symptoms. Associated issues with functional mobility and reduced capacity to perform activities of daily living among people with PD, can reduce the quality of life. Wearable devices can provide insight and serve as a tool for assessing the impact of interventions. However, despite the potential benefits, it is fraught with challenges and risk factors. This scoping review attempts to address the challenges and possible risk factors associated with using wearable devices in assessing motor symptoms in people with PD.

Methods: This scoping review adhered to the guidelines in the PRISMA-ScR framework. The Scopus database was analysed using the MeSH key search terms to retrieve all eligible studies and peer-reviewed papers using wearable devices to assess motor symptoms in people with PD published from 2019 to 2024 according to the defined criterion.

Results: Forty-six articles were analyzed in the final review. The results were organized into the type of wearable devices used and the related motor symptoms being assessed. The included articles were investigated thoroughly to identify the challenges and possible risk factors in using wearable devices to assess motor symptoms among people with PD.

Conclusion: The challenges and possible risk factors retrieved from the studies were classified into 5 perspectives. The use of wearable devices may lead to inconsistency in data collection, causing incomplete data sets, which not accurately reflect an individual's condition. This leads to misdiagnosis, affecting clinical decision-making. Future studies should aim to incorporate a wider range of databases and include non-motor symptoms to provide a more comprehensive understanding of the impact on all people with PD.

Keywords: Parkinson's Disease, Wearable devices, Motor symptoms, Assessment, Diagnostic tools, Challenges, Scoping review

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APPROVAL SHEET

This Research project entitled **"CHALLENGES AND POSSIBLE RISK FACTORS ASSOCIATED WITH USING WEARABLE DEVICES FOR ASSESSING THE MOTOR SYMPTOMS OF PEOPLE WITH PARKINSON'S DISEASE: A SCOPING REVIEW"** was prepared by LEE WEN KE and submitted as partial fulfilment of the requirements for the degree of Bachelor of Physiotherapy (Honours) at Universiti Tunku Abdul Rahman.

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PERMISSION SHEET

It is hereby certified that **LEE WEN KE** (ID No: **22UMB00411**) has completed this Research project entitled "CHALLENGES AND POSSIBLE RISK FACTORS ASSOCIATED WITH USING WEARABLE DEVICES FOR ASSESSING THE MOTOR SYMPTOMS OF PEOPLE WITH PARKINSON's Disease: A SCOPING REVIEW" under the supervision of Ms Nur Aqliliriana Binti Zainuddin (Supervisor) from the Department of Physiotherapy, M Kandiah Faculty of Medicine and Health sciences, and Mr Tarun Amalnerkar (Co-Supervisor) from the Department of Physiotherapy, M Kandiah Faculty of Medicine and Health sciences.

Yours truly,

(LEE WEN KE)

DECLARATION

I hereby declare that the Research Project is based on my original work except for the quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UTAR or other institutions.

Name: LEE WEN KE

Date: 20th DECEMBER 2024

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LIST OF ABBREVIATIONS

Abbreviations

FOG	Freezing of Gait
IMU	Inertial Measurement Unit
PD	Parkinson’s Disease
PKG	Parkinson’s KinetiGraph
TUG	Time Up and Go
UPDRS	Unified Parkinson’s Disease Rating Scale
UTAR	Universiti Tunku Abdul Rahman

CHAPTER 1

1.0 BACKGROUND

1.1 Background of Study

Parkinson's disease (PD) is a central nervous system (CNS) disorder that progresses over time. PD can be classified into idiopathic PD, secondary parkinsonism, and Parkinson's-plus syndrome (Jankovic & Tan, 2020). Idiopathic PD can be due to unknown reasons or genetic factors. It can be divided into two different subgroups. The first subgroup has postural instability and gait disturbances as dominant symptoms, and the second subgroup has a tremor as a main feature, along with bradykinesia or postural instability (National Institute of Neurological Disorders and Stroke, 2023). The genetic factor is due to the genetic mutation that involves the gene PARK1, PINK1, LRRK2, and SNCA (Vázquez-Vélez & Zoghbi, 2021). On the other hand, secondary parkinsonism is a disease that exhibits similar clinical features as idiopathic PD yet to have a distinct etiologic. Examples of secondary parkinsonism are postencephalitic parkinsonism, toxic parkinsonism, and drug-induced parkinsonism (Berlot et al., 2024). Parkinson-plus syndrome are diseases that affect the substantia nigra which causes the parkinsonian symptoms. The diseases are parkinsonian degeneration (SND), Shy-Drager syndrome, progressive supranuclear palsy (PSP), Juvenile Huntington's disease, etc (Berlot et al., 2024). The stages of PD can be classified by observing the symptoms of the people by using the Hoehn and Yahr scale (Kataoka & Sugie, 2021). It is a five-point scale that is commonly used in the clinical setting (refer to Appendix 1). Other than this, there is another scale known as Braak's staging model which breaks PD into six stages according to the pathological changes in the brain (Laansma et al., 2021) (refer to Appendix II). Assessment of non-motor symptoms in PD is crucial for comprehensive management, as these symptoms significantly impact the quality of life. Non-Motor Symptoms Questionnaire (NMSQuest) is a 30-item self-reported questionnaire which can identify the presence of various non-motor symptoms (Zis et al., 2015). It covers nine domains, including gastrointestinal, urinary, cognition and sleep (refer to Appendix III). Nevertheless, the Non-Motor Symptoms Scale (NMSS) which is a clinician-rated scale assesses the severity and frequency of non-motor symptoms across multiple domains (Joshi et al., 2022). It is particularly useful for evaluating the effect of these symptoms on daily living and quality of life (refer to Appendix IV). These scales enable clinical professionals to assess and evaluate the disease progression which helps to guide the decision making in the plan of care.

PD causes motor and non-motor symptoms through a variety of mechanisms. The primary pathological feature of PD is the degeneration of dopaminergic neurons in the pars compactus of the substantia nigra in the basal ganglia (Kouli et al., 2018). Its function is to produce a neurotransmitter known as dopamine. The degeneration of the dopaminergic neurons leads to the cease of the production of dopamine, which disrupts the balance between excitatory and inhibitory signals required for normal motor functions (Wu et al., 2012). The loss of dopamine alters the functioning of various neurotransmitters within the basal ganglia, including glutamate and GABA (gamma-aminobutyric acid).

This imbalance exacerbates the motor control issues, as the pathways that typically facilitate movement become impaired. The dorsal striatum, which receives input from the substantia nigra, becomes less responsive, leading to difficulties in initiating and executing movements. As dopamine levels decrease, the brain attempts to compensate through changes in other neurotransmitter systems (Radad et al., 2023). However, these compensatory mechanisms are often insufficient to restore normal function. This leads to the progression of motor symptoms over time. Hence, this histological hallmark of PD contributes to the four cardinal symptoms (Jankovic & Tan, 2020). The four cardinal motor symptoms include 1) Rigidity, 2) Bradykinesia/Akinesia, 3) Tremor (4 – 6 Hz), and 4) Postural instability.

According to Moustafa et al. (2016), akinesia, bradykinesia and rigidity are strongly related to dopamine depletion in basal ganglia. They concluded that akinesia and bradykinesia are caused by the lack of D2 receptor stimulation. This reduction contributes to the hyper-excitability of striatal neurons, known as medium spiny neurons (MSNs) (Magrinelli et al., 2016). The MSNs are categorized into two main types based on their projections: 1) Direct Pathway MSNs and 2) Indirect Pathway MSNs (Barry et al., 2018). The direct pathway involves the expression of dopamine D1 receptors to the substantia nigra pars reticulata and internal segment of the globus pallidus to facilitate the movements. In contrast, the indirect pathway helps to express dopamine D2 receptors and project to the external segment of the globus pallidus to inhibit movement. The striatal neurons become hyper-excited is a significant factor contributing to akinesia and bradykinesia by disrupting the balance between the direct and indirect pathways, ultimately impairing motor control (Piantadosi et al., 2024). The hyper-excitability is characterized by changes in action potential firing and membrane potential dynamics, making these neurons more responsive to synaptic inputs (Jáidar et al., 2019). The loss of dopaminergic modulation leads to unopposed excitatory inputs from glutamatergic afferents, which further enhance the excitability of the indirect pathway of MSNs. As the indirect pathways become overactive, it leads to an increased inhibition of movement, resulting in symptoms such as akinesia, bradykinesia and rigidity. Additionally, the rigidity in people with PD is not only associated with dopamine depletion but also increases the discharge of neurons in the subthalamic nucleus (Zhao et al., 2023). The increased firing rates of STN neurons contribute to enhanced inhibitory output to the globus pallidus internus (Gpi) and substantia nigra reticulata (SNr), which in turn leads to increased inhabitation of the motor thalamus.

Tremor is among the earliest motor symptoms of PD (Abusrair et al., 2022). The common type of tremor is the resting tremor, which will be reduced upon movement as well as sleeping (Abusrair et al., 2022). The resting tremor is often described as a “pill-rolling” movement. It usually starts asymmetrically during early stages of PD (Abusrair et al., 2022). As the disease progresses, both sides may become affected. In addition to resting tremors, people with PD may also experience postural tremors and kinetic tremor (Abusrair et al., 2022). Postural tremor occurs when the body maintains a position against gravity, while kinetic tremor occurs during voluntary movements (Puschmann & Wszolek, 2011). Those with tremor-dominant PD tend to have a slower disease progression compared to other subtypes (Moustafa et al., 2016). It rarely continues to worsen beyond a certain point and may even improve over time in some cases. The pathophysiology of tremor in PD is complex and involves multiple interacting mechanisms within the central and peripheral nervous system (Onanong Jitkritsadakul et al., 2017). It is caused by the abnormal oscillatory activity within the basal ganglia-thalamo-corticol circuits (Abusrair et al., 2022). The imbalance activity of pathways can contribute to the generation of tremor, similar to the pathophysiology of movement symptoms in PD. Nevertheless, the cerebellum plays a crucial role in modulating tremor amplitude via the cerebello-thalamo-cortical circuit (Zhong et al., 2022). A recent study discovered that cerebellar over-activity, driven by α-synuclein-related pathological changes in the cerebellum, plays a role in the development of resting tremor in PD (Zhong et al., 2022). Besides, other pathological changes such as lower climbing fiber length and higher Purkinje cell count may also tend to show symptoms of resting tremor in people with PD (Wu & Hallett, 2013). The gradual degeneration of serotonergic neurons in the raphe nuclei and the depletion of serotonin in areas such as the cortex, thalamus, and basal ganglia contribute to the development of tremors (Zhong et al., 2022). This damage appears to have a greater impact on tremor than the degeneration of striatal dopaminergic neurons.

Postural instability is a significant and challenging symptom of PD that affects balance and increases the risk of falls (Palakurthi & Burugupally, 2019). Postural instability refers to the loss of the ability to remain balanced under both dynamic and static conditions (Palakurthi & Burugupally, 2019). This symptom in PD is primarily linked to the degenerative of dopaminergic neurons in the substantia nigra (Skidmore et al., 2022). This degeneration disrupts the normal functioning of the basal ganglia circuity, impairing the ability to control posture and balance (Skidmore et al., 2022). Maintaining postural stability requires the integration of motor outputs and sensory inputs such as visual, vestibular and proprioceptive (Appeadu & Gupta, 2021). There may be deficits in processing these sensory inputs, leading to impaired balance. People with PD commonly experience altered reflexes and impaired motor control, and this significantly contributes to postural instability (Palakurthi & Burugupally, 2019). These factors lead to delayed or inadequate responses to perturbations, making it challenging for people to recover balance when faced with external forces or uneven surfaces. Moreover, people with PD who have cognitive impairment symptoms can further exacerbate postural instability as they face difficulties in attention and executive function (Appeadu & Gupta, 2021). Freezing of gait (FoG) and postural instability are intertwined, as they influence each other behaviourally and neurologically (Heremans et al., 2013). FoG is characterized by a sudden, transient absence in the forward movement of the feet, although to walk (Rahimpour et al., 2021). People with PD often describe their feet are stuck to the ground, with episodes lasting from a few seconds to over 30 seconds (Rahimpour et al., 2021). Freezing episodes are often triggered by specific situations, including initiating movement from a standing position, turning through narrow spaces, approaching doorways and multitasking or experiencing stress (Rahimpour et al., 2021). The underlying mechanisms of FoG remain poorly understood, but several factors contribute to its occurrence. FoG involves a combination of motor and cognitive deficits, specifically difficulties in gait pattern generation and execution function (Heremans et al., 2013). These impairments can hinder the initiation of movement and the adaptation to a changing environment. Approximately 30% of people with PD experience falls each year (Cui & Lewis, 2021). Falls associated with FoG tend to result in more severe injuries compared to falls occurring during standing or other activities (Cui & Lewis, 2021). Studies have shown that people with PD who experience FoG demonstrate significantly poorer postural control compared to those without FoG (Schlenstedt et al., 2016). For instance, people with FoG have been found to have a posterior shift in their centre of pressure (COP) during the stance phase (Schlenstedt et al., 2016). This may limit their ability to initiate forward movement, thereby contributing to freezing episodes (Schlenstedt et al., 2016).

Besides, as the disease progresses, Lewy bodies, which are the cytoplasmic inclusion bodies, will further inhibit the production and transmission of dopamine (Huber et al., 2019). It disrupts the normal functioning of dopaminergic pathways, leading to impaired neurotransmission. The Lewy bodies can be found in multiple brain regions, which are in the olfactory bulb, brainstem, limbic structures and neocortex (Rocha Cabrero & Morrison, 2020). The presence of Lewy bodies in limbic and neocortical regions is associated with cognitive decline and dementia (Patterson et al., 2019). Besides, it can also lead to neuropsychiatric symptoms such as depression, anxiety, and psychosis due to the degeneration of dopaminergic circuity. The other nonmotor symptoms are altered bladder function, excessive saliva, changes in integumentary, dysarthria (difficulty in speaking), dysphagia (difficulty in swallowing), and cognitive issues. These symptoms appear after years of underlying neurodegeneration has started. Thus, this period can be known as prodromal PD. It can be up to fifteen to twenty years.

Healthcare professionals need to assess and monitor the symptoms during the first session as well as at each follow-up visit to gauge how the patient is responding to treatment and how the disease is progressing over time. The most commonly used assessment tools are the timed up-and-go (TUG) test, the Unified Parkinson's Disease Rating Scale (UPDRS), and the freezing of gait questionnaire (FOG-Q). The TUG test is a valuable clinical tool used to assess mobility and fall risk in people with PD (Nocera et al., 2013). The TUG test can assess the ability of a person to perform basic mobility movements, which include sitting to stand, walking for 3 meters, turning and walking back to the chair, and then sitting down (Nocera et al., 2013). According to Morris et al. (2001), the cut-off score in people with PD is 11.5 seconds. Thus, a time of 11.5 seconds or longer indicates a higher risk of falls in these patients (Morris et al., 2001). Next, the UPDRS is also a comprehensive tool for assessing the severity and progression of PD (Ivey et al., 2012). It consists of four components: 1) Part I (Mentation, Behavior, and Mood), 2) Part II (Activities of Daily Living), 3) Part III (Motor Examination), and 4) Part IV (Complications of Therapy) (Morris et al., 2001). Parts I to III contain a Likert scale ranging from 0 indicating normal to 4 indicating severe impairment whereas Part IV uses closed-ended questions (Yes or No) to assess the complication of the treatment (Morris et al., 2001). The total scores from Parts I to III will be summed up, in which higher scores indicate greater disease severity (Morris et al., 2001). However, the UPDRS can only be assessed when the patient is in the "ON" state (Morris et al., 2001). The FOG-Q is a valuable tool for assessing FOG in people with PD (Cronin et al., 2024). It is designed to quantify the frequency and severity of freezing episodes (Cronin et al., 2024). The FOG-Q consists of 6 items, each containing a Likert scale ranging from 0 to 4 (Cronin et al., 2024). The first 2 items assessed the difficulty initiating walking, the third item assessed the frequency of freezing, whereas items 4 to 6 assessed the duration of the freezing episodes (Cronin et al., 2024). The higher the score, the more severe the freezing episodes. However, all the conventional assessment tools have their limitation when it comes to evaluating individuals with PD. Therefore, the use of wearable devices could help address these shortcomings. Besides, clinical decision-making in PD can be significantly hindered by the reliance on traditional assessment methods. These methods often involve subjective evaluations and can be time-consuming, leading to potential inaccuracies in diagnosis and treatment. Traditional assessments often require extensive time for both the clinician and the patient. The need for detailed history taking physical examinations and possibly multiple follow-up visits can delay timely diagnosis and treatment adjustments. A study done by Rossi et al. (2021) reported that the time required for final diagnosis in a clinical setting lasts for 2.75 years in people with PD. Furthermore, studies also showed that symptoms of burnout such as emotional exhaustion and depersonalization were suffered by physiotherapists who were working in an acute care hospital (Rogan et al., 2019). Burnout among physiotherapists treating people with PD is a significant concern, influenced by various factors inherent to the profession and the complexities of managing chronic conditions like PD (Rodríguez-Nogueira et al., 2022).

Several wearable devices are currently being used to assess various aspects of PD, particularly motor symptoms. Accelerometers and gyroscopes are sensors commonly used in wearable devices to measure movement parameters (Godoi et al., 2019). They are typically worn on the waist, wrists and legs to collect data on tremors, bradykinesia and gait disturbance (Godoi et al., 2019). Data from the accelerometers can be used to derive measures of symptom severity, such as amplitude and frequency of tremor, while gyroscopes provide information about body orientation and rotational movements, which is useful for assessing postural instability and gait abnormalities in PD (Channa et al., 2020; Daneault et al., 2021). The combination of these two sensors helps to provide a better detection of turns and a more accurate assessment of gait parameters (Channa et al., 2020; Daneault et al., 2021). Another wrist-worn device, Parkinson's KinetiGraph (PKG) uses an accelerometer to continuously monitor movement (Lu et al., 2020). It resembles a standard watch, making it user-friendly and easy to wear throughout daily activities (Lu et al., 2020). This device also helps to provide objective data on bradykinesia, dyskinesia and tremor, which can help in medication management (Lu et al., 2020). The device employs a fuzzy logic-based algorithm to analyze the collected data, generating scores for bradykinesia and dyskinesia in 2-minute epochs (Ramdhani et al., 2018). This allows for detailed insights into the patient's motor function over time. After the data collection period, the PKG generates a report for healthcare providers, summarizing key metrics such as fluctuation scores (FS) and dyskinesia scores (DKS) (Moreau et al., 2023). Its integration into routine clinical practice has the potential to address unmet needs in PD care, making it a valuable tool for both people with PD and healthcare. Inertial Measurement Units (IMUs), which combine accelerometers and gyroscopes are used in wearable devices to assess postural instability and lower limb impairments in people with PD (Rose et al., 2021). These devices can be worn on the waist or 2020). IMUs provide real-time data on motion and orientation, which is critical for applications requiring immediate feedback (Moreau et al., 2023). They can be used in various environments and applications, from aerospace to consumer electronics (Tirado et al., 2024). IMUs improve GPS reliability in challenging environments, such as indoors or in urban canyons, where satellite signals may be obstructed (Tirado et al., 2024). Moreover, pressure sensors embedded in shoes or insoles can measure gait parameters, such as stride length and cadence, which are affected in people with PD with FoG (Lu et al., 2020). Besides, magnetometers are sensors used in accelerometers and gyroscopes to provide more accurate measurements of movements and posture in people with PD (Sica et al., 2021). This device helps in accurately detecting turns and changes in direction during walking, which is particularly important for people with PD, who often experience difficulties with gait and may freeze during movements (Sica et al., 2021). Nevertheless, this device can also assist in characterizing tremors by providing data on the frequency and amplitude of the tremors experienced by people with PD (Daneault et al., 2021).

Various machine learning models are applied to the extracted features to predict motor symptom severity. The common algorithms used are Random Forest, Linear Regression, Support Vector Machines (SVM), and k-Nearest Neighbors (Knn) (Sotirakis et al., 2023). The Random Forest model constructs multiple decision trees during training and for classification tasks, each tree votes on the predicted class, in which the majority vote determines the final prediction (di Biase et al., 2024). Once relevant features are selected, it will be trained to use the labelled data, where each instance corresponds to a known outcome such as the scores from MDS-UPDRS) (di Biase et al., 2024). So, the model can be used to predict motor symptoms based on the sensor data after training (di Biase et al., 2024). Next, linear regression serves as a straightforward yet effective tool for understanding how various kinematic features correlate with the assessment of motor symptoms. The data such as the MDS-UPDRS score will become the dependent variable while the selected kinematic features from wearable devices will become the independent variable (Lu et al., 2020). The model is then trained using historical data after both variables are known. After training, the model's performance is evaluated using metrics performance such as R-squared and Root Mean Square Error (RMSE) to measure prediction accuracy (Lu et al., 2020). Hence, by inputting new kinematic measurements into the model, researchers can estimate the severity of the motor symptoms without requiring direct assessment (Lu et al., 2020).

Wearable devices allow real-world data collection as they enable continuous monitoring of people with PD in their natural environment, capturing data that may not be evident during clinical assessments (Daneault et al., 2021). This is essential for understanding the variability of symptoms throughout the day and across different contexts (Channa et al., 2020). These wearable devices offer several advantages over traditional clinical assessments, such as the UPDRS. They provide objective, continuous and quantitative data on motor symptoms which can help in monitoring disease progression and optimizing treatment. While wearable technologies offer exciting potential for improving the evaluation of motor symptoms in PD, it's essential to recognize that their implementation is not without obstacles. Careful consideration of the challenges and risk factors involved is necessary to ensure these devices' effective and appropriate use in clinical settings.

1.2 Problem Statement

The growing incidence of Parkinson's disease (PD) highlights the pressing demand for innovative approaches to efficiently monitor and manage the motor and non-motor symptoms of people with PD. The roles of physiotherapists are mostly in assessing and managing the motor symptoms of people with PD.

Concerning recent advances and developments, there is an increasing adoption of wearable devices in various research to identify the effectiveness of these devices in assessing motor symptoms among people with PD. Current works of literature show the accuracy of the assessment of the symptoms, indicating that wearable devices can provide valuable insights into motor symptom progression.

However, there is a lack of comprehensive understanding regarding the challenges and possible risk factors in using wearable devices in assessing motor symptoms among people with PD. These challenges and possible risk factors can potentially affect the treatment decisions.

This scoping review aims to systematically investigate the challenges and possible risk factors with the use of wearable devices for assessing motor symptoms among people with PD. By identifying existing research, this study seeks to identify knowledge gaps and provide recommendations for future research and development. The research will contribute to future planning, testing, and implementation of wearable devices in assessing motor symptoms of people with PD.

1.3 Research Question

1. What challenges and potential risk factors have been studied regarding the use of wearable devices as diagnostic tools in assessing the motor symptoms of people with Parkinson's Disease?
2. How do these challenges and potential risk factors associated with the use of wearable devices impact the assessment and management of people with Parkinson's Disease?

1.4 Aims

To review the comprehensive analysis of existing literature, including meta-analysis, systematic review, observational study, and experimental study to provide a thorough understanding of the challenges and potential risk factors in using wearable devices in assessing motor symptoms of people with Parkinson's Disease.

1.5 Objectives

1. To review the recent literature and to understand current challenges and potential risk factors in using wearable devices in assessing motor symptoms of people with Parkinson's Disease.
2. To evaluate how the challenges and possible risk factors can affect the effectiveness and reliability of wearable devices in assessing and managing people with Parkinson's Disease.

1.6 Operational Definition

1.6.1 Parkinson's Disease

A progressive neurodegenerative disorder primarily affecting the central nervous system (CNS), characterized by the degeneration of dopaminergic neurons in the substantia nigra, leading to a deficiency of dopamine (AlMahadin et al., 2020). It manifests both motor and non-motor symptoms (AlMahadin et al., 2020).

1.6.2 Wearable Devices

Electronic devices that can be worn on the body, often in close contact with the skin, continuously monitor both motor and non-motor symptoms of the patients, enabling healthcare professionals to understand the patient's condition better (Lu et al., 2020).

1.6.3 Scoping Review

A form of evidence synthesis designed to systematically identify and outline the range of available evidence on a specific topic, field, concept, or issue (Munn et al., 2022). It typically encompasses a variety of sources, including primary research, reviews, and non-empirical evidence, and can be conducted within or across contexts (Munn et al., 2022).

1.7 Rationale of Study

There is an increasing trend in the prevalence of Parkinson's Disease (PD) worldwide. PD is the second most common neurodegenerative disorder that is affecting millions globally. Hence, innovative solutions came up as a promising avenue for the continuous assessment of both motor and non-motor symptoms.

The motor symptoms are the hallmark of PD, which significantly affect the activities of daily living (ADLs) of the people with PD thus, decreasing their quality of life (QoL). Our roles as physiotherapists are to improve motor symptoms, functional mobility, and gait, which then leads to our ultimate goal – to reduce the risk of falls and improve the QoL. However, a shortage of manpower as well as time constraints can limit the ability of the physiotherapists to perform a comprehensive assessment. For example, the average time to perform the full UPDRS is approximately 20 minutes. Additionally, it may be necessary for a single physiotherapist to treat multiple patients during a session.

The introduction of wearable devices in physiotherapy assessment offers real-time monitoring of people with PD, providing information about the functional capacities inside or outside of the clinical settings. Besides, the data collected from the sensors are more precise, which may be neglected or missed in conventional assessments. However, despite the potential benefits of wearable devices, there are some challenges and possible risk factors associated with integrating wearable devices into clinical practice, which will be thoroughly investigated in this study. By synthesizing existing research, the study seeks to provide valuable insights that can inform future research and development, ultimately enhancing the utility of wearable devices in clinical practice and improving patient outcomes.

1.8 Scope of Study

This study focuses on examining various types of wearable devices that serve as diagnostic tools in assessing the motor symptoms of people with PD. The analysis included their functionalities and the specific motor symptoms they are designed to assess for example tremors, bradykinesia, and freezing of gait. This study also identified and analysed the challenges and potential risk factors of using wearable devices in assessing people with PD in clinical settings. The scoping review aims to highlight the gaps in existing literature regarding the use of wearable devices for PD assessment. This scoping review also aims to serve as the basis for future systematic review and interventional studies.

CHAPTER 2

LITERATURE REVIEW

2.1 Prevalence of Parkinson's Disease

According to the research done by Ou et al (2021) provides a comprehensive analysis of the global trends in the incidence, prevalence, and years lived with disability associated with PD from the year 1990 to 2019 across 204 countries and territories. Based on the study, the overall age-standardized incidence rate (ASIR) of PD has significantly increased, showing a 159.73% rise in new cases since 1990, and reaching 1081.72 thousand cases by the year 2019 (Ou et al, 2021). Additionally, the age-standardized prevalence has also risen sharply, highlighting an escalating public health challenge. The highest incidence and prevalence rates were found in older populations, especially among individuals over 80 years of age (Ou et al, 2021). This demographic trend highlights the influence of an ageing population on the burden of Parkinson's disease (Ou et al, 2021). Other than this, there is a notable increase in PD was reported in specific countries. The United States of America and Norway showed the largest increasing percentages in PD incidence, with estimated annual percentage changes (EAPCs) of 2.87 (95% CI: 2.35–3.38) and 2.14 (95% CI: 2.00–2.29) respectively (Ou et al, 2021). Furthermore, the global count of years lived with disability (YLDs) attributed to PD has risen by 154.73% since the year 1990, accompanied by an increase in the age-standardized rate (Ou et al, 2021).

A nationwide study in Norway analyzed data from the Norwegian Prescription Database to assess the incidence, prevalence, and mortality of PD between the years 2004 to year 2017 (Brakedal et al., 2022). The study showed the prevalence of PD increased over the observational period, particularly among older age groups, with the highest prevalence in individuals aged 85 and older (Brakedal et al., 2022). The male-to-female prevalence ratio is 1.5 across all age groups (Brakedal et al., 2022). The incidence ratio increased from 1.4 in individuals aged 60 to 2.03 in those over 90 years old (Brakedal et al., 2022).

Another systematic review done by Muangpaisan et al (2009) provided valuable insights into the epidemiology of PD in Asian countries. The study involves several countries in Asia, specifically: China, Japan, Singapore, India, Israel, and Saudi Arabia (Muangpaisan et al, 2009). From the systematic review, the standardized all-age prevalence of PD in door-to-door surveys in Asia ranged from 51.3% to 176.9 per 100,000 population, which is slightly lower than in Western countries (Muangpaisan et al, 2009). Besides, the incidence rates were 8.7 per 100.000 person-years in door-to-door surveys and 6.7 to 8.3 per 100,000 person-years in record-based surveys in Asia (Muangpaisan et al, 2009).

A large-scale, nationwide epidemiological study in China provides important insights into the current prevalence of PD in older adults aged 65 and above (Song et al., 2021). The study showed that the overall crude prevalence of PD in this population is 1.86% with a standardized prevalence of 1.60% (Song et al., 2021). This translates to an estimated 1.98 million people aged 65 and older having PD in China (Song et al., 2021). This study also stated that men have a higher prevalence of PD compared to women with a standardized prevalence of 2.00% and 1.59% respectively (Song et al., 2021). In addition, the study showed the prevalence of PD is higher in urban areas compared to rural areas with a standardized prevalence of 1.98% and 1.49% respectively (Song et al., 2021).

According to the Malaysian Parkinson's Disease Association (MPDA), the prevalence of PD in Malaysia is estimated to be around 20,000 people with PD currently (Hassandarvish, 2019). This number is expected to increase significantly, potentially rising fivefold to 120,000 people with PD in the year 2040 (Hassandarvish, 2019). Furthermore, PD is ranked as the 28th leading cause of death in Malaysia (*Parkinson's Disease in Malaysia*, n.d.). Despite the increasing prevalence of PD, more targeted epidemiological studies are needed to precisely assess the prevalence of PD in the Malaysian population.

There is a rising trend in the global prevalence of Parkinson's disease, with significant trends noted across various regions and populations. An increase in the number of PD cases correlates with a higher overall burden of motor symptoms, such as tremors, rigidity, bradykinesia, and postural instability. These motor symptoms can greatly impact individuals with PD in multiple ways, influencing their daily activities, functional abilities, and overall quality of life (QoL). Therefore, it is essential for healthcare professionals to understand the motor symptoms of PD, as this knowledge facilitates timely assessments and the development of appropriate treatment plans.

2.2 Motor Symptoms of Parkinson's Disease

Parkinson's Disease (PD) is a progressive neurodegenerative disorder primarily central nervous system (CNS), characterized by a range of motor symptoms due to the degeneration of dopaminergic neurons in the substantia nigra (Thorp et al., 2018). The primary motor symptoms of PD include tremors, bradykinesia, rigidity, and postural instability. In addition to the primary symptoms, PD is also associated with a range of other motor-related symptoms, such as freezing of gait, decreased arm swing, and dystonia (Thorp et al., 2018).

2.2.1 Tremor

One of the most distinctive signs of PD is a resting tremor, which often starts distally on one side of the body, typically hands or fingers with a frequency of 4 to 6 Hz (Thorp et al., 2018).

According to a multi-cohort observational study done by Gupta et al (2020), resting tremor is the most common type of tremor among people with PD, comprising 58.2% across all baseline data while action tremor is also common, impacting nearly 40% of the people with PD. This study analyzed data from three distinct cohorts: the Parkinson Progression Marker Initiative (PPMI), the Fox Investigation for New Discovery of Biomarkers (BioFND), and the Parkinson's Disease Biomarkers Program (PDBP). The study stated that people with PD who experience resting tremors have a significantly higher prevalence of action tremors in comparison with people with PD who do not experience resting tremors (Gupta et al, 2020). This trend is consistent across all three cohorts studied. In the PPMI cohort, the prevalence of action tremors was 40.0% in people with PD who experience resting tremors, compared to 30.1% in those without resting tremors (Gupta et al, 2020). In the BioFIND cohort, 48.0% of people with PD who experience resting tremors exhibit action tremors while the prevalence was 40.0% among those without resting tremors (Gupta et al, 2020). In the PDBP cohort, the prevalence of action tremors was 49.9% in people with PD who experienced resting tremors, compared to 21.0% in those without resting tremors.

According to Pasquini et al. (2018), a study was done to investigate the prevalence and progression of different types of tremors in people with early PD as well as to explore the relationship between dopaminergic and serotonergic dysfunction and tremor severity. The study showed that 87.8% of 378 people with PD presented with tremors at baseline, with rest tremors being the most prevalent type with a decreasing trend to 67.9% at a 2-year follow-up (Pasquini et al., 2018). Besides, the study mentioned that postural and kinetic tremors occurred in about 50% of people with PD at both baseline and 2-year follow-up (Pasquini et al., 2018). In addition, the number of people with PD with isolated rest tremors significantly decreased by the follow-up, suggesting a progression in tremor types as the disease advances. The study found that rest tremor severity was inversely correlated with serotonergic transporter availability, indicating that greater serotonergic dysfunction is associated with more severe tremor symptoms (Pasquini et al., 2018).

Tremors are often the first motor symptom of PD and can interfere with daily activities such as writing, dressing, eating, and using technology. Many patients may report that tremors hinder their ability to perform fine motor tasks, which can lead to frustration and a sense of loss of independence. Besides, the presence of tremors can lead to significant emotional distress, which can diminish their self-esteem and overall mental well-being.

1.6.4 Quality of Life

An individual’s perceived well-being and satisfaction with their physical, mental, emotional, and social functioning, as influenced by a health condition, disability, or the physiotherapy treatment itself. It encompasses various aspects of a person’s life that are affected by their physical and mental state (Schramlová et al., 2024).

2.2.2 Bradykinesia

Bradykinesia is one of the hallmark symptoms of PD, which is characterized by the slowness of movement, particularly in the context of initiating voluntary actions.

According to Achbani et al. (2020), the study investigated the differences in clinical profiles of people with PD based on age and gender in Southern Morocco. Among 180 participants, 17% of it exhibited bradykinesia (Achbani et al., 2020). Besides, the study stated that bradykinesia is more prevalent in males (37.6%) compared to females (23.8%) at the early stage of the disease (Achbani et al., 2020). In addition, the study revealed a rising trend in the prevalence of bradykinesia as age increases (Achbani et al., 2020).

The prevalence of bradykinesia is associated with significant functional impairments. Bradykinesia will reduce autonomic movements in people with PD, they may experience diminished spontaneous movements, significantly seen in arm swings and eyes blinking (Deal et al., 2019). This will reduce the fluid motion pattern, leading to a more rigid movement (Herz & Brown, 2023). Besides, they will experience difficulty in initiating a movement (Sarasso et al., 2024). For example, a simple sit to stand task will be challenging for them as rising from a chair can become particularly challenging. Hence, this can lead to fatigue and frustration for patients due to increased time and effort.

2.2.3 Rigidity

Rigidity is the increased resistance to passive movement that is uniform and velocity-independent (Baradaran et al., 2013). It can be classified into lead pipe rigidity and cogwheel rigidity (Baradaran et al., 2013).

A systematic review done by Ferreira-Sánchez et al. (2020) showed an extensive analysis of various objective methods for assessing rigidity in people with PD. Based on the study, rigidity is the primary symptom of PD, which is present in up to 89% of patients (Ferreira-Sánchez et al., 2020). A cross-sectional study was conducted by Achbani et al. (2020) involving 180 people with PD which consists of 117 males and 63 females. The study showed that rigidity symptoms are more prevalent in younger patients and those aged 61 to 70 years old (Achbani et al., 2020). In this study, 33% of the total participants exhibited rigidity symptoms (Achbani et al., 2020).

The constant tension in the muscles can lead to pain and discomfort, contributing to fatigue (Ferreira-Sánchez et al., 2020). This significantly impedes their abilities to engage in ADLs. In addition, stiffness can also happen to facial muscles, causing a mask-like expression. This may be misinterpreted by others as a lack of interest or engagement, affecting social interactions (Borrione, 2014). In conclusion, the presence of rigidity correlated with lower scores on quality-of-life assessments, indicating that those experiencing more severe stiffness reported greater difficulties in daily living and higher levels of distress related to their condition (Cano-de-la-Cuerda et al., 2010).

2.2.4 Postural Instability

Postural instability (PI) is a common and debilitating symptom of PD that significantly impacts the daily lives of those living with the condition (Palakurthi & Burugupally, 2019). It is characterized by the inability to maintain balance and equilibrium under both static and dynamic conditions, such as standing still, preparing to move, or responding to perturbations (Palakurthi & Burugupally, 2019).

A review was done by Palakurthi and Burugupally (2019), postural instability affects approximately 16% of the people with PD, with falls occurring in about 60% of this population. According to Cao et al. (2022), the study provided a comprehensive analysis of the prevalence of axial postural abnormalities in people with PD. The study found that the overall prevalence of axial postural abnormalities among people with PD is 22.1% (Cao et al., 2022).

Postural instability often leads to challenges in maintaining balance, causing a higher risk of falls (Li et al., 2023). Impaired postural control can negatively impact functional tasks like stair climbing and transitioning activities such as supine to sitting, leading to increased dependency on others as well as decreased quality of life (Luna et al., 2024).

2.2.5 Freezing of Gait

Freezing of Gait (FOG) is an unpredictable event that happens in people with PD which may lead to falls, instability, impaired functional independence, and gait issues (Korkusuz et al., 2023).

One meta-analysis by Ge et al. (2020) consisted of 29 studies using 3 databases conducted in China to assess the prevalence of FOG in Parkinson's disease among patients with PD worldwide. It includes patients with PD from China, Europe, Australia, the United States of America, and Israel. The overall prevalence of FOG among patients with PD with FOG is 39.9%. %. The subjects in this study are patients with PD with varying disease durations, hence, this study aimed to study the impact of disease duration on the FOG episodes (Ge et al., 2020). The study indicated that for patients with PD for more than 10 years, the prevalence is the greatest which is 70.8% (Ge et al., 2020). The prevalence of FOG in patients with PD for more than 5 years is 53.3% while the lowest prevalence is 22.4% for patients with PD for less than 5 years (Ge et al., 2020).

A Danish cohort study found that the prevalence of FOG in people with PD was around 39.9% (Terkelsen MH et al., 2023). The outcome measure used in the study is the Freezing of Gait Questionnaire (FOG-Q) (Terkelsen MH et al., 2023). The study mentioned that the prevalence of FOG increases as the disease advances (Terkelsen MH et al., 2023).

A cross-sectional study conducted by Choi et al. (2019) in South Korea to determine the factors associated with FOG in patients with PD was carried out on 157 patients with PD. The setting was in a hospital. The tool utilized in this study is the FOG-Q. Participants who may not have previously recognized FOG in themselves were provided with video prescriptions of FOG to educate them about its characteristics. Hence, this can prevent errors in answering the questionnaire as the patients themselves may not realize that they experienced FOG. Thus, this showed that patients have low awareness of their FOG episodes, which can lead to underreporting and an underestimation of the true prevalence of FOG. The study reported a high prevalence of FOG among patients with PD in South Korea, which is 70.7%. However, FOG rarely happens in a clinical setting compared to when the patients are at home as the patients are taken care of well in the hospital (Amboni et al, 2015). Besides, most of the FOG episodes might be triggered by emotions, environmental factors, and unfixed routines in taking medications (Amboni et al, 2015).

In summary, the motor symptoms of PD significantly impact patients' quality of life. Hence, it is crucial that healthcare professionals assess these symptoms accurately to develop targeted interventions and improve patient outcomes.

2.3 Conventional Assessment of Parkinson's Disease

Conventional assessment methods for Parkinson's disease (PD) primarily rely on rating scales, questionnaires, patient diaries, and clinically based tests (AlMahadin et al., 2020). These tools, known as conventional outcome measures (COMs), evaluate various aspects of the disease, including motor symptoms, non-motor symptoms, and overall disease severity (AlMahadin et al., 2020).

2.3.1 Time Up and Go Test

The timed up and go (TUG) test is a widely used clinical assessment tool in various conditions designed to evaluate a person's mobility, balance, and functional ability (Zeltzer, 2008). It was developed by D. Podsiadlo and S. Richardson in the year 1991(Nicolini-Panisson & Donadio, 2013). It is based on an earlier version called the "Get-up and Go" test, which was proposed by Mathias et al. in 1986 (Nicolini-Panisson & Donadio, 2013).

A systematic review done by Mollinedo and Cancela (2020) included 24 studies that assessed the TUG test's psychometric properties in people with PD, focusing on its reliability, validity, and sensitivity to change. Among the 24 studies, 9 studies analyzed the reliability of the TUG test as moderate to good (Mollinedo and Cancela, 2020). Nest, 17 out of the 24 studies evaluated the validity of the TUG test, reporting good quality scores, especially in assessing balance (Mollinedo and Cancela, 2020). Only 2 out of the 24 studies examined the sensitivity of the TUG test to change, both of the studies reported poor quality scores. Hence, the TUG test may fail to register a significant change even if the patient improves. In certain instances, the TUG test may fail to differentiate between individuals with different levels of mobility, especially those who are less impaired. This can result in ceiling effects, where individuals with higher performance levels receive similar scores (Silva et al., 2017). According to Silva et al. (2017), the study found that 22% of the participants, predominantly those with mild stage PD achieved the highest possible scores on the TUG test, indicating a ceiling effect. In addition, the performance of PD patients on the TUG test can fluctuate considerably based on whether they are in the "on" or "off" phase of their medication cycle (Silva et al., 2017). This inconsistency in results can make it challenging to interpret the findings accurately.

2.3.2 Unified Parkinson's Disease Rating Scale

The Unified Parkinson's Disease Rating Scale (UPDRS) is a comprehensive clinical tool used to assess the severity and progression of PD (Ivey et al., 2012). It was developed in the year 1987 and has become the gold standard in monitoring the response to treatment and understanding the impact of the disease on patients' daily lives. It consists of 6 components that evaluate different aspects of PD (Ivey et al., 2012).

A study done by Siderowf et al. (2002) assessed the test-retest reliability of UPDRS. In this study, the patients were assessed using the UPDRS on two separate occasions (screening and baseline visits) by the same neurologist, with an average interval of 14.6 days between assessments (Siderowf et al., 2002). The reliability was measured using intraclass correlation coefficients (ICCs) for total and subscale scores, while weighted kappa statistics were calculated for individual items (Siderowf et al., 2002). The result showed that the total UPDRS score showed excellent test-retest reliability with an ICC of 0.92 (Siderowf et al., 2002). Besides, the derived symptom-based scales had ICCs ranging from 0.69 to 0.88 (Siderowf et al., 2002). However, the use of UPDRS in assessing people with PD, especially those in early-stage requires clinicians who are expert and well-trained (Hendricks & Khasawneh, 2021). The rating relies on clinician assessments and patient self-reports, which can introduce variability due to subjective interpretations of symptoms and performance (Hendricks & Khasawneh, 2021). In addition, factors such as environmental conditions during assessment or psychological factors can impact the scores, leading to variability that does not reflect the true disease progression (Hendricks & Khasawneh, 2021). Furthermore, the administration of the full scale can take significant time around 10 to 20 minutes, which may be impractical in busy clinical settings, potentially leading to a rushed assessment and less reliable score (Hendricks & Khasawneh, 2021).

Another study done by Abdolahi et al. (2013) assessed the reliability and validity of the modified UPDRS (Mupdrs), which excludes rigidity and retropulsion items. The study measured cross-sectional and longitudinal reliability through interclass correlation coefficients (ICC), internal consistency with Cronbach's alpha, and concurrent validity using Pearson's correlation coefficients (Abdolahi et al., 2013). The result of the study indicated that the Mupdrs exhibited high cross-sectional (ICC $\geq$ 0.92) and longitudinal reliability (ICC $\geq$ 0.92) across the treatment groups (Abdolahi et al., 2013). Moreover, the internal consistency was also high with Cronbach's alpha $\geq$ 0.96 (Abdolahi et al., 2013). Hence, the Mupdrs demonstrated strong concurrent validity with the standard UPDRS, with correlation coefficients reaching up to 0.96 (Abdolahi et al., 2013). However, the removal of the rigidity and retropulsion items will increase the challenges in evaluating the disease progression and severity, especially those in the advanced stage of PD. This will lead to the failure to optimize therapy for the patients.

2.3.3 Freezing of Gait Questionnaire

The freezing of gait questionnaire (FOG-Q) is a clinical tool designed to assess FOG in people with PD (Nilsson et al., 2010). The questionnaire was created by N. Giladi et al. (2000) and was published in the journal *Parkinsonism and Related Disorders.* The questionnaire can be administered by healthcare professionals or completed by patients themselves.

A study done by Giladi et al. (2009) studied the reliability and validity of the FOG-Q as a measurement tool for FOG in people with PD. The research involved a cohort of patients diagnosed with Parkinson's disease who completed the FOGQ. The study evaluated both test-retest reliability and internal consistency, as well as construct and concurrent validity by correlating the FOGQ scores with other established measures of gait and motor function (Giladi et al., 2009). According to the result, the FOG-Q showed excellent test-retest reliability, indicated by high ICCs (Giladi et al., 2009). In addition, the internal consistency was strong, with a Cronbach's alpha confirming that the items within the questionnaire effectively measure the same construct (Giladi et al., 2009). Thus, the FOG-Q demonstrated good construct validity, showing significant correlations with other measures related to gait and motor function, which supports its effectiveness in assessing FOG (Giladi et al., 2009).

The FOG-Q has been translated into different languages. Research done in China focuses on developing a Chinese version of the FOG-Q to assess people with PD and evaluate its reliability and validity (Tao et al., 2021). The study involved translating the original FOGQ into Chinese using a forward-backward translation approach, followed by cultural adaptation through expert review and pretesting. The final version, FOGQ-CH, was then tested for reliability and validity. The FOGQ-CH demonstrated good internal consistency with a Cronbach's alpha (Cα) of 0.823. Test-retest reliability was also satisfactory, with an intraclass correlation coefficient (ICC) of 0.786 for the total score, indicating that the questionnaire produces stable results over time. The FOGQ-CH showed moderate correlations with other established measures, including the Unified Parkinson's Disease Rating Scale (UPDRS) Parts II and III, the Timed Up and Go Test (TUGT), and walking speed (Tao et al., 2021). The area under the ROC curve (AUC) for predicting falls was 0.777, indicating good predictive validity for identifying patients at risk of multiple falls (Tao et al., 2021).

However, the FOG-Q relies on patient self-reporting, which can introduce variability due to differences in individual perceptions of freezing episodes. In addition, the FOG-Q is unable to capture other related motor symptoms that can impact overall mobility and quality of life (QoL) in people with PD (Nilsson et al., 2010). Moreover, the FOG-Q may not be sensitive enough to detect small but clinically significant changes in FOG, making it less effective for monitoring progression or response to treatment in clinical trials (Nilsson et al., 2010).

Due to the limitations of conventional assessments in PD, wearable devices have been introduced and have gained significant attention recently for their potential in assessing motor symptoms in people with PD. The growing interest in using these devices may potentially overcome the limitations of the conventional assessments of the PD, hence, enhancing the accuracy of assessments as well as empowering patients in their disease management.

2.4 Wearable Devices in Assessing People with Parkinson's Disease

To date, wearable devices have been introduced to the rehabilitation field to reduce the burden of physiotherapists as well as to increase the accuracy of the assessments.

A study done by Vescio et al. (2021) reviews the advancements in wearable sensor technology in assessing tremors associated with PD. The review categorizes wearable devices into 3 main classes: 1) Assessment devices, 2) Monitoring devices, and 3) Differential diagnosis devices (Vescio et al., 2021). This study mentioned that wearable devices have shown promising results in accurately assessing tremor characteristics (Vescio et al., 2021). A wrist-mounted accelerometer showed an accuracy of 90% in discriminating essential tremors (Vescio et al., 2021).

According to the review done by Lu et al. (2020), it provides an overview of the current status and prospects of using wearable devices in evaluating motor symptoms in people with PD. The study showed that the wearable devices having gyroscopes or accelerometers have high specificity which is 88% and a high sensitivity of 95% in comparison with the conventional assessment tools (Lu et al., 2020). The wearable devices can effectively quantify bradykinesia parameters such as speed, amplitude, and rhythm (Lu et al., 2020). In addition, the study stated that wearable devices can help identify the symptoms of people with PD in the early stages (Lu et al., 2020). Furthermore, this study stated that gyroscopes and accelerometers also can be used to detect changes in gait patterns among people with PD (Lu et al., 2020). When the sensors are strategically placed on the various body parts, such as the chest, waist, thigh, leg, and foot, the sensors can provide a detailed kinematic and dynamic gait parameter (Lu et al., 2020). The key gait parameters used in assessing the movement patterns are rhythm, symmetry, stride length, amplitude, and periodicity (Lu et al., 2020).

A study done by di Biase et al. (2018) investigated the use of wearable sensors to quantitatively assess bradykinesia and rigidity in people with PD. In the study, 4 indexes were extracted from the magnetoinertial wearable sensor data, which are fatigability, total time, total power, and smoothness (di Biase et al., 2018). The sensors were strategically placed on various anatomical locations, including the middle phalanx of the index finger, the distal phalanx of the thumb, the midpoint of the third metacarpal bone, the midpoint between the radius and ulna, and the midpoint between the greater tubercle of the humerus and the lateral epicondyle (di Biase et al., 2018). The study indicated that the sensors placed on the middle phalanx of the index finger and wrist can provide the most accurate assessments of bradykinesia and rigidity (di Biase et al., 2018).

According to Huang et al. (2023), a systematic review was done to investigate the importance of wearable devices in detecting FOG and falls among patients with PD. A total of 75 articles found from 2 databases were studied on the type of devices, site of wearing, how they function, and the overall performances of the devices (Huang et al., 2023). The wearable devices used in the studies are accelerometers and gyroscopes, which are especially in detecting falls; force sensors, IMU, and bending sensors (Huang et al., 2023). The overall accuracy of these devices was identified, which is from 71.3% to 99.7%, and the overall specificity has a range of 59% to 100% (Huang et al., 2023). The sensitivity of the accelerometer has a range of 70.1% to 99.2% (Huang et al., 2023). According to Pardoel et al. (2022), the sensitivity of the pressure sensor is 77.3% while the specificity is 82.9%. This study investigated the effectiveness of using plantar pressure data from the most affected side (MAS), least affected side (LAS), or both sides for predicting FOG (Pardoel et al., 2022). Another systematic review was done by Demrozi et al. (2020) to examine the mean sensitivity and specificity of accelerometer in detecting FOG. Three axial accelerometer sensors are worn on the back, hip, and ankle (Demrozi et al., 2020). The study was able to predict FOG by identifying the pre-FOG events with an average sensitivity of 94.1% and specificity of 97.1% (Demrozi et al., 2020).

To sum up, the wearable devices provide objective data on motor symptoms, which may help to overcome the limitation of the conventional assessments which only rely on clinician observations and patient self-reports. Besides, the use of wearable devices can enable continuous monitoring of the symptoms in both clinical and real-world settings, allowing a more comprehensive understanding of the patient's condition over time. Furthermore, wearable devices are highly sensitive and can detect subtle changes in motor function that may not be captured during infrequent clinical evaluations. This sensitivity can help in early diagnosis as well as the timely adjustment to the treatment plans (AlMahadin et al., 2020). On the other hand, everything is not always ideal. While wearable devices hold promise for enhancing the assessment of motor symptoms in PD, understanding the challenges and risk factors associated with their use is crucial for optimizing their implementation in clinical practice.

CHAPTER 3

METHOD AND METHODOLOGY

3.1 Research Design

A scoping review.

3.2 Search Strategy

This scoping review adhered to the guidelines detailed in the Preferred Reporting Items for Systematic Reviews and Meta-analysis Extension for Scoping Reviews (PRISMA-ScR) framework (Tricco et al., 2018).

The Scopus database was searched using the medical subject heading (MeSH) key search terms to retrieve all eligible studies and peer-reviewed papers that use randomised controlled trials (RCTs), experimental studies and observational studies published from year 2019 to year 2024 involving the assessment of the motor symptoms in people with Parkinson's Disease. The following keywords were used: Parkinson's Disease, motor symptoms, wearable sensors, wearable devices, inertial measurement units (IMUs), accelerometer, gyroscope, magnetometer, pressure sensors, force sensors, physiotherapy assessment, physical examination, analysis, rehabilitation, challenges, limitations, cost, data administration, and battery life. The keywords are shown in Table 3.2.

The Scopus database is chosen as the only search database due to several reasons. Firstly, Scopus database is an extensive database that indexes over

27000 serial titles and more than 14000 peer-reviewed journals (Gusenbauer & Haddaway, 2020). Thus, this ensures that this study had accessed a broad spectrum of searches relevant to the topic of this study. Next, the Scopus database employs a strict selection process for journals, ensuring only high-quality, peer-reviewed publications are indexed (Gusenbauer & Haddaway, 2020). This ensures quality assurance and enhances the reliability of the literature that has been reviewed. In addition, the Scopus database updates daily, ensuring that this study incorporated the most current research findings available (Gusenbauer & Haddaway, 2020).

Number	**Keywords**
1	<Parkinson’s Disease>
2	<Motor symptom>
3	<Wearable devices> OR <Wearable sensors> OR <Inertial measurement units> OR <Accelerometer> OR <Gyroscope> OR <Magnetometers> OR <Pressure sensors> OR <Force sensors>
4	<Physiotherapy assessment> OR <Physical examination> OR <Analysis>
5	<Challenges> OR <Limitations> OR <Cost> OR <Data administration> OR <Battery life>
Final search:	**Combined search Numbers 1 and 2 and 3 and 4 and 5**

Table 3.2. Keywords for search strategy

3.3 Outcome Measure

There are no strict criteria for the outcomes specified.

3.4 Inclusion Criteria

Study characteristics	**Inclusion criteria**
Study design	1. Randomised controlled trials (RCTs) 2. Observational studies 3. Experimental studies
Assessment tool	1. Studies that used non-invasive wearable devices. 2. Studies that addressed challenges and potential risk factors in using wearable devices in assessment.
Population	People with Parkinson's Disease
Outcome	No restriction applied.

Table 3.4. Inclusion criteria

3.5 Exclusion Criteria

Study characteristics	**Exclusion criteria**
Study design	1. Non-English publication. 2. Studies that were published before the year 2019.
Assessment tool	1. Studies that use non-wearable devices as diagnostic tools. 2. Studies that use technologies in assessing the psychological domain of people with Parkinson's Disease. 3. Studies that do not address the challenges and possible risk factors in using wearable devices.
Population	1. People with other neurological conditions. 2. Parkinsonism.
Outcome	No restriction applied.

Table 3.5. Exclusion Criteria

3.6 Data Charting

Research title, study designs, number of participants, types of wearable devices used, symptoms assessed by the wearable devices, challenges and potential risk factors in using the wearable devices will be extracted from the included studies. The overall findings will be presented in Table 3.6.

Research title	Study designs	Number of participants	Type of wearable devices used	Symptoms assessed	Challenges and potential risk factors

Table 3.6. Head Rows of Data Charting

3.7 Synthesis of Results

Narrative methods were used to summarize and synthesize the collected data, followed by a constructivist approach to analyze the studies and identify research gaps. Constructivism is a framework to critically analyze research findings, highlight current knowledge gaps, and establish study limitations. Furthermore, by using a constructivist approach in narrative synthesis, existing research can be developed by discussing the implications of the current findings. A combination of text, tables, and graphs was used to describe the study characteristics of the final included publications. Graphs were used to present key data such as the number and type of wearable devices used as well as the challenges and possible risk factors in using the wearable devices to assess motor symptoms of people with PD.

3.8 Ethical Approval

This study is subjected to ethical approval by the Scientific and Ethical Review Committee (SERC) of Universiti Tunku Abdul Rahman (UTAR).

CHAPTER 4

RESULTS

4.1 Search Results

A total of 85 articles were screened initially based on the title and abstract. 70 (82.4%) papers were selected for full-text evaluation based on their titles and abstracts based on our inclusion and exclusion criteria. A total of 46 papers fitted the conditions and were finally retained. 24 articles were excluded during full-text screening. One study was excluded for not involving people with PD. Two studies were excluded for not using any wearable devices. Four studies were excluded for not assessing the motor symptoms. Next, one study was excluded because it studied the management of motor symptoms. Ten studies were excluded because they did not have the relevant outcome data. Then, two non-peer-reviewed papers were excluded. Lastly, four studies were excluded due to the full text not available.

Figure 4.1 shows the flow of information through the different search phases of this scoping review.

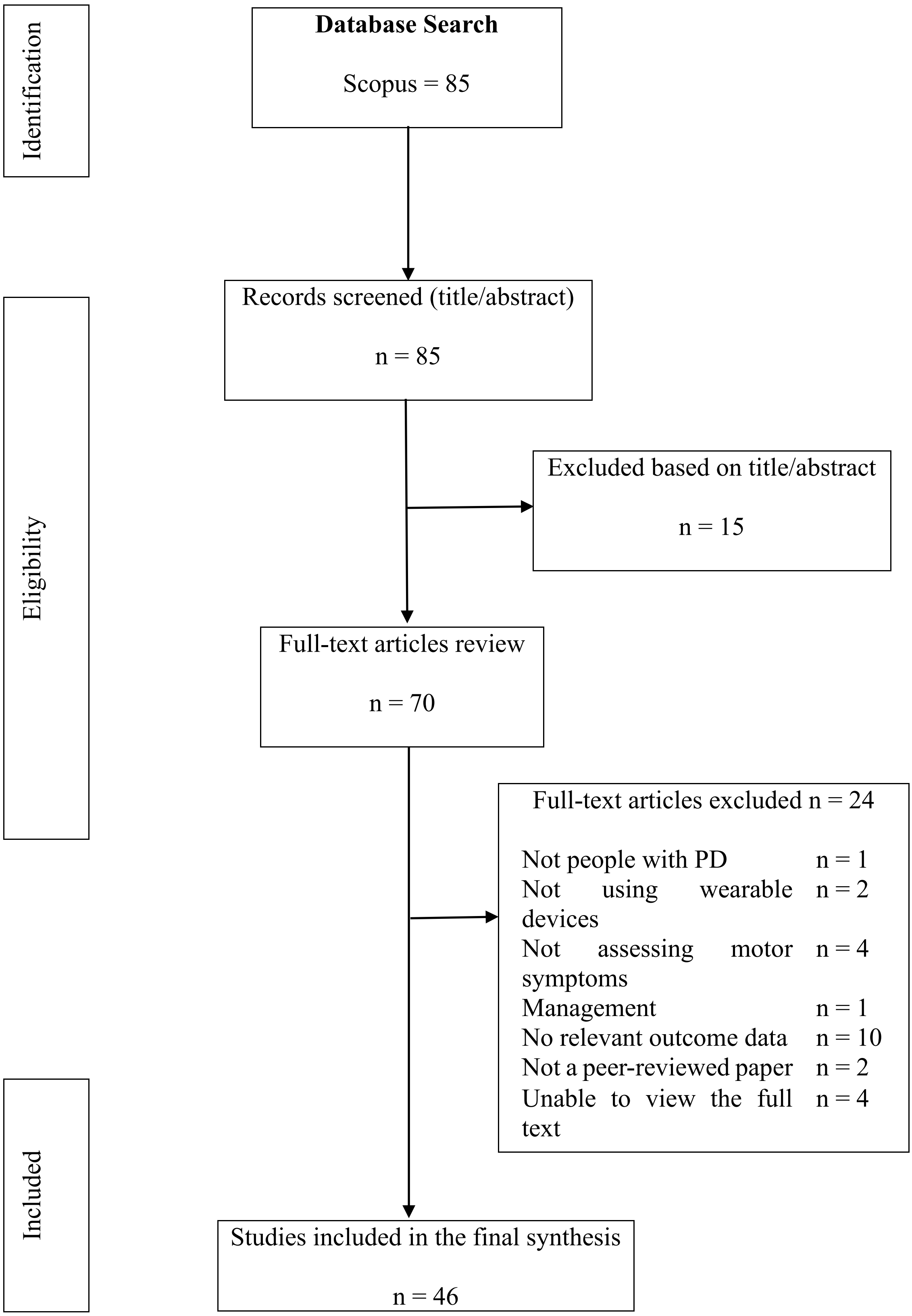

Figure 4.1. Review flow chart based on the PRISMA-ScR guidelines.

4.2 Characteristics of Sources of Evidence

Study	Author (Year)	Study Design	Sample size
1.	Wodarski et al. (2024)	Observational study	29
2.	Sigcha et al. (2024)	Observational and Experimental study	38
3.	Maas et al. (2024)	Observational cohort study	200
4.	Cox et al. (2023)	Systematic review	677
5.	Hagar Elbatanouny et al. (2024)	Meta-analysis	223
6.	Kazemi et al. (2024)	Observational study	36
7.	Bremm et al. (2024)	Observational study	33
8.	Kehagia et al. (2024)	Experimental study	100
9.	Panda and Bhuyan (2024)	Observational study	16
10.	Rodriguez et al. (2024)	Observational study	24
11.	Burtscher et al. (2024)	Observational study	50
12.	Gent Ymeri et al. (2023)	Experimental study	30
13.	Sotirakis et al. (2023)	Prospective observational study	91
14.	Spooner et al. (2023)	Observational study	24
15.	Gourrame et al. (2023)	Experimental study	14
16.	Sigcha et al. (2023)	Systematic review	243
17.	Vasileios Skaramagkas et al. (2023)	Observational study	22
18.	Xie et al. (2023)	Observational study	30
19.	Ravichandran et al. (2023)	Observational and Experimental study	10
20.	Cohen et al. (2023)	Randomized controlled trial	32

Study	Author (Year)	Study Design	Sample size
21.	Ohara et al. (2023)	Experimental study	19
22.	Uhlig and Prell. (2023)	Observational study	79
23.	Klaver et al. (2023)	Comparative observational study	70
24.	Li et al. (2023)	Systematic review	1407
25.	Wang et al. (2023)	Observational study	81
26.	Antonini et al. (2023)	Observational and experimental study	65
27.	Debelle et al. (2023)	Observational study	29
28.	Meng et al. (2023)	Experimental study	21
29.	Geritz et al. (2023)	Prospective observational study	47
30.	Chatzaki et al. (2022)	Experimental study	44
31.	Geritz et al. (2022)	Observational study	74
32.	Domingues et al. (2021)	Randomized controlled trial	18
33.	Sringean et al. (2022)	Observational study	32
34.	Habets et al. (2021)	Prospective observational study	20
35.	Sieberts et al. (2021)	Observational study	30
36.	Rissanen et al. (2021)	Prospective observational study	16
37.	Sigcha et al. (2021)	Experimental study	592
38.	Chen et al. (2020)	Observational study	100
39.	Evans et al. (2020)	Experimental study	61
40.	Elm et al. (2019)	Experimental study	51

Study	Author (Year)	Study Design	Sample size
41.	Aghanavesi et al. (2020)	Observational study	19
42.	Shawen et al. (2020)	Observational study	13
43.	Lee et al. (2020)	Observational study	74
44.	Sigcha et al. (2020)	Experimental study	187
45.	Aghanavesi et al. (2020)	Observational study	19
46.	Nguyen et al. (2019)	Cohort study	119
	Total sample size		**5209**

Table 4.2. Overview of the included studies

Based on Table 4.2, the characteristics of the included studies are tabulated according to the authors and year, study designs, and sample size. A total of 6366 sample sizes were obtained from 46 studies. The included studies were published between 2019 to 2024. Most of the studies were published in 2023 (19/46, 41.3%).

Most of the studies included are observational studies, comprised of 26 out of 46 (56.5%). Among these 26 observational studies, there were 2 cohort studies included. This is followed by experimental studies, which comprised 10 out of 46 (21.7%). Besides, some included studies are mixed studies of observational and experimental studies (3/46, 6.5%). 3 systematic reviews were included (6.5%). Only 2 randomized controlled trial and meta-analysis were included respectively.

The number of participants across the studies varied significantly. Studies with smaller cohorts like Ravichandran et al. (2023) with only 10 participants, Wodarski et al. (2024) with 29 participants, Rodriguez et al. (2024)

and Spooner et al. (2023) with 24 participants, Gourrame et al. (2023) with 14 participants, Vasileios Skaramagkas et al. (2023) with 22 participants, Ohara et al. (2023), Aghanavesi et al. (2020) and Aghanavesi et al. (2020) with 19 participants, Debelle et al. (2023) with 29 participants, Meng et al. (2023) with 21 participants, Domingues et al. (2021) with 18 participants, Habets et al. (2021) with 20 participants Rissanen et al. (2021) and Panda and Bhuyan. (2024) with 16 participants, and Shawen et al. (2020) with 13 participants. Conversely, larger studies like Li et al. (2023) included over 1407 participants, providing a broader perspective to the research.

4.3 Wearable Devices Used, and the Corresponding Symptoms Assessed

Study	Author (Year)	Type of wearable devices	Number of wearable devices	Motor symptom(s) assessed
1.	Wodarski et al. (2024)	IMU sensors	3	Postural balance
2.	Sigcha et al. (2024)	IMU sensors Accelerometer	7 3	FOG
3.	Maas et al. (2024)	Smartwatch (contained an accelerometer and gyroscope)	1	FOG
4.	Cox et al. (2023)	PKG	2	Tremor Dyskinesia Bradykinesia
5.	Hagar Elbatanouny et al. (2024)	Accelerometer Gyroscope IMU sensors EEG EMG ECG Skin conductance	5 2 4 2 2 1 3	FOG
6.	Kazemi et al. (2024)	IMU sensors	3	Arm swing Gait
7.	Bremm et al. (2024)	IMU sensors	2	UL motor symptoms
8.	Kehagia et al. (2024)	PKG	2	Tremors Dyskinesia Bradykinesia
9.	Panda and Bhuyan (2024)	IMU sensors	2	Gait
10.	Rodriguez et al. (2024)	IMU sensors	4	Tremor
11.	Burtscher et al. (2024)	IMU sensors	6	Gait
12.	Gent Ymeri et al. (2023)	GENEActiv wrist device	1	UL motor symptoms

Study	Author (Year)	Type of wearable devices	Number of wearable devices	Motor symptom(s) assessed
13.	Sotirakis et al. (2023)	IMU sensors	6	Gait Postural sway
14.	Spooner et al. (2023)	Accelerometer	2	Fine motor movement
15.	Gourrame et al. (2023)	IMU sensors	4	Gait
16.	Sigcha et al. (2023)	Accelerometer Gyroscope Magnetometer Force sensor	4 3 1 32	FOG Gait Bradykinesia Tremor Dyskinesia Balance Rigidity
17.	Vasileios Skaramagkas et al. (2023)	Accelerometer	2	Tremor
18.	Xie et al. (2023)	Wearable multisource insole	2	Gait
19.	Ravichandran et al. (2023)	iTex gloves contained: a. Flex sensors b. Pressure sensors	2 6 4	Tremor
20.	Cohen et al. (2023)	Tri-axial accelerometer	1	Gait
21.	Ohara et al. (2023)	IMU sensor	1	Gait
22.	Uhlig and Prell. (2023)	IMU sensors	2	Gait
23.	Klaver et al. (2023)	IMU sensors	7	FOG
24.	Li et al. (2023)	Actiwatch	1	Dyskinesia
25.	Wang et al. (2023)	IMU sensors	10	Gait

Study	Author (Year)	Type of wearable devices	Number of wearable devices	Motor symptom(s) assessed
26.	Antonini et al. (2023)	IMU sensors	5	Gait Bradykinesia Dyskinesia Tremor On/off fluctuations FOG
27.	Debelle et al. (2023)	Smartwatch IMU sensor	1 1	Dyskinesia Motor fluctuations
28.	Meng et al. (2023)	IMU sensors	11	Gait
29.	Geritz et al. (2023)	IMU sensor	1	Gait
30.	Chatzaki et al. (2022)	Pressure sensor insoles	1	Gait FOG
31.	Geritz et al. (2022)	IMU sensor	1	Gait
32.	Domingues et al. (2021)	Tri-axial accelerometer	1	Gait
33.	Sringean et al. (2022)	NIGHT-Recorder	4	Supine to sitting
34.	Habets et al. (2021)	Accelerometer	2	Bradykinesia
35.	Sieberts et al. (2021)	Gyroscope Accelerometer	4 1	Tremor Dyskinesia Bradykinesia
36.	Rissanen et al. (2021)	EMG	2	Tremor Rigidity Bradykinesia
37.	Sigcha et al. (2021)	Smartwatch (contained a tri-axial accelerometer)	1	Resting tremor
38.	Chen et al. (2020)	PKG	1	Bradykinesia Tremor Dyskinesia Rigidity

Study	Author (Year)	Type of wearable devices	Number of wearable devices	Motor symptom(s) assessed
39.	Evans et al. (2020)	PKG	1	Bradykinesia Tremor Dyskinesia Rigidity
40.	Elm et al. (2019)	Smartwatch	1	Tremor Dyskinesia
41.	Aghanavesi et al. (2020)	IMU sensors	5	Gait Arm swing
42.	Shawen et al. (2020)	Skin-mounted sensor Commercial smartwatch	1 1	Tremor Bradykinesia
43.	Lee et al. (2020)	Shoe-type IMU	2	Gait
44.	Sigcha et al. (2020)	Accelerometer	1	FOG
45.	Aghanavesi, Bergquist, et al. (2020)	Motion sensors	2	Dyskinesia
46.	Nguyen et al. (2019)	IMU sensors	2	Gait

Table 4.3. Type of wearable devices and motor symptoms assessed in the included studies.

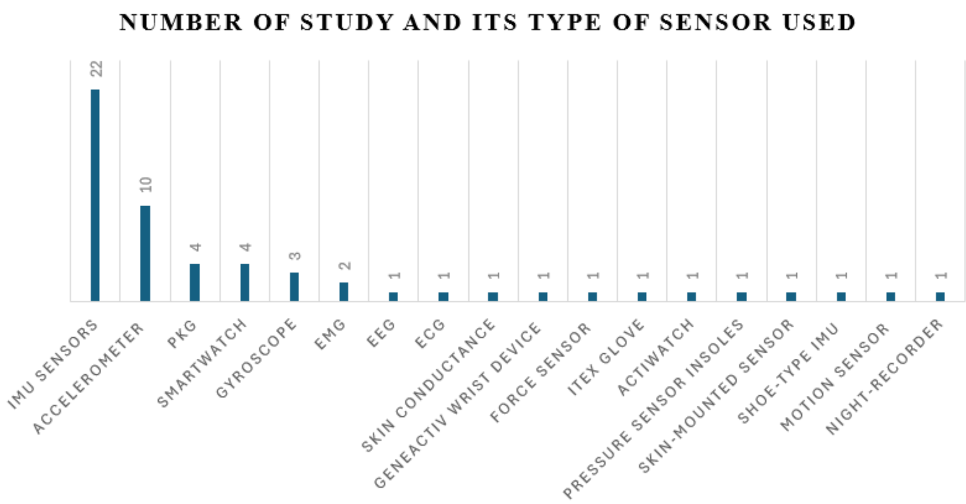

Figure 4.3. Number and Types of Wearable Devices

Table 4.3 presents the types and number of wearable devices, and the features of the wearable devices used in each study. The number of studies that utilized each type of wearable device was illustrated in a graph shown in Figure 4.3.

Most studies (40/46, 87%) used a single wearable device, whereas the remaining studies (6/46, 13%) used more than 1 wearable device to assess motor symptoms in people with PD. The IMU sensor was the most popular type of wearable device used (22/46, 47.8%). The IMU sensor typically consists of an accelerometer, gyroscope, and magnetometer, commonly used to assess gait. Next, the second most commonly used wearable device is the accelerometer (10/46, 21.7%), followed by PKG wearable devices (4/46, 8.7%). PKG contains light and temperature sensors, commonly used to assess dyskinesia, bradykinesia, and tremor. 4 studies also involved smartwatches (8.7%) while a smartwatch with accelerometer and gyroscope as well as a smartwatch with tri-axial accelerometer were each used only in one study (1/46, 2.1%). Next, it was followed by the gyroscope (3/46,6.5%), then the wearable multisource insole and EMG (2/46, 4.4%) respectively. The remaining wearable devices were used in only one study each (1/46, 2.1%). These devices include EEG, ECG, skin conductance, GENEActiv wrist device, force sensor, iTex gloves, Actiwatch, pressure sensor insoles, NIGHT-Recorder, skin-mounted sensor, shoe-type IMU, and motion sensor.

4.4 Challenges and Possible Risk Factors in Using Wearable Devices

To establish a structured framework that improves the clarity and comprehensiveness of this review, the challenges and potential risk factors identified from the 46 studies will be organized into five perspectives: ethical, human, cost, technical, and research. This categorization enables a clearer presentation of findings, making it easier to navigate complex information and enhancing understanding. Additionally, it aims to guide future research directions by providing targeted recommendations, recognizing that different stakeholders may have varying interests in the challenges presented.

4.4.1 Ethical Perspective

Challenges and Possible Risk Factors	Author(s)	Number of Studies
Privacy concerns	Cox et al, 2024; Sieberts et al, 2021	2
User compliance	Kazemi et al, 2024; Gent Ymeri et al, 2023; Spooner et al, 2023; Sigcha et al, 2023; Ravichandran et al, 2023; Domingues et al, 2021; Sieberts et al, 2021; Elm et al, 2019; Shawen et al, 2020; Rissanen et al, 2021	10

Long-term acceptance	Gent Ymeri et al, 2023; Aghanavesi et al, 2020	2

Table 4.4.1. Challenges and possible risk factors from the ethical perspective

According to Table 6, there are 3 challenges and possible risk factors grouped into ethical perspective, which are privacy concerns, user compliance, and long-term acceptance of the wearable devices. User compliance is a significant concern, highlighted by 10 studies (20%) (Kazemi et al, 2024; Gent Ymeri et al, 2023; Spooner et al, 2023; Sigcha et al, 2023; Ravichandran et al, 2023; Domingues et al, 2021; Sieberts et al, 2021; Elm et al, 2019; Shawen et al, 2020; Rissanen et al, 2021), indicating that users might not be adherence to researchers' instructions. Next, privacy concerns are also one of the possible risk factors in using wearable devices highlighted by Cox et al (2024) and Sieberts et al (2021) (2/50, 4%), reflecting users may perceive privacy risk in adopting wearable devices. Lastly, the challenges associated with the long-term acceptance of wearable devices are highlighted by 2 studies (4%) (Gent Ymeri et al, 2023; Aghanavesi et al, 2020).

4.4.2 Human Perspective

Challenges and Possible Risk Factors	Author(s)	Number of Study(s)
Wear-related discomfort	Maas et al, 2024; Hagar Elbatanouny et al, 2024	2
Logistical constraints	Kehagia et al, 2024	1
Patient preference for in-person consultations	Kehagia et al, 2024	1
Size compatibility	Ravichandran et al, 2023	1
Sensor aesthetics	Antonini et al, 2023; Aghanavesi et al, 2020	2
Issues related to don and doff	Ravichandran et al, 2023; Antonini et al, 2023; Geritz et al, 2022	3

Table 4.4.2. Challenges and possible risk factors from the human perspective

From a human perspective, several challenges and possible risk factors arise that affect the adoption and effectiveness of wearable devices. Issues related to donning and doffing the wearable devices highlighted by Ravichandran et al (2023), Antonini et al (2023), and Geritz et al (2022) (3/46, 6.5%), emphasizing the need for designs that facilitate ease of use. Next, size compatibility (Ravichandran et al, 2023) (1/46, 2.1%) and sensor aesthetics (Antonini et al, 2023; Aghanavesi et al, 2020) (2/46, 4.3%) reflect users' desire for devices that fit comfortably and look appealing. Besides, wear-related discomfort is highlighted by Maas et al (2024) and Hagar Elbatanouny et al (2024) (2/46, 4.4%), indicating that users might be struggling with the physical aspects of wearable devices. In addition, Kehagia et al (2024) highlighted 2 challenges, which are the logistical constraints of the wearable devices and a preference for in-person consultations by people with PD as the challenges and possible risk factors in using wearable devices, suggesting that practical issues can hinder technology use.

4.4.3 Cost Perspective

Challenges and Possible Risk Factors	Author(s)	Number of Study
Cost-prohibitive	Cox et al, 2024; Hagar Elbatanouny et al, 2024; Sigcha et al, 2021; Evans et al, 2020	4
Need for multiple sensors	Bremm et al, 2024; Klaver et al, 2023; Meng et al, 2023; Shawen et al, 2020; Nguyen et al, 2019; Panda and Bhuyan, 2024; Vasileios Skaramagkas et al., 2023; Li et al., 2023	8
Potential for damage, theft, or loss	Cox et al, 2024	1

Table 4.4.3. Challenges and possible risk factors from the cost perspective

From the cost perspective, the need for multiple sensors to assess multiple motor symptoms is a significant concern, as highlighted in 8 studies (17.4%) (Bremm et al, 2024; Klaver et al, 2023; Meng et al, 2023; Shawen et al, 2020; Nguyen et al, 2019; Panda and Bhuyan, 2024; Vasileios Skaramagkas et al., 2023; Li et al., 2023). It is followed by cost-prohibitive factors, addressed by Cox et al (2024), Hagar Elbatanouny et al (2024), Sigcha et al (2021), and Evans et al (2020) (4/46, 8.7%). These 2 challenges are closely related, limiting the access to necessary devices. Last but not least, concerns about the potential for damage, theft, or loss of devices stated by Cox et al. (2024) highlight the financial risk associated with investing in technology.

4.4.4 Technical Perspective

Challenges and Possible Risk Factors	Author(s)	Number of Study
Data variability from sensor placement	Wodarski et al, 2024; Hagar Elbatanouny et al, 2024; Rodriguez et al, 2024; Spooner et al, 2023; Gourrame et al, 2023; Ohara et al, 2023; Wang et al, 2023; Chatzaki et al, 2022	8
Complexity of data interpretation	Hagar Elbatanouny et al, 2024; Kazemi et al, 2024; Gourrame et al, 2023; Sigcha et al, 2023; Chatzaki et al, 2022; Burtscher et al., 2024; Debelle et al., 2023	7
Connectivity problem	Sieberts et al, 2021; Lee et al., 2020	2

Challenges and Possible Risk Factors	Author(s)	Number of Study
Short battery life	Maas et al, 2024; Hagar Elbatanouny et al, 2024; Sotirakis et al, 2023	3
Lack of calibration and sensitivity of the sensors	Spooner et al, 2023; Sigcha et al, 2023; Domingues et al, 2021; Habets et al, 2021; Sigcha et al, 2021; Sigcha et al, 2020	6
Overlapping of signals from multiple sensors	Sieberts et al, 2021; Xie et al, 2023; Sringean et al., 2022	3
Require experienced consultant	Evans et al, 2020	1

Table 4.4.4. Challenges and possible risk factors from the technical perspective

Based on Table 9, data variability from sensor placement is one of the challenges and possible risk factors in using wearable devices (8/46, 17.4%) (Wodarski et al, 2024; Hagar Elbatanouny et al, 2024; Rodriguez et al, 2024;

Spooner et al, 2023; Gourrame et al, 2023; Ohara et al, 2023; Wang et al, 2023; Chatzaki et al, 2022). This can lead to inconsistent results, making the data interpretation challenging. Next, 6 studies (13.0%) highlighted a lack of calibration and sensitivity of the sensors will affect the adoption and effectiveness of the wearable devices (Spooner et al, 2023; Sigcha et al, 2023; Domingues et al, 2021; Habets et al, 2021; Sigcha et al, 2021; Sigcha et al, 2020). Furthermore, the complexity of the data interpretation (Hagar Elbatanouny et al, 2024; Kazemi et al, 2024; Gourrame et al, 2023; Sigcha et al, 2023; Chatzaki et al, 2022; Burtscher et al., 2024; Debelle et al., 2023) (7/46, 15.2%) indicates the needs of the experienced consultant which was highlighted by Evans et al. (2020) (1/46, 2.1%). Furthermore, short battery life posed practical hurdles that impacted the adoption and effectiveness of wearable devices (Maas et al, 2024; Hagar Elbatanouny et al, 2024; Sotirakis et al, 2023) (3/46, 6.5%). Moreover, connectivity problems with wearable devices add another layer of technical complexity that can deter effective use (Sieberts et al, 2021; Lee et al., 2020) (2/46, 4.3%). Lastly, due to the multiple adoptions of wearable devices over different parts of the body, there might be overlapping of the signals which were highlighted by Sieberts et al. (2021), Sringean et al. (2022) and Xie et al. (2023) (3/46. 6.5%), which can lead to inaccurate results, affecting the effectiveness of the wearable devices.

4.4.5 Research Perspective

Challenges and Possible Risk Factors	Author(s)	Number of Study
Issues with generalizability in real-world settings	Sigcha et al, 2024; Sotirakis et al, 2023; Vasileios Skaramagkas et al, 2023; Cohen et al, 2023; Uhlig and Prell, 2023; Klaver et al, 2023; Aghanavesi et al., 2020	7

Table 4.4.5. Challenges and possible risk factors from the research perspective

From a research perspective, concerns about generalizability in real-world settings raise questions about how well the study results can be translated into practical applications. The concern was highlighted by 7 studies (15.2%) (Sigcha et al, 2024; Sotirakis et al, 2023; Vasileios Skaramagkas et al, 2023; Cohen et al, 2023; Uhlig and Prell, 2023; Klaver et al, 2023; Aghanavesi et al., 2020). This highlights a critical gap between a controlled research environment and everyday usage scenarios.

CHAPTER 5

DISCUSSION

5.1 Discussion

In this scoping review, we have identified 46 studies describing the challenges and possible risk factors in using wearable devices to assess motor symptoms of people with PD. The first instance included studies identifying the effectiveness of using wearable devices in assessing motor symptoms of people with PD. However, despite the potential benefits, the integration of wearable technology into clinical practice is fraught with challenges and risk factors.

5.1.1 Ethical Perspective

From the ethical perspective, 3 challenges and possible risk factors are identified. First of all, user compliance was the main challenge and possible risk factor in using wearable devices to assess motor symptoms of people with PD. The perception of people with PD about the value of wearable devices can influence their willingness to use them (Reichmann et al., 2023). They might not understand how the data collected can benefit their symptom management. In addition, they might not feel that the wearable devices can provide meaningful insights into their condition, making them less motivated to wear them regularly as told by the researchers (Wendling, 2024). Besides, it can also be related to the technical perspectives of the wearable devices, where the user might feel discomfort in wearing the wearable devices, leading to non-compliance with the adoption of the wearable devices (Kenny et al., 2022).

Moreover, people with PD might experience difficulty in using wearable devices as the devices might be difficult to put on or take off or require frequent charging, leading them to perceive the wearable devices as a burden, hence, further discouraging the regular use of the devices (Kenny et al., 2022). Furthermore, the psychological impact of being continuously monitored can also affect compliance. People with PD are more susceptible to stress and anxiety (van der Heide et al., 2021). Thus, they may experience anxiety or stress related to the constant tracking of their symptoms, resulting in a reluctance to engage with the device. This is also can be linked to the second challenge and possible risk factor which is the long-term acceptance of wearable devices, in which low user compliance will affect the long-term acceptance of the wearable devices.

The second challenge and possible risk factor is privacy concerns. This is because the devices will collect sensitive health information, including real-time data on motor symptoms, activity levels, and potentially other personal health metrics (Minen & Stieglitz, 2020). This data is inherently sensitive as it can reveal not only the presence of a medical condition but also the severity of symptoms and daily functioning. There are valid privacy concerns among patients due to the potential for such personal health information to be accessed or exploited (Vivian Genaro Motti & Caine, 2015). People with PD may fear that their data could be exposed to unauthorised parties or used for purposes beyond their consent, such as marketing or research without sufficient anonymity (Asma Channa et al., 2024). In addition, the data collected by wearable devices is another critical concern. Many devices transmit data over the internet, making it susceptible to hacking and data breaches (Jorge et al., 2024). People with PD may be discouraged from using these wearable devices if there are insufficient security measures in place because they may not believe that their data will be sufficiently safeguarded (Jiang & Shi, 2021).

5.1.2 Human Perspective

According to the challenges stated in the human perspective, the main challenge and possible risk factors are issues related to donning and doffing. People with PD suffer from motor difficulties, which significantly inhibit their ability to don and doff wearable devices (Kenny et al., 2022). Motor symptoms such as rigidity, tremors, and bradykinesia will make fine motor movements such as fastening the strap challenging. This further decreases their confidence, leading to frustration and stress (van der Heide et al., 2021). In addition, some people with PD may be suffering from cognitive impairments, for example, executive dysfunction, which can affect their ability to don and doff the devices (Capato et al., 2024). They may suddenly become confused and forget how to use the devices. This may lead to improper usage of wearable devices, affecting the quality of the data collected (Goncu-Berk & Topcuoglu, 2017). Furthermore, the design of wearable devices also plays a vital role as these devices are not tailored specifically for individuals with PD, hindering them from using them efficiently (Godoi et al., 2019). Not only this, but some of them may require thorough training on how to use these devices effectively (Asma Channa et al., 2024). If they do not receive adequate training, they may struggle with donning and doffing procedures.

Next, wear-related discomfort can significantly affect the effectiveness of wearable devices in physiotherapy assessment. As we mentioned above, the design and fit of wearable devices play a critical role in user comfort, however, most wearable devices may not be ergonomically designed for each user, especially those in the advanced stage. In addition, the skin of people with PD can become easily irritated due to some skin changes (Ravn Jørgensen et al., 2017). Hence, if the device does not fit and too heavy it can lead to irritation or pain after prolonged use. Additionally, if the material of the device is not friendly to sensitive skin, it can cause extra pressure or friction against the skin, heightening the sensitivity, and leading to discomfort (Henrique et al., 2021). Even if the individual does not have any skin conditions mentioned above, prolonged contact with the wearable devices may result in allergic reactions, especially when the materials used are not hypoallergenic (Group, 2023). Over time, the individuals may suffer from rashes, preventing them from wearing the devices consistently. Besides, people with PD can be mentally discomfort while wearing the devices, as they may feel shame or embarrassed (Henry, 2020). This internal stigma can lower their self-esteem and contribute to anxiety about being judged by others (Maffoni et al., 2017). They might believe that their symptoms become apparent after wearing the devices, making them seem “different”. Furthermore, they might also fear of discrimination by the society.

The following challenge and possible risk factor is sensor aesthetics. First, it can be related to the challenge mentioned above, which is wear-related discomfort. Next, if the design of the devices is not attractive, it may exacerbate their reluctance to use them (Rovini et al., 2017). Aesthetically pleasing designs can significantly increase user acceptance. Next, wearable devices can carry a social stigma, particularly for those who feel shame or embarrassed and will become more self-conscious about wearing the devices (Sampsom, 2023). So, if the devices are designed that look overly clinical, they will avoid wearing the devices in social settings. In addition, some individuals may need to wear the devices for a longer period, hence, the design should be seamlessly integrated into users' daily lives without drawing any attention or causing any inconvenience (Cox, 2024). In a nutshell, the ability of a device to blend into everyday attire can enhance its usability and encourage individuals to wear it consistently (Cox, 2024). Apart from this, people nowadays often seek customization and personalization. However, this can also lead to other challenges that may inhibit the effectiveness of the wearable devices.

On top of that, the preference for in-person assessments is one of the challenges. This is because they often have established relationships with their physiotherapists, which fosters a sense of trust and security (Kenny et al., 2022). In-person visits allow for direct communication, in which they can communicate their symptoms and how they feel as well as clarify their concerns to the physiotherapists directly (Boege et al., 2024). Thus, the lack of a physical presence can lead to scepticism about the accuracy and reliability of the data collected by the wearable devices (Cox, 2024). Moreover, some individuals may perceive that in-person are more effective for comprehensive evaluations of their condition. They might think that trained physiotherapists can yield a more accurate assessment than the wearable device alone (Luc et al., 2023). In addition, some individuals may face technological barriers, which they may feel difficulties in using or understanding how to operate wearable devices. Besides, people with PD are more prone to stress and anxiety, hence they may require social interaction with physiotherapists and other individuals with the same health condition (van der Heide et al., 2021).

Since there are no more in-person consultations, the wearable devices will be sent out to the individuals logistically, especially in regions that are not accessible to healthcare services and will require a more well-coordinated distribution strategy so that the wearable devices are always feasible to anyone who needs them (Li, Richard van Wezel, et al., 2023). Hence, the manufacturer and the supply chain play an important role. Any delays in production or shipping can lead to a shortage or inconsistent availability of devices (Laar et al., 2023). This can disrupt the research studies or ongoing patient assessments. Additionally, such interruptions can affect the continuity of care which is vital in managing the motor symptoms of PD.

Individuals of different sizes may find that standard-sized wearables do not fit comfortably. Thus, size compatibility becomes one of the challenges and possible risk factors in using wearable devices to assess motor symptoms of PD. Potential users who do not fall into normal sizing categories may become alienated due to the existing market's frequent lack of enough size diversity (Silva de Lima et al., 2017). If the sensor does not have a size that suits an individual's anatomy, it may not adhere precisely to the site mentioned by the researchers or it may shift during movement, leading to inaccurate readings (Adams et al., 2021). In addition, individuals may consider a sensor that is too large to be a burden as it could cause them problems. A poorly fitted sensor can further decrease user compliance towards wearable devices (Adams et al., 2021).

5.1.3 Cost Perspective

First of all, PD affects motor function in various ways, affecting different body parts including limbs, trunk, and facial muscles. Hence, multiple sensors are needed to detect the symptoms of each body part for a comprehensive assessment. However, the need for multiple sensors would be a challenge in using the wearable device due to cost implications. To assess tremors, wearable devices are recommended to be placed at the dorsal aspect of the hands, wrists, fingers, and trunk (Sotirakis et al., 2023). The devices can detect tremors during hand movements and tasks by placing them over the dorsal part of the hands and wrists, providing real-time data on tremor frequency and amplitude (Moreau et al., 2023). In addition, placing the devices on the index finger can enhance tremor detection during fine motor tasks (Moreau et al., 2023). A sensor must also be placed on the trunk to detect overall body dynamics and posture; hence, this can understand how tremors will affect movement as a whole (Rovini et al., 2017). Not only this, but the trunk also serves as a central point of reference for limb movements (Rovini et al., 2017). Next, to assess bradykinesia and dyskinesia, the devices will be placed on the upper arm, forearm, wrist, and hands (Shawen et al., 2020). Besides, to detect FOG, the sensors are placed above the ankle, thigh, waist, and insoles (Ren et al., 2022).

The need for multiple wearable devices to detect a single motor symptom significantly increases the financial burden of people with PD. Not only this, but the development of advanced wearable devices also involves significant investment in research, design, and manufacturing. On top of that, wearable devices such as IMU sensors incorporate accelerometers, gyroscopes and magnetometers, which further increase the cost of production (Sotirakis et al., 2023). Additionally, the integration of machine learning algorithms for data analysis further increases cost, as it requires specialized expertise and resources to develop effective models that can accurately interpret the data collected from people with PD (Godoi et al., 2019). Besides, these wearable devices have a limited market, in which they will only be used by people with PD or other neurological conditions, leading to higher prices due to lower economies of scale in production (Godoi et al., 2019). If only fewer units sold means that the manufacturers may not be able to reduce prices significantly, making these devices less accessible to a broader patient population. Moreover, insurance coverage for wearable devices is often inadequate or does not exist, which can hinder individuals from buying them (Antonini et al., 2023). As PD is a chronic disease that requires long-term rehabilitation, the financial burden falls entirely on the people with PD, making the wearable technology prohibitively expensive for most of them. In addition to that, the devices might require ongoing maintenance, software updates, or even technical support (Antonini et al., 2023). When these additional costs accumulate over time, this can make the long-term use of these devices less financially feasible.

To assess the motor symptoms effectively, people with PD are required to wear them daily. Hence, the devices are often subjected to wear and tear, which can lead to physical damage (Lu et al., 2020). People with PD may inadvertently drop or bump the devices during ADLs, especially if they have tremors or rigidity. This vulnerability can result in malfunction or complete dysfunction of the device, hindering the continuous monitoring of the motor symptoms. Besides, the devices are often visually appealing or technologically advanced and have a higher risk of theft (Cox, 2024). When people with PD wear these devices in public settings, the devices could be easily stolen. In addition, this raises concerns about personal data security (Minen & Stieglitz, 2020). Not only this, but people with PD may also be suffering from cognitive issues along with motor symptoms, which can be confusion or forgetfulness (van der Heide et al., 2021). This can result in misplacing or forgetting to wear the devices, affecting the continuity of assessment.

5.1.4 Technical Perspective

Due to the varying human anatomical structures and movement patterns across different regions, this anatomical variability can lead to differences in the data collected (Azodo et al., 2020). There is no agreed site for placement, which can yield distinct readings for the same movement due to differences in how force and motions are transmitted through the body (Caballol et al., 2023). When the devices are placed differently across people with PD, this variability can lead to inconsistent data outputs, complicating comparisons and assessments across different individuals (Shawen et al., 2020). In addition, when only a single device was placed on the arm may detect tremors effectively during tasks such as writing, however, this placement may not yield accurate data during other activities such as walking or standing still (Yang et al., 2016).

Moreover, there is a lack of calibration and sensitivity in wearable devices. the wearable devices may have built-in inaccuracies that require regular calibration to maintain precision (Cho et al., 2021). Besides, movement during the data collection process can result in errors, challenging the calibration process (Canali et al., 2022). When the devices are not calibrated correctly, the positional error can exceed acceptable limits, leading to inaccurate readings of motor symptoms such as bradykinesia and dyskinesia (Li, Cristiano, et al., 2023). Moreover, different types of wearable devices may have inherent variability in their sensitivity and accuracy based on their design and operational principles. For example, IMU can vary in performance due to different placements on the body, leading to inconsistent data collection, and making it challenging to reliably assess symptoms across different individuals (Tahri Sqalli & Al-Thani, 2020). In addition to that, improper placement of the devices can result in missed signals or inaccurate readings.

Moreover, compared to conventional physiotherapy assessments, the process of data interpretation after using wearable devices to assess motor symptoms of people with PD is more complex. The wearable devices will collect a vast array of data from multiple sensors, resulting in high dimensions of datasets that contain numerous variables related to movement patterns, speed, and direction (Van et al., 2024). Analysing such complex data requires sophisticated statistical and machine-learning techniques to extract meaningful insights, making interpretation challenging. In addition, the devices often gather multimodal data that need to be integrated for a comprehensive assessment (Ferrara, 2024). It is vital to combine these diverse data streams can provide a coherent picture of the individual's motor function, however, it involves complex algorithms for feature extraction and fusion (Ferrara, 2024). Moreover, if the devices require a machine-learning model to analyse the data, it can introduce additional complexity as these models need extensive training on diverse datasets to generalize well across different individuals (Ortiz, 2024). The complexity of data interpretation can be associated with the next challenge, which is the need for experienced consultants (Bove, 2019). One of the challenges and possible risk factors listed from the technical perspective is the need for experienced consultants to handle wearable devices. This is because experienced consultants possess specialized knowledge of the various wearable devices available, their functionalities and how to effectively integrate them into existing healthcare systems (Bove, 2019).

The battery life of wearable devices presents significant challenges in assessing the motor symptoms of an individual. Firstly, wearable devices are mostly designed to be compact and lightweight, restricting the size of the battery that can be used (Beniwal et al., 2023). Most wearable devices rely only on small lithium-ion batteries, typically with capacities from 130mAh to 410mAh, leading to limited operational time before recharging is required (Beniwal et al., 2023). Furthermore, the wearable devices are equipped with advanced features which further increase power consumption, this complexity often results in a trade-off between functionality and battery life, making it difficult to achieve long runtimes without frequent charging (Rong et al., 2021). Moreover, wearable devices do not effectively manage power consumption during idle periods (Contoli et al., 2024). The devices do not enter a low-power mode even when they are not actively collecting or processing data, making them consume significant energy (Workineh Tesema et al., 2024).

As mentioned above the challenges from the cost perspective, there is a need for multiple sensors in assessing a single motor symptom. These sensors operate on similar frequencies, leading to electromagnetic interference, and causing the overlapping of signals from different sensors, distorting each other (Ates et al., 2022). Moreover, some sensors may be placed close to each other, for example when assessing tremors, the sensors are placed over the wrist, hand, and finger (Sotirakis et al., 2023). This can cause crosstalk between sensors, in which the signal of each sensor interferes with one another. Otherwise, even though some sensors are placed away from each other, the signals may be overlapping due to the physical movement of an individual (Heikenfeld et al., 2018). For instance, the sensors that are placed over the hand and ankle may overlap when the individual squats down. Besides, inadequate filtering and amplification techniques can lead to signal overlapping (Liu et al., 2022).

The overlapping of the signals can sometimes lead to connectivity problems (Ikharo & Aliu, 2023). Besides, wearable devices use different communication protocols, causing difficulties in data transfer between devices from different manufacturers (Ikharo & Aliu, 2023). This lack of standardization creates barriers that prevent seamless interoperability, making it difficult for physiotherapists or charge persons to incorporate the data into electronic health records (Canali et al., 2022). In addition, wearable devices that have short battery life can also lead to connectivity failures especially when the devices run out of power (Beniwal et al., 2023). Next, software issues can also lead to connectivity problems. If there are bugs in the firmware or application software, it may cause the devices to fail to establish or maintain connections with other devices or networks (Canali et al., 2022). When the devices are incompatible in size with the individuals, this can lead to inadequate sealing against moisture, leading to connectivity issues (Adams et al., 2021).

5.1.5 Research Perspective

There is only one challenge and a possible risk factor that arises from the research perspective, which is issues with generalizability in real-world settings. Wearable devices often encounter significant data quality issues that can affect their reliability and applicability in clinical settings (Chang et al., 2019). These challenges include data entry errors, non-wear periods, and missing data, leading to incorrect conclusions about the health of an individual (Chang et al., 2019). In addition to that, controlled research environments often involve highly structured conditions that do not reflect the complexities of daily life (Khakurel et al., 2018). For example, participants' behaviour, environmental factors, and device usage are strictly regulated in the research settings (Khakurel et al., 2018). The lack of variability can lead to results that do not translate well to the diverse and unpredictable nature of real-life settings (Belal Abboushi et al., 2022). Next, when the research only recruited those 50 years old and above, the result may not represent the broader population. The lack of diversity can skew results, limiting the applicability to different demographic groups or individuals with more than one health condition (Belal Abboushi et al., 2022).

5.2 Implication of The Challenges and Possible Risk Factors to Physiotherapy Assessment and Management

The challenges and possible risk factors mentioned above have significant implications for the physiotherapy assessment of motor symptoms in PD. Privacy concerns related to the use of wearable devices can lead to decreased trust in wearable technologies among people with PD (AlMahadin et al., 2020). They will most likely be disengaged from these devices. If not, people with PD can choose to limit the amount of data shared or stop sharing the data, resulting in gaps in symptom monitoring. In addition, non-compliance and the issue with long-term acceptance of the devices can also lead to inconsistent use of wearable devices, causing incomplete data sets, which do not accurately represent a patient’s condition over time (Bergh et al., 2023). This inconsistency complicates clinical decision-making, leading to missing opportunities for timely management or adjustments in treatment strategies (Moreau et al., 2023). Additionally, some specific events such as falls and tremors might be missed due to inconsistent and short-term usage, potentially overlooking critical changes that require attention (Lu et al., 2020). A slower response to necessary new treatment from the physiotherapists occurred due to delayed recognition of changes or new symptoms (Moreau et al., 2023). As a result, patients might become even less motivated to engage with their treatment plan as they might think that the treatment plan is not effective (Lu et al., 2020), creating a detrimental feedback loop.

The handling of sensitive health information raises ethical and legal issues that must be navigated carefully (Rodgers et al., 2019). Failure to adequately address these concerns could lead to legal repercussions and damage the professional reputation of a physiotherapist (Rodgers et al., 2019). Next, preference for face-to-face consultations may create a barrier to integrating wearable devices into routine care. Besides, the financial burden associated with the use of wearable devices will limit access for both patients and healthcare providers, resulting in a decreased implementation of wearable devices in the physiotherapy field (Tina Binesh Marvasti et al., 2024). Moreover, the challenges mentioned from the technical perspective may lead to inconsistent data interpretation, obscuring true changes in the individuals (Yue et al., 2024). Additionally, inconsistency in data interpretation may lead to misdiagnosis, affecting clinical decision-making. The complexity of utilising wearable devices may further increase the burden of a physiotherapist as additional works have to be done (Smuck et al., 2021). Wearable devices may perform well in clinical settings where conditions are controlled, but the accuracy of the collected data may diminish in real-world settings, leading to which the data collected may not truly reflect the individual's condition (Singh et al., 2024).

5.3 Perspective That Causes Major Impact on Physiotherapy Aspect

Among the five perspectives: human, ethical, cost, technical, and research, the human perspective is likely to have the most significant impact on the physiotherapy field.

The human perspective emphasizes the importance of patient-centred care, which is fundamental in physiotherapy. Understanding patients' needs, preferences, and experiences can lead to more effective treatment plans and improved outcomes (Bastemeijer et al., 2020). A focus on the human aspect ensures that therapy is tailored to individual patients, enhancing engagement and adherence to rehabilitation protocols.

Besides, strong therapeutic relationships between physiotherapists and patients are crucial for successful treatment (Worum et al., 2020). The human perspective highlights the importance of communication, empathy, and trust, which can significantly influence a patient's motivation and willingness to participate in their rehabilitation process. Positive interactions can foster a supportive environment that encourages recovery (Worum et al., 2020).

In addition, physiotherapy often requires a holistic approach that considers not only physical impairments but also psychological, social, and emotional factors affecting a patient's health. By prioritizing the human perspective, physiotherapists can address these multifaceted issues, leading to more comprehensive care that acknowledges the whole person rather than just their physical condition (Liang et al., 2022).

The human perspective also encompasses issues related to advocacy for patient rights and accessibility to care (Liang et al., 2022). Addressing barriers faced by diverse populations such as socio-economic factors or cultural differences can improve access to physiotherapy services. This focus can lead to more equitable healthcare delivery and better health outcomes for underserved groups.

Focusing on the human perspective encourages physiotherapists to engage in continuous professional development regarding interpersonal skills and cultural competence (Débora Petry Moecke & Camp, 2024). This emphasis can enhance practice standards and foster an environment of compassion and understanding within the profession.

In summary, while all five perspectives are important, the human perspective stands out as it directly influences patient outcomes through personalized care, strong therapeutic relationships, a holistic approach to treatment, advocacy for accessibility, and enhancement of professional practice. Prioritizing this perspective can lead to significant advancements in the effectiveness and quality of physiotherapy services.

5.4 Limitations

The search database was only limited to Scopus, which might lead to incomplete retrieval of relevant studies, resulting in a biased sample. In addition, the search strategy was limited to a few of the main established peer-reviewed databases and the peer-reviewed paper publications were reviewed only if they were written in English. Therefore, the identified publications may not be completely representative of the research available, as contributions made by technologically advanced such as Germany were excluded. Furthermore, the publication search was conducted only by one person. Although the inclusion of the eligible studies and the search strategy methodology were supervised by the research supervisor and co-supervisor, studies may have been missed or there may have been some variation during the screening process.

Moreover, the study only focused on motor symptoms. Non-motor symptoms were not included as conducting a comprehensive review that includes both motor and non-motor symptoms may require significantly more resources in terms of time, literature search, and result synthesis. Furthermore, study participants with PD tended to be older, and there is little information on how wearable devices could benefit patients with young onset PD (YOPD) and how the different challenges faced by patients with YOPD can impact the results.

In addition, some articles were not able to be viewed in full text. An attempt was made to contact respective authors for the not available studies, however, there is no reply from the authors.

5.5 Recommendation for Future Study

For the recommendations for future study, researchers should incorporate assessing non-motor symptoms involving the use of wearable devices to enhance the understanding of this complex condition. While this study primarily focused on motor symptoms, the multifaceted nature of PD necessitates a broader approach that includes non-motor aspects such as cognitive decline, mood disorders, and sleep disturbances. This is because the non-motor symptoms significantly impact the QoL of people with PD. By integrating these symptoms into wearable device assessments, researchers can provide a more holistic view of the disease's progression and its effects on daily living. Hence, this scoping review should be followed by assessing the capacity of the mentioned devices in assessing non-motor symptoms of PD.

Next, future studies can be done to solve the challenges and possible risk factors mentioned in this study. Researchers can conduct a user-centred design, engaging people with PD in the design process to create more comfortable and aesthetically pleasing devices that meet their needs. Additionally, researchers can perform cost-effectiveness analyses to determine the financial viability of implementing wearable devices in clinical practice.

Besides, given the complexity and diversity of challenges and potential risk factors identified in the use of wearable devices in assessing motor symptoms in PD, a systematic review followed by a meta-analysis could synthesize existing literature more comprehensively. Hence, this scoping review serves as a basis for further systematic review and meta-analysis. A systematic review can provide a structured synthesis of evidence regarding the efficacy and challenges associated with wearable devices, integrating findings from various studies to draw more robust conclusions. A meta-analysis would allow for statistical analysis of data across studies, potentially revealing trends or effects that are not apparent in individual studies due to small sample sizes or varying methodologies. By consolidating evidence, these reviews can inform clinical practices and guidelines regarding the implementation and use of wearable devices in assessing people with PD.

5.6 Conclusion

This scoping review provides an overview of the challenges and possible risk factors associated with the use of wearable devices in assessing motor symptoms of people with PD. The findings indicate that a variety of challenges exist across ethical, human, cost, technical, and research perspectives, which collectively influence the efficacy and acceptance of these devices as well as the impacts on physiotherapy assessment and management.

The ethical concerns emphasise how these challenges can result in inconsistency in data collection, as well as trust and engagement of the user. Next, the human perspective emerged as a critical barrier that could deter the acceptance of the devices and the compliance in using the devices. Furthermore, the cost perspective revealed the financial limitations towards the devices, thus, limiting the widespread adoption of the devices. From a technical perspective, it suggested that there is a need for improvement in updating the device feature as well as the function. These challenges not only affect the assessment of motor symptoms but also have broader implications for patient care. The potential for inaccurate data collection can lead to misinterpretation, thereby affecting clinical decisions. Future studies should focus on developing strategies to mitigate these challenges so that we can fully utilize the advantages of wearable devices.

CHAPTER 6

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CHAPTER 7

APPENDICES

APPENDIX A - ETHICAL APPROVAL FORM

UNIVERSITI TUNKU ABDUL RAHMAN
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Re: U/SERC/78-363/2024

23 September 2024

Mr Muhammad Noh Zulfikri bin Mohd Jamali
Head, Department of Physiotherapy
M. Kandiah Faculty of Medicine and Health Sciences
Universiti Tunku Abdul Rahman
Jalan Sungai Long
Bandar Sungai Long
43000 Kajang, Selangor

Dear Mr Muhammad Noh,

Ethical Approval For Research Project/Protocol

We refer to your application for ethical approval for your students' research project from Bachelor of Physiotherapy (Honours) programme enrolled in course UMFD3026. We are pleased to inform you that the application has been approved under Expedited Review.

The details of the research projects are as follows:

No	Research Title	Student's Name	Supervisor's Name	Approval Validity
1.	The Effect of Diaphragm Muscle Exercise on Dynamic Balance among Post-COVID-19 Older Adults in Klang Valley, Malaysi	Goh Le Yi	Ms Premala a/p Krishnan	23 September 2024 – 22 September 2025
2.	Relationship Between Cognitive Domains, Dynamic Postural Stability and Fall Risk in Elderly Individuals with Mild Cognitive Impairment: A Pilot Study	Chaw Jade Wern		
3.	Smartphone Addiction and Its Relationship with Forward Head Posture and Grip Strength Among University Students in Klang Valley	Chuar Yu Cheng	Mr Chew Wai Hoong	
4.	Dynamic Balance and Life-Space Mobility Among Community Dwelling Older Adults: A Correlation Study	Grace Wong Mui Kar		
5.	Relationship Between Neck Disability, Sleep Quality, and Perceived Stress Among University Students in Klang Valley	Low Jun Kai		
6.	Association Between Medial Longitudinal Arch and Body Mass Index Among Young Adults in Klang Valley and Selangor, Malaysia	Mahaasiri a/p Kamalavallo	Ms Ambusam a/p Subramaniam	
7.	Effectiveness of Mulligan's Traction Straight Leg Raise Technique on Young University Students with Symptoms of Restless Leg Syndrome	Lim Chun Qi	Mr Tarun Amalnerkar Ms Swapneela Jacob	
8.	Effect of 4-week Inspiratory Muscle Training (IMT) Program on Young Adult with Mild Obstructive Sleep Apnea (OSA)	Sia Cai Ni	Mr Tarun Amalnerkar Ms Swapneela Jacob Mr Sathish Kumar Sadagobane	

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No	Research Title	Student's Name	Supervisor's Name	Approval Validity
9.	Assessment Of Diagnostic Clinical Reasoning Skills Among Undergraduate Physiotherapy Students	Jason Ho Yi Zeng	Mr Avanianban Chakkarapani	23 September 2024 – 22 September 2025
10.	Awareness, Knowledge, Attitude and Perception of Active Isolated Stretching Among Physiotherapy Academics and Students in a Private University: A Cross Sectional Study	Law Jing Tien		
11.	Knowledge Of Quadriceps Angle (Q-Angle) Among Physiotherapy Students	Tay Yu Xin		
12.	Cortical Excitability and Body Awareness in Individuals with Adolescent Idiopathic Scoliosis: An Exploratory Study	Mark Isaac Fernandez	Dr Deepak Thazhakkattu Vasu	
13.	Exercise Interventions in Primiparous Women for the Prevention and Management of Pelvic Floor Dysfunction: A Systematic Review	Jenny Peng Mei Shi		
14.	Exploring the Novel Sensor System for Detecting Postural Reactions Among Healthy Younger Adults: A Pilot Study	Ooi Xin Rou		
15.	Prevalence of Chronic Fatigue Syndrome (CFS) and Its Association on Quality of Life and Sleep Quality Among Young Adults: A Cross-sectional Study	Delphine Yeo Sze Qi	Mr Sathish Kumar Sadagobane Co-Supervisor: Mr Tarun Amalnerkar	
16.	Association Between Level of Ergonomic Knowledge and Prevalence of Neck Pain Among Part-time Postgraduate Students in Klang Valley	Ng Jia Xuan	Mr Sathish Kumar Sadagobane Co-Supervisor: Mr Edwin Gaspar	
17.	Effectiveness of Kinesiotaping with Static Stretching and Proprioceptive Neuromuscular Facilitation Stretching for Gastrocnemius Tightness Management Among Adults	Tan Jia Yin	Ms Heaw Yu Chi	
18.	Awareness, Knowledge and Perceptions of Chronic Fatigue Syndrome/ Myalgic Encephalomyelitis Between Student and Working Physiotherapists: A Comparative Study	Tee Yee Pei		
19.	Effect of Pulmonary Rehabilitation on Dyspnea and Quality of Life Among Chronic Obstructive Pulmonary Disease Patients: A Systematic Review	Chin Jay Ven	Mr Imtiyaz Ali Mir	
20.	Efficacy of Music Therapy and Mindfulness Meditation on Blood Pressure and Mental Health Among University Students	Tan Pei Chen		
21.	Effects of Music Therapy on Haemodynamic Variables and Mental Health in Patients with Coronary Artery Disease: A Systematic Review	Foong Ei Yan		
22.	Effects of Different Phases of the Menstrual Cycle on Daytime Drowsiness and Muscular Fatigue Among Recreational Female Badminton Players	Lee Kae Shyan	Mr Muhammad Noh Zulfikri Bin Mohd Jamali Co-supervisor: Mr Tarun Amalnerkar	
23.	Association between Gastrocnemius Tightness, Hallux Valgus and Physical Activity Among University Students	Chong Yi Xian	Ms Siti Hazirah Binti Samsuri	
24.	The Prevalence of Lower Urinary Tract Symptoms (LUTS) and Its Associated Risk Factors Among Male University Students	Gan Xinyi		
25.	Examining Doms Reduction in Recreational Versus Competitive Athletic Populations	Jona Kong Zong Na	Ms Kamala a/p Krishnan	
26.	Effectiveness of Virtual Reality Games on Hand Movement and Strength rehabilitation in Stroke Patients: A Systematic Review	Rachel Hew Zi Qi		

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No	Research Title	Student's Name	Supervisor's Name	Approval Validity
27.	Prevalence of Menstrual Migraine Among University Students and Its Impact on Quality of Life: A Cross Sectional Study	Jing Ni Wong	Ms Swapneela Jacob Co- supervisor Mr Tarun Amalnerkar	23 September 2024 – 22 September 2025
28.	Prevalence of Functional Constipation and Its Impact on Quality of Life Among Young Adults: A Cross Sectional Study	Ow Yong Jie Min		
29.	A Study to Anlayse the Correlation Between Migraine Symptoms, Motion Sensitivity and Balance Impairment: A Cross-sectional Study Among University Students	Stella Chen Sing Yi	Ms Kiruthika Selvakumar	
30.	A Study to Analyse the Impact of Headache on Level of Physical Activity and Dynamic Balance Among University Students	Lee Wan Fei		
31.	Comparison of the Attitudes and Awareness of Elderly Falls and Fall Prevention Across Diverse Age Groups: A Cross-sectional Study	Ng Sin Ru	Ms Mahadevi A/P Muthurethina Barathi	
32.	A Cross-sectional Study on the Knowledge of Knee Osteoarthritis and Attitude Towards Prevention of Knee Osteoarthritis in Young Adults	Lim Shi Qi		
33.	Challenges and Possible Risk Factors Associated with Using Wearable Devices for Assessing the Motor Symptoms of People with Parkinson's Disease: A Scoping Review	Lee Wen Ke	Pn Nur Aqliliriana Binti Zainuddin Co-supervisor: Mr Tarun Amalnekar	
34.	The Utilization and Barriers of Adoption of Wearable Devices for Rehabilitation Among Physiotherapists: A Cross-Sectional Study	Yap Wei Qi	Pn Nur Aqliliriana Binti Zainuddin	
35.	Knowledge and Awareness of Parkinson's Disease and Its Associated Factors Among General Population in Malaysia: A Cross-sectional Survey	Jolyn Cheah En		
36.	Association Between Breast Size and Upper Crossed Syndrome Among Perimenopausal Aged Women	Connie Chuo Yi Ching	Ms Meneka Naidu a/p Mohnaraju	
37.	Awareness of Cervical Cancer Among Premenopausal Women in Klang Valley, Malaysia: A Cross-sectional Study	Havilah Wong Sie Chii		
38.	Prevalence and Risk Factors of Postpartum Depression and Anxiety After COVID-19 Pandemic: A Systematic Review	Lee Shi En	Pn Nadia Safirah Binti Rusli	
39.	Post-natal Functional Abilities and Its Association with Depression Following Cesarean Section: A Cross-sectional Study	Seah Yi Shean		
40.	Prevalence and Associated Risk Factors of Musculoskeletal Disorders Among Food Delivery Riders in Klang Valley: A Cross-Sectional Study	Odelia Chew Yong Xin		
41.	Impact of Academic Stress on Executive Functions and Sleep Quality Among University Students: An Observational Study	Lai Yu Wei	Mr Nizar Abdul Majeed Kutty	
42.	Knowledge and Awareness of Re-Warm Up Programs on Physical Performance Among University Athletes. A Cross Sectional Study	Emmanuel James Loh Kuan Hung		

The conduct of this research is subject to the following:

(1) The participants' informed consent be obtained prior to the commencement of the research;

(2) Confidentiality of participants' personal data must be maintained; and

(3) Compliance with procedures set out in related policies of UTAR such as the UTAR Research Ethics and Code of Conduct, Code of Practice for Research Involving Humans and other related policies/guidelines.

(4) Written consent be obtained from the institution(s)/company(ies) in which the physical or/and online survey will be carried out, prior to the commencement of the research.

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Should the students collect personal data of participants in their studies, please have the participants sign the attached Personal Data Protection Statement for records.

Thank you.

Yours sincerely,

Professor Ts Dr Faidz bin Abd Rahman
Chairman
UTAR Scientific and Ethical Review Committee

c.c Dean, M. Kandiah Faculty of Medicine and Health Sciences
Director, Institute of Postgraduate Studies and Research

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APPENDIX B - PRISMA-SCR CHECKLIST

Preferred Reporting Items for Systematic Reviews and Meta-Analyses extension for Scoping Reviews (PRISMA-ScR) Checklist

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
TITLE			
Title	1	Identify the report as a scoping review.	i
ABSTRACT			
Structured summary	2	Provide a structured summary that includes (as applicable): background, objectives, eligibility criteria, sources of evidence, charting methods, results, and conclusions that relate to the review questions and objectives.	ii – iii
INTRODUCTION			
Rationale	3	Describe the rationale for the review in the context of what is already known. Explain why the review questions/objectives lend themselves to a scoping review approach.	16 – 17
Objectives	4	Provide an explicit statement of the questions and objectives being addressed with reference to their key elements (e.g., population or participants, concepts, and context) or other relevant key elements used to conceptualize the review questions and/or objectives.	15
METHODS			
Protocol and registration	5	Indicate whether a review protocol exists; state if and where it can be accessed (e.g., a Web address); and if available, provide registration information, including the registration number.	-
Eligibility criteria	6	Specify characteristics of the sources of evidence used as eligibility criteria (e.g., years considered, language, and publication status), and provide a rationale.	39 – 40
Information sources*	7	Describe all information sources in the search (e.g., databases with dates of coverage and contact with authors to identify additional sources), as well as the date the most recent search was executed.	38
Search	8	Present the full electronic search strategy for at least 1 database, including any limits used, such that it could be repeated.	38
Selection of sources of evidence†	9	State the process for selecting sources of evidence (i.e., screening	38 – 40

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
		and eligibility) included in the scoping review.	
Data charting process‡	10	Describe the methods of charting data from the included sources of evidence (e.g., calibrated forms or forms that have been tested by the team before their use, and whether data charting was done independently or in duplicate) and any processes for obtaining and confirming data from investigators.	40 – 41
Data items	11	List and define all variables for which data were sought and any assumptions and simplifications made.	41
Critical appraisal of individual sources of evidence§	12	If done, provide a rationale for conducting a critical appraisal of included sources of evidence; describe the methods used and how this information was used in any data synthesis (if appropriate).	-
Synthesis of results	13	Describe the methods of handling and summarizing the data that were charted.	41
RESULTS			
Selection of sources of evidence	14	Give numbers of sources of evidence screened, assessed for eligibility, and included in the review, with reasons for exclusions at each stage, ideally using a flow diagram.	42 – 43
Characteristics of sources of evidence	15	For each source of evidence, present characteristics for which data were charted and provide the citations.	44 – 47
Critical appraisal within sources of evidence	16	If done, present data on critical appraisal of included sources of evidence (see item 12).	-
Results of individual sources of evidence	17	For each included source of evidence, present the relevant data that were charted that relate to the review questions and objectives.	48 – 62
Synthesis of results	18	Summarize and/or present the charting results as they relate to the review questions and objectives.	48 – 62
DISCUSSION			
Summary of evidence	19	Summarize the main results (including an overview of concepts, themes, and types of evidence available), link to the review questions and objectives, and consider the relevance to key groups.	63 – 77
Limitations	20	Discuss the limitations of the scoping review process.	78
Conclusions	21	Provide a general interpretation of the results with respect to the review questions and objectives, as well as potential implications and/or next steps.	81

SECTION	ITEM	PRISMA-ScR CHECKLIST ITEM	REPORTED ON PAGE #
FUNDING			
Funding	22	Describe sources of funding for the included sources of evidence, as well as sources of funding for the scoping review. Describe the role of the funders of the scoping review.	-

JBI = Joanna Briggs Institute; PRISMA-ScR = Preferred Reporting Items for Systematic reviews and Meta-Analyses extension for Scoping Reviews.
* Where *sources of evidence* (see second footnote) are compiled from, such as bibliographic databases, social media platforms, and Web sites.
† A more inclusive/heterogeneous term used to account for the different types of evidence or data sources (e.g., quantitative and/or qualitative research, expert opinion, and policy documents) that may be eligible in a scoping review as opposed to only studies. This is not to be confused with *information sources* (see first footnote).
‡ The frameworks by Arksey and O'Malley (6) and Levac and colleagues (7) and the JBI guidance (4, 5) refer to the process of data extraction in a scoping review as data charting.
§ The process of systematically examining research evidence to assess its validity, results, and relevance before using it to inform a decision. This term is used for items 12 and 19 instead of "risk of bias" (which is more applicable to systematic reviews of interventions) to include and acknowledge the various sources of evidence that may be used in a scoping review (e.g., quantitative and/or qualitative research, expert opinion, and policy document).

From: Tricco AC, Lillie E, Zarin W, O'Brien KK, Colquhoun H, Levac D, et al. PRISMA Extension for Scoping Reviews (PRISMAScR): Checklist and Explanation. Ann Intern Med. 2018;169:467–473. doi: 10.7326/M18-0850.

APPENDIX C - HOEHN-YAHR CLASSIFICATION

Stage	Character of disability
I	Minimal or absent: unilateral if present.
II	Minimal bilateral or midline involvement. Balance not impaired.
III	Impaired righting reflexes. Unsteadiness when turning or rising from chair. Some activities are restricted, but patient can live independently and continue some forms of employment.
IV	All symptoms present and severe. Standing and walking possible only with assistance.
V	Confined to bed or wheelchair.

APPENDIX D - BRAAK'S STAGING

Stage	Anatomy	Clinical symptoms
1	Dorsal motor nucleus of the vagal nerve Anterior olfactory structures	Olfactory loss Autonomic dysfunction
2	Lower raphe nuclei Locus coeruleus	Affective impairment Anxiety Sleep disturbance
3	Susbstantia nigra Amygdala Nucleus basilis of Meynert	Motor symptoms – clinical diagnosis
4	Temporal mesocortex	Worsening motor symptoms Emotional disturbances
5	Temporal neocortex Sensory association and premotor areas	Worsening motor symptoms Cognitive changes

APPENDIX E - TURNITIN REPORT

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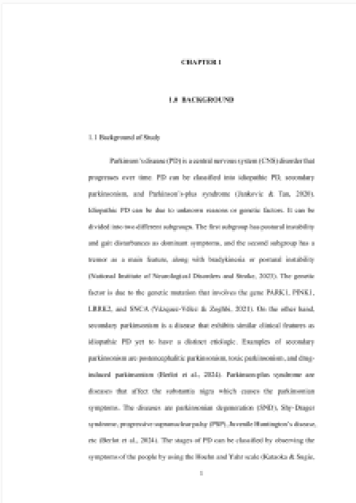
CHAPTER 1

1.0 BACKGROUND

1.1 Background of Study

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6	"Abstract book of the 5th World Parkinson Congress, Kyoto, Japan, June 4–7, 2019", Journal of Parkinson's Disease, 2019 Publication	<1%
7	Luis Sigcha, Luigi Borzì, Federica Amato, Irene Rechichi, Carlos Ramos-Romero, Andrés Cárdenas, Luis Gascó, Gabriella Olmo. "Deep learning and wearable sensors for the diagnosis and monitoring of Parkinson’s	<1%