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Parkinson's Disease Management via Wearable **Sensors: A Systematic Review**

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ABSTRACT Wearable technology has played an essential role in the Mobile Health (mHealth) sector for diagnosis, treatment, and rehabilitation of numerous diseases and disorders. One such neuro-degenerative disorder is Parkinson's Disease (PD). It is categorized by motor symptoms that affect a patient's motor skills and non-motor symptoms that affect the general health of a PD patient. The quality of life of a patient with PD is highly compromised. To date, there is no cure for the disease, but early intervention and assistive care can help a PD patient to perform daily activities with considerable ease. Many research works in PD management discuss the challenges that healthcare professionals face in the early detection and management of this disease. Sensor devices have been promising to overcome these challenges to a certain degree because of the low cost and accuracy in measurement, yielding precise conclusive results to detect, monitor, and manage PD. This paper presents a Systematic Literature Review (SLR) that provides an in-depth analysis of the PD symptoms, Motor and Non-Motor Symptoms (NMS), the current diagnosis and management techniques used and their efficacy. The paper also highlights the work of various researchers in wearable sensors and their proposals to improve the quality of life of a PD patient by diagnosing, monitoring, and managing PD symptoms remotely via wearable sensors. Another area of focus is commercially available wearables for PD management and a few promising works in progress. This paper will be beneficial for future researchers to identify existing gaps and provide the clinicians better insight into the disease progression, and avoid complications. This paper analyzes around 50+ articles from 2016 to 2021 and concludes that there is still much room for improvement in wearables for PD management during the research process. While much work has been attributed to PD Motor Symptom management, there is little focus on the management of PD NMS via wearable sensors. Furthermore, this paper also presents future work for PD management.

INDEX TERMS Parkinson's, wearable sensors, tremors, gait disturbances, sleep dysfunction, remote monitoring, freezing of gait (FoG), depression, cognition, machine learning, early detection.

I. INTRODUCTION

Among neurodegenerative diseases, PD has been ranked as the second most common disease and impacts a large segment of the elderly population worldwide each year [1]. The exact cause of PD is unknown, but genetic, environmental factors, and age play an important role in the risk of disease progression [2]. It mostly affects patients over the age of 60 [1], [3]. It attacks the dopamine-producing ("dopaminergic") neurons in the substantia nigra, a part of the brain. It results in the loss of cells in specific areas of the central nervous system

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over time, resulting in reduced movement and the development of typical Parkinson's motor symptoms [4]. Symptoms increase in intensity over time. Due to the unpredictable nature of the condition, the symptoms vary from individual to individual, necessitating a unique treatment approach for each patient. Clinical examination is crucial because there are no standard diagnostic criteria or bio-markers for PD. The clinical evaluation is influenced by several external factors such as drug timing, food choices, and mental health. People with PD experience the following symptoms. A list of prominent motor symptoms and non-motor symptoms that a PD patient suffers from is illustrated in Table 1.

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MOTOR AND NON-MOTOR SYMPTOMS OF PARKINSONS

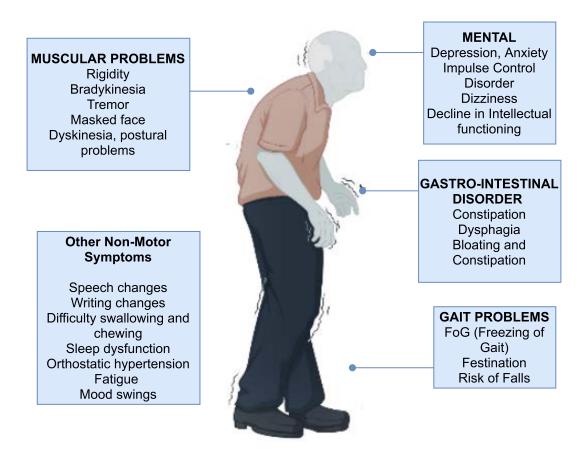


FIGURE 1. Most common symptoms of PD.

TABLE 1. Motor and non-motor symptoms.

| Motor Symptoms | Non-Motor Symptoms |
|------------------|---------------------------|
| Festination | Orthostatic Hypotension |
| Freezing of gait | Sleep dysfunction |
| Hypomimia | Impulse control disorder |
| Bradikynesia | Cognition |
| Tremors | Depression |
| Dyskinesia | Gastrointestinal symptoms |
| Rigidity | |
| Myotonia | |

Among the first signs of PD are tremors and dyskinesia. These are involuntary, spontaneous, abnormal twitching movements of the facial, arm, and leg muscles. The gait of a PD patient is characterized by a shuffling gait and festination where the patient takes shortened and quick steps during normal walking and has a bent posture. Bradykinesia, characterized by the patient's very sluggish movements, is a

significant sign used to diagnose PD. Another typical PD prognosis is Freezing of Gait (FOG), which occurs when a PD patient cannot begin, maintain, or control his or her gait. The combination of bradykinesia and stiffness results in a masked face (hypomimia). The PD patient also has serious balance problems. The patient is at risk of falling because he or she is unable to keep a stable and erect posture [5].

While motor symptoms are evident and act as disease progression markers, NMS that significantly affect a PD patient's life are often ignored. Several researchers have highlighted the importance of managing NMS since they are correlated with Motor symptoms. Management of Motor symptoms and the NMS mentioned in Table 1 contribute to the PD patients' well-being and treatment plan. Figure 1 gives a brief overview of the symptoms experienced by a PD patient.

These symptoms can be highly debilitating for a PD patient and require constant monitoring and management through medication. Early management is critical for avoiding complications and slowing the disease's course. The most common technique used to assess PD symptoms is the Unified



THE CURRENT REMOTE HEALTH MONITORING PROCESS OF A PD PATIENT

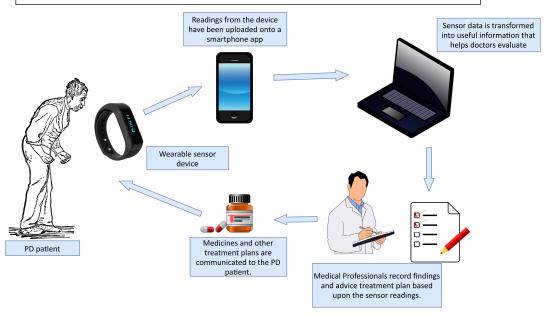


FIGURE 2. The remote symptom monitoring process.

Parkinson's Disease Rating Scale (UPDRS), Hoehn and Yahr (HY), and TimeD Up and Go (TUG) [5], [6]. During the PD diagnostic test, the neurologist records the patient's responses while performing different tasks and assigns ratings according to the UPDRS requirements. The UPDRS scale can be tedious and takes much time. It needs roughly 30 minutes of administration time and specialized training to improve the process of data gathering and evaluation. As a result, it is unsuitable for ordinary clinical practice [7].

Furthermore, PD patients and caregivers are expected to keep a symptom diary [8]. These diaries are subjective, and they rarely represent what happened during the day. The results acquired are unclear and unreliable in detecting disease progression and related problems. Getting a detailed and precise evaluation of a patient's current health from one outpatient session is challenging [9]. Improved symptom monitoring throughout patients' everyday lives, in between clinical appointments, is a challenge in PD management [10].

Wearable sensors in the form of inertial sensors like accelerometers and gyroscopes, combined with short-range communication devices like Bluetooth and Zigbee, are now being considered worldwide because of their low power consumption, design simplicity, lightweight and ease of use to monitor people with health conditions [11]–[14]. At present, only a few health practices employ wearable sensors whereby a patient gets a tiny box in the mail several weeks before a typical clinical check-up, including a body-wearing sensor. After following easy instructions and using the gadget for one week, the data collected by the sensor devices would automatically be uploaded to the cloud, processed and

summarised, submitted to the physician for evaluation, and the patient would receive feedback [15]. At the clinic appointment, this gathered data and the physician's evaluation would complement the physical exam, and hence a comprehensive treatment plan is made. The clinical visit would be changed into a more productive meeting and give the treatment plan a more personalized touch [16]. Such practices are still not very common and are among the emerging trends. Figure 2 illustrates the current remote monitoring process of patients with PD.

According to a research conducted by *IDTechEx*, a leading organization that works to provide independent market research and business intelligence on emerging technology, The market for medical wearable has grown tremendously during the past decade and is forecasted to show a compound growth rate of 13.5 percent in the next decade. In a research conducted in 2019 *IDTechEx* has forecasted 19.7 Billion dollar market for medical wearables [17]. Figure 3 represents a forecast of the wearable market for different medical devices.

Furthermore, the rapidly growing research conducted in the last ten years indicates the rapid advancements in wearable devices in the field of medicine generally and specifically for PD. Many studies have proposed and evaluated wearable sensors for monitoring different motor and NMS of PD. An in-depth review and analysis into the latest techniques is a need of the hour.

A. MOTIVATION

PD is the second most common neurodegenerative disease worldwide [1]. It mostly affects the elderly and can severely physically incapacitate them. While continuous and precise

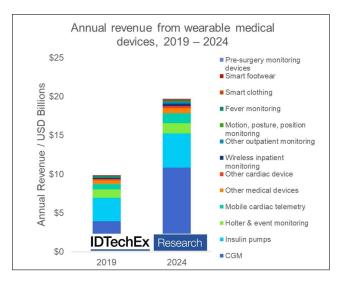


FIGURE 3. IDTech forecast for medical wearables.

monitoring is the only way to manage the disease progression, attending regular clinical appointments can be a huge challenge for a PD patient due to the excessive time, cost, and energy involved and their lack of physical ability. Furthermore, it is essential to manage the PD patients remotely to keep the elderly and vulnerable population safe from unnecessary exposure to public health facilities due to the pandemic. Hence remote monitoring of PD patients is possible only with the help of state-of-the-art wearable sensors. We explore the current and future directions in wearable sensor technology to manage PD symptoms. The SLR intends to assist health care workers and researchers in furthering the works of previous researchers and developing practical models when needed the most.

B. CONTRIBUTION

The use of wearable devices to diagnose, monitor, and manage PD symptoms can tremendously decrease the burden on health facilities and make consultations for PD patients more convenient and fruitful. NMS have been ignored, although they contribute majorly to PD patients' quality of life. We present an SLR focusing on motor symptoms of PD patients and many non-PD-specific papers that discussed wearables to manage NMS like depression, anxiety, sleep dysfunction, and gastrointestinal problems. It is the need of time to study the work of various authors to incorporate these wearables in the management process of PD patients. Furthermore, we explore the market trends and list down several commercially available wearable devices presently being used to manage different symptoms. Another contribution of this paper is a systematic research process conducted to categorically analyze and present the work of various authors in the field of wearable sensors for PD motor symptoms and NMS management. It is imperative to compile the most recent research to include the latest technological advancements in wearables so future researchers can include the latest techniques to design a more comprehensive wearable mechanism to manage PD symptoms; we incorporate most research papers from 2020 to 2021. We gather the fundamental research into an organized and structured paper so that future researchers aiming to create a fully integrated PD home management system can be fully aware of the state-of-the-art wearables that are available and can be incorporated into their system design.

C. ORGANIZATION

The rest of the paper is organized as follows: Section II gives a brief overview of different literature reviews already presented on the topic. Section III discusses the research methodology. Section IV presents the results obtained from the research. Section V provides a discussion on the wearables proposed for Motor Symptom management, wearables proposed for NMS management, the commercially available wearable devices for PD management, and the future prospects. Section VI finally concludes the paper.

II. RELATED WORK

Our research was limited to the past 5 years, i.e., 2016-2021. Various authors have compiled several review papers during these 5 years. A comparative analysis between various review papers is conducted to obtain research gaps.

The author in [12] identified five areas for application of PD devices. Early detection and diagnosis, tremor, body-motion (motor) analysis, motor fluctuations (ON-OFF phases), and home long-term monitoring. The author discusses proposals of different authors to evaluate these five areas and discusses the recommendations and trends in each area. Early detection, management, and monitoring are evaluated in light of Motor symptoms only.

A literature review of different studies conducted regarding different automated systems tested in a home environment, proposed for the management of PD symptoms, have been analyzed in-depth in [18]. The categorization of the available solutions is based upon In-Home evaluation of PD symptoms and impairments, the use of mobile applications for PD, and the design of e-Health systems for remote PD management.

The authors [19] reviewed different studies proposing the use of wearable sensors for fall estimation and prevention and FoG in PD It is an overview of research validating the use of sensor-based assessment techniques to quantify and objectify FoG and Fall risk. By comparing different researches, the author has categorized different sensors used, their placement on the body, and their efficacy in objectively assessing FoG and fall risk.

Reference [20] is a review on how the use of wearable sensors can enhance clinical examination, diagnosis, monitoring, and management of PD patients. The author explores different sensors and categorizes them under different PD motor symptoms, i.e., Gait, Tremors, Bradykinesia, and Dyskinesia, and discusses the commercial devices presently being used to evaluate these symptoms. Furthermore, a review of different predictive models to analyze the sensor data is also discussed.



The review does not highlight the NMS and the works related to that.

In [21] the author evaluates the use of wearables in clinical application in three neurological conditions epilepsy, Parkinson's, and stroke. The use of wearables in laboratory settings, hospitals, and free-living/ In-home have been assessed and their validity compared. They also highlight the limitations of using wearable sensors for these three neurological conditions. Issues like a patient's lack of trust, adherence, and consideration for individual needs have been evaluated and reviewed. Since the paper covers three medical conditions, PD-related discussion was superficial and brief.

In [22] the author has studied different studies assessing a range of sensors and commercially available wearables used to analyze the movements of PD patients and evaluate which wearables are more effective in assessing PD symptoms by comparing no. of sensors, placement of wearable on the body and the clinical application of the device.

Reference [23] is a systematic review, where the validity of articles has been established by using the PEDro technique. It includes an analysis of different wearable devices used for early detection, monitoring, and managing PD symptoms. The review highlights existing trends in PD symptom assessment, state-of-the-art wearables used to monitor motor symptoms, and the future of PD wearables. Furthermore, it discusses the role of wearable insoles in PD gait-related symptom management and its role in rehabilitation.

In [5] wearable sensors used for bradykinesia, gait, tremors, and myotonia have been analyzed. The article also discussed proposed work for sleep dysfunction in PD. Reference [24] is a review of different studies evaluating FoG detection and prediction techniques, their validation, and limitations.

Reference [25] is another systematic review that discusses different wearable sensors used to monitor and manage PD motor symptoms. In [26] the author has evaluated different works to assess the efficacy of technology-based gait analysis techniques and has highlighted the current research gaps in the area of gait analysis, thus highlighting the future work in the area. Reference [27] is a review of different studies regarding PD monitoring using inertial sensors and has included research where data is gathered at home during unsupervised activities.

The author of [28] reviews different studies to give an overview of different technological devices that are being used to test PD symptoms in a home-based environment. He has further provided a review on the validation of different technological devices to determine their efficacy in clinometric testing.

The sensor review is not symptom-specific. In [29] the author has presented a systematic literature review of the different types of sensors, their placement on the body for measuring PD symptoms, and a review of the modern home-based assessment techniques of motor symptoms. He has also highlighted research gaps hence laying doing foundation for future work. Reference [6] is a review of different techniques

used to monitor motor and non-motor PD symptoms. A comparison of different techniques like wearables, biopotential devices, audio recording, motion tracker, smartphones, cueing, video recording, force pressure to evaluate PD symptoms has been made in this review.

Reference [30] is a literature review of studies conducted to monitor fall risk assessment in the elderly. The analysis is based upon the type of sensors, no. of participants, no. of sensors used, placement of sensors on the body, and the no. of tasks assigned to evaluate fall risk in elderly patients. The author has included Parkinsonism and non-Parkinsonism fall risk assessment techniques in the paper. In [31] a comparison of different mHealth technologies for PD motor and NMS detection has been made, identifying their pros and cons in practical applications. Furthermore, research gaps have been identified in existing clinical approaches and mHealth technologies.

Reference [32] provides a systematic review of research papers on present techniques for objective gait analysis and evaluates both current, and future trends for assessing the gait features retrieved from wearable sensors. The author has highlighted some practical issues in the clinical use of wearable sensors for monitoring gait symptoms like cost, and design, which can act as a research gap hence providing future direction for research and clinical implementation.

By analyzing the existing work done in the domain, we concluded that many reviews had been formulated on the topic of "Management of PD symptoms using wearable sensors/devices." Motor symptoms have been the key area of interest for most researchers, and NMS has been given little importance. Only a few papers included in this review mentioned commercially available wearable devices for PD management, but the most recent developments in the domain still need to be highlighted. Only 3 review papers included research till the year 2020—the remaining review papers incorporated research till 2019 and earlier. There has been a rapid increase in the wearable market during the covid era; hence, research for 2021 was missing from most review papers that this SLR incorporates. Table II presents a summary of our findings.

III. RESEARCH METHODOLOGY

An SLR approach was used to structure this review paper. The SLR is a very famous literature review process whereby research work done by different authors on a specific topic is gathered, and work relevant to their particular topic is evaluated and compiled.

A. PLANNING

PD management domain is very vast since PD patients experience many varying and overlapping symptoms throughout their lives. Medical professionals have employed several techniques to improve the quality of life of a PD patient. The planning process of this SLR involves identifying research goals and objectives foremost. The paper is planned according to our research goals and objectives. Research questions

| TABLE 2. Comparison of similar works. Key: Impulse control disord | ey: Impuls | e control dis | order-IC | D, freez | ing of § | şait-FoG, Fall risk | ւ- FR, gն | er-ICD, freezing of gait-FoG, Fall risk- FR, gait disturbance-GD, sleep dysfunction-SD, commercial wearables-CW | eep dysfunctior | 1-SD, col | nmercia | I wearables-CW. | |
|---|------------|---------------|-------------|-------------|-------------|---------------------|-----------|---|-----------------|-------------|-------------|------------------|----------------|
| Author | Year | Tremors | СD | FoG | FR | Bradykinesia | SD | Gastro-Intestinal | Depression | ICD | CWs | Future Prospects | Current Trends |
| Erika Rovini et al. [12] | 2017 | > | > | > | × | × | × | × | X | × | × | > | > |
| Erika Rovini et al. [18] | 2018 | > | > | > | > | × | × | × | X | × | × | > | > |
| Ana Lı'gia Silva de Lima et al. [19] | 2017 | × | × | > | > | X | × | X | X | × | × | X | X |
| Ritesh A Ramdhani et al. [20] | 2018 | > | > | × | × | > | × | X | X | × | > | X | > |
| Dongni Johansson et al. [21] | 2018 | > | > | > | > | > | > | X | X | × | × | X | X |
| Andrea C. Albán-Cadena et al. [22] | 2021 | > | > | > | > | > | × | × | X | × | > | > | X |
| Asma Channa et al. [23] | 2020 | > | > | > | > | > | × | × | X | × | > | > | > |
| Ruirui Lu et al. [5] | 2020 | > | > | × | × | `> | > | × | × | × | × | > | × |
| Scott Pardoel et al. [24] | 2019 | × | × | > | × | × | × | × | X | × | × | > | × |
| Christiana Ossig et al. [25] | 2016 | > | > | × | × | > | × | × | X | × | > | <i>></i> | <i>></i> |
| Raquel Bouc et al. et al. [26] | 2020 | X | > | × | > | X | X | X | X | X | × | X | ſ |
| Marco sica et al. [27] | 2021 | > | > | × | × | > | × | × | X | × | × | > | <i>></i> |
| CMorgan et al. [28] | 2020 | > | > | X | X | > | > | X | X | X | > | <i>></i> | ſ |
| Stefania Anacona et al. [29] | 2021 | X | X | X | X | X | X | X | X | X | <i>></i> | <i>^</i> | ſ |
| Randeep Deb et al. [6] | 2021 | <i>></i> | <i>></i> | <i>></i> | <i>></i> | <i>></i> | > | X | <i>^</i> | <i>></i> | X | <i>^</i> | X |
| Rosaria Rucco et al. [30] | 2018 | X | <i>></i> | X | <i>></i> | X | X | X | X | X | X | X | X |
| Hanbin Zhang et al. [31] | 2021 | > | <i>></i> | > | X | X | > | X | <i>^</i> | X | X | <i>^</i> | ſ |
| ShanShan Chen et al. [32] | 2016 | X | <i>></i> | X | X | X | X | X | X | X | X | <i>^</i> | ſ |
| Proposed SLR | 2021 | <i>></i> | <i>></i> | <i>></i> | ^ | <i>^</i> | > | <i>></i> | 1 | <i>></i> | ſ | <i>^</i> | <i>^</i> |

TABLE 3. Research questions (RQs).

| RQ-1 | What wearable technologies are used to detect and manage |
|------|--|
| | motor symptoms of PD? |
| RQ-2 | What wearable technologies are used to monitor and manage |
| - | non-motor symptoms of PD? |
| RQ-3 | What are some state-of-the-art wearable devices used in PD |
| | management? |
| RQ-4 | What are the future directions of wearable sensors in PD? |

have been formulated to gather information systematically. We searched several databases to gather all relevant articles and papers.

B. RESEARCH GOALS

This paper presents a systematic review of the wearable technology presently being used to assess PD motor and non-motor symptoms. To the best of our knowledge, we could not find a literature review that comprehensively detailed the work of different authors regarding the role of wearable sensors to manage motor and NMS and a description of the wide variety of commercially available devices being used to manage PD symptoms. This paper will also bring to light some constructive work by researchers to assist future developments in wearable sensors for PD.

C. RESEARCH QUESTIONS

The first phase of the research involves identifying the scope of the paper. We designed a few research questions that will focus on discussion in this paper. Table 3 lists down the proposed research questions.

D. RESEARCH OBJECTIVES

The paper intends to address the following objectives:

RO-1:Investigate different techniques used for early detection and management of PD motor symptoms via wearable sensors

RO-2:Investigate different techniques used to diagnose and manage PD NMS.

RO-3:Highlight state-of-the-art wearable devices presently being used to detect and manage PD.

RO-4:Discuss future directions in the field of wearable sensors to manage PD.

E. SELECTION OF SOURCES

An e-search was performed in different databases from 2016 to 2021. Different articles, journal publications, conference proceedings, and transaction papers were reviewed within IEEE Xplore, Multidisciplinary Digital Publishing Institute (MDPI), Springer, Elsevier, and other Journals to identify articles concerning the use of wearable sensors for PD applications. The initial search yielded some 9890 articles in different databases. Most articles of our interest were found in different journals and conference proceedings of IEEE and MDPI "sensor journal." Figure 4 shows the contribution of different databases in the research process. Duplicates



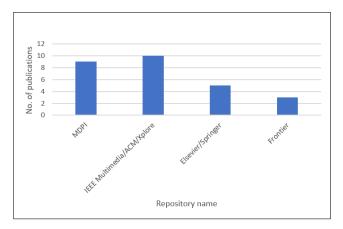


FIGURE 4. Contributions of various databases in the research process.

TABLE 4. Search strings.

| | GROUPED SEARCH STRINGS |
|------|--|
| GR-A | "Parkinsons disease" + "wearable sensors" + "management" |
| GR-B | "Motor symptoms"+ "wearable sensors" + "management" |
| GR-C | "Non-motor symptoms" + "wearable sensors"+ "management" |
| GR-D | "Bradykinesia" +"wearable device/sensors" |
| GR-E | "FoG" +"wearable device/sensors" |
| GR-F | "Fall Risk management" +"wearable device/sensors" |
| GR-G | "Sleep dysfunction" +"Wearable devices/sensors" |
| GR-H | "Depression in Parkinsons" +"wearable devices" |
| GR-I | "Future of PD"+"wearable sensors" |
| GR-J | "Commercial devices"+"Parkinsons management" |

and articles in languages other than English were excluded. Articles were then evaluated based upon the inclusion and exclusion criteria; 4781 articles were excluded. The remaining 1974 articles were further screened by comparing titles and reviewing abstracts, and a further 832 articles were excluded. We then evaluated the remaining 1142 articles based upon the paper's main idea and compared them to our research objectives. Articles that were not in line with our research objectives were excluded from the survey. A total of 334 articles were shortlisted. After an in-depth study, Almost 60+ articles were incorporated into our SLR. The selected articles were then studied in depth.

F. SELECTION/SEARCH CRITERIA

For this research, we have gathered different research papers on motor and NMS of PD to develop a thorough understanding of the disease. This review paper combines two domains; Parkinson's and Wearable sensors. Then individual motor and NMS were searched along with the search string "wearable devices/sensors." A combination of strings was designed to gather all related articles. The results yielded different wearable techniques used/proposed to manage individual symptoms. Table 4 lists the search strings used in our research process.

G. INCLUSION AND EXCLUSION CRITERIA

A clear and precise inclusion and exclusion criteria need to be formulated so that we do not sway from our research goals

TABLE 5. Inclusion criteria.

| 1 | Articles in the English language. |
|---|--|
| 2 | Articles published in the last five years, i.e., 2016-2021 |
| 3 | Articles that specifically discussed management and diagnosis of |
| | PD via wearable sensors. |
| 4 | Articles specific to PD Motor symptoms |
| 5 | Non-PD specific articles were included that discussed manage- |
| | ment of NMS since NMS can be non-PD specific. |
| 6 | Journal publications and conference papers were included |

TABLE 6. Exclusion criteria.

| 1 | Articles in languages other than English |
|---|--|
| 2 | Articles that were duplicates |
| 3 | Articles that used techniques other than wearable sensors for PD |
| | management. |
| 4 | Articles that addressed other diseases or incorporated general |
| | wearables used in health industry. |
| 5 | Literature that was published earlier than 2016 |
| 6 | White papers and Non-peer reviewed researches were not in- |
| | cluded. |

and objectives. The Table 5 lists down the criteria that were established while selecting the research that we include.

We included articles that are non-specific to PD management for NMS since symptoms like depression, gastrointestinal problems, sleep dysfunction are non-specific to PD, and these symptoms overlap with many other diseases. Therefore, wearables used to diagnose and manage them are universal.

Researches included were essentially from 2016 to 2021 because of the steady increase in the wearable market since 2015. Another research conducted by "IDTechEx," a leading ma organization that works to provide independent market research and business intelligence on emerging technology, indicated a steady increase of 9% from 2015-2018 and a rapid increase of 23% from the year 2018 onwards [33]. In 2020 as an attempt to contain the pandemic, remote monitoring and home-based management of patients increased, thus contributing to the further growth of the wearable market and the rapid technological advancement. Therefore, articles from 2016 to 2021 gave the best insight into the technological advancements in wearable technology.

After a thorough examination, we excluded research papers that did not match the inclusion criteria. All researches that discussed non-wearable solutions were excluded. Table 6 is the criteria of exclusion that we followed.

H. RESEARCH PROCESS

The process of selection was rigorous and thorough. From a vast pool of articles and papers, about 60 articles were short-listed that have been included in this paper for the purpose of research. Figure 5 illustrates the selection process.

The 60 shortlisted articles were inspected and classified according to the research objectives, research domain, and year. Since this review paper intends to address the motor and NMS both, we made a carefully balanced selection in both domains. 25 papers discussed the motor symptoms that mainly include bradykinesia, rigidity, tremors, FoG, fall risk,



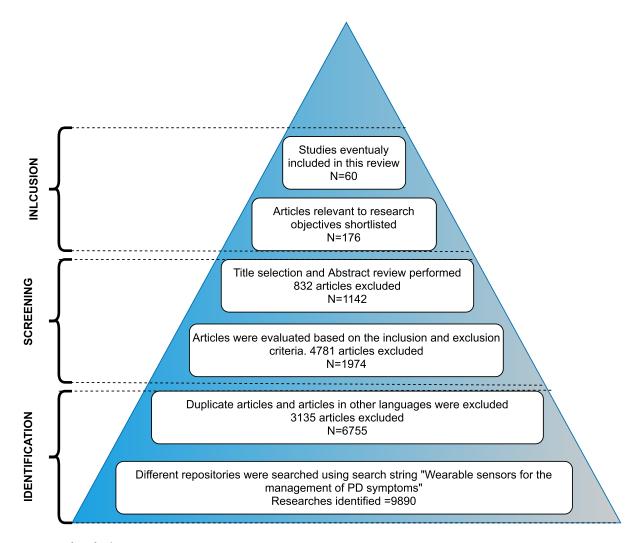


FIGURE 5. The selection process.

and other gait-related problems. Around 16 papers were related to NMS like constipation, depression, Impulse Control Disorder, and Sleep Dysfunction. The rest of the papers discussed general PD management and future directions. Figure 6 is an illustration of our findings.

IV. RESULTS

Of the selected papers, most of the work was associated with the Motor symptoms like tremor, bradykinesia, rigidity, and FoG. NMS of PD overlap with many other diseases hence very few studies for NMS specific to PD were found. Figure 7 illustrates the topic-wise classification of the articles selected.

The articles were classified according to the year of publications. This helped prioritize more recent articles and technical advances that needed to be incorporated. Most selected articles were from the years 2020 and 2021. This can be attributed to the sudden increase in demand in remote monitoring owing to the advent of Covid so that PD patients who were at high risk could be managed at home. Figure 8 illustrates the year wise classification.

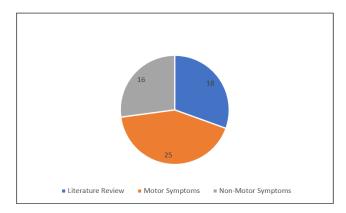


FIGURE 6. Classification of selected papers according to motor or non-motor.

We also observed that the most relevant papers were published in journals. The MDPI "sensor" and "data" journals generously contributed to our literature review. Since our discussion was an integration of health and technology, we found



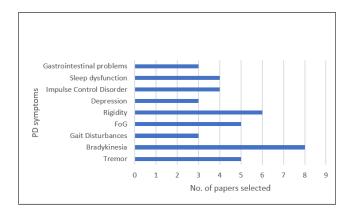


FIGURE 7. Classification of selected papers according to research topic.

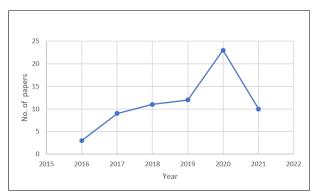


FIGURE 8. Classification of selected papers according to year of publication.

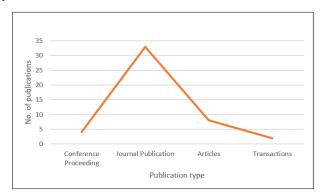


FIGURE 9. Classification of selected papers according publication type.

several useful articles from Medical Journals too, e.g., "The Journal of Neurology," "The Journal of Mental Health," and "The Journal of Parkinson's Disease," which had many relevant articles that addressed wearables for PD management. Figure 9 shows the types of publications selected.

Figure 10 is a taxonomy of the selected papers. The papers have been classified according to different symptoms and the research objectives.

V. DISCUSSION

A. R0-1: WEARABLE TECHNOLOGY FOR EARLY DETECTION AND MANAGEMENT OF MOTOR SYMPTOMS

For clarity, motor symptoms have been grouped into two groups. One group explicitly discusses gait symptoms, and the other discusses symptoms that affect the entire body.

1) GAIT DISTURBANCES, FALL DETECTION, AND FOG MANAGEMENT

A patient with PD experiences a range of motor symptoms during their life. These symptoms intensify as the disease progresses and can affect the quality of life of PD patients. Gait-related motor symptoms include Parkinsonism gait disturbance, fall detection, and FoG. *Gait Disturbance* is associated with reduced speed, shorter steps, hesitation in steps, freezing of gait, and festination. *Festination* is described as quick short steps coupled with an inclined posture that can increase the chances of falls.

FoG is another significant PD motor symptom. FoG is a temporary disruption of gait in which the patient feels he is unable to walk. Sudden episodes of FoG might put PD patients at risk for falling [34]. The FoG incidents are generally short-lived, the patient's control is soon restored, and they return to regular walking [35]. Since gait problems play a huge role in improving the quality of life of a PD patient, it has been a popular topic of research. These three symptoms generally overlap, whereby the occurrence leads to another. Therefore, most researchers have addressed these symptoms in unison. Ten papers were selected that focused on FoG, fall risk, and gait disturbances. Almost all the papers used Inertial sensors (IMU) [36]-[45]. They are electronic sensors used to calculate angle, velocity, orientation and gravitational force of the subject. They are made with a combination of triaxial accelerometers, gyroscopes, and sometimes magnetometers. Micro-electro-mechanical system (MEMS) another sensor used is a specialized gyroscope used to calculate the rate of turn [46].In most researches, 2-3 IMUs were placed at the lower extremities of the body of the PD patients. Figure 11 illustrates the no. of researches that used more than, less than, and exactly three sensors. Most common sensor location were feet [37], [41]-[43], shin [37], [44], ankles [36], [38], [45] and legs [36], [38], [39]. Figure 12 shows that the most common location for placement of sensors were the legs.

Authors in [40] included the use of a wearable necklace for the detection of falls. The author gathered data from subscribers to a Personal Emergency Response System (PERS-Philips Lifeline service). PERS is a necklace-style device with many integrated sensors (such as a tri-axial accelerometer and barometer) meant to detect falls in the elderly. The quantitative analysis of the falls helped identify the efficacy of such wearable devices in categorizing the falls according to different variable factors. Another multimodal sensing system to detect and monitor FoG and gait disturbance was proposed in [36] that included the use of wearable sensor bands, Zenith cameras, and Kinect. Data was collected using 3D accelerometers attached to the ankles, knees, and waist. The system was trained using the Recurrent Neural Network model by capturing movement information. Among the ten papers selected for gait disturbances, all experimentation was done in lab/clinic settings only [40], and [37] proposed home-based management via wearable sensors. Commercially available sensors were employed in a



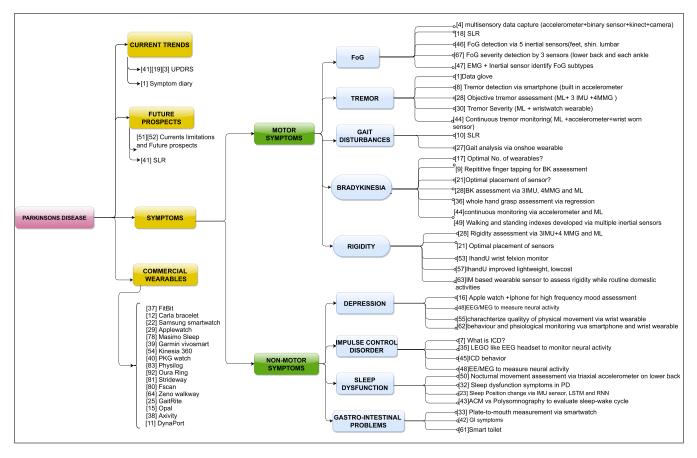


FIGURE 10. Taxonomy of selected publications.

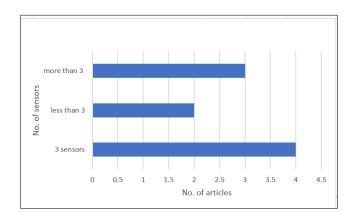


FIGURE 11. The average number of sensors used to detect gait disturbances and FoG episodes.

few research works, confirming their efficacy. Reference [42] employed the JiBuEn sensor system to evaluate gait parameters, [37] and [38] used OPAL sensors by APDM in their proposed design. Reference [39] used a BIO2bit Move surface EMG device to detect muscular changes to differentiate FoG subtypes. Table 7 demonstrates a summary of findings for monitoring gait disturbances, FoG, and fall risk with the help of wearable sensors from the selected papers.

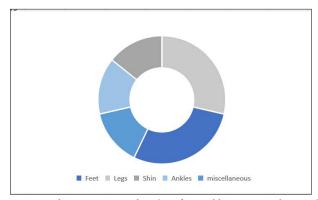


FIGURE 12. The most common location of wearable sensors to detect gait problems and FoG episodes.

2) BRADYKINESIA, RIGIDITY, AND TREMORS

Other than gait-related symptoms, a PD patient experiences motor symptoms that affect the entire body like bradykinesia, rigidity, and tremors. *Bradykinesia* is a key symptom used to assess the stage of disease of PD patients. *Bradykinesia* is defined as slowness of movement. A PD patient experiences hesitation, slow response, and decreased displacement of amplitude [4].

Alongside bradykinesia, a patient also experiences *Tremors*. Tremors are mostly one of the first signs of PD.



| TABLE 7. Selected articles survey for | gait disturbances. FoG and fall risk. |
|--|---------------------------------------|
|--|---------------------------------------|

| | Sensor technology | No. of | Location | PD participants | Objective | Setting | Result |
|------|-------------------------------|---------|------------------------------|-------------------|---------------|----------|---------------|
| | | sensors | | | | | |
| | Smart Band (3D Accelerome- | 5 | Ankle, knees,waist | 18 | FoG | Home | 200 episodes |
| [36] | tor) +Zenith camera+Kinect | | | | monitoring | | detected |
| | Study1: OPAL IMU sensors | 8 | Shin, feet, wrists, sternum, | 45 | FoG | Lab | 79 episodes |
| [37] | | | trunk | | monitoring | | detected |
| | Study 2: IMU sensors | 3 | One on each foot, one over | 23 | FoG | Home | 69% |
| [37] | | | lumbar area | | | | outcome |
| | OPAL IMU sensors | 3 | Lower back side of leg | 71 | FoG | Lab | 1487 |
| [38] | | | above ankle | | monitoring | | detected |
| | BIO2bit Move sensor + Sur- | 2 | GC and TA leg muscles | 7 | FoG subtype | Lab | 99 episodes |
| [39] | face EMG | | | | detection | | detected |
| | 3D accelerometer + capacitive | 13 | Feet | 20 | FoG | Lab | 140 episodes |
| [43] | pressure sensor | | | | | | detected |
| | Shimmer IMU(triaxis acc +tri- | 2 | Mounted on each shoe | 108 | Gait patterns | Lab | not shared |
| [41] | axis gyro) | | | | | | |
| | JiBuEn sensor system (MEMS | 6 | Behind upper and lower | 32 | Gait | Lab | not shared |
| [42] | sensor) | | limb and shoe heels | | disturbances | | |
| | PERS (Triaxial accelerometer | 1 | Necklace | 2063 (preexisting | Fall risk | Home | 6436 cases in |
| [40] | +barometer) | | | data set | | | 2 yrs |
| | Smartphone IMU (3D acc, | 3 | Trouser pocket lateral side | 32 | FoG | Hospital | 110 detected |
| [45] | gyro and magnetometer | | of waist ankle | | monitoring | | |
| | ETHOS miniature IMUs | 3 | Shin above ankles lower | 11 | Gait evalua- | Home | not shared |
| [44] | | | back | | tion | | |

It generally starts on one side of the upper arm or leg and extends to the lower side of the body. It can occur at rest and increase during periods of excitement and may settle during sleep [5]. Resting tremors are an important illness indicator. Clinical examination is still the most common method of assessing tremors, and a variety of measures have been devised to be able to perform an effective evaluation of PD patients [4].

A PD patient also experiences stiffness in joints and muscles when using the limbs for routine tasks like dressing, walking, or turning over. This is classified as rigidity,monje2019new. As with bradykinesia, rigidity is also very difficult to assess objectively. Clinical evaluation is the primary tool used to evaluate rigidity too. Presently the UPDRS scale is used to assess the patient's intensity of bradykinesia, rigidity, and tremors. Another typical approach is the "Timed Up and Go" (TUG), a comprehensive test that measures a patient's mobility status, such as standing, walking, turning, or sitting down [5]. Several researchers have proposed different assessment techniques to detect and monitor the progression of bradykinesia, rigidity, and tremors. Use of IMUs consisting triaxial accelerometer, triaxial gyroscope and triaxial magnetometer was the most common sensor used for evaluation of bradykinesia, rigidity and tremors [47]–[59].

Authors in [48] coupled IMUs with Mechanomyography to quantify different types of tremors like kinetic tremors, rest tremors, and postural tremors. Only two articles [60] and [8] used a mechanisms other than IMUs. The author in [8] proposes a data glove using flex sensors that are worn over the hand to measure finger postures to detect tremors and bradykinesia. Most researches used commercially existing IMUs or accelerometers like [47] used iPhone's built-in accelerometer, [50] used OPAL sensors, [52] used miniature

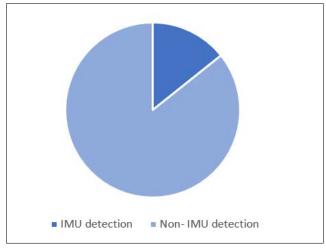


FIGURE 13. Researches that used IMU for detection of bradykinesia, rigidity and tremors.

lightweight IMUs named L3G4200, [58] used BioKin chip system to evaluate back movements to assess rigidity and the author in [59] has used TREMITAS system to quantify tremors. Figure 13 represents the classification of research papers based upon using IMUs for detection of bradykinesia, rigidity, and tremors.

To evaluate these three symptoms, sensors have been placed on various body locations. Most common body location for quantifying tremors are the upper limbs that include hands [8], [59], arms [48], wrist and fingertips [49]. In order to quantify bradykinesia and rigidity, sensors have been placed all over the body, including upper and lower limbs [51], arms, legs, and torso [50] and upper, and lower back [58]. No. of sensors were also variable depending upon the assessment criteria and the objectives.



TABLE 8. Articles selected for tremors, bradykinesia and rigidity.

| | Sensor technology | No. of sensors | Location | PD partici- pants | Objective | Setting |
|----------------|--|----------------|--|-------------------------|---|----------------------------|
| [8] | Data Glove (flex sensors + android app) | 1 | Hand | 4 | Measure finger posture in tremor and bradykinesia patients | Lab |
| [47] | Accelerometer reading from iPhone | 1 | Legs above the knee | 24 | Tremor frequency via app compared to surface EMG scores | Lab |
| [48] | MMG (mechanomyography) IMUs (acc, gyro, magneto) Force sensor | 8 | Arm, elbow, wrists | 23 | Distinguish PD from healthy subjects, detect kinetic tremor, rest tremor, and postural tremor | Lab |
| [49] | Wrist watch type device (triaxial accelerometer, gyroscope) | 2 | Wrist and figertip of middle finger | 85 | Automatic scoring of resting tremors | Lab |
| [50] | OPAL IMU sensor (acc, gyro, magneto) | 11 | Arms, legs, torso | 35 | Developing digital biomarkers for bradykinesia and rigidity | Lab |
| [51] | Triaxial accelerometer | Variable | Upper and lower limb upper arm, forearm, thigh and shank | 10 | Determine the relationship between accurate diagnosis and minimum no. of sensors | Three sittings in 8 months |
| [52] | Miniature ligthweight IMU (L3G4200) +machine learning | 2 | Thumb and finger nails | 56 | Assess bradykinesia scores by analyzing repetitive finger tapping task | Lab |
| [53] | Magnetometer IMU | 5 | Index finger, thumb, meta carpus, wrist | 14 | Sensor readings for UPDRS tasks | Lab |
| [54] | Wrist worn IMU(3axis acc, 3axis gyro)+MCU(Microcontroller unit) | 1 | Index finger | 15 | Comparing hand grasping angle | Lab |
| [55] | Light weight head cap(head sensor) fingerless gloves, IMUs | 17 | 1 on each body part | 30 | Establish braykinesia index for walking and standing | Lab |
| [56] / [57] | iHandU (3D acc, 3D gyro, magnetometer, temperature sensor) | 4 | Hand | | Novel invention to detect rigidity | Lab |
| [60] | PD Meter | | | 7 | To evaluate stiffness in the joint. | Lab |
| [61] | BioKin chip +minimum no. of IMU) | 4 | Two upper right back two lower right back | 15 | Measuring back movements to assess rigidity | Lab |
| [59] | TREMITAS (ACC, 3D gyro, 3D magneto) pen shaped sensor | 2 | Hand | 14 | Correlate TREM values with UPDRS score | Lab |

Table 8 is a summary of findings for management of Tremors, Bradykinesia and Rigidity via wearable sensors from the selected papers.

B. R0-2: WEARABLE TECHNOLOGY FOR EARLY DETECTION AND MANAGEMENT OF NON-MOTOR SYMPTOMS

1) SLEEP DYSFUNCTION

Insomnia, Rapid eye movement (REM), sleepiness during the day, restless leg syndrome, and restless night-time sleep are all sleep problems associated with PD. Sleep problems affect up to 90% of people with PD [62]. An increase in motor illness, NMS, and quality of life have been linked to night-time sleep irregularities. Several wearable sensor mechanisms are presently being used to evaluate sleep disorders. Five different research works were selected that proposed different techniques for sleep monitoring. Polysomnography is one of them, which uses video records and body sensors to provide information on changes in the body positions throughout the night during sleep and analyzes sleep patterns [63]. It is the most commonly used and comprehensive method to gather data related to sleep. A polysomnogram is a tool used to study

sleep data of a patient that includes an electroencephalogram, electrooculogram, electromyogram, ECG, and pulse oximetry, as well as airflow and respiratory effort [64]. Due to the significant resource overhead necessary for data collection is a time-consuming, labor-intensive, and costly study. Another commonly used method is Actigraphy which, although not as comprehensive as Polysomnography, is an assessment that calculates body movements 24 hours a day [65].

A small wristwatch-type actigraph is worn for a prescribed time to measure gross motor activity. The actigraph unit's movements are continually recorded, and some units also measure light exposure. Actigraphy can investigate the problems pertaining to the sleep/wake cycle. The actigraph is a watch-like device worn on the wrist and incorporates an accelerometer [66]. Triaxial accelerometers like *Axivity AX3* body-fixed sensor or *DynaPort MiniMod Module* have also been proposed to assess the sleep-wake cycle in PD patients [67]. Ambulatory Circadian Monitoring (ACM)is another method of evaluating sleep that calculates variables like skin temperature, acceleration, wrist position, exposure to light. Data obtained can then be useful in quantifying the sleep-wake cycle and other health variables associated with



TABLE 9. Articles selected for sleep dysfunction.

| | Sensor technology | Location | PD participants | Objective | Outcome |
|------|--|---------------------------------------|-----------------|--|---|
| [66] | Actigraph- wristworn accelerometer device | Wrist | 35 | Quantifying circadian rest-activity rhythms to predict disease progression | Altered circadian rhythm contributes to cognitive decline |
| [67] | Triaxial accelerometer (Axivity AX3 or Dynaport MiniMod Module) | Lowerback | 305 | Monitoring sleep-wake cycle and Nocturnal movements | Advanced stage PD had more upright periods |
| [68] | Ambulatory Circadian Monitoring(ACM) - temperature sensor+ MEM sensor+triaxial sensor+light sensor | Wrist | 70 | Comparison between polysomno- graphic findings and ACM readings to detect sleep-wake state | PD patient showed sleep alterations, poor sleep efficiency and lengthy night time movements |
| [69] | Inertial Measurement Unit(IMU) | Left arm | Not mentioned | Capture 3D motion data | Nocturnal movements recorded |
| [64] | Polysomnography- EMG +EOG+ EEG+pulse oximeter | Body | Not mentioned | Gather sleep-wake cycle informa- tion and other health biomarkers while asleep | The gold standard for assessing sleep dysfunction |
| [70] | Sensor modules, data repeater and monitor- ing host computer | Abdomen, both wrists and ankles | 29 | Nocturnal parameters assessed | PD sufferers have a reduced sleep quality |

PD symptoms [68]. Moreover, IMUs are also being used to capture 3D motion data that can be used to assess nocturnal movements and detect sleep patterns in PD patients, thus giving key insight into disease progression [69]. Reference [70] employs a system that records movements and consists of five sensor modules, a data repeater, and a monitoring host computer. The data is transferred from the sensors to the host computer over WIFI. The sensors are tied with an elastic band and worn above the clothes below the waist and on both wrists and ankles. Several parameters like turning in bed, waking to urinate, and many more were assessed to establish a correlation between nocturnal movements and PD progression. Table 9 is a summary of findings for monitoring sleep dysfunction via wearables from the selected papers.

2) GASTROINTESTINAL DISORDERS

related problems are common in PD patients; as a result, many patients suffer from malnutrition, intestinal blockage, and perforation and are sometimes hospitalized. In addition, about 40-50% of PD patients say they suffer from constipation [71]. Constipation is caused by delayed GI movements and irregular muscular contractions during feces. It has been observed that the severity of constipation is directly linked to the increase of motor and non-motor symptoms in PD [71]. Impulsive eating disorders, dysphagia, bloating, and constipation are a few of the gastric issues [72]. Very few papers discussed the use of wearables for PD-specific gastrointestinal problems. Plate-to-mouth time has been verified as an objective measure of eating behavior in people with PD, using a tri-axial wrist-worn sensor in [73]. It supports the notion that we can measure PD motor and NMS deterioration by assessing in-meal behavior via a standard smartwatch device. Reference [74] suggests the correlation between Bradykinesia (BKS), Dyskinesia (DKS), and Gastrointestinal problems. The author used Global Kinetics Corporation's Parkinson's KinetiGraphTM (PKG), a sensor device worn on the wrist that helps monitor functional movement throughout the day. The device is attached to the arm experiencing symptoms and generates scores for BKS and DKS every 2 minutes. Higher BKS and DKS scores prompt medical professionals to look at gastrointestinal problems since they are proportional to each other.

Reference [75] is a non-PD digital approach to evaluating constipation via the FitBit monitoring device through which several health bio-markers were gathered, and regression models were used to assess activity on days with constipation and without. The study was a 16-week program with 1540 participants. The outcomes indicated reduced step count, sleep time, and inactivity on constipated days. Another promising study to evaluate gastrointestinal problems is the 'smart' toilet [76]. The toilet automatically analyses urine and stool and uses deep learning to classify stool and urine using pressure and motion sensors. The data is securely transferred to a server and can be used by medical professionals to evaluate PD progression and help monitor associated gastrointestinal problems. Table 10 presents a summary of findings for monitoring gastrointestinal problems via wearable sensors from the selected papers.

3) DEPRESSION

Anxiety, depression, impulse control disorder are common in PD patients. Often they are misdiagnosed and ignored and can significantly decrease the quality of life of a PD patient and make it difficult for carers to manage a PD patient. Mental health is a key indicator of the well-being of a PD patient [77]. Correlation between depression and physical activity and health bio-markers are the primary tools to assess depression in PD patients. In [78] a wrist-wearable device was used to measure physical movement objectively for one whole week in elderly patients with depression. The wearable monitor



| | Sensor Technology | Location | PD participants | Objective | Outcome |
|------|------------------------|----------|-----------------|---------------------------------------|------------------------------------|
| [73] | Smart watch -IMU | Wrist | 21 | Calculate average time hand spends | PD patients have a high plate-to- |
| | | | | transferring food from plate to the | mouth value |
| | | | | mouth | |
| [74] | PKG (Parkinsons | Wrist | 107 | Establish correlation with Bradyki- | BK scores in PKG is a strong |
| | Kinetigraph) | | | nesia(BK) scores and constipation | marker for constipation |
| [75] | FitBit monitoring | Wrist | 1540 | Establish relation between physical | Constipation leads to reduced step |
| | | | | activity, sleep patterns | count, reduced sleep |
| [76] | Smart Toilet- pressure | N/A | N/A | Gather urine and stool data to assess | |
| | sensor motion sensor | | | overall health | |

TABLE 10. Articles selected for gastrointestinal problems.

consisted of three accelerometers to track physical movements. The gadget was created to be as discrete as possible to increase usage, and data could be obtained in the most natural and realistic environment. Specific activity assessments showed that depression patients had 'slowed' motor function. This finding was valuable in assessing the disease's progression and helping PD patients fight depression. With the advent of smartphones tracking mood and behavior throughout the day has become considerably easier [79]. Authors in [80] used the Apple Watch that provides a small touch screen and contains many sensors, including accelerometers and a heart rate sensor. Assessments like mood assessment cognitive assessment were prompted to gather 24 hr data throughout the day. Heart rate and activity data were gathered through the iPhone and Apple watch and compared. This data was then gathered and analyzed to evaluate the fluctuations in mood and the stimuli.

A fully integrated system is needed to evaluate the mental health of a PD patient; hence [58] proposed a detailed depression evaluation model where participants were supposed to wear two E4 Empatica wristbands on each wrist, all the time. The E4 uses actigraphy to monitor electrodermal activity, temperature, heart rate, motion using a 3-axis accelerometer, and sleep parameters. The phone app recorded social activities (e.g., number of calls, messages), physical activity (e.g., still, walking), and the number of applications utilized. Information was extracted using machine learning algorithms to quantify changes in depression severity due to variable factors. Authors in [81] further included other health and daily life indicators to differentiate between depressed and healthy individuals. With the use of a wearable device, SlimeW20 wrist band biosensor device that calculates several steps, movements, sleep hours, heart rate, temperature, and light exposure, a comparison can be made between healthy and depressed individuals. Compared with healthy adults, these physiological markers can also be a good indicator of disease progression. Table 11 presents a summary of findings from selected researches regarding the diagnosis of depression with the help of wearable sensors.

4) IMPULSE CONTROL DISORDER

Impulse Control Disorders (ICDs) are disorders whereby a patient involves himself in something that gives him pleasure repetitively and uncontrollably. The patient does actions compulsively, again and again. The key symptom in all of these disorders is that the patient cannot control the temptation to indulge in certain behavior or actions that can harm himself or others. It interferes in daily life functioning [82], [83].

Reference [84] illustrates how Electrophysiological markers like electroencephalogram (EEG) sensors can be used to provide direct measures of neural activity. The use of EEG sensors suggests the possibility of objectively studying the cognitive decline in a neurodegenerative disease like Parkinson's. Based on this idea, a customized low-cost LEGO-like EEG sensing headset coupled with an assessment procedure has been proposed in [85] that can detect early symptoms and advancement in stages of PD by assessing brain activity and comparing responses with standard ICD indicating markers. Reference [36] is a comprehensive, fully integrated proposal of a system involving data capture via multiple sensors and processing based on multiple sensing technologies. The design includes Internet of Things (IoT)-based devices. Multimodal fusion (MF) techniques are applied to medical and behavioral data to detect unusual behavior abnormalities and diagnose and evaluate PD, integrating all the relevant people like clinicians, caregivers, and patients. The system aims to gather information from the medical perspective and other information like location to fully understand the behavior and context and trigger relevant medical and social decisions responses. The integrated system consists of a wrist band, which provides health biomarkers like heart rate and body temperature and collects movement data (via accelerometer, gyroscope, and magnetometer) and multiple other sensors around the house and outdoors. RGB-D(Microsoft Kinect v2) camera and a Zenith 360-degree camera allow movement analysis to monitor user activity status and gather data from surroundings. Very little work has been done to monitor ICD via wearable sensors. Reference [86] suggests ICD detection by analyzing abnormal day and night behavior patterns. E.g., sitting for long hours in front of the computer, doing a task repeatedly or unnecessarily, or lying in bed are good physical indicators of normal or abnormal behavior.

C. RO-3: COMMERCIALLY AVAILABLE WEARABLE DEVICES FOR THE MANAGEMENT OF PD

Due to the effectiveness, reliability, and accuracy of the readings of wearable devices in the management and diagnosis



TABLE 11. Selected articles for depression.

| | Sensor technology | Location | PD participants | Objective | Outcome |
|------|------------------------|----------|-----------------|---------------------------------------|--------------------------------------|
| [78] | Activity monitor | Wrist | 29 | To measure continuous physical | Depressed individuals showed |
| | (Actigraph) | | | movement in elderly | slowed motor function |
| | accelerometer | | | | |
| [80] | Apple Watch built-in | Wrist | 30 | 24hr mood assessment, cognitive | Validity and feasibility of mood and |
| | accelerometer, heart | | | assessment alongside heart rate and | cognitive assessments |
| | rate sensor | | | activity data | |
| [81] | SlimeW20 wristband, | Wrist | 45 | To measure different health mark- | Step count, sleep duration, and |
| | biosensor device, | | | ers like temperature, heart rate also | heart rate varied for depressed in- |
| | temperature sensor, | | | steps, and movement patterns | dividuals compared to healthy indi- |
| | heart rate sensor, | | | | viduals. |
| | accelerometer, etc. | | | | |
| [58] | E4 Empatica wrist- | Wrist | not mentioned. | Monitor electrodermal activity skin | Was able to quantify changes in |
| | band actigraph, three- | | | temperature, heart rate, motion, and | mood using the markers. |
| | axis accelerometer | | | sleep. | |

TABLE 12. Wearables commercially being used.

| | Device Name | Company | Purpose |
|----|---|------------------|---|
| 1 | Cala Trio Bracelet [87], [88] | Cala Trio | Reduce tremors |
| 2 | Samsung Galaxy smartwatch [89] | Samsung | Measure blood pressure, heart rate and pulse etc. |
| 3 | FitBit4 [90] | FitBit | Sleep monitoring and evaluation |
| 4 | Apple Watch [91] | Apple | Sleep dysfunction |
| 5 | Masimo Sleep [92] | Masimo | Sleep dysfunction |
| 6 | Garmin vívosmart [93] | Garmin | Footstep and activity tracker |
| 7 | Kinesia 360 [94] | Great Lake Neuro | Measures tremor, dyskinesia and mobility and maintains an e-diary |
| | | Technologies | |
| 8 | The Personal KinetiGraph (PKG) watch [95] | Global kinetics | Records motor symptoms |
| 9 | Physilog [96] | Gait-up | Detecting tremors and slowed movements |
| 10 | Oura Ring [97] | Oura | Heart rate monitoring and sleep analysis |
| 11 | StrideWay [98] | Tekscan | Gait Analysis |
| 12 | FScan and FScan64 [99] System | Tekscan | In shoe gait analysis system |
| 13 | Zeno Walkway [100] | ProKinetics | Gait analysis system |
| 14 | GAITRite [101] | GaitRite | Gait assessment |
| 15 | Opal V2C [102] | Clario | Gait, balance and mobility assessment |
| 16 | Dynaport MiniMod [103] MoveMonitor | McRoberts | Assess falla risks |
| 17 | Axivity AX3 [104] | Axivity | Fall risk assessment and gait pattern tracker |
| 18 | Tremelo [105] | Five Microns | Reduces mild to severe essential tremor |
| 19 | Steadi Two [106] | Steadiwear | Reduces essential and PD tremor |
| 20 | ReadiSteadi AntiTremor orthotic glove [107] | Readi-Steadi | Reduces action and resting tremor |

of PD, the industry of wearables is growing at a very rapid rate. Here we will mention some of the commercial wearable devices that PD patients and health professionals are using in order to be able to evaluate disease progression and provide PD patients assistive care and management options. Table 12 highlights some of the wearable devices that are currently being used and are available commercially

D. RO-4: FUTURE PROSPECTS

Although many wearables have been proposed to manage PD, there is still much room for improvement and advancement. Current research is limited to laboratory and clinical settings. The future of wearables for PD management lies in testing and feasibility design in real-world scenarios and integrating wearables in the home environment. Algorithms for proposed system design do not consider the challenging ground realities. Furthermore, for motor symptom detection, the most common sensor used is an accelerometer alone which might classify some daily activities as a motor symptom [40]. Future wearables should consider other sensors for remote evaluation of PD motor symptoms. One of the barriers

to digital health monitoring is integration between different wearable systems [108]. Furthermore, most researches include a limited number of PD patients; hence the reliability and accuracy of results are doubtful. Future research should be conducted on large datasets and a heterogeneous population.

Several research foundations have surfaced dedicated to integrating PD patients with technology and wearables to improve their quality of life. *The Davis Phinney foundation* suggests a whole list of treatment options, tools, and technology, some of which are still in the pipeline for PD patients [109]. One such work in progress is the Tango belt that opens up an airbag in case of a fall, thus preventing injuries. Gyro glove [88] is another design in the making that reduces hand tremor. Vercise DBS [110] is a neural stimulator used to facilitate PD patients by reducing motor symptoms like essential tremor. The Emma watch [111] a work in progress by Microsoft Research, is a device that introduces a soft vibration effect through small motors around the wrist that acts as white noise and interferes with the brain's initial tremor signals.



VI. CONCLUSION

The health industry has evolved considerably in the past few decades. Rising population, new researches, sudden challenges, and world crisis have changed the face of medicine worldwide. The lack of resources available to provide face-toface medical facilities has led to rapid technological advancements in this field. With the help of wearable devices, remote monitoring and precise and timely management of diseases, especially neurodegenerative diseases like Parkinson's, has become possible. This can tremendously help manage symptoms and assist in monitoring disease progression. This SLR highlights the work of different authors regarding the management of motor and NMS of PD via wearable sensors. It was observed that extensive research had been done to diagnose and monitor motor symptoms, but there is very little research regarding NMS of PD patients. In the research process, we extensively researched different databases and narrowed down over 60 articles discussing the management of Motor and NMS. Researches non-specific to PD include promising work related to NMS that can be integrated with Parkinson's. To the best of our ability, we included the most recent reviews and research papers to include new and emerging technology in the field of wearables for Parkinson's Management. The SLR is intended for future researchers to find better, fully integrated home management systems for PD. Future researchers can explore other non-quantifiable NMS and create measures to quantify them so that precise diagnosis and management are possible. Emerging technologies include nanotechnology and embedded sensors that can enhance the practicality of wearable devices and hence give much more accurate results. It was beyond our scope to include non-wearable solutions to monitor and manage PD. However, much research has been done with promising results to include biopotential devices, audio recording, motion-trackers, smartphones, cueing, and video recording to compliment wearable readings to gain an accurate insight into PD patients' well-being.

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