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# Understanding Wearing-Off Symptoms in Parkinson's Disease Patients using Wrist-Worn Fitness Tracker and a Smartphone

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**Abstract**

Parkinson's disease (PD) patients experience motor and non-motor symptoms, which affect their quality of life (QoL). Despite the use of Levodopa treatment to alleviate these symptoms, the "wearing-off phenomenon" (WO) occurs, and symptoms resurface. Thus, PD patients have to closely monitor and report their symptoms, the effects, and the duration of levodopa treatment to their doctors for a customized treatment. Towards predicting the WO among PD patients, this paper aims to understand the relationship between the WO symptoms and the collected fitness tracker data using a fitness tracker and a smartphone application. Our preliminary study among two patients within a 30-day collection period showed that PD patients experience WO symptoms with a unique relationship and association with fitness tracker datasets. The participant's sleep duration was negatively correlated with sharp pain and tremors. On the other hand, the other participant's total sleep duration was positively correlated with symptoms. Our analysis also showed that the time elapsed since the last medicine intake was a strong predictor of WO, aside from sleep duration and step count. These results suggest the possibility of using the fitness tracker dataset to estimate the WO among PD patients. The results would be helpful in the management of WO and PD in general.



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## 1. Introduction

Parkinson's disease (PD) is a slowly progressive disorder of the nervous system due to the loss of dopamine-producing brain cells [1]. It mainly affects the motor abilities of the patient, but it also affects non-motor functions over time. Tremors, muscle stiffness, and trouble with walking and balance are some of the patients' symptoms. Then, it disturbs the sleep, speech, and mental functions of the patients [2] until it influences the patients' quality of life (QoL) [3], [4].

PD patients work closely with their doctors and other medical staff to manage the symptoms since there is no cure for PD [1], [2]. Levodopa treatment (L-dopa) is one of the common approaches in handling PD to make dopamine in the brain and relieve the PD symptoms [2]. However, extended use of L-dopa often leads to the "wearing-off phenomenon" (WO) [5]–[8]. The effectiveness of L-dopa shortens, and symptoms start to emerge again. Thus, patients need to communicate the effects and duration of L-dopa to their doctors. Doctors build a personalized treatment plan to manage PD and its symptoms effectively.

With smartphones and fitness trackers, patients can continuously monitor their health. Towards the goal of predicting the wearing-off phenomenon among PD patients, we utilize these tools to monitor patients' health, record WO periods, and record the effects of L-dopa intake with their experienced symptoms. This paper aims to understand the relationship between the WO symptoms and the collected fitness tracker data. This paper also uses a commercially available fitness tracker and its data such as heart rate, stress score, number of steps, and sleep to estimate WO and its symptoms. By the end of this paper, we would learn which fitness tracker features help estimate WO and its symptoms.

This paper is organized as follows: Section 2 provides a review of related works. Then, Section 3 describes our data and data collection procedure and the participants included in our case study. Next, Section 4 presents the results and our discussion of the results. Finally, Section 5 shows our conclusion of this paper.

## 2. Related Works

Previous studies have investigated the associated effects of PD and the WO. PD affects the autonomic nervous system (ANS). ANS is part of the nervous system that automatically regulates and controls internal body functions such as blood pressure and heart rate [9]. Blood pressure and heart rate in PD patients were studied for the WO [10], [11]. In addition, the association of heart rate and heart rate variability (HRV) with PD and freezing of gait (FoG) were also analyzed [12], [13].

Other factors such as sleep patterns and psychological stress affect PD patients. Studies have examined the associated risk factors of rapid eye movement (REM) sleep behavior disorder (RBD) in PD patients [14], [15]. There were also reports on sleep disturbances, communication, and other psychosocial problems in PD patients [16], [17]. In a recent study, PD patients showed high sensitivity to the effects of psychological stress, depression, and anxiety with high prevalence rates. It suggested that these episodes worsen tremors, FoG, and dyskinesia. Further investigation using wearable sensors to identify motor symptoms was recommended [18].

Different wearables and smartphone applications were used to detect PD symptoms and WO periods. The data mainly involved accelerometer, electromyography (EMG), and gyroscope data to identify tremors, FoG, and WO periods [19]–[21]. Smartwatches have also been used to record and monitor motor fluctuations based on accelerometer data in a real-world environment [22], [23]. However, these studies have used medical-grade wearable sensors and utilized the data mentioned above. There are still opportunities in using commercially available wearables. These tools provide other health data points such as heart rate, number of steps, and sleep quality. These data points offer other aspects that are yet to be utilized in studying PD and WO. With certain limitations and acknowledgment of their reliability [24], this paper presents the utilization of the fitness tracker and its datasets to help manage WO among PD patients. Towards predicting the WO among PD patients, this paper aims to understand the relationship of WO and its symptoms with the data provided by the fitness tracker.

## 3. Methodology

This section explains the data, data collection tools, and the preliminary experiment with our two participants.

### 3.1. Data and Data Collection Tools

Garmin vivosmart4 fitness tracker was used to collect the heart rate, steps, stress score, and amount of sleep. The data was not directly retrieved from the fitness tracker but through Garmin Health Application Programming Interface (Garmin Health API) [27]. Garmin Health API automatically sent the data to our web server, which was deployed in Amazon Web Services (AWS). It only pushes the data towards our web server whenever the data has been synced with Garmin. Thus, different datasets have different time intervals, as shown in Table 1. Figure 1 provides a data flow overview from the fitness tracker to our web server.

Table 1. Garmin vivosmart4 fitness tracker dataset.

| Data type | Granularity | Description |
|---|---|---|
| Heart rate | 15-second interval | Beats per minute |
| Steps | 15-minute interval | Cumulative count per interval, with a minimum value of 0 |
| Stress score | 3-minute interval | Estimated stress score from 0 to 100 [25], 100 being the highest, -1 not enough data to detect stress, -2 too much motion |
| Sleep classification & Sleep period | Varying interval, with a specific Calendar Date | Start & End Time per Sleep Classification [26]: Light sleep, Rapid eye movement (REM) sleep, Deep sleep, Awake |


Fig. 1. Data collection overview using Garmin vivosmart4 and FonLog smartphone application.

Garmin Health API provided different datasets captured by Garmin vivosmart4. First, the resting heart rate (RHR) in beats per minute (bpm) was provided every 15 seconds. Second, the number of steps was accumulated every 15 minutes. Third, the stress score was based on the heart rate variability (HRV), where the less variability, the higher the stress score, and vice versa [25]. Unfortunately, the raw HRV data were not provided by Garmin Health API. Instead, a stress score from 0 to 100 was returned, where 100 is the most stressful. A value of "-1" meant not enough data to detect stress, while "-2" represented too much motion [25]. Finally, the start and end times for each sleep stage for each day were given.

FonLog is a smartphone application used as a data collection tool for human activity recognition in nursing services [27]. We have customized FonLog to collect Wearing-Off Questionnaire (WoQ-9) responses using Japanese translation [5], [28]. WoQ-9 covers nine PD symptoms: (1) tremors, (2) slowing down of movement, (3) change in mood or depression, (4) rigidity of muscles, (5) sharp pain or prolonged dull pain, (6) impairment of complex movements of the hand and fingers, (7) difficulty integrating thoughts or slowing down of thought, (8) anxiety or panic attacks, and (9) muscle spasm. The second step of the WoQ-9 is the effects of drug intake on the symptoms, whether the symptom subsided or not [5]. FonLog also included gender, age, Hoehn and Yahr's PD stage [29], [30], and Parkinson's Disease Questionnaire (PDQ-8) for a self-reported QoL among PD patients [31].

### 3.2. Preliminary Experiment

A preliminary experiment among two participants was conducted with their informed consent. Both participants were female and in their late 30s to early 40s. According to their Hoehn & Yahr Scale scores, the first participant had a bilateral involvement without impairment of balance (score of 2). On the other hand, the second participant reported

mild to moderate bilateral disease with impaired postural reflexes (score of 3) [29], [30]. Thus, their self-reported QoL was substantially different from each other. Nonetheless, both were experiencing WO before our study.

Table 2. Participants' demographics.

| | Age | Gender | Hoehn & Yahr Scale | PDQ-8 |
|---|---|---|---|---|
| Participant 1 | 43 | Female | 2 | 12 |
| Participant 2 | 38 | Female | 3 | 21 |

The two participants received the two data collection tools for our preliminary study. The data collection lasted for 30 days from February 23, 2021, until March 24, 2021, with a one-day set-up for the participants. In addition, participants created their own Garmin Connect account to enable synchronization, as shown in Figure 1.

There were no strict limitations or constraints with the use of Garmin vivosmart4 and the FonLog app. Participants were instructed to always wear their Garmin vivosmart4. On recording their experienced symptoms, participants could retroactively use the FonLog smartphone application. We asked them to make the best estimation of the WO period. Furthermore, participants can correct and review their responses. Figure 2 shows the main screen of FonLog, where the participant can choose the questionnaire.

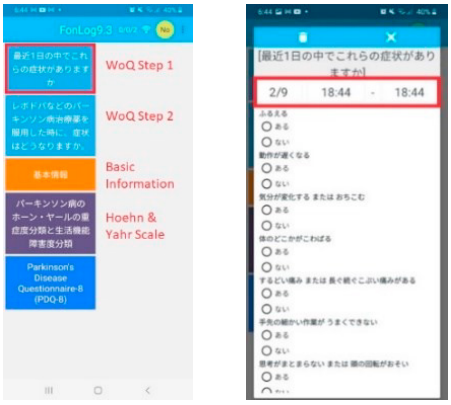


Fig. 2. The customized FonLog smartphone application. The left figure shows the different questionnaires, while the right figure shows the Japanese WoQ-9.

### *3.3. Data Preprocessing*

As shown in Table 1, the different datasets provided by Garmin Health API were in different time intervals. Thus, we resampled the dataset into a 1-minute interval to monitor the behavior on a per-minute basis. The steps and the stress score were interpolated based on the nearest value. Meanwhile, the excess heart rate records were discarded. As for the sleep dataset, each record was associated with a calendar date for the raw sleep dataset, with the start and end time for each sleep stage category. Hence, the duration for each sleep stage was computed. Then, the period for each sleep stage was aggregated for each calendar date. Finally, this aggregated sleep data was combined with the rest of the Garmin datasets.

Like the raw sleep dataset, the raw FonLog dataset was recorded with a start time and an end time for each WO period. In addition, each reported WO was checked if it falls within the 1-minute timestamp of the processed Garmin dataset. If so, a value of "1" was assigned for each symptom; otherwise, a value of "0" was set.

Part 2 of WoQ-9 inquired the participants about the drug intake and its effect on the symptoms. If the symptom subsides after taking their medicine, the symptom is marked with "0". However, if the symptom continues to persist, a value of "1" is assigned. Moreover, the time elapsed between drug intake has been computed. During the start of the drug intake, the time elapsed resets to "0". This timer increases per minute until another drug intake has been reported.

### *3.4. Analysis*

Towards predicting wearing-off using the tools and data above, we aim to understand the relationship between the wearing-off symptoms and the collected fitness tracker dataset. This paper includes a descriptive statistical analysis for each feature, a correlation analysis among each feature, and a linear regression analysis using Ordinary Least Squared (OLS) error estimation between the processed Garmin dataset and wearing-off symptoms. For each wearing-off symptom $Y_{1...9}$, we analyze the linear regression function $f(X)$ such that,

$$y_i = f(x) = b + w_1x_1 + w_2x_2 + w_3x_3 + w_4x_4 + w_5x_5 + w_6x_6 + w_7x_7 + w_8x_8 + w_8x_8 \quad (1)$$

where $b$ refers to a bias, $x_1$ is the heart rate, $x_2$ is the stress score, $x_3$ is the number of steps, $x_4$ is the deep sleep duration, $x_5$ is the light sleep duration, $x_6$ is the REM sleep duration, $x_7$ is awake sleep duration, $x_8$ is the total sleep duration, $x_9$ is the time elapsed from the last drug taken, and $w_1 \dots w_8$ are the weights for each feature. $w_1 \dots w_8$ are estimated by minimizing the sum of squares between the $y$ and the estimated $y$.

## 4. Results and Discussion

After the data preprocessing described in Section 3.3, the combined dataset consisted of 43,200 records, with a 1-minute interval between each record. Figures 1, 2, 3, and 4 show the distribution of the records for each participant.

Participant 1 had an average heart rate of 86.41 ± 15.61 bpm over the 30 days. While participant 2 had an average heart rate of 71.39 ± 15.81. Both participants' heart rate distribution exhibits a positively skewed distribution with an interquartile range of 18 (Q1 = 77, Q3 = 95) and 24 (Q1 = 59, Q3 = 83), respectively. These suggest where most of the heart rate falls during the 30 days.

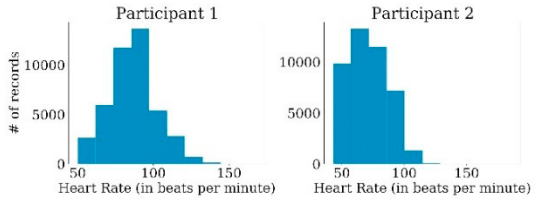


Fig. 3. Heart rate distribution over 30 days.

Participant 1 had an average of 34.11 ± 109.17 steps for the 30 days for the number of steps. Meanwhile, participant 2 had an average of 106.24 ± 189.61 steps for the same period. These averages are computed over the 1-minute interval. Thus, when the steps dataset are aggregated by hour, there were some hours with no step count for both participants.

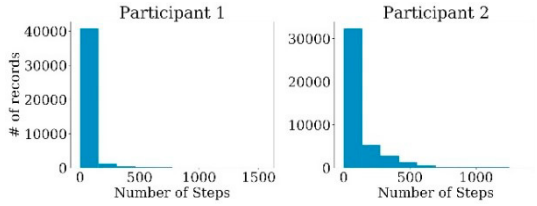


Fig. 4. Step count distribution over 30 days.

The average stress score for participant 1 was 29.67 ± 32.51 or low stress in Garmin's Stress Classification [26]. On the other hand, participant 2 had a stress score of 10.17 ± 20.14 or resting state. In addition, participant 1's distribution of stress score showed a more spread on the tail than participant 2's distribution of stress score. Therefore,

according to Garmin's Stress Classification, both participants show a positively skewed stress score distribution, suggesting a resting to a low-stress classification [26].

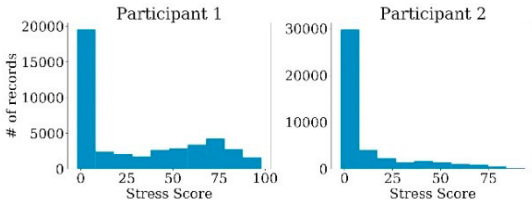


Fig. 5. 30-day Stress score distribution.

Next, the total sleeping hours and total hours per sleep stage were computed for each participant. Participant 1 had an average total sleep ($n$ = 29) of 4 hours and 35 minutes ($\sigma$ = 1.554 hours) per day over the 30 days, with one day of missing sleep data. Meanwhile, participant 2 had an average total sleep ($n$ = 25) of 4 hours and 4 minutes ($\sigma$ = 1.304 hours) per day, with six days of missing sleep data. Figure 6 shows that participant 1 had a longer light and REM sleep than participant 2. On the other hand, participant 2 had more light and deep sleep than participant 1.

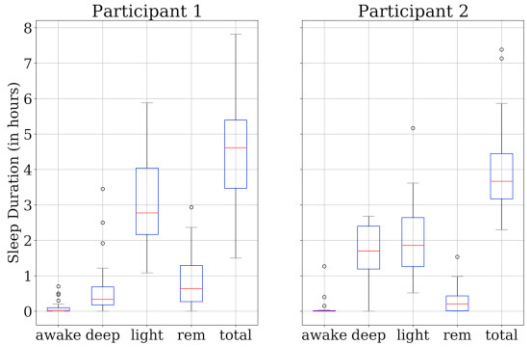


Fig. 6. 30-day Sleep duration by Sleep stages.

Table 3 shows the percentage of the self-reported WO periods and the experienced symptoms. The first row was based on the presence of any symptoms in the participant's report. Over 30 days of 1-minute interval, participant 1 had 31.815% ($n$ = 13,744) of wearing-off. She mainly experienced rigidity (31.606%), sharp pain, and prolonged dull pain (22.310%). Anxiety and mood change were the least reported symptoms by participant 1. On the other hand, participant 2 had fewer WO reports of 1.817% ($n$ = 785). She reported slowing of thoughts (1.597%) as the most experienced symptom, followed by rigidity (1.465%) and impairment of the hands and finger (1.322%).

### *4.1. Correlation analysis*

A correlation analysis was employed to understand the relationship between the WO symptoms and the collected fitness tracker data.

For participant 1, the total sleep duration negatively correlated with sharp pain (-0.110) and tremors (-0.129). Moreover, the elapsed time from the last drug taken positively correlated with rigidity (0.129), slow movement (0.277), impairment of hands and fingers (0.383), and mood change (0.101).

Albeit with a smaller magnitude, the stress score also revealed a positive correlation with anxiety (0.038) and slow thoughts (0.075). Furthermore, the number of steps negatively correlated the motor-related symptoms such as pain (-0.085), tremors (-0.079), rigidity, slow movement (-0.076), and impairment of hands and fingers (-0.066). Finally, the heart rate variable came with varying correlation patterns with the symptoms.

Table 3. Percentage of collected self-reports on WoQ-9 symptoms among participants.

| WO and symptoms | Participant 1 | | Participant 2 | |
|---|---|---|---|---|
| | Good (0) | WO (1) | Good (0) | WO (1) |
| WO | 68.185 | 31.815 | 98.183 | 1.817 |
| Sharp Pain / Prolonged dull pain | 77.690 | 22.310 | 98.910 | 1.090 |
| Tremors | 83.831 | 16.169 | 99.044 | 0.956 |
| Anxiety | 99.086 | 0.914 | 99.185 | 0.815 |
| Rigidity of muscles | 68.394 | 31.606 | 98.535 | 1.465 |
| Slowing of movement | 81.225 | 18.775 | 99.352 | 0.648 |
| Slowing of thoughts | 86.572 | 13.428 | 98.403 | 1.597 |
| Impairment of hands & fingers | 84.366 | 15.634 | 98.678 | 1.322 |
| Mood change | 99.773 | 0.227 | 99.421 | 0.579 |
| Muscle spasm | 93.569 | 6.431 | 99.398 | 0.602 |

For participant 2, the elapsed time from the last drug taken negatively correlates all symptoms with Pearson $r$ values ranging from -0.110 (rigidity of muscles and slowing of thoughts) to -0.066 (mood change). However, among the most reported symptoms from participant 2, total sleep positively correlates with rigidity ($r = 0.088$), slowing of thoughts ($r = 0.089$), and impairment of hands and fingers ($r = 0.069$).

### *4.2. Linear regression analysis*

Linear regression analysis was done for each participant due to the assumption that each PD patient experiences PD symptoms differently.

For participant 1, the focus was on the rigidity of muscles and sharp pain because these symptoms were the most reported. Except for the stress score, the independent variables significantly influenced the rigidity of muscles and sharp pain ($p < 0.05$). For rigidity, the elapsed time from the last drug intake had the highest coefficient of $0.0357 \pm 0.001$ ($t(8) = 35.853$, $p < 0.01$), followed by light sleep with a coefficient of $0.0224 \pm 0.003$ ($t(8) = 7.234$, $p < 0.01$). For sharp pain, the awake duration has the highest coefficient of $0.0525 \pm 0.01$ ($t(8) = 5.471$, $p < 0.01$), followed by the elapsed time from the last drug intake with a coefficient of $0.0193 \pm 0.001$ ($t(8) = 21.484$, $p < 0.01$).

For participant 2, the linear regression analysis results for rigidity of muscles, impairment of hands and fingers, and slowness of thoughts were closely observed. Across the three symptoms, light sleep duration and deep sleep duration had the highest coefficients for the analysis. This analysis supported our earlier findings in the descriptive summary for participant 2.

## 5. Conclusion

This paper presented the use of a commercially available fitness tracker and a smartphone application to monitor WO periods and symptoms in PD patients. Specifically, this paper analyzed the relationship between the fitness tracker's heart rate, stress score, number of steps, and sleep datasets in WO periods and symptoms. As previous studies have mentioned, PD patients experience symptoms differently, as shown by the different correlated features. Moreover, an individual-level analysis and modeling should cater to PD patients' unique PD experience. Towards the potential use of the fitness tracker dataset to predict WO periods, intensive model development should be undertaken.

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