# Monitoring Parkinson's Disease Progression Using Behavioural Inferences and Smartphones

This research aims to monitor Parkinson's Disease (PD) in a longitudinal, naturalistic, non-disruptive and non-intrusive way. It uses smartphones to log social, environmental, and interaction data about patients and their surroundings. This data is then processed to infer a set of behavioural metrics (a latent behavioural variable or LBV) of people's activities and habits. Then, the LBV's trends are quantified and mapped to the progression of the disease. As a part of the pilot study to test the proposed methodology, we collected ~290 million records from 2 patients, that is 34.5x more records logged from 4x more data sources than state-of-the-art sets. This project aims to get a more accurate disease picture and to reduce the physical and psychological burden of traditional assessment methods. Ultimately, the work has the potential to save patients' time and improve the efficiency and effectiveness of health services.

## Problem

PD is a neurodegenerative disorder affecting around ten million people worldwide [12]. Its motor and non-motor symptoms worsen patients' quality of life, especially in the elderly population. Traditionally, the severity of PD is quantified using clinical scales during regular visits to health centres [4]. However, this approach is unsuitable for long-term, periodic monitoring because it is subjective, expertise-dependant [16, 21] and prone to recall [6, 13, 18] and cognitive bias [1]. Likewise, brief assessment sessions provide an inaccurate picture of PD as its symptoms fluctuate throughout the day [14, 15]. Thus, a sporadic assessment makes it difficult to tailor treatments to the patient's real condition [19, 22].

Some of these issues are tackled using electronic devices which are objective, more concise and more precise than traditional methods. Nevertheless, the device type, the way it is used and the chosen monitoring methodology have different outcomes. Although wearable devices are a popular choice, they are often attached to uncomfortable body locations and patients need to follow scripted assessment routines. This makes it impractical to monitor PD for a long time outside the laboratory. Recently, inertial sensors, touchscreens and cameras in smartphones have been utilised to assess PD by measuring people's movement patterns [9], hand tremor [2, 7, 8, 11], freeze of gait [14], gait difficulty [11] and upper-limb bradykinesia [17]. Nevertheless, almost all identified smartphone-based projects monitor participants during a single day, performing short scripted tasks under controlled conditions. Although [9] was the exception and participants were followed doing their regular activities, the authors only used one data source (GPS) and only found a suggested relationship to PD clinical scores. We believe this is an idea that can be further explored and improved.

## Methodology

Our work monitors PD in a ***longitudinal***, ***naturalistic***, ***non-intrusive*** and ***non-disruptive*** way. Additionally, we follow a ***macro-scale*** approach assessing trends of human activities and habits instead of measuring fine motor movements (micro-scale) which have been the focus of previous research [8, 11, 22]. Furthermore, we propose to combine multiple data sources (***multi-source***) to simplify the quantification of complex behavioural features. Altogether, these six monitoring attributes are unique in the context of PD progression assessment.

Our project explores PD progression assessment using Latent Behavioural Variables (LBV) derived from heterogeneous data. Such data is collected using a smartphone and processed to infer behavioural metrics. We define an LBV as a set of metrics that quantify a human activity or habit. These LBVs can be analysed over an extended period to identify trends and obscure outliers. Thus, the trends' changes can be mapped to the disease's evolution.

To accomplish all this, we propose a four stage methodology for PD monitoring (Figure 1). During the first stage, ***data collection***, each participant receives a smartphone to log their social, environmental and interaction

data using all the sensors and interfaces within it. This is complemented by ambient, spatial and other web data sources. We do not require participants to perform any assessment tasks (*non-intrusive*) or to attach the phone to a particular body location or in any orientation whatsoever (*non-disruptive*). We ask participants to carry the device while they follow their daily routine (*naturalistic*) for several months (*longitudinal*). Then in the ***data processing*** phase, raw data is modified, filtered and ranked to reduce the complexity and dimensionality of the original dataset.

The ***data analysis*** stage has two tasks, LBV Identification and "Profile of Living" (PL) generation. In the first one, we carry out a combinatorial analysis of a group of data sources to infer a human activity or habit. Then, we compute a set of metrics that quantify distinctive features of these inferences. For example, if we were analysing the "human mobility" LBV, we could infer the time and location when an individual is running, walking or standing. These inferences would be based on location, spatial, accelerometer, Wi-Fi and Bluetooth data in order to calculate metrics like the duration of the movement sessions, the average walking speed, the maximum travelled distance or the places visited by the monitored person. During the second task, the evolution of the LBV is quantified using a PL. A PL is a proposed concept where each of the LBV's metrics is divided into two. The portion obtained at the beginning of the monitoring period produce a personal baseline while the rest is considered as deviations over time. If we go back to our example, we could analyse each of our metrics (i.e., walking speed) at different time granularities (i.e., daily, weekly, monthly) and decide at what point in time we should split them into two groups based on the chosen time cycle(s). Then, the second group (deviations) can be compared against the first one (baseline) to quantify any differences in the magnitude of a metric and generate one score for each time cycle. This process would be done for each metric of an LBV.

Finally, in the ***evaluation*** step, LBV variations (shifts in behaviour) are mapped to changes in PD severity. This mapping is evaluated using clinical scores produced at regular intervals by trained staff as a ground truth. Such scores will come from the Movement Disorder Society-Unified Parkinson's Disease Rating Scale (MDS-UPDRS) [4] that assess motor and non-motor symptoms and is widely used as a golden reference in research projects outside clinical environments [10]. Thus, we will study the correlation between the variation scores of the LVB's metrics and the disease's MDS-UPDRS scores and sub-scores. Besides this and as a secondary measure, we will analyse the trends of the different LBV(s)' metrics, to see if their changes are related to each other and to the theoretical progression of the PD symptoms they quantify according to the literature.

We expect two main contributions from this approach. The first one is a methodology to investigate behavioural LBVs related to PD using time series data. The second one is the identification of at least one LBV that, if correlated with PD severity, will be a proof of concept of non-intrusive and non-disruptive PD monitoring based on passive mobile sensing.

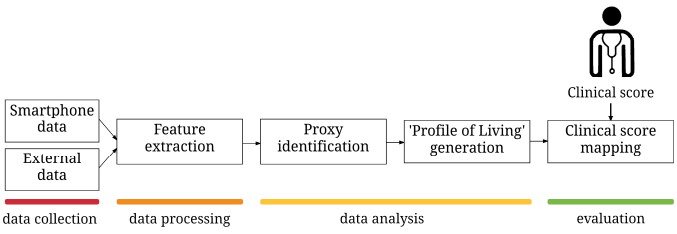


Figure 1. Methodology for PD monitoring using latent behavioural variables.

## Results to date

To first test this methodology, we carried out a pilot monitoring study where 29 types of data sources (smartphone's interfaces and sensors and web sources) were logged from two patients over 83 days using the Android app AWARE [3] modified in-house to allow data encryption and cloud synchronisation. The resulting dataset (D1) has ~290 million data points. In comparison to existing smartphone collected datasets for PD monitoring (D2 [5] & D3 [20]), ours has a higher resolution (107,680 records per person per monitored hour

(R/P/Hr)) and semantic richness (29 sources). This means, D1 is 34.5x bigger than D3 (2,060 R/P/Hr from 7 sources), and although it is 5x smaller than D2 (359,243 R/P/Hr), the latter has only one source of data. This approach to data collection will increase the potential for inferring complex PD-related behavioural habits.

Next, we identified six LBVs, each composed of several metrics based on the collected data, the symptoms of PD [7], the assessment tasks of the MDS-UPDRS [4] and everyday human activities or habits that might be influenced by PD symptoms according to what other works have measured using alternative approaches (i.e. [2, 10]). These LBVs are typing patterns, phone usage patterns, episodes of going up/down stairs, participant's indoors routine, motor activities, and social patterns. The "social patterns" LBV combines Bluetooth (BT), Wi-Fi, location, spatial, calls, and messages data and has metrics like BT surrounding devices (a potential indicator of human presence) or communication patterns (a possible indicator of a positive mood), among others. We preliminarily analysed the "social patterns" LBV using three days of data from one participant. From the Wi-Fi and BT data, it was possible to identify periods during which the participant was outside the home. Furthermore, spatial and Wi-Fi data was used to infer that the patient visited different urban locations including his/her home. In the BT log, a sporadic device was recorded while the person was at home indicating social interaction with another individual. All these parameters can be weighted and put together to generate a social interaction score. Following a similar process, other LBVs and their metrics can be identified and analysed. The next step is to take into account data from a longer period and study patients' routines to then proceed to evaluate these inferences against the PD clinical scores.

## Conclusions

The pilot results provide good evidence that PD progression monitoring based on behavioural inferences extracted from data collected using mobile devices is worth exploring further. Due to the exploratory nature of this work, there are several LBVs that can be analysed, all promising leads that might be related to PD severity. If there is a positive outcome at the end of this proof-of-concept PD monitoring methodology, future work under the same line of research could have a significant impact on the quality of life of PD patients by saving them time, reducing the physical and psychological burden related to traditional and alternative assessment methods, and improving the precision of treatments and interventions. This will help to lessen the clinicians' workload and improve the efficiency of health services.

## Ethical statement

All adults involved in our study were taken care of. The study is of a voluntary character and can be ceased once the participant does not want to be involved any longer. The pilot study was approved by the [REMOVED FOR ANONIMITY] comitte.

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