

A SPEECH ANALYSIS COMPARISON OF PEOPLE WITH PARKINSON'S DISEASE AND HEALTHY CONTROLS

ASHKAN KARIMI

**A THESIS SUBMITTED TO
THE FACULTY OF GRADUATE STUDIES
IN PARTIAL FULFILLMENT OF THE REQUIREMENTS FOR
THE DEGREE OF MASTER OF ARTS**

GRADUATE PROGRAM IN INTERDISCIPLINARY STUDIES

YORK UNIVERSITY

TORONTO, ONTARIO

December 2024

©Ashkan Karimi, 2024

Abstract

This study explores the effects of Parkinson's Disease (PD) and a dance intervention on vocal features—specifically fundamental frequency standard deviation (F0SD) and intensity standard deviation (IntSD)—in individuals with PD and healthy controls over five years. The findings suggest that while both groups exhibited changes in these vocal features over time, the differences between the PD and control groups were moderate and likely masked by individual variability. F0SD, in particular, showed distinct patterns of change over time between the two groups, aligning with known voice impairments in PD. However, changes in IntSD appeared to be more influenced by the normal aging process rather than PD itself. Despite the lack of significant post-dance improvements, the study highlights the potential value of speech features as biomarkers for PD, emphasizing the need for larger, more intensive studies to fully understand the effects of interventions like dance on vocal performance in PD.

Acknowledgments

I would like to express my deepest gratitude to my family. To my mom, Marjan, my dad, Ali, and my little sister, Rozan—thank you for bearing with me through the challenges and sacrifices that came with studying for my master’s degree. Your unwavering support, patience, and understanding have been invaluable throughout this journey. I am especially thankful to my parents for their generous financial support, without which this academic pursuit would not have been possible. Your belief in me and your commitment to my education have been the foundation of my success.

I would like to extend my heartfelt thanks to my supervisor, Professor Joseph F.X. DeSouza. Your guidance, expertise, and encouragement have been instrumental in the completion of this project. I am deeply grateful for the time and effort you invested in helping me navigate this research.

I would like to express my deepest gratitude to my supervisory committee, Professor Joel Zylberberg and Professor Brian Huss for their invaluable guidance and support throughout this journey. Special thanks to my friends and all the members of the JoeLab for their unwavering support and patience during the completion of this thesis.

Additionally, I would like to sincerely thank Dr. Hamidreza Ramezanpour for reviewing my thesis and providing valuable comments that significantly enhanced the quality of my work.

Thank you all for your support and contributions to this significant chapter of my life.

Table of Contents

<i>Abstract.....</i>	<i>ii</i>
<i>Acknowledgments.....</i>	<i>iii</i>
<i>Table of Contents</i>	<i>iv</i>
<i>List of Tables</i>	<i>v</i>
<i>List of Figures</i>	<i>vi</i>
<i>Abbreviation Table.....</i>	<i>vii</i>
 PART I	
<i>Preface.....</i>	<i>1</i>
CHAPTER 1:	
<i>INTRODUCTION: PARKINSON'S DISEASE</i>	<i>3</i>
CHAPTER 2:	
<i>LITERATURE REVIEW.....</i>	<i>8</i>
<i>PHONATORY ASPECT CHANGES IN PARKINSON'S DISEASE.....</i>	<i>10</i>
<i>ARTICULATION AND PROSODY ASPECT CHANGES IN PARKINSON'S DISEASE.....</i>	<i>20</i>
 PART II	
CHAPTER 3:	
<i>VOICE ANALYSIS OF PEOPLE WITH PARKINSON'S DISEASE AND CONTROLS.....</i>	<i>24</i>
<i>A. INTRODUCTION.....</i>	<i>24</i>
<i>B. HYPOTHESES/ REASONS FOR MEASURES USED.....</i>	<i>26</i>
<i>C. METHODOLOGY</i>	<i>28</i>
<i>D. A NOTE ON SELECTED FEATURES</i>	<i>37</i>
<i>E. RESULTS</i>	<i>41</i>
CHAPTER 4:	
<i>DISCUSSION AND CONCLUSION</i>	<i>70</i>
<i>LIMITATIONS AND FUTURE WORK</i>	<i>76</i>
<i>BIBLIOGRAPHY</i>	<i>83</i>
<i>APPENDIX – NOTES, CODES and FORMS.....</i>	<i>96</i>

List of Tables

Table 1: Motor and Non-Motor Symptoms of Parkinson's Disease	5
Table 2: Phonatory Aspects Investigated in Parkinson's Disease	9
Table 3: Phonatory Aspect Changes in Parkinson's Disease	19
Table 4: Articulatory Aspects Investigated in Parkinson's Disease	21
Table 5: Time Points of MDS-UPDRS Examinations	35
Table 6: Voice features that Showing Significant Differences Between PD and Control Groups	45
Table 7: Age and Sex Distribution of the PwPD and Healthy Controls Groups	45
Table 8: ANOVA results for comparing 2014 and 2019 F0SD	56
Table 9: Post hoc (Bonferroni's correction) Results Table for F0SD	56
Table 10: ANOVA results for comparing 2014 and 2019 IntSD	57
Table 11: Post hoc (Bonferroni's correction) Results Table for IntSD	57
Tables 12, 13, 14, 15, 16: F0SD Mixed Effect ANOVA Tables for Pre and Post-Dance Sessions for PwPD and Healthy Controls	60, 61, 62
Tables 17, 18, 19, 20, 21: IntSD Mixed Effect ANOVA Tables for Pre and Post-Dance Sessions for PwPD and Healthy Controls	64, 65, 66

List of Figures

Figure 1: Prevalence of Parkinson’s Disease in Institutional Population in Canada by Age Group and Sex	6
Figure 2: The Drawing Described in MDS-UPDRS Part III Examination	31
Figure 3: The Illustration of Extracting the Voice Files and Number of Files in Each Group	38
Figure 4: An Illustration of the Intensity Contour of a Common Sentence Between a Subject with PD and a Control Subject for Visualizing the Difference Between the Intensity of the Voice....	40
Figure 5: Histogram Diagrams of Voice Features	42
Figure 6: Box Plots of Voice Features	43
Figure 7: Mean difference and Confidence intervals	44
Figures 8, 9, 10, 11: Descriptive statistics of the voice features.....	46, 47, 48, 49
Figure 12: F0SD Pre- and Post-Dance Across Time Points for PD and Healthy Control Groups	50
Figure 13: IntSD Pre- and Post-Dance Across Time Points for PD and Healthy Control Groups	51
Figure 14: Fundamental frequency standard deviation comparison between one Subject with Parkinson and one Healthy control from before and after the dance session	52
Figure 15: Intensity standard deviation comparison between one Subject with Parkinson and one Healthy control from before and after the dance session	53
Figure 16: Fundamental frequency standard deviation and Intensity standard deviation for one subject with Parkinson from before and after the dance session.....	54
Figure 17: Fundamental frequency standard deviation and Intensity standard deviation for one Control subject from before and after the dance session	55

Abbreviation Table	
Abbreviations	Non-abbreviated format
ANOVA	Analysis of Variance
BOLD	Blood Oxygenation Level Dependent
CPP	Cepstral Peak Prominence
DA	Dopamine
DBS	Deep Brain Stimulation
DDKR	DiaDochoKinetic Rate
DPI	Duration of Pause Intervals
F0	Fundamental Frequency
F0SD	Fundamental Frequency standard deviation
FCR	Formant Centralization Ratio
fMRI	functional Magnetic Resonance Imaging
GNE	Glottal to Noise Excitation ratio
HC	Healthy Controls
HNR	Harmonic to Noise Ratio
IntSD	Intensity standard deviation
LPC	Linear Predictive Coding
MDS-UPDRS	Movement Disorder Society's Unified Parkinson's Disease Rating Scale
MFCC	Mel Frequency Cepstral Coefficients
MPT	Maximum Phonation Time
NHR	Noise to Harmonic Ratio
NSR	Net Speech Rate
PD	Parkinson's Disease
PLP	Perceptual Linear Prediction
PPE	Pitch Period Entropy
PSI	Proportion of Subharmonic Interval

PwPD	People with Parkinson's Disease
QoL	Quality of Life
RAP	Relative Average Perturbation
RFA	Resonant Frequency Attenuation
RPDE	Recurrence Period Density Entropy
SMA	Supplementary Motor Area
SNpc	Substantia Nigra pars-compacta
SPI	Soft Phonation Index
VAI	Voxel Articulation Index
VOT	Voice Onset Time
VSA	Voxel Space Area

PART I

Preface

Over the last two years, while I was studying for my master's degree, the project that I wanted to work on changed a few times. Initially, my project had a broad focus on perception and the external world, specifically how the human brain defines and perceives the external world. However, some exemplified means were needed to reduce the measures and numbers to something that can be evaluated. While searching for objectified means and during my Advanced Topics in Theoretical Physics course, which Professor Joel Zylberberg taught, I got interested in comparing computers, especially deep learning methods, to the human brain. The course was about how to apply deep learning to science. My supervisor in the psychology department, Professor Joseph F.X. DeSouza, and his team were among the first scientists to demonstrate that dance improves motor symptoms and promotes brain plasticity using fMRI and EEG in individuals with Parkinson's disease, through a 7-year longitudinal study. At that time, a comparison between the human brain and a deep learning model could be an indicator of the logic that these two models (human brain and computers) were built on. One of them was built through the course of evolution and based on its rules and the other was based on mathematics, an invention of the human brain that was claimed by a group of scientists that is

perception-less. In the course of finding if it is rational to compare the rationality of human brains versus computers, I found my philosophy supervisor, Professor Brian Huss. When we started working on the subject, Professor Huss introduced defining the term “Rationality”. Although the subject was of interest, it was well pointed out by my committee that this project is broad and contains at least two sub-projects. Therefore, I chose to work on only one part of the project, the speech analysis of people with Parkinson’s Disease (PwPD), and compare that analysis with the control group. For the analysis, I used a machine learning model to extract the speech features. Although this project diverged from my initial Master’s degree proposal, it holds significant potential for advancing our understanding of perception and neuroplasticity. The journey that I went through during this two-year program has led me to more interesting subjects such as other logic for perception, or as we know evolution is based on survival of the fittest to the environment, so if the condition went other ways, would there be creatures with different means of perception on the Earth, and finally since there are a lot of aspects in any material, is there a universal perception that perceives the whole matter I would like to express my deepest gratitude to Professor Joel Zylberberg and Professor Joseph F.X. DeSouza, for their invaluable guidance and support throughout this journey. My sincere thanks to Professor Brian Huss for his insightful discussions on rationality and perception. Special thanks to my friends and all the members of the JoeLab for their unwavering support and patience during the completion of this thesis

Ashkan Karimi, York University, 2024

CHAPTER 1

INTRODUCTION: PARKINSON'S DISEASE

This study aims to describe the differences in voice parameters between individuals with Parkinson's Disease (PD) and healthy controls who participated in a community dance class over a period of five years.

Parkinson's Disease (PD) is the second most common neurodegenerative disease which affects 2-3 percent of people living over 65 years old (Poewe et al., 2017). It is a progressive bradykinetic disorder and can be characterized by the severe loss of substantia nigra pars-compacta (SNpc) cells (Lees et al., 2009). James Parkinson first described this disease in 1817, and it was more than a century after that the loss of SNpc neurons was associated with PD. Subsequently, the discovery of dopamine (DA) in the mammalian brain by Arvid Carlsson in 1958 accelerated the understanding of the disease's etiology. This was mainly because SNpc neuronal loss leads to striatal DA deficiency, which is responsible for PD's major symptoms. Additionally, administration of the DA precursor, levodopa, can alleviate most of the symptoms (Dauer & Przedborski, 2003).

Deep Brain Stimulation (DBS) is an alternative surgical method that shows promising results, not only in advanced stages of PD but also in patients with early motor complications (Malek, 2019).

There are four fundamental features of PD: **Resting Tremor, Rigidity, Akinesia (or Bradykinesia), and Postural Instability.**

Resting Tremor is the most common and easily recognizable sign in people with PD. The frequency of these tremors is usually between 4 and 6 Hz and is more prominent at the distal part of the extremities (i.e. hands and feet). This sign rarely involves the head and neck and disappears during action and sleep.

Rigidity. Increased muscular resistance, usually followed by the “cogwheel” phenomenon, which is more prominent when accompanied by underlying tremors. In mild cases, it may be misdiagnosed as arthritis, bursitis, or rotator cuff injuries.

Akinesia or Bradykinesia. Bradykinesia is the slowing of movements, usually a hallmark of diseases involving the basal ganglia. Manifestations associated with bradykinesia involve slow reaction time, slowness in daily activities, loss of spontaneous movements and gestures, and drooling.

Postural Instability. Axial rigidity may occur, resulting in a flexed neck and trunk posture, as well as elbow and knee flexion (Jankovic, 2008).

In addition to motor symptoms, there are non-motor signs and symptoms associated with PD (Müller et al., 2013). Some of these symptoms are mentioned in **Table 1.**

Table 1. Motor and Non-Motor Symptoms of Parkinson's Disease

Motor symptoms	Non-Motor symptoms
Communication	Sensory complaints
Personal needs	Autonomic dysfunction
Tremor	Cognitive impairment
Rigidity	Depression
Bradykinesia	Fatigue
Gait	Apathy
Axial symptoms	Sleep disturbances
Nocturnal motor symptoms	Daytime sleepiness
Dyskinesia and fluctuations	

According to Statistics Canada, in 2011/2012 an estimated 55,000 Canadians over the age of 18 have been diagnosed with PD (Wong et al., 2014). According to this report, the mean age of first symptoms was 64.4 years, where the diagnosis was made 1.9 years later at 66.3 years old.

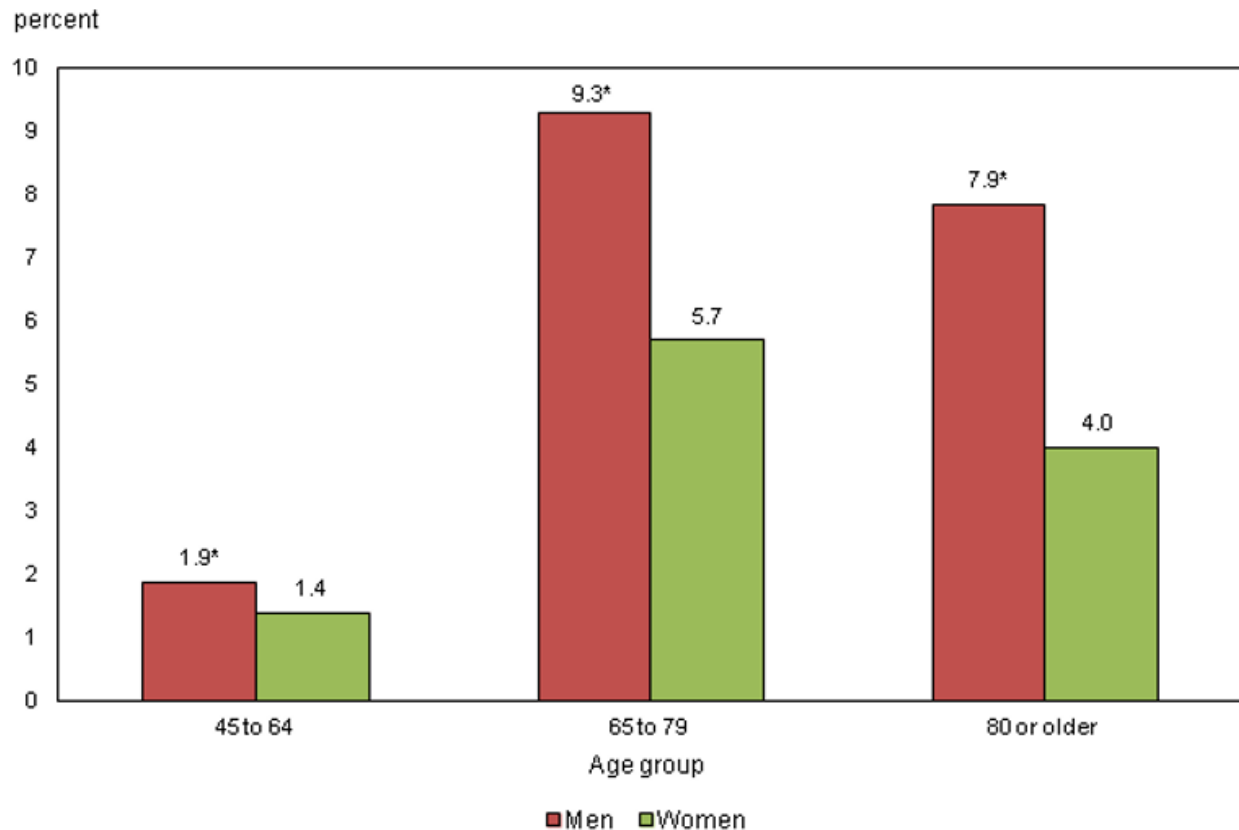


Figure 1. Prevalence of Parkinson's Disease in Institutional Population in Canada by Age Group and Sex [Source: (Wong et al., 2014)]

Figure 1 is based on research conducted in 2014 (Wong et al., 2014) and plots the prevalence of PD in 2011/2012. The prevalence of PD in the institutional population: 1.9% of men and 1.4% of women in the 45 to 64 age group, 9.3% of men and 5.7% of women in the 65 to 79 age group, and 7.9% of men and 4.0% of women in the 80 or older age group.

The proportion of people in Canada aged 65 years and older with PD increased from 15.6% (5,541,888 people) in 2011/2012 to 18.9% (7,568,308 people) in 2017 (Statistics Canada, 2017).

The number of people with PD is increasing, therefore, greater recognition and improved diagnostic methods are necessary.

In 2008, the total cost of direct and indirect costs in Canada for neuropsychiatric conditions (including PD) was over \$12.5 billion (Gaskin et al., 2017).

The burden of PD worldwide was reported to be over 9 million in 2020 (Pauwels & Boer, 2023).

As there are currently no treatments that can stop or reverse the progression of PD (Yang et al., 2022), early diagnosis and intervention can help reduce the severity of PD progression, improve the quality of life, and lessen the socioeconomic burden.

Speech impairment is prevalent, affecting up to 90 percent of individuals with PD, both in the early and late stages (Smith & Caplan, 2018). Speech is one of the first functions in PD to be disrupted which makes it a promising indicator in PD diagnosis (Azadi et al., 2021). A

case-control longitudinal study that investigated the fundamental frequency variability by Harel et al. showed that this measure started to deteriorate five years before the diagnosis of PD (Harel et al., 2004). This highlights the importance of speech analysis as an early detector of PD, which can be a cost-effective, targeted, and accessible method for screening PD (Azadi et al., 2021).

CHAPTER 2

LITERATURE REVIEW

The degree of communication impairment varies widely in individuals with PD and can result in inaudible voices, creating challenges in communication between people living with PD and their caregivers (Smith & Caplan, 2018). A cross-sectional survey in Sweden reported that 92.5 percent of respondents in the study had at least one symptom related to communication (Schalling et al., 2018).

Speech production results from the coordination of various motor activities, including respiration, phonation, articulation, and resonance. In people with PD, speech impairment arises from both motor and non-motor deficits (Dashtipour et al., 2018).

A review by Moro-Velazquez et al. (2021) on the phonatory aspects of speech. These features are outlined in **Table 2** (Moro-Velazquez et al., 2021).

Table 2. Phonatory Aspects Investigated in Parkinson's Disease

PHONATORY ASPECTS	
Jitter	RPDE⁵
Shimmer	Fundamental frequency
HNR¹	MPT⁶
NHR²	D₂
GNE³	SPI⁷
Subglottal pressure	Tremor
PPE⁴	MFCC⁸

1. (Harmonic to Noise Ratio), 2. (Noise to Harmonics Ratio), 3. (Glottal to Noise Excitation ratio), 4. (Pitch Period Entropy), 5. (Recurrence Period Density Entropy), 6. (Maximum Phonation Time), 7. (Soft Phonation Index), 8. (Mel-Frequency Cepstral Coefficients)

PHONATORY ASPECT CHANGES IN PARKINSON'S DISEASE

Rusz et al. (2011) reviewed the phonation, articulation, and prosody in people with PD and healthy controls. Among phonation features, they found a significant difference between PD and healthy control groups in Jitter (local), Jitter (RAP), Jitter (PPQ5), Jitter (DDP), Shimmer (local), Shimmer (APQ3), Shimmer (APQ5), Shimmer (APQ11), Shimmer (DDA), NHR, and HNR (dB), but not the pitch variations (F0SD [Fundamental frequency standard deviation]) (Rusz et al., 2011).

Upadhyaya et al. (2017) investigated Jitter, Shimmer, and their variants in people with PD and healthy controls. Their findings showed higher metrics of central tendency for all parameters in Parkinson-affected individuals (Upadhyaya et al., 2017). Irregular vocal fold vibration, as a result of motor impairment in PD, causes random modulation of the sound signal's amplitude (shimmer) and its period (jitter) (Asgari & Shafran, 2010).

Vikas et al. (2014) explored the detection of PD through voice in the early stages. They have shown higher pitch in the PD group compared to healthy adults, along with more variations in Formants, higher values of Jitter and Shimmer, and an abnormal pattern in the glottal pulse (Vikas & Sharma, 2014).

Rahn et al. (2007) studied the correlation dimension (D_2) in parallel with Jitter and Shimmer. Their results showed increased D_2 in phonatory signals in the PD-affected group compared with control subjects. They also found that the PD group had significantly higher values for Jitter, but not for Shimmer values, compared with control subjects (Rahn et al., 2007).

Jimenez-Jimenez et al. (1997) also researched acoustic voice features in untreated people living with Parkinson's Disease. Their results showed higher F0 in PD females as compared to matched controls. Higher values for Jitter in PD males were reported (this was in the case that the female's values were nearly significant). The Shimmer values in this study were significantly higher in the PD-affected group. The HNR values were controversial. The value obtained from the laryngograph signals was significantly lower in the PD-affected group, whereas the results from the microphonic signal showed the value was lower only in the female subgroup (Jiménez-Jiménez et al., 1997).

GNE is a feature of voice that is useful in machine learning techniques for automatic detection and assessment of Parkinson's Disease (Galaz et al., 2018; Tsanas et al., 2013; Arora et al., 2018; Viswanathan et al., 2019).

Below is a brief definition of each voice feature that can be extracted from the voice signal:

1. **Jitter (absolute) and Jitter (relative)**, refer to the cycle-to-cycle variation in the fundamental frequency. The Jitter (relative) is the average absolute difference between consecutive periods, divided by the average period (Vikas & Sharma, 2014).

$$Jitter (absolute) = \frac{1}{N-1} \sum_{i=1}^{N-1} |T_i - T_{i-1}|$$

Equation 1

$$Jitter (relative) = \frac{\frac{1}{N-1} \sum_{i=1}^{N-1} |T_i - T_{i-1}|}{\frac{1}{N} \sum_{i=1}^N T_i}$$

Equation 2

where T_i s are the extracted pitch period length (fundamental frequency and pitch period length are reversely related by $f = 1/T$, the unit for the pitch period length is in seconds [s] and the fundamental frequency's unit is in Hertz [Hz]).

The threshold value to detect pathologies in adults is 83.2 μ s for Jitter (absolute) and 0.0104 for Jitter (relative) (Teixeira et al., 2013).

Another variant of Jitter is relative average perturbation Jitter or Jitter (RAP):

$$Jitter (RAP) = \frac{\frac{1}{N-1} \sum_{i=1}^{N-1} |T_i - (\frac{1}{3} \sum_{j=i-1}^{i+1} T_j)|}{\frac{1}{N} \sum_{i=1}^N T_i}$$

Equation 3

The threshold value to detect pathologies is 0.68% for Jitter (RAP) (Teixeira et al., 2013). The other variant is Jitter (PPQ5), which represents the amount of periodic disturbance within 5 periods. It can be calculated as follows (Upadhya et al., 2017):

$$Jitter (PPQ5) = \frac{\frac{1}{N-1} \sum_{i=2}^{N-2} |T_i - (\frac{1}{5} \sum_{j=i-2}^{i+2} T_j)|}{\frac{1}{N} \sum_{i=1}^N T_i}$$

Equation 4

2. **Shimmer (dB) and Shimmer (relative)** is the variability of the peak-to-peak amplitude in decibels, or in other words, the average absolute of 20 times the base-10 logarithm of the ratio between the amplitude of consecutive periods. The shimmer (relative) is the

average absolute difference between the amplitude of consecutive periods divided by the average amplitude (Vikas & Sharma, 2014).

$$Shimmer (dB) = \frac{1}{N-1} \sum_{i=1}^{N-1} |20 \log(\frac{A_{i+1}}{A_i})|$$

Equation 5

$$Shimmer (relative) = \frac{\frac{1}{N-1} \sum_{i=1}^{N-1} |A_i - A_{i+1}|}{\frac{1}{N} \sum_{i=1}^N A_i}$$

Equation 6

where A_i s are the extracted peak-to-peak amplitude data, and N is the number of extracted pitch periods.

The limit to detect pathologies is 0.350 dB for Shimmer and 0.0381 for the Shimmer (relative) measure (Teixeira et al., 2013)

Other variants of Shimmer can be calculated as follows (Upadhya et al., 2017):

$$Shimmer (local absolute) = \frac{1}{N-1} \sum_{i=1}^{N-1} |A_i - A_{i+1}|$$

Equation 7

Shimmer (APQ3), shimmer (APQ5), and shimmer (APQ11) represent the amount of amplitude disturbance within three, five, and eleven periods respectively, and can be calculated as follows:

$$Shimmer (APQ3) = \frac{\frac{1}{N-1} \sum_{i=1}^{N-1} |A_i - (\frac{1}{3} \sum_{j=i-1}^{i+1} A_j)|}{\frac{1}{N} \sum_{i=1}^N A_i}$$

Equation 8

$$Shimmer (APQ5) = \frac{\frac{1}{N-1} \sum_{i=2}^{N-2} |A_i - (\frac{1}{5} \sum_{j=i-2}^{i+2} A_j)|}{\frac{1}{N} \sum_{i=1}^N A_i}$$

Equation 9

3. **HNR (Harmonic to Noise Ratio)** is an indicator of the overall periodicity of the voice signal, and this is articulated as the ratio between the periodic (harmonic part) and aperiodic (noise) components (Teixeira & Fernandes, 2014).

$$HNR (dB) = 10 \log_{10} \frac{AC_v(T)}{AC_v(0) - AC_v(T)}$$

Equation 10

where $AC_v(0)$ is the autocorrelation coefficient at the origin, consisting of all energy signals. The highest peak in the autocorrelation function beyond the zero-lag peak (at the origin) corresponds to the fundamental period ($AC_v(T)$).

4. **NHR (Noise to Harmonic Ratio)** is the average ratio of inharmonic (noise) to harmonic spectral energy (KILIÇ et al., 2011).

$$NHR (dB) = 10 \log_{10} \left(\frac{P_{noise}}{P_{harmonic}} \right)$$

Equation 11

where P is the power of the component. In this context and how the HNR was calculated (in dB) the following relation is true between HNR and NHR:

$$NHR (dB) = - HNR (dB)$$

Equation 12

5. **GNE (Glottal to Noise Excitation ratio)**. It was introduced in 1997 by Michaelis et al. and was to quantify the amount of voice excitation by vocal-fold oscillations against the excitation by turbulent noise (Michaelis et al., 1997).

For calculating GNE, first a band-pass filter is applied to remove the irrelevant frequency components. Then the voice signals are segmented into overlapping frames, typically 20-40 milliseconds long, with a 50% overlap. At the next step the frequency range, which is usually between 0-4000 Hz, will be divided into three sub-bands. The energy for each of the three frequency sub-bands and the total energy will be calculated using the following formula:

$$E_{sub-band}(i) = \sum_{k \in sub-band} |X(k)|^2$$

Equation 13

$$E_{total} = \sum_{k=0}^{N-1} |X(k)|^2$$

Equation 14

where $X(k)$ is the magnitude of the frequency component in the k bin. Finally, the GNE is calculated as follows:

$$GNE = \frac{E_{\text{central sub-band}}}{E_{\text{total}}}$$

Equation 15

6. **Subglottal pressure.** is a representative of the available energy for causing the vocal cord vibration. There are different means to measure this pressure:

- 1) a direct measurement by tracheal puncture,
- 2) direct measurement by placing a miniaturized pressure transducer under the glottis,
- 3) an estimation based on esophageal pressure,
- 4) body plethysmograph,
- 5) an estimation of airway pressure during sudden interruption of vowel production, and
- 6) an estimation based on the peak intraoral pressure during the production of the letter /p/ surrounded by vowels (Kitajima & Fujita, 1990).

7. **PPE (Pitch Period Entropy).** It quantifies the impaired control of fundamental frequency (F_0) by using a logarithmic scale (Abdurrahman & Sintawati, 2020).

To calculate the PPE measure, pitch periods must first be extracted from the voice data.

A histogram is then computed to determine the frequency of each pitch period. The

histogram should be normalized to obtain the probability distribution, $p(i)$:

$$p(i) = \frac{\text{number of occurrence of pitch period } i}{\text{total number of pitch periods}}$$

Equation 16

and finally, the PPE can be calculated using the following formula:

$$PPE = - \sum_i p(i)(p(i))$$

Equation 17

8. **RPDE (Recurrence Period Density Entropy)** is a method for determining the periodicity or repetitiveness of a signal (A. Thomas & D. P. Gopinath, 2012):

$$RPDE = - \frac{\sum_{t=1}^{T_{max}} P(t) \ln P(t)}{\ln T_{max}}$$

Equation 18

where T_{max} is the largest recurrence value, and $P(t)$ is the recurrence period density function.

9. **Fundamental frequency** is the physiological parameter of the frequency of vibration of the vocal cords measured in cycles per second or the equivalent acoustic parameter of fundamental frequency (f_0), measured in hertz (Hz) (Knight & Setter, 2021).

For determining the fundamental frequency in a speech signal, the highest peak in the autocorrelation function beyond the zero lag will be identified (refer to HNR calculation)

The peak corresponds to the fundamental period (T_0), and the inverse function of the fundamental period will give the fundamental frequency.

10. **SPI (Soft Phonation Index)**. It is an evaluation of the weakness of the high-frequency harmonic components that can be an indicator of vocal cords being loosely adducted during phonation. Higher values are related to incomplete adduction of vocal cords (Mathew & Bhat, 2009).

11. **Tremor.** It happens when there is a rhythmical, involuntary fluctuation in the vocal tract and is referred to as pathologic voice tremor (related to neurological diseases). It causes fluctuations in fundamental frequency (F0) and amplitude of the voice (Gillivan-Murphy et al., 2019).

To calculate the Tremor in the voice data, the fundamental frequency and amplitude contours will be extracted from the voice data. The rate of the rhythmic fluctuations in the fundamental frequency and amplitude, which is usually between 3-12 Hz corresponds to the **tremor rate**, and the extent of these fluctuations determines the **tremor magnitude**.

Table 3 summarizes the Phonatory aspect of voice that is influenced by PD and the studies that investigated their values in the People with Parkinson's Disease group and healthy controls, and their findings.

Higher values of Jitter and its variants, Shimmer and its variants, NHR, D2, PPE, RPDE, SPI, subglottal pressure, fundamental frequency, and voice tremor were reported in the PD group. MPT and HNR (which is the inverse of NHR), were reported to be lower in the PD group with respect to the healthy controls.

Table 3. Phonatory Aspect Changes in Parkinson's Disease

	Influence by Parkinson's Disease	Studies including the Feature Family
Jitter	Several studies have reported higher values in the PD group	(Jiménez-Jiménez et al., 1997), (Holmes et al., 2000), (Rahn et al., 2007), (Majdinasab et al., 2016), (Schoentgen et al., 2019), (Moro-Velázquez et al., 2019), (Ramig et al., 1988)
Shimmer	Several studies have reported higher values in the PD group compared to the controls	(Ramig et al., 1988), (Jiménez-Jiménez et al., 1997), (Holmes et al., 2000), (Rahn et al., 2007), (Rusz et al., 2011), (Midi et al., 2008), (Tanaka et al., 2011), (Sakar et al., 2013), (Skodda et al., 2013), (Rusz et al., 2013), (Bang et al., 2013), (Little et al., 2008), (Tsanas et al., 2009), (Tsanas et al., 2012), (Bocklet et al., 2013), (Bayestehtashk et al., 2015), (Majdinasab et al., 2016), (Orozco-Arroyave et al., 2018), (Schoentgen et al., 2019), (Moro-Velázquez et al., 2019), (Ramig et al., 1988), (Jiménez-Jiménez et al., 1997), (Rusz et al., 2011), (Yüçetürk et al., 2002), (Sakar et al., 2013), (Rusz et al., 2013), (Little et al., 2008), (Tsanas et al., 2009), (Tsanas et al., 2012), (Majdinasab et al., 2016), (Khan et al., 2014)
NHR	Several studies have suggested higher values in PD group compared to the controls	(Holmes et al., 2000), (Rahn et al., 2007), (Tanaka et al., 2011), (Sakar et al., 2013), (Skodda et al., 2013), (Bang et al., 2013), (Little et al., 2008), (Tsanas et al., 2009), (Tsanas et al., 2012)
D2	Higher values of this feature were reported in several studies for the PD group	(Rahn et al., 2007), (Little et al., 2008), (Tsanas et al., 2009), (Tsanas et al., 2012)
PPE	The results of several studies suggested higher values in the PD group with respect to the controls	(Rusz et al., 2013), (Little et al., 2008), (Tsanas et al., 2009), (Tsanas et al., 2012)
RPDE	Results of several studies suggested a slightly higher value for PD group with respect to controls	(Rusz et al., 2013), (Little et al., 2008), (Tsanas et al., 2009), (Tsanas et al., 2012)
MPT	Lower values were reported in several studies	(Yüçetürk et al., 2002), (Midi et al., 2008), (Rusz et al., 2013), (Little et al., 2008), (Tsanas et al., 2009), (Tsanas et al., 2012)
SPI	Higher values were reported in several studies	(Tanaka et al., 2011), (Mekyska et al., 2015), (Orozco-Arroyave et al., 2014), (Midi et al., 2008)
Subglottal pressure	People with PD had higher subglottal pressure with respect to controls when producing a sentence with the same Sound Pressure Level	(J. Jiang et al., 1999), (Hammer & Barlow, 2010)
Fundamental frequency	Some studies suggested higher values for the PD group with respect to controls	(Yüçetürk et al., 2002), (Midi et al., 2008), (Tanaka et al., 2011), (Majdinasab et al., 2016), (Abur et al., 2018)
Vocal tremor	Tends to be higher in the PD group with respect to controls	(Logemann et al., 1978), (LO, 1994), (Perez et al., 1996), (Jiménez-Jiménez et al., 1997), (Little et al., 2008), (Tanaka et al., 2011), (Villa-Canas et al., 2015), (Brückl et al., 2018)

ARTICULATION AND PROSODY ASPECT CHANGES IN PARKINSON'S DISEASE

As the dataset in this study includes participants describing a drawing, phonatory voice features cannot be investigated. Only the F0SD and IntSD were investigated in people with PD and healthy controls (for more details about the reason for using these two features, refer to **Part II, Chapter 3, Section D**)

Articulatory aspect changes in PD involve hypokinetic articulation, i.e. imprecise consonants and vowels due to limitations in articulatory movements.

Dysprosody, characterized by reduced pitch inflections, monotone, rushed, dysfluent, hesitant, or stuttered-like speech, is also common in PD (Skodda, 2011).

- Articulatory decay (RFA [dB]), F0SD, and IntSD have been reported to differ significantly between healthy and PD groups (Rusz et al., 2022). A review article by Ma et al. (2020) revealed that prosody features are both decreased in people living with PD. VAI and F0SD showed significant differences between the PD and control groups both in males and females (Skodda et al., 2011). Kowalska-Taczanowska et al.(2020) showed a significant difference in F0 dev and reduced loudness between PD and the control group.
- J. Holmes et al. (2000) showed deterioration of breathiness, F0SD, and IntSD in the later stages of PD.

- Skodda et al. (2009) showed reduced F0 variation in male and female subjects with PD compared to the controls but the progression of prosodic impairment over time showed no correlation to the disease duration or UPDRS motor score.

Table 4 illustrates the articulatory aspects of voice that can be evaluated in individuals with PD.

Table 4. Articulatory Aspects Investigated in Parkinson's Disease

ARTICULATORY ASPECT	
FCR ¹	Duration of voiced segments
BBE ²	Stop silence length
MFCC	VAI ⁵
PLP ³	VOT ⁶
LPC ⁴	VSA ⁷ -related

1. Formant Centralization Ratio, 2. Band Bark Energies, 3. Perceptual Linear Prediction, 4. Linear Predictive Coding, 5. Vowel Articulation Index, 6. Voice Onset Time, 7. Vowel Space Area

1. **Formant Centralization Ratio (FCR).** It was designed to maximize sensitivity to vowel centralization while minimizing sensitivity to inter-speaker variability. It is expressed as:

$$FCR = \frac{(F2u+F2a+F1i+F1u)}{(F2i+F1a)}$$

Equation 21

where F2u is the frequency of the second formant of the vowel /u/, F2a is the frequency of the second formant of the vowel /a/, F1i is the frequency of the first formant of vowel /i/, F1u is the frequency of the first formant of the vowel /u/, F2i is the frequency of the

second formant of the vowel /i/, and F1a is the frequency of the first formant of vowel /a/ (Sapir Shimon et al., 2010).

2. **Perceptual Linear Prediction (PLP)** is an approach that models a perceptually motivated auditory spectrum by a low-order all-pole function, using the autocorrelation of linear prediction and was introduced in 1985 (H. Hermansky et al., 1985).

The low-order all-pole function in PLP refers to a mathematical model used to approximate the spectral envelope of the perceptual loudness spectrum. This model is characterized by having only poles (resonances) and no zeros in its transfer function, which makes it an all-pole model. In all-pole models, the denominator is a polynomial, but the numerator is a constant (and non-zero).

3. **Vowel Space Area (VSA)** refers to a two-dimensional area bounded by lines connecting the first and second formant frequency coordinates (F1/F2) of vowels (Sandoval et al., 2013).

In the VSA measure, the area is defined as the polygon formed by plotting the first formant (F1) and second formant (F2) frequencies of specific vowels on a two-dimensional plane and connecting these points with straight lines.

The pathophysiological interpretation with respect to hypokinetic dysarthria is that in the IntSD, hypokinesia leads to decreased amplitude of respiratory and thyroarytenoid muscles (which is called Monoloudness). Also, in the F0SD, hypokinesia causes reduced amplitude of vocal cord movements, leading to glottal incompetence (which is called Monopitch) (Rusz et al., 2022).

Summary of Literature Review

The literature review provides an overview of the communication impairments in individuals with Parkinson's Disease (PD), noting the significant variability in speech and voice challenges faced by people living with PD. It highlights key studies that investigate the phonatory aspects of speech, such as jitter, shimmer, Harmonic to Noise Ratio (HNR), and subglottal pressure, all of which are found to differ between PD patients and healthy controls. For example, studies by Rusz et al. (2011) and Upadhyaya et al. (2017) found that phonation features such as jitter and shimmer are significantly higher in individuals with PD. The review also discusses articulation and prosody changes in PD, where features like F0 standard deviation (F0SD) and intensity standard deviation (IntSD) have shown significant differences between PD and control groups. Additionally, acoustic features such as correlation dimension (D2) and voice tremor are examined for their role in distinguishing PD from healthy individuals.

While previous studies have provided valuable insights into the voice and speech impairments in PD, they have largely been cross-sectional or focused on short periods. There is a notable gap in the literature regarding comprehensive longitudinal investigations that track changes in speech and voice characteristics over an extended period. This study helps fill that gap by examining voice features in participants over a 5-year period, with repeated measures taken before and after engaging in dance sessions. By investigating both short-term and long-term effects of the intervention, the study provides a more complete understanding of how voice features evolve in PD patients and how movement-based interventions like dance may influence these changes over time. This longitudinal approach offers a unique contribution to the existing body of research, addressing the limitations of previous cross-sectional studies.

PART II

CHAPTER 3

VOICE ANALYSIS OF PEOPLE WITH PARKINSON'S DISEASE AND CONTROLS

The study's investigation aims to analyze the speech features of people living with PD and compare these features to those of healthy controls. These features include the F0SD and IntSD, due to the limitations of the speech samples format.

A. INTRODUCTION

Identifying a correlation between two conditions—specifically, observing one condition with a ratio above a defined threshold while the other condition is consistently present—could potentially suggest a causal relationship between the primary cause and the observed condition. In the context of this study and the primary hypotheses, finding a correlation between the presence of PD and different voice feature values will add more to the strength of PD's influence on voice features. Also, comparing the voice feature values measured at different times in PwPD and controls who attended the dance classes, could potentially reveal the effect of dance on the voice features.

Finally, the results of this study and the other studies conducted on the same group can potentially propose the effect of dance on neuroplasticity in the brain.

As there has not been a definitive cure for PD, investigating multiple aspects of the disease can contribute to determining the etiology and mechanism of the disease, which is beneficial for gaining recognition of PD and finding a cure (Stoker & Barker, 2020).

In addition to the advantages of identifying the etiology and enabling early detection of the disease, exploring the effects of dance and demonstrating its potential to improve both motor and non-motor symptoms could provide therapeutic options that enhance Quality of Life (QoL) and alleviate depression and anxiety, which are commonly associated with Parkinson's disease in those already affected.

B. HYPOTHESES/ REASONS FOR MEASURES USED

The primary aim of this study is to identify and compare the voice parameters of individuals with Parkinson's Disease (PD) to those of healthy controls from a database collected around a dance for Parkinson's intervention where the experimenters videotaped the MDS-UPDRS over the years. The secondary aim is to determine which specific voice parameters are affected by the disease. The final aim is to explore the potential of speech analysis as an early detection tool for PD.

Speech impairments, which can occur in up to 90% of PD patients, may develop at any stage of the disease, whether early or late (Smith & Caplan, 2018). This suggests that if relevant speech features are systematically extracted and healthy reference ranges are established, these measures could be utilized as an effective early detection method for PD.

The literature review, as discussed in Part I, Chapter 2, highlights a range of voice features that could be investigated. The dataset for this study is derived from a longitudinal investigation by Bearss and DeSouza (2021), which examined the impact of regular weekly participation in dance with Parkinson's classes on the progression of Parkinson's Disease.

The primary hypotheses of this study are as follows:

1. **Fundamental Frequency Standard Deviation (F0SD) and Voice Intensity**

Standard Deviation (IntSD): These parameters will differ between individuals with Parkinson's Disease and healthy controls, as PD is known to affect voice features.

2. **Progression of PD:** It is expected that the progression of PD will lead to a deterioration in voice features over a five-year period, while the voice features of healthy controls will remain stable.

3. **Effect of Dance:** Dance, by promoting neuroplasticity in the brain, is hypothesized to mitigate the deterioration of voice features in individuals with PD.

The results of this study are anticipated to enhance our understanding of the effects of dance on voice features in both individuals with PD and healthy controls. We hypothesize that the neuroplastic changes induced by dance will manifest in improved speech measures.

Previous research by Bar and DeSouza (2016) on expert young dancers at the National Ballet of Canada has shown that dance promotes signal changes in the supplementary motor area (SMA) as dancers learn, practice, and perform novel ballets. These signal changes suggest that dance may help slow the progression of motor symptoms in individuals with PD by stimulating neuroplasticity in the SMA. The study observed that the rehearsal of complex ballet sequences initially led to increased activity within the SMA and auditory cortical regions up to the 7th week, followed by decreased activation between the 7th and 34th weeks.

Similarly, Simon et al. (2023 & 2024), using the same neuroimaging paradigm, reported modulation of BOLD (Blood Oxygenation Level Dependent) signals in the SMA in a single case study over eight months of dance classes. Notably, the subject in this study was one of the 29 individuals with PD followed in the current investigation.

C. METHODOLOGY

This study investigates voice features, specifically the standard deviation of fundamental frequency (F0SD) and intensity (IntSD), in individuals with Parkinson's Disease (PwPD) compared to healthy controls.

Ethical considerations

This study is a secondary analysis of previously collected data, conducted in adherence to the ethical standards of the Faculty of Graduate Studies at York University. The project received ethical approval (certificate number: 217-296), ensuring compliance with institutional guidelines and regulations.

The original data collection involved informed consent from all participants, who were fully briefed on the study's purpose, procedures, and their right to withdraw at any time without penalty. This consent included permission for future use of their data in subsequent research.

In conducting this secondary analysis, the following ethical considerations were addressed:

1. **Confidentiality and Anonymity:** All data was anonymized, with personal identifiers removed to protect participants' privacy. Data was securely stored and access was restricted to authorized personnel only.
2. **Data Integrity and Security:** Data integrity and security were prioritized. All data was stored in encrypted files and accessed through secure systems, in compliance with York University's data protection policies.

3. **Beneficence and Non-maleficence:** The analysis was conducted to maximize benefits while minimizing potential harm to participants. The results aim to contribute to scientific knowledge without causing harm or distress to the individuals whose data was analyzed.
4. **Transparency and Accountability:** The methods and procedures used in this analysis are transparently reported, ensuring that the study can be replicated and scrutinized, thus maintaining the integrity of the research process.
5. **Respect for Persons:** The rights and dignity of participants were respected throughout the research process, ensuring that their autonomy was honored.
6. **Ethical Approval:** The study adhered to the ethical guidelines provided by the Faculty of Graduate Studies at York University, with ethical approval obtained before the commencement of the analysis.

1. Speech Dataset

Voice features were collected from individuals who attended the dance classes for PD at Canada's National Ballet School and Trinity St. Paul's church in Toronto, Ontario from 2014 to 2019. The participants were part of a longitudinal study by Bearss & DeSouza (Bearss & DeSouza, 2021). In that study, people were filmed during the evaluation of the Movement Disorder Society's Unified Parkinson's Disease Rating Scale (MDS-UPDRS). They described a picture drawing for 30-60 seconds (**Figure 2**). The MDS-UPDRS evaluation was recorded twice for each participant before and after the dance session. In Part III (Item 3.1) of the scale, participants were examined for their speech. The UPDRS was originally developed in the 1980s and in 2001, a new version of it, termed the Movement Disorder Society (MDS) sponsored by UPDRS was created. This scale has four parts such as evaluating motor and non-motor subjectively and examining the person (Goetz et al., 2008).

(A sample part of the MDS-UPDRS questionnaire is provided in **Appendix C**).

Both PD patients and healthy controls participated in the weekly dance classes.

Participants were filmed for the MDS-UPDRS evaluation. In the video files, people are sitting on a chair 4-5 meters away from the camera and an examiner is performing the examination. Each video file was investigated during the parts where the person was describing the drawing. Those parts were trimmed using QuickTime Player version 10.5 and extracted to audio. The chosen section was the one that involved the participant's voice only. Files including background noise, a sudden loud noise, or music playing in the background were excluded.

A total of 281 audio files were created from the video files. 173 of these files were extracted from people with PD (nPD=173), and 108 were from healthy controls (nHC=108). These video

files were recorded from 2014 to 2019: $n=34$ ($nHC=16$; $nPD=18$) of these files were from 2014, $n=49$ ($nHC=22$; $nPD=27$) were from 2015, $n=71$ ($nHC=20$; $nPD=51$) were from 2016, $n=44$ ($nHC=12$; $nPD=32$) from 2017, $n=39$ ($nHC=18$; $nPD=21$) from 2018, and $n=44$ ($nHC=20$ HC; $nPD=24$) were from 2019.

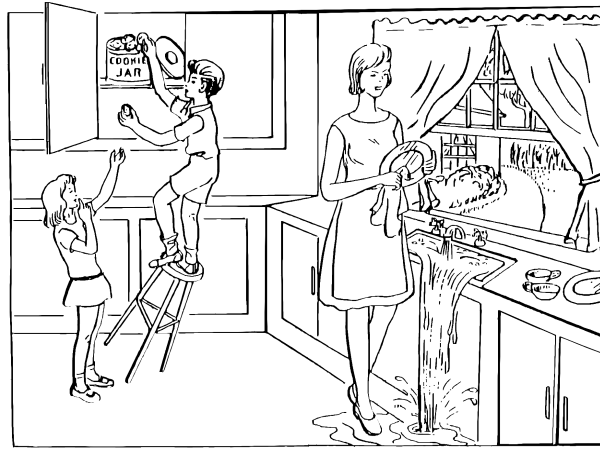


Figure 2. The Drawing Described in MDS-UPDRS Part III Examination

After excluding files with background noise (e.g., piano playing in the background) or files containing more than one person's voice, a total of 266 files remained. Of these, 135 files were extracted from data collected before the dance session, including 29 people with Parkinson's disease (PD) and 29 healthy controls (HC).

The after-dance session files included 131 recordings, consisting of 28 PD subjects ($nPD=28$; one subject's post-session file was excluded) and 29 healthy controls ($nHC=29$).

2. Extracting voice features

A Python machine learning pipeline was used to extract voice features from all 29 individuals with PD (PwPD) and 29 healthy controls (HC), resulting in a total of 266 voice file samples. This code has Praat scripts implemented in Parselmouth for Python (Feinberg, 2022). (The code for extracting the features can be found in the **Appendix B**).

The extraction of voice features was performed using a combination of machine learning-based frameworks integrated with Python libraries, including Praat, Parselmouth, and Librosa. The goal was to extract relevant acoustic features such as the standard deviation of fundamental frequency (F0SD) and intensity (IntSD) from recorded speech samples of PwPD and healthy controls.

1. ML Framework Overview:

The feature extraction pipeline was designed as an automated process using Python-based scripts that applied pre-trained models and algorithms embedded in Praat and Parselmouth libraries:

- Praat (Boersma, 2011): A speech analysis platform powered by a feedforward neural network-based learning algorithm. This algorithm performs supervised classification for extracting key acoustic features such as pitch, formant, and intensity patterns from voice files.
- Parselmouth (Jadoul et al., 2018): An open-source Python interface enabling integration with Praat's core functionalities, ensuring efficient batch processing of audio files.

- Librosa (McFee et al., 2015): A machine learning library widely used for audio signal processing, utilized for extracting the intensity standard deviation (IntSD).

2. Audio Processing Workflow:

- Audio Preprocessing: Audio files were initially stored in the .m4a format and converted to .wav for compatibility with Praat [using the Music application (version 1.4.2.83)].
- Automated Voice Analysis: The machine learning pipeline processed each audio file using [PraatScripts hosted on GitHub](#), applying feature extraction models tuned to measure specific acoustic parameters.
- Output Generation: Extracted features were saved as .csv files, providing a structured format for statistical analysis and visualization.

3. Feature Extraction Details:

- Standard Deviation of Fundamental Frequency (F0SD):
 - Extracted using Praat's pitch-tracking algorithm.
 - F0SD reflects variability in pitch, which is often reduced in individuals with PD due to hypokinetic dysarthria.
- Standard Deviation of Intensity (IntSD):
 - Computed using Librosa's feature extraction functions.
 - IntSD measures amplitude variability, another critical marker in speech studies involving neurodegenerative disorders.

4. Statistical Analysis Integration:

The extracted features were analyzed using ANOVA models in R Studio (Version 2024.04.0+735) to evaluate the effect of time and group on F0SD and IntSD. This integration between the

ML-based feature extraction pipeline and statistical analysis framework enabled an end-to-end data processing pipeline, ensuring accuracy and reproducibility.

Given the study's observational and exploratory nature, the use of pre-existing ML models embedded in Praat and Parselmouth provided reliable and validated methods for feature extraction. These models are recognized for robust pitch and intensity analysis, making them ideal for research on voice features affected by PD. Additionally, the modular structure of the codebase allowed for customization and batch processing, ensuring scalability and reproducibility.

The Librosa library in JupyterLab (version 3.6.3) from ANACONDA Navigator (version 2.5.2) was used to compute the standard deviation of intensity (IntSD) from the processed voice files. (The code for extracting Intensity standard deviation can be found in the **Appendix B**).

The extracted audio files from healthy controls and people with PD were processed by the PraatScripts-Master before and after the dance sessions respectively.

Then, a .csv file of selected voice features: standard deviation of fundamental frequency, and standard deviation of intensity was created.

Additionally, a modified version of the 'Diagnosing Parkinson's Disease using Voice Sample Data Analysis' project by Maheshwor Tiwari ([GitHub Repository](#)) was used in the Google Colaboratory environment for further statistical analysis.

Voice features were measured across 11 time points from 2014 to 2019, as outlined in **Table 5**.

Table 5. Time Points of MDS-UPDRS Examinations

Time 1	2014
Time 2	2015
Time 3	2016 (Jan-Apr)
Time 4	2016 (May-Aug)
Time 5	2016 (Sep-Dec)
Time 6	2017 (Jan-Jun)
Time 7	2017 (Jul-Dec)
Time 8	2018 (Jan-Jun)
Time 9	2018 (Jul-Dec)
Time 10	2019 (Jan-Jun)
Time 11	2019 (Jul-Dec)

To enhance data visualization, the 11 time points were consolidated into four-time slots.

Time A (2014/2015): Time 1 and Time2

Time B (2016): Time 3, Time 4, and Time 5

Time C (2017): Time 6 and Time 7

Time D (2018/2019): Time 8, Time 9, Time 10, and Time 11

The decision to merge and average the 11-time points into 4 was based on both the proximity of certain data collections and the need to address variability in participant numbers. The first two time points, collected at the end of 2014 and the beginning of 2015, were merged due to their temporal closeness, allowing for a more accurate representation of that period. Similarly, the data from 2018 and 2019 were averaged together (time 4), as the number of voice samples in these later collections was significantly reduced due to lower participation rates. For the other two time points (2016 and 2017), an average was calculated to represent a measure for each year. By averaging these collections, the analysis could maintain statistical power while still capturing the longitudinal changes in voice features over the 5-year span of the study. This approach provided a balanced representation across the different stages of the intervention. Visualization and plotting of the voice feature's values across time were conducted using Python code (see **Appendix “F. Plotting Python code”** for the code that was used).

D. A NOTE ON SELECTED FEATURES

Various features can be extracted and analyzed based on the task performed by the subjects.

Ruzs et al. 's (2022) study summarized the phonatory, articulatory, prosody, and speech timing acoustic features, and the tasks that the features can be extracted from. In phonation features, Harmonics-to-Noise Ratio (HNR), Cepstral Peak Prominence (CPP), and Proportion of Subharmonic Intervals (PSI) all can be extracted from sustained phonation tasks.

In a sustained vowel phonation task, the participants are asked to sustain the voicing of a vowel, usually /a/, at a comfortable pitch and loudness level for at least 5 seconds after a deep breath.

The same process is typically repeated three times. The task can be extended to assess sustained phonation at different pitches and loudness. The articulatory acoustic features involve Voice Onset Time (VOT), which can be extracted from syllable repetition tasks, and Resonant Frequency Attenuation (RFA), which can be extracted from reading passage tasks.

Prosody acoustic features involve standard deviation of intensity (IntSD) and standard deviation of fundamental frequency (F0SD), which both can be extracted from reading passage tasks.

Duration of Pause Intervals (DPI) and Net Speech Rate (NSR) can be extracted from reading passage tasks, while Diadochokinetic Rate (DDKR) extraction needs syllable repetition tasks (Rusz et al., 2022).

Studies investigating phonatory voice features affected by Parkinson's Disease, such as jitter, shimmer, HNR, and NHR, typically employ sustained phonation of vowels (e.g., /a/, /u/, /e/, /i/).

Most have found significant differences between PD and healthy groups, with higher jitter and shimmer and lower HNR in the PD group (Moro-Velazquez et al., 2021).

Figure 3 illustrates the process of extracting voice features and the number of files in each category.

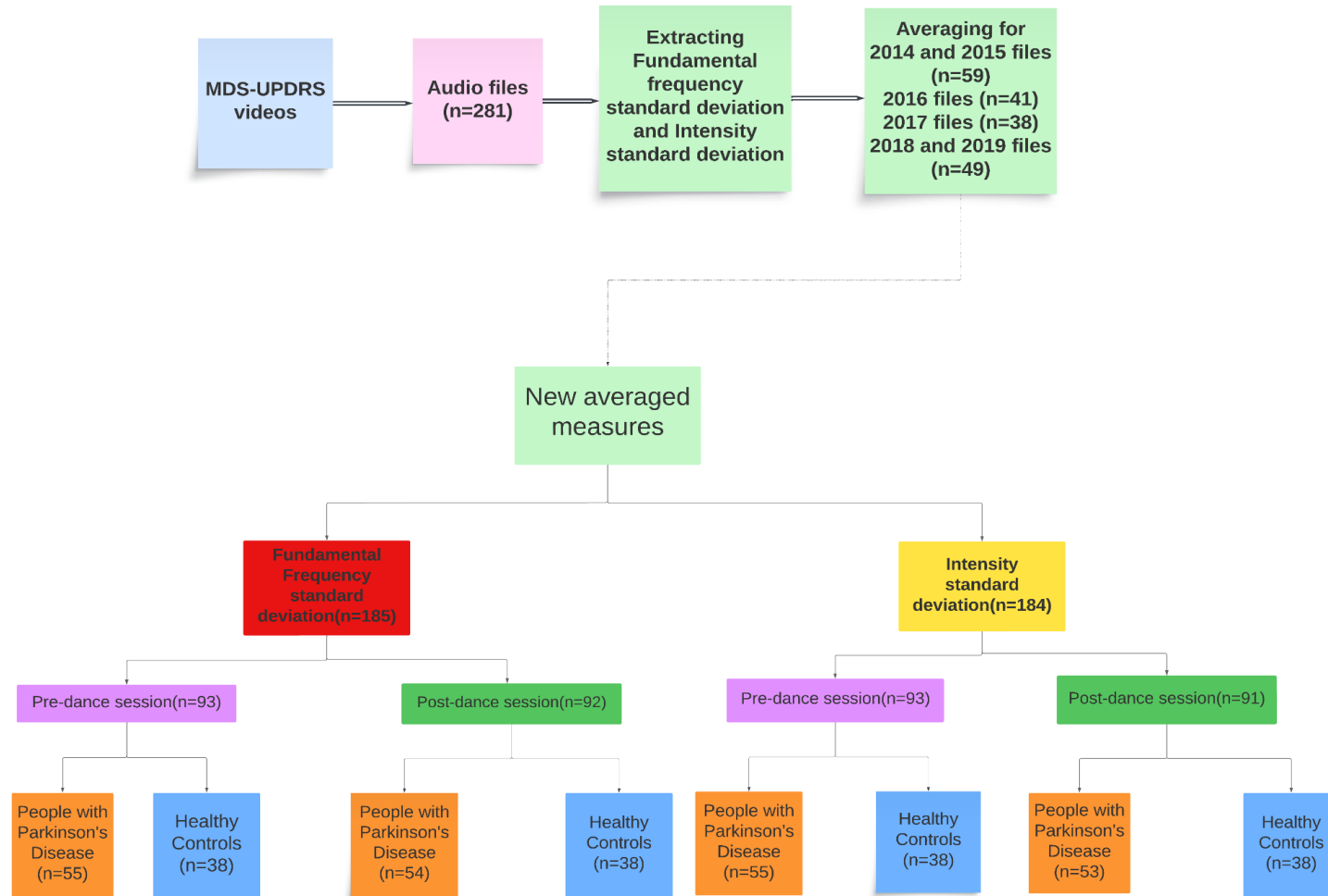


Figure 3. The Illustration of Extracting the Voice Files and Number of Files in Each Group

To visualize and compare the intensity contour between a subject with PD and a healthy control, a common sentence (“**water is overflowing**”) from their descriptions was extracted, and the intensity contours were drawn using Praat software. (**Figure 4**).

It is worth noting that this illustration was created using just one sentence for comparison purposes, whereas the entire description of the image was used for analyzing the voice features.

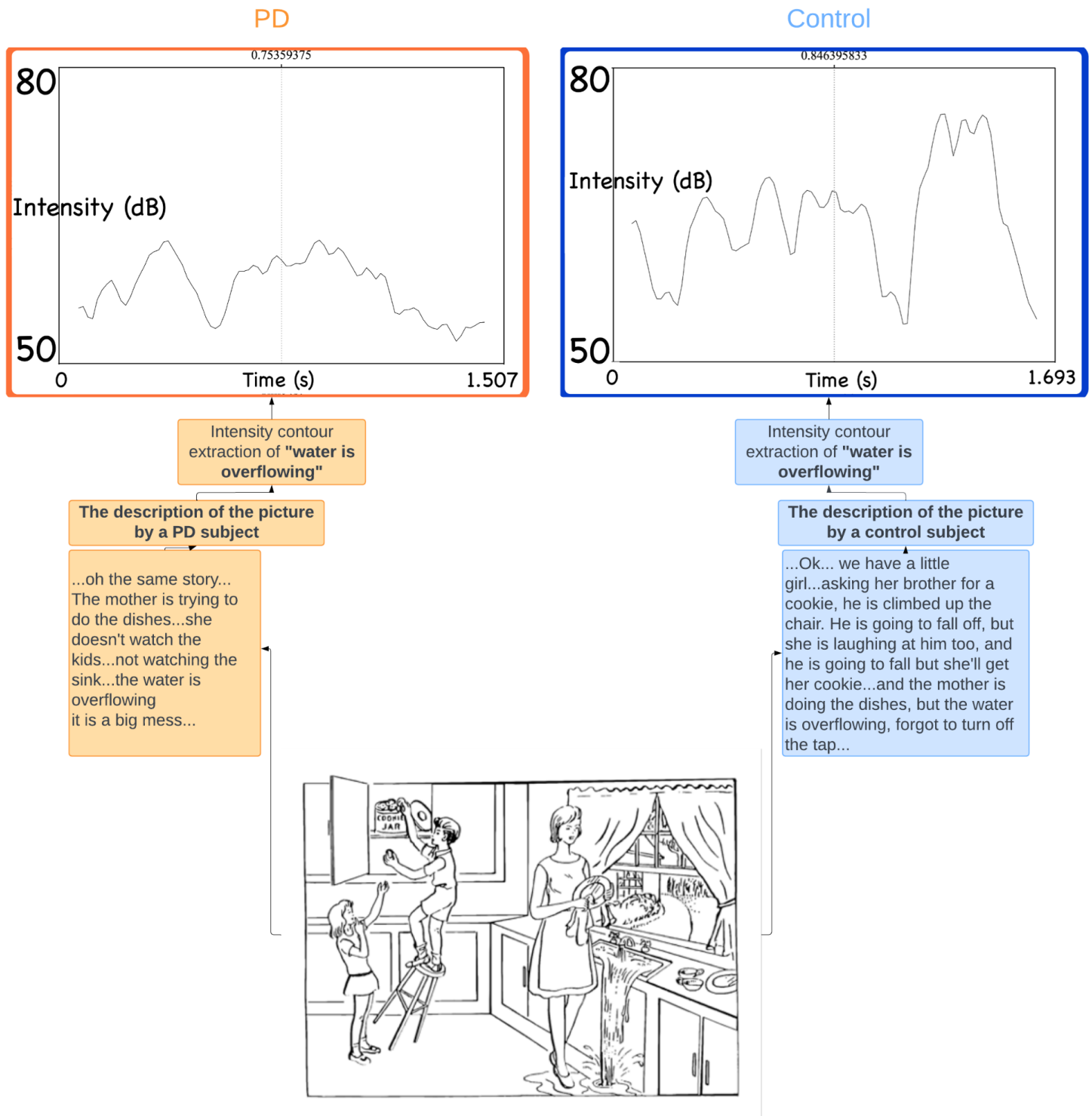


Figure 4. An Illustration of the Intensity Contour of a Common Sentence Between a Subject with PD and a Control Subject for Visualizing the Difference Between the Intensity of the Voice

E. RESULTS

The output tables from PraatScripts-Master are provided in the appendix. **Figure 5** illustrates the distribution of different voice features through histogram diagrams.

Histogram Comparison for Healthy controls and People with Parkinson

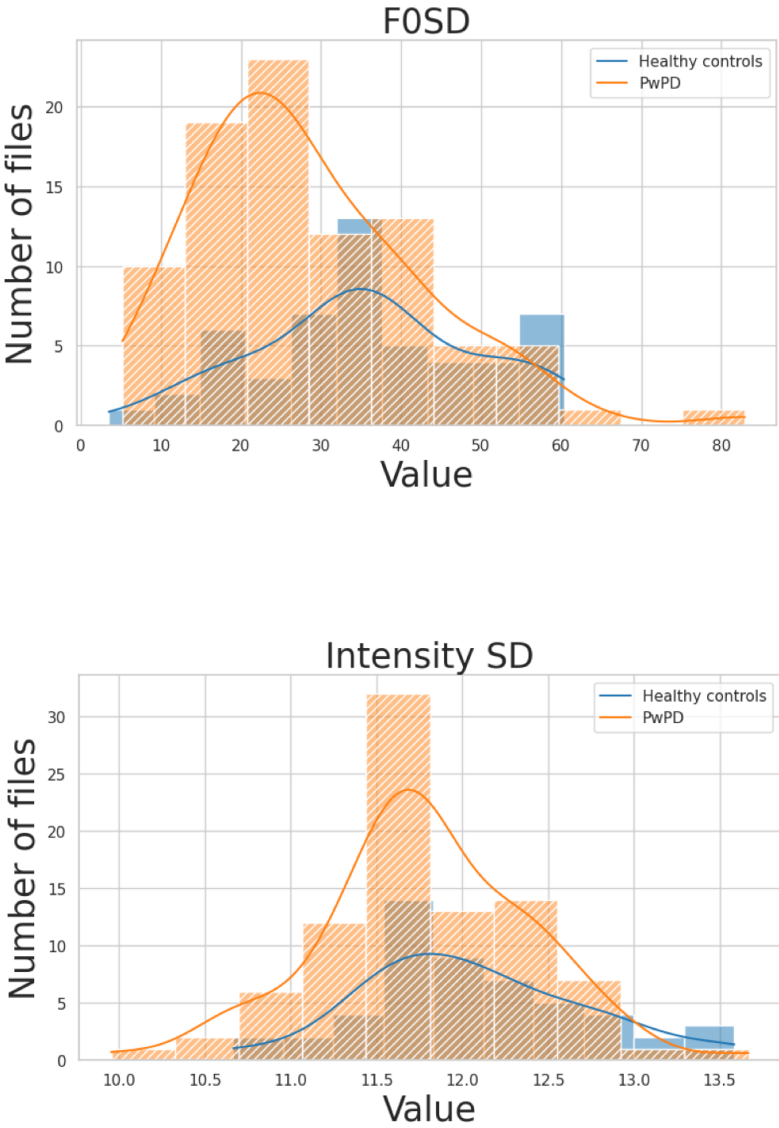


Figure 5. Histogram Diagrams of Voice Features

Box plots of different voice features are found in **Figure 6**.

Box Plot Comparison for Healthy controls and People with Parkinson

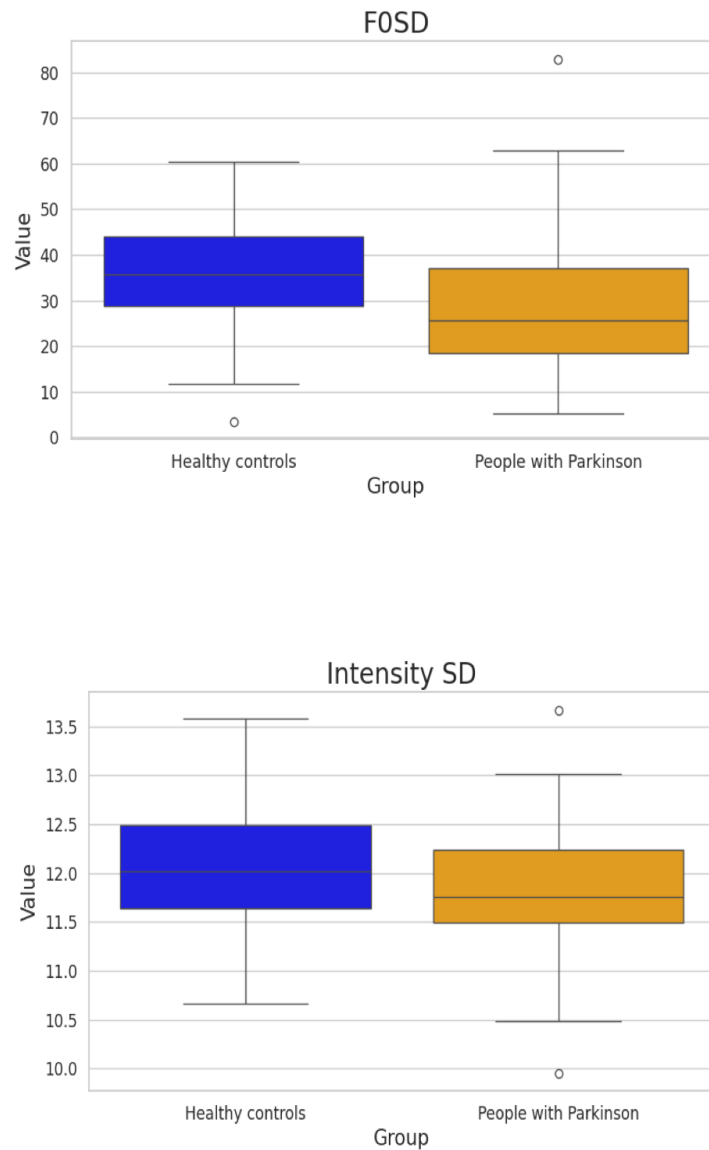


Figure 6. Box Plots of Voice Features

Figure 7 displays the mean differences between the two groups along with their confidence intervals.

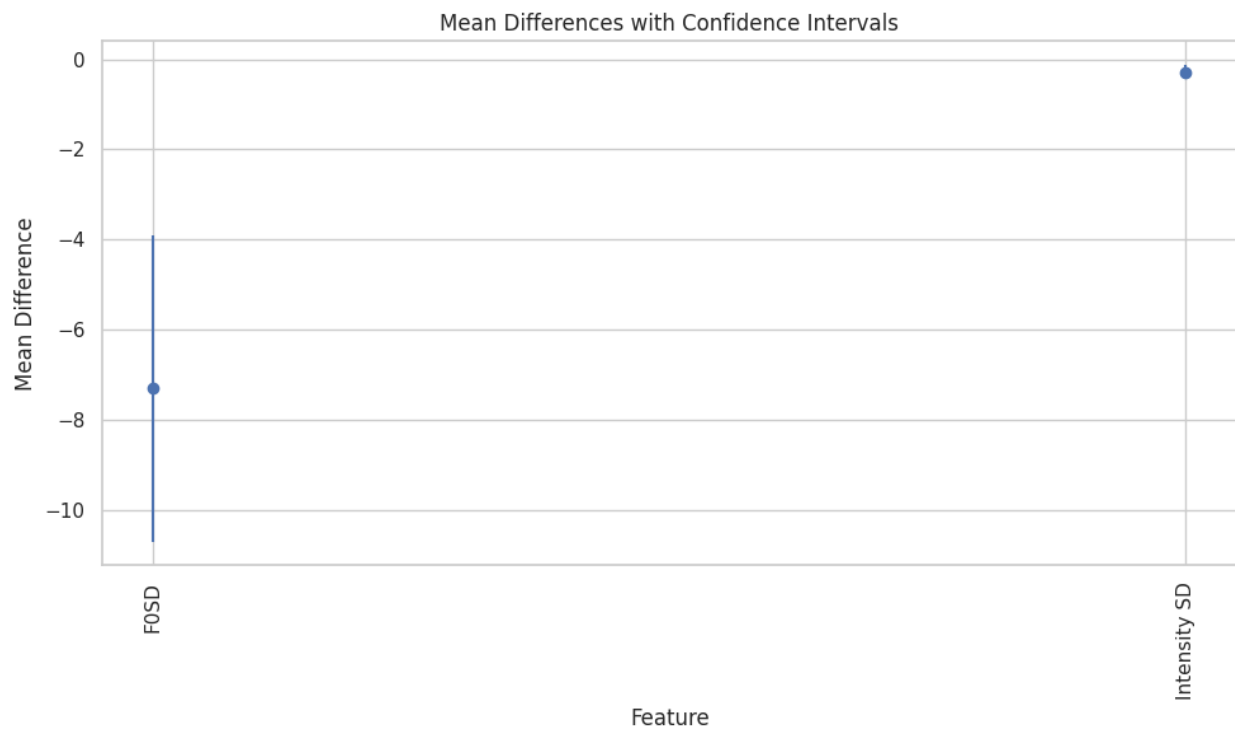


Figure 7. Mean difference and Confidence intervals

Table 6 summarizes the voice features that showed significant differences ($p < 0.05$) between PwPD and healthy controls.

Table 6. Voice features that Showing Significant Differences Between PD and Control Groups

Feature	Z-Score	Critical Z-Value	Result
Intensity standard deviation	-2.504312889788850	1.959963984540050	Reject H0
Fundamental frequency standard deviation	-2.9973199674744600	1.959963984540050	Reject H0

Table 7. Age and Sex Distribution of the PwPD and Healthy Controls Groups

	Age at 2014	Sex
PwPD (n=29)	68.2 (54-80)	Female:18 Male:11
Healthy Controls (n=29)	63.5 (50-75) *	Female:19 Male:10

* The age of 4 people was not available

Descriptive statistics of the voice features are presented in **Figures 8, 9, 10, and 11.**

Descriptive statistics for fundamental frequency standard deviation (FOSD)-PwPD

Group	count	mean	std	min	25%	50%	75%	max
	2014/2015							
PwPD-post	13	26.5390021	7.84034378	12.3207502	21.5096341	25.4335718	29.5627959	42.6200739
PwPD-pre	13	25.986851	12.9765431	9.15597417	17.5385211	22.7823244	31.8164081	55.0795046
	2016							
PwPD-post	14	27.4953197	11.2574281	11.5639506	19.3145526	24.3411463	32.2200486	46.4769009
PwPD-pre	15	24.7953814	9.84110696	10.7532737	19.5188762	22.3881456	29.7224937	46.7550156
	2017							
PwPD-post	14	26.0623771	10.6388365	13.7531536	17.5639129	25.3385544	32.1245208	49.846792
PwPD-pre	14	28.7494524	11.3615426	12.9352111	21.3169198	26.9123721	35.6145548	54.0921438
	2018/2019							
PwPD-post	13	34.9470419	19.9786556	12.547341	18.1625557	30.5609049	44.7362835	75.2458537
PwPD-pre	13	36.4314177	16.2772146	11.8834711	24.5284557	32.1899279	51.6146882	65.0856978

Figure 8

Descriptive statistics for fundamental frequency standard deviation (FOSD)-Healthy Controls

Group	count	mean	std	min	25%	50%	75%	max
	2014/2015							
Healthy controls-post	14	33.9179171	13.5353645	6.48490652	25.0178574	34.4460765	45.0014798	54.3435036
Healthy controls-pre	15	34.1042332	16.3771145	3.46880541	23.4132758	34.6642034	44.6802223	60.3555254
	2016							
Healthy controls-post	6	40.2664709	14.2663547	20.8138263	32.2841191	40.465993	46.3547857	61.9784686
Healthy controls-pre	6	35.4339572	16.2022103	13.9531469	24.243453	35.3768564	47.5386379	55.772
	2017							
Healthy controls-post	6	34.3940717	10.9144931	24.6389527	26.4716472	30.3387735	40.5233161	51.9471619
Healthy controls-pre	6	36.5725869	16.2039924	14.876908	27.6178924	33.5268342	50.2631198	56.0148184
	2018/2019							
Healthy controls-post	12	38.5638951	14.5144117	10.9020145	30.5805174	37.1482639	48.1204327	63.4874069
Healthy controls-pre	11	35.9200651	11.8632678	12.0789568	34.0645848	37.994231	42.0771613	52.4222289

Figure 9

Descriptive statistics for Intensity standard deviation (IntSD)-PwPD

Group	count	mean	std	min	25%	50%	75%	max
	2014/2015							
PwPD-post	13	11.8138287	0.41160897	11.1598339	11.6193686	11.8263097	12.0024691	12.4490786
PwPD-pre	16	11.938764	0.4145833	11.3258419	11.6485601	11.8749366	12.2300108	12.7721329
	2016							
PwPD-post	14	11.7292836	0.38558425	11.0240083	11.6078608	11.7273311	12.0012499	12.264029
PwPD-pre	13	11.6361002	0.47805516	10.7227192	11.4555292	11.7239873	11.9151416	12.387054
	2017							
PwPD-post	13	11.8887099	0.46419415	11.26227	11.582325	11.7987194	12.222414	12.9680595
PwPD-pre	13	11.7622516	0.59478251	10.7802525	11.3663797	11.6732845	12.1137676	12.8909101
	2018/2019							
PwPD-post	13	11.8041358	0.48981582	11.082325	11.5056324	11.8023951	12.0266609	12.708437
PwPD-pre	13	11.9483278	0.50859143	11.2661588	11.5574179	11.7990551	12.3272181	12.8751307

Figure 10

Descriptive statistics for Intensity standard deviation (IntSD)-Healthy Controls

Group	count	mean	std	min	25%	50%	75%	max
	2014/2015							
Healthy controls-post	15	11.96313	0.49076895	10.8729763	11.6919723	12.0390558	12.2918525	12.6506872
Healthy controls-pre	15	12.1117342	0.52404123	11.2358923	11.7802791	12.0187836	12.4495187	13.0171556
	2016							
Healthy controls-post	6	11.9903882	0.61565942	11.2469778	11.5139518	12.1299792	12.2252646	12.8697573
Healthy controls-pre	6	11.5241675	0.52343466	10.6658783	11.3021973	11.6235406	11.8204577	12.150866
	2017							
Healthy controls-post	6	12.3628756	0.30268637	12.0521097	12.1517832	12.2914567	12.5034876	12.8628407
Healthy controls-pre	6	12.5250638	0.6719002	11.6762791	12.1364028	12.482523	12.8148258	13.5624352
	2018/2019							
Healthy controls-post	11	12.3304036	0.69459792	11.3960943	11.844284	12.179677	12.6342135	13.8073997
Healthy controls-pre	11	12.1410076	0.82072152	10.6805058	11.7845268	11.9587657	12.3315373	13.585371

Figure 11

A. The Standard Deviation of Fundamental Frequency

The standard deviation of fundamental frequency values measured over time, from 2014 to 2019 is presented.

Figure 12 compares F0SD over four-time points for PwPD and healthy controls, both pre-dance and post-dance sessions.

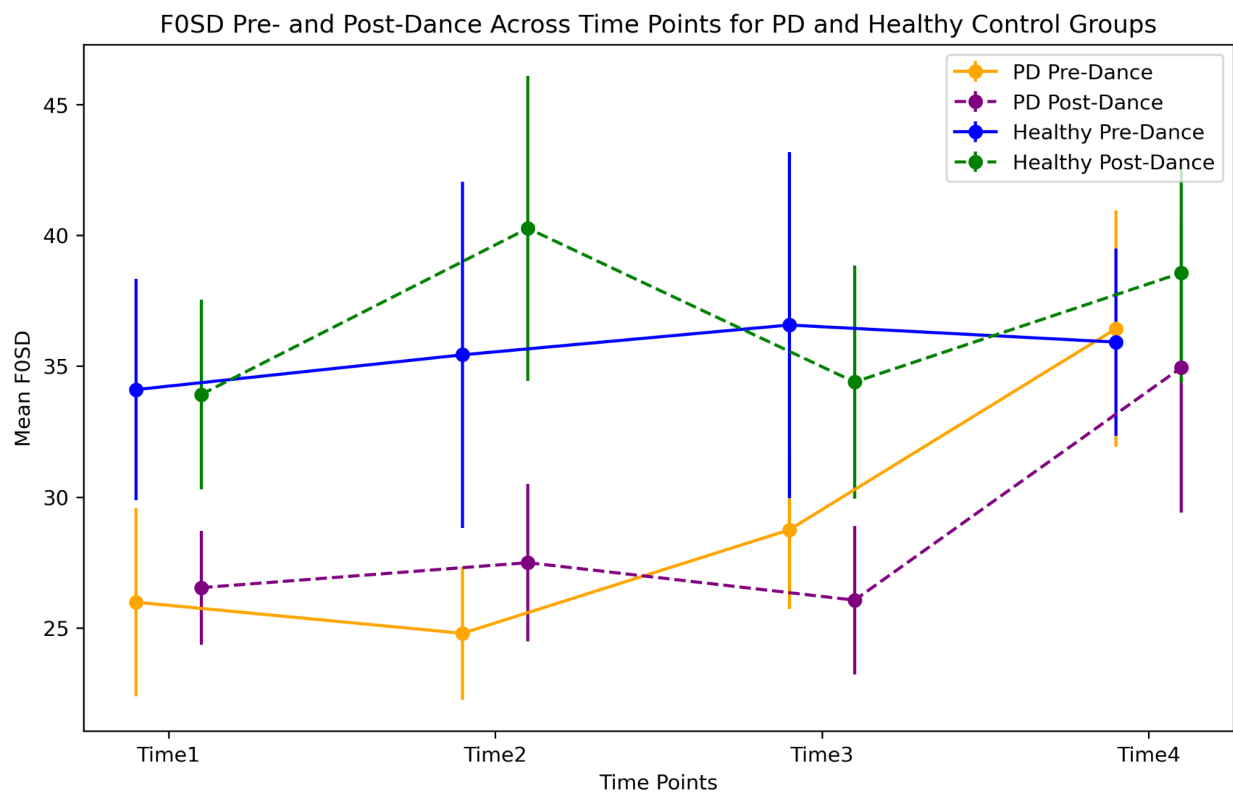


Figure 12

B. The Standard Deviation of Intensity

The standard deviation of intensity values measured over time, from 2014 to 2019 is presented.

Figure 13 compares IntSD over four-time points for PwPD and healthy controls, both pre-dance and post-dance sessions.

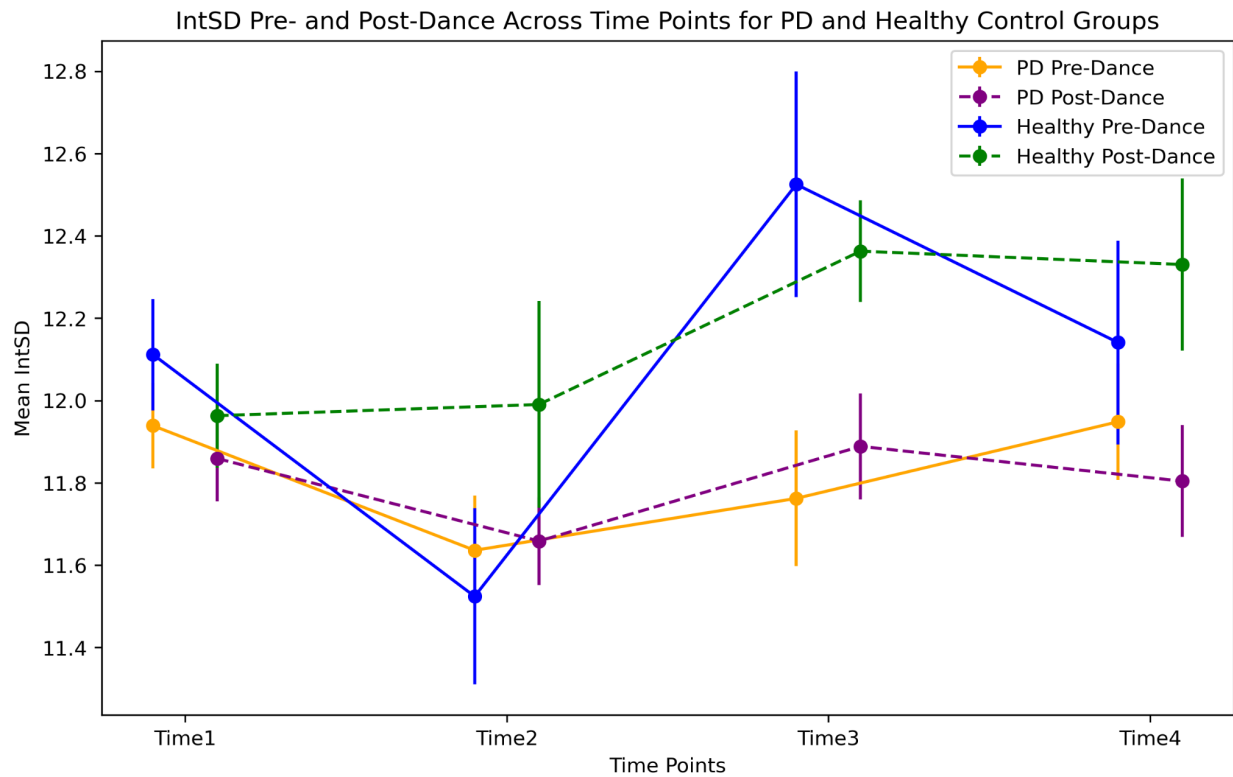
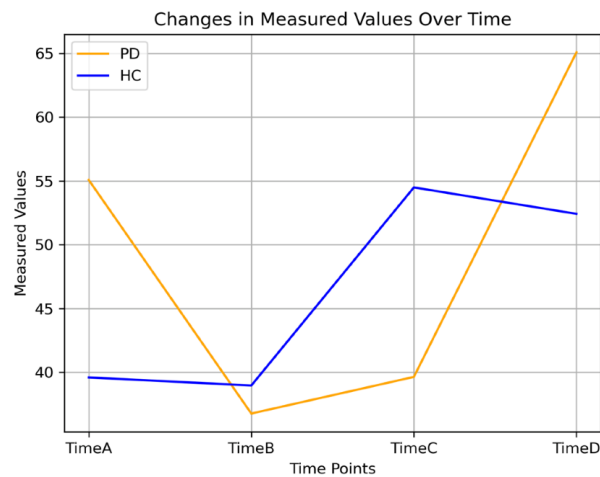


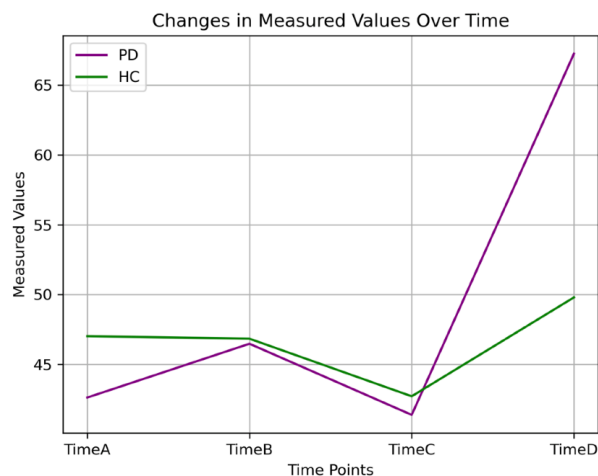
Figure 13

Changes in voice features over the four-time points for individual subjects, one with PD and one healthy control, are illustrated in **Figures 14** through **17**.

Fundamental frequency standard deviation comparison
between one Subject with Parkinson and one Healthy control
from before and after the dance session



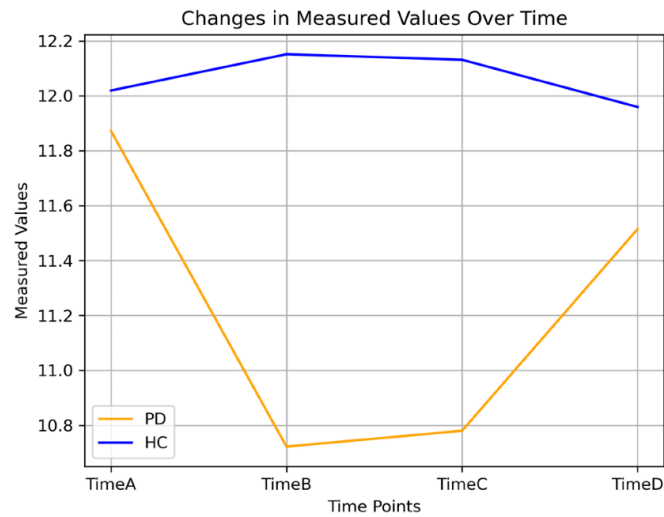
Before the dance session



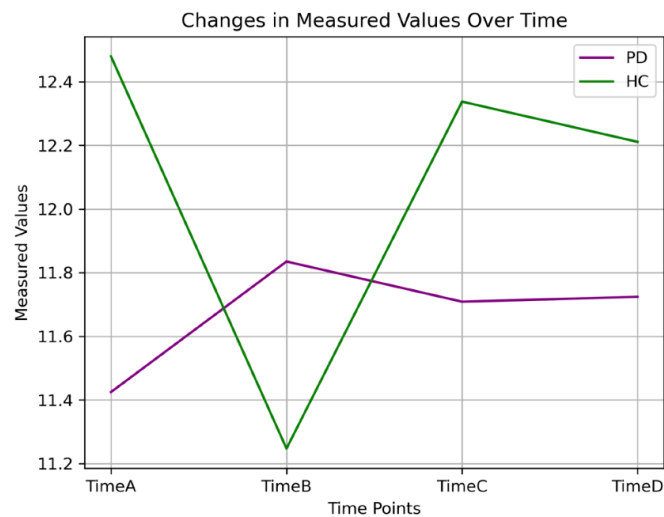
After the dance session

Figure 14

Intensity standard deviation comparison between one Subject with Parkinson and one Healthy control from before and after the dance session



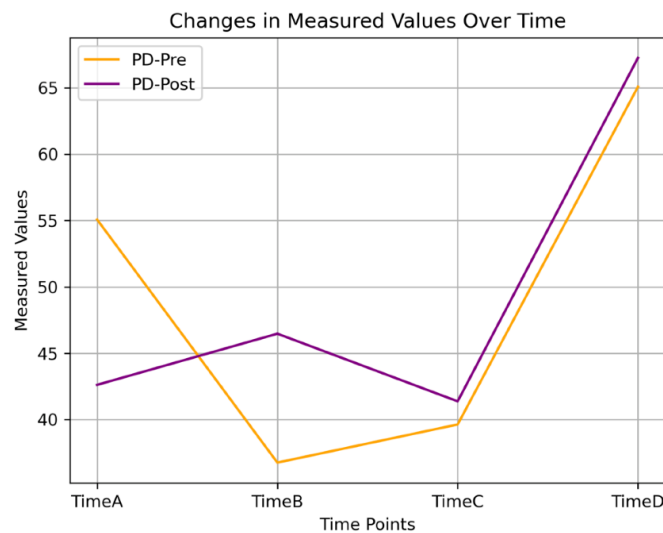
Before the dance session



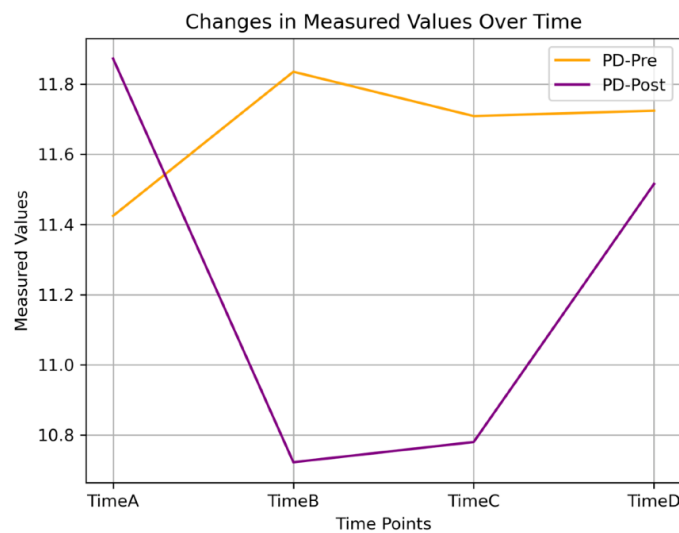
After the dance session

Figure 15

Fundamental frequency standard deviation and Intensity standard deviation for one subject with Parkinson from **before** and **after** the dance session



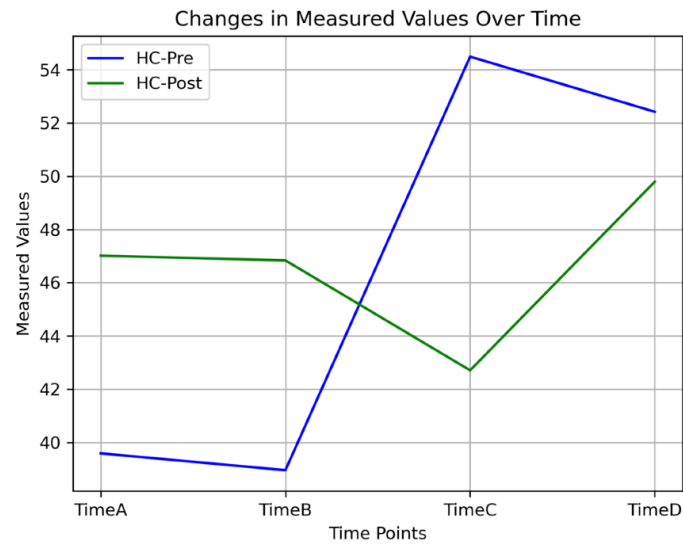
Fundamental frequency standard deviation



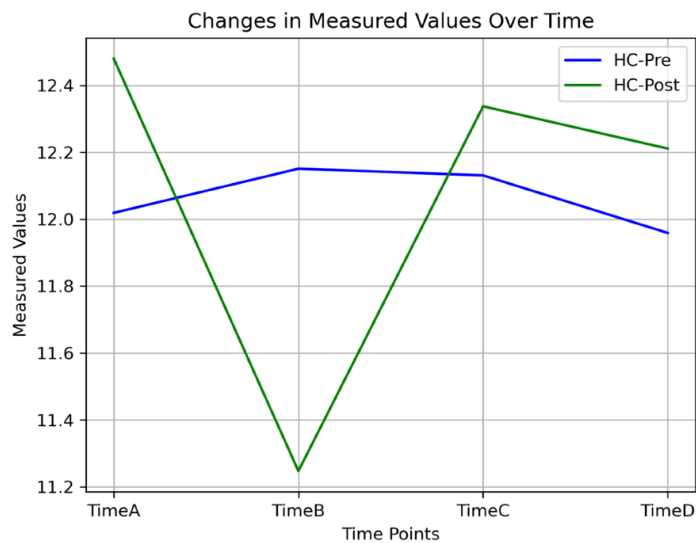
Intensity standard deviation

Figure 16

Fundamental frequency standard deviation and Intensity standard deviation for one Control subject from **before** and **after** the dance session



Fundamental frequency standard deviation



Intensity standard deviation

Figure 17

Table 8 presents the ANOVA results for comparing the standard deviation of fundamental frequency (F0SD) between 2014 (initial) and 2019 (final) in the two groups.

Table 8. ANOVA results for comparing 2014 and 2019 F0SD

ANOVA Table for Error: Subject					
Source	Df	Sum Sq	Mean Sq	F value	Pr(>F)
GroupTime	1	323.0	322.9	1.18	0.289
Residuals	23	6294.0	273.7		
ANOVA Table for Error: Subject: GroupTime					
Source	Df	Sum Sq	Mean Sq	F value	Pr(>F)
GroupTime	2	602.7	301.37	3.906	0.0346*
Residuals	23	1774.4	77.15		

Table 9 demonstrates the Post hoc test (Bonferroni's correction) results of comparing the Fundamental frequency standard deviation between 2014 and 2019 files in the 2 groups.

Table 9. Post hoc (Bonferroni's correction) Results Table for F0SD

Contrast	Estimate	SE	df	t.ratio	p.value
HC_Post - HC_Pre	2.048	5.41	46	0.379	1.0000
HC_Post - PD_Post	1.398	5.30	46	0.264	1.0000
HC_Post - PD_Pre	10.824	5.30	46	2.042	0.2817
HC_Pre - PD_Post	-0.651	5.30	46	-0.123	1.0000
HC_Pre - PD_Pre	8.776	5.30	46	1.655	0.6281
PD_Post - PD_Pre	9.426	5.19	46	1.815	0.4566

Table 10 demonstrates the ANOVA results of comparing the Intensity standard deviation between the 2014 and 2019 files in the 2 groups.

Table 10. ANOVA results for comparing 2014 and 2019 IntSD

ANOVA Table for Error: Subject					
Source	Df	Sum Sq	Mean Sq	F value	Pr(>F)
GroupTime	1	0.979	0.9791	5.904	0.0242*
Residuals	21	3.483	0.1658		
ANOVA Table for Error: Subject:GroupTime					
Source	Df	Sum Sq	Mean Sq	F value	Pr(>F)
GroupTime	2	0.155	0.07752	0.363	0.7
Residuals	21	4.487	0.21364		

Table 11 demonstrates the Post hoc test (Bonferroni's correction) results of comparing the Intensity standard deviation between the 2014 and 2019 files in the 2 groups.

Table 11. Post hoc (Bonferroni's correction) Results Table for IntSD

Contrast	Estimate	SE	df	t.ratio	p.value
HC_Post - HC_Pre	0.1592	0.186	42	0.857	1.0000
HC_Post - PD_Post	0.3460	0.182	42	1.903	0.3833
HC_Post - PD_Pre	0.3972	0.182	42	2.185	0.2073
HC_Pre - PD_Post	0.1869	0.182	42	1.028	1.0000
HC_Pre - PD_Pre	0.2381	0.182	42	1.309	1.0000
PD_Post - PD_Pre	0.0512	0.178	42	0.288	1.0000

The ANOVA results for F0SD (**Table 8**) showed:

- The subject-level analysis revealed no significant main effect of the group over time ($F = 1.18$, $p = 0.289$), suggesting that the overall change in F0SD between 2014 (initial) and 2019 (final) was not significantly different between the PD and healthy control groups.
- However, the interaction analysis indicated a significant effect ($F = 3.906$, $p = 0.0346$), showing that the two groups followed different patterns of change in F0SD between 2014 and 2019.

In the post hoc test (**Table 9**), although no statistically significant differences were found in the pairwise comparisons, these results suggest that both groups exhibited similar variability in fundamental frequency over time. For example, the difference between HC Final (2019) and PD Initial (2014) had an estimate of 10.824 but was not statistically significant ($p = 0.2817$). These results suggest that although the overall pattern of F0SD change over time differs between the two groups, no specific pairwise comparison reached statistical significance, likely due to high variability and the conservative nature of Bonferroni corrections. This high intra-group variability may have masked more subtle differences in vocal features between the PD and healthy control groups. Larger sample sizes in future studies could help to capture these distinctions more effectively.

The ANOVA results for IntSD (**Table 10**) indicated:

- In the **Subject-level analysis**, a significant effect of time was found ($F = 5.904$, $p = 0.0242$), showing that IntSD changed significantly between 2014 (initial) and 2019 (final).

This indicates that the overall intensity standard deviation either increased or decreased between these time points.

- However, the interaction analysis was not significant ($F = 0.363$, $p = 0.7$), suggesting that both the PD and healthy control groups experienced similar changes in IntSD over time.

The post hoc test results (**Table 11**) showed no significant differences between the groups or time points after the Bonferroni correction. For instance, the contrast between HC Final (2019) and PD Initial (2014) had an estimate of 0.3972 but was not statistically significant ($p = 0.2073$). Therefore, although there were significant overall changes in IntSD between 2014 and 2019, these changes were not significantly different between the two groups.

For analyzing the time and group effect on the two features (F0SD and IntSD), a mixed-effect ANOVA test was conducted. Given that different subjects had varying numbers of samples and some had missing data for either pre- or post-dance sessions, the mixed-effect ANOVA is best suited for investigating the impact of dance on voice features in the two groups. The results of the mixed-effect ANOVA for Fundamental Frequency Standard Deviation are summarized in **Tables 12 through 16.**

F0SD Mixed Effect ANOVA Table for Pre and Post-Dance Sessions for PwPD and Healthy Controls

Table 12. Scaled Residuals

Statistic	Value
Min	-3.2883
1Q	-0.5092
Median	-0.0631
3Q	0.4768
Max	3.2413

Table 13. Random Effects

Group	Name	Variance	Std. Dev.
Subject	(Intercept)	111.15	10.543
Residual		65.31	8.082

Table 14. Correlation of Fixed Effects

Factor	(Intercept)	Time	Measure pre	Group PwPD	Time: Measure pre	Time: Group PwPD	Measure pre: Group PwPD
Time	-0.799						
Measure pre	-0.513	0.495					
Group PwPD	-0.738	0.590	0.379				
Time: Measure pre	0.447	-0.550	-0.884	-0.330			
Time: Group PwPD	0.614	-0.768	-0.380	-0.786	0.423		
Measure pre: Group PwPD	0.369	-0.356	-0.719	-0.522	0.636	0.535	
Time: Measure pre: Group PwPD	-0.323	0.398	0.639	0.465	-0.723	-0.590	-0.899

Table 15. Type III Analysis of Variance Table

Factor	Sum Sq	Mean Sq	NumDF	DenDF	F value	Pr(>F)
Time	464.16	464.16	1	175.52	7.1065	0.008397 **
Measure	22.64	22.64	1	124.33	0.3466	0.557116
Group	207.32	207.32	1	128.09	3.1743	0.077177
Time: Measure	7.72	7.72	1	124.02	0.1182	0.731591
Time: Group	37.43	37.43	1	175.52	0.5730	0.450066
Measure: Group	13.51	13.51	1	124.33	0.2069	0.650033
Time:Measure: Group	46.66	46.66	1	124.02	0.7144	0.399601

Table 16. Pairwise contrast: Adjusted for Bonferroni Method

Contrast	Estimate	SE	df	t-ratio	p-value
Time2 post Healthy controls - Time2 pre Healthy controls	1.6247	1.87	123.5	0.870	1.0000
Time2 post Healthy controls - Time2 post PwPD	6.4828	3.34	71.3	1.941	0.3373
Time2 post Healthy controls - Time2 pre PwPD	6.4017	3.34	71.0	1.919	0.3537
Time2 pre Healthy controls - Time2 post PwPD	4.8581	3.33	71.2	1.457	0.8967
Time2 pre Healthy controls - Time2 pre PwPD	4.7770	3.33	70.8	1.435	0.9343
Time2 post PwPD - Time2 pre PwPD	-0.0811	1.55	122.7	-0.052	1.0000

The mixed effect ANOVA for fundamental frequency standard deviation (F0SD) revealed a significant effect of time ($F = 7.1065$, $p = 0.0084$), indicating that the F0SD varied significantly between pre- and post-dance sessions across all participants. These results suggest that the dance sessions had a measurable impact on the variability of fundamental frequency in the speech of both the PD and healthy control groups. However, the lack of a significant interaction between time and group ($p = 0.4501$) indicates that this effect of time was not significantly different between the two groups, implying that both the PD group and healthy controls exhibited similar changes in F0SD over time.

The analysis also showed a marginally significant **main effect of the group** ($F = 3.1743$, $p = 0.0772$), suggesting a trend toward differences in F0SD between the PD and healthy control groups. However, this result did not reach the traditional significance threshold ($p < 0.05$), and thus, no firm conclusions can be drawn about group differences. None of the interaction effects between measure, group, and time were significant, indicating no substantial combined effect of these variables on F0SD.

Pairwise comparisons further support these results, with no significant differences found between pre- and post-dance F0SD for either the healthy control or PD groups. As shown in **Figure 12**, the fundamental frequency variability appears to diverge at later time points, with the PD group showing a more pronounced increase compared to controls. Despite these visible trends, particularly an increase in F0SD for the PD group at Time 4, these changes were not statistically significant, likely due to high variability within the groups. Overall, while time had a significant effect on F0SD, the interaction between time and group did not reveal significant differences, and variability within the groups likely contributed to the non-significant findings for pairwise comparisons.

The results of the mixed-effect ANOVA for Intensity Standard Deviation are summarized in **Tables 17 through 21**.

IntSD Mixed Effect ANOVA Table for Pre and Post-Dance Sessions for PwPD and Healthy Controls

Table 17. Scaled Residuals

Statistic	Value
Min	-2.37964
1Q	-0.54084
Median	0.03201
3Q	0.50156
Max	2.69539

Table 18. Random Effects

Groups	Name	Variance	Std.Dev.
Subject	(Intercept)	0.1300	0.3606
Residual		0.1852	0.4303

Table 19. Correlation of Fixed Effects

Factor	(Intercept)	Time	Measure pre	Group PwPD	Time: Measure pre	Time: Group PwPD	Measure pre: Group PwPD
Time	-0.839						
Measure pre	-0.574	0.531					
GroupPwPD	-0.736	0.617	0.422				
Time: Measure pre	0.505	-0.603	-0.880	-0.372			
Time: Group PwPD	0.635	-0.757	-0.402	-0.834	0.456		
Measure pre: Group PwPD	0.418	-0.386	-0.727	-0.591	0.640	0.562	
Time: Measure pre: Group PwPD	-0.370	0.441	0.644	0.525	-0.732	-0.628	-0.892

Table 20. Type III Analysis of Variance Table

Source	Sum Sq	Mean Sq	NumDF	DenDF	F value	Pr(>F)
Time	0.41400	0.41400	1	172.21	2.2354	0.1367
Measure	0.05151	0.05151	1	114.85	0.2781	0.5989
Group	0.23231	0.23231	1	117.37	1.2544	0.2650
Time: Measure	0.08934	0.08934	1	114.43	0.4824	0.4888
Time: Group	0.03441	0.03441	1	172.21	0.1858	0.6670
Measure: Group	0.04175	0.04175	1	114.85	0.2254	0.6358
Time:Measure: Group	0.11964	0.11964	1	114.43	0.6460	0.4232

Table 21. Pairwise contrast: Adjusted for Bonferroni Method

Contrast	Estimate	SE	df	t-ratio	p-value
Time2 post Healthy controls - Time2 pre Healthy controls	0.0485	0.0988	122.8	0.491	1.0000
Time2 post Healthy controls - Time2 post PwPD	0.3266	0.1360	85.9	2.401	0.1109
Time2 post Healthy controls - Time2 pre PwPD	0.3051	0.1351	84.7	2.259	0.1588
Time2 pre Healthy controls - Time2 post PwPD	0.2780	0.1360	85.9	2.044	0.2638
Time2 pre Healthy controls - Time2 pre PwPD	0.2565	0.1351	84.7	1.899	0.3656
Time2 post PwPD - Time2 pre PwPD	-0.0215	0.0832	124.0	-0.259	1.0000

The mixed effect ANOVA for intensity standard deviation (IntSD) showed no significant main effects or interactions. Specifically, the effect of time ($F = 2.2354$, $p = 0.1367$) was not significant, indicating that the IntSD did not vary significantly between pre- and post-dance sessions across all participants. Similarly, the group effect ($F = 1.2544$, $p = 0.2650$) was not statistically significant, suggesting that there was no clear difference in IntSD between the Parkinson's Disease (PD) group and the healthy controls. Additionally, none of the interactions between time, measure, and group were significant, indicating that the combined effect of these variables on IntSD was minimal.

The pairwise comparisons adjusted for the Bonferroni correction further confirmed the lack of significant differences. No significant differences were found between pre- and post-dance IntSD for either the healthy control or PD groups. Although the plot indicated trends, such as a slight increase in IntSD for the healthy control group at later time points, these changes were not statistically significant, likely due to the large within-group variability, as reflected by the error bars.

Overall, the results suggest that the intensity standard deviation remained stable across pre- and post-dance sessions, with no substantial differences between the PD and healthy control groups. The lack of significant findings may be attributable to the high variability within each group, which could have masked smaller effects.

Summary

In summary, the ANOVA analysis comparing fundamental frequency standard deviation (F0SD) and intensity standard deviation (IntSD) between 2014 (initial) and 2019 (final) revealed distinct patterns for each measure. For F0SD, the interaction between group and time was significant ($F = 3.906$, $p = 0.0346$), indicating that changes in F0SD over time were influenced by group membership (PD vs. healthy controls). However, post hoc comparisons using Bonferroni's correction did not show statistically significant differences between specific time points or groups, likely due to variability within the groups. Additionally, a mixed effect ANOVA revealed a significant effect of time ($F = 7.1065$, $p = 0.0084$) for F0SD, suggesting that dance sessions influenced F0SD variability across all participants, although no significant interaction between time and group was found ($p = 0.4501$). Pairwise comparisons supported these findings, showing no significant differences in F0SD between pre- and post-dance sessions for either group.

For IntSD, the original analysis found a significant main effect of time ($F = 5.904$, $p = 0.0242$), indicating changes in IntSD between 2014 (initial) and 2019 (final), but no significant interaction effects between time and group. The mixed effect ANOVA further supported these findings, showing no significant main effects or interactions for IntSD ($F = 2.2354$, $p = 0.1367$), suggesting that IntSD remained stable across pre- and post-dance sessions for both groups. Pairwise comparisons, adjusted for Bonferroni correction, confirmed the lack of significant differences, with high within-group variability likely contributing to the non-significant results.

Overall, these findings suggest that F0SD is more sensitive to changes over time, particularly in PD patients, while IntSD appears less affected by both time and group factors. Future studies should investigate whether targeted interventions, such as speech therapy or dance programs, could more effectively address these changes in vocal features.

CHAPTER 4

DISCUSSION AND CONCLUSION

Discussion

The analysis of speech features, specifically the fundamental frequency standard deviation (F0SD) and intensity standard deviation (IntSD), reveals significant insights into how Parkinson's disease (PD) affects vocal patterns over time, as well as the potential therapeutic effects of dance on these features.

The results for F0SD showed that while there was no significant difference between the PD and healthy groups at the subject level, the interaction of group and time was significant. This suggests that the pattern of change in F0SD over the five years differed between the PD and healthy control groups. These findings align with existing literature, which suggests that voice features, particularly related to pitch and frequency, are often impacted in PD, with decreased pitch variability being a hallmark symptom of hypokinetic dysarthria (Skodda, 2011). However, the post hoc pairwise comparisons did not reveal significant differences between any specific time points. This could be attributed to the high variability within each group, potentially masking smaller, more nuanced changes.

To further quantify the differences between the groups, Cohen's d was calculated to assess the effect size for F0SD. The overall Cohen's d for F0SD between the PD and healthy control groups was 0.54, suggesting a moderate effect size. This indicates that while there is a noticeable difference in F0SD between the two groups, the effect is moderate, and individual variability within the groups could have masked more significant effects. A moderate effect size suggests that PD does have a measurable impact on pitch variability, even if it was not large enough to reach statistical significance in this sample size. While the moderate effect size is a positive finding, the high variability and relatively small sample size likely limited the study's power to detect significant pairwise differences. Clinically, moderate effect sizes can be important in tracking disease progression or evaluating therapeutic interventions, even in the absence of statistical significance. These findings may still hold relevance for treatment decisions, where moderate changes in vocal features could indicate early intervention points.

For the IntSD, the results were more straightforward. The ANOVA indicated a significant effect of time but no significant interaction between time and group. This indicates that both PD and healthy participants experienced changes in vocal intensity over the study period, with no significant differences between the groups. This could be explained by the normal aging process, which is associated with decreased vocal intensity and other voice changes in healthy individuals. As individuals age, changes in respiratory and laryngeal function can contribute to reduced vocal intensity, making it difficult to distinguish these changes from those caused by PD. Similar to the F0SD results, post hoc analyses did not show any significant pairwise differences between the time points, reinforcing the idea that individual variability was likely a contributing factor.

The effect size for IntSD was also calculated using Cohen's d . The overall Cohen's d for IntSD between the PD and healthy control groups was 0.57, also suggesting a moderate effect size. This implies that there is a moderate difference in vocal intensity variability between the PD and control groups. However, similar to the FOSD results, the moderate effect size indicates that while the groups differ, the variability within each group may have reduced the ability to detect statistically significant differences. The effect of aging on vocal intensity likely contributed to the lack of significant group differences, as both PD and control subjects experienced similar reductions in intensity over time. While the moderate effect sizes are a promising indication of the impact of PD on these vocal features, future studies with larger sample sizes or more intensive interventions may be needed to detect more pronounced effects.

Given that this study was observational and exploratory in nature, serving as a pilot investigation into the effects of dance on vocal features in PwPD, selecting appropriate statistical models was crucial. This study employed ANOVA and mixed-effect ANOVA models to explore changes in FOSD and IntSD over time, and more advanced models, such as Linear Mixed-Effects Models (LMMs) and LISREL, were not implemented due to specific methodological considerations.

LMMs are particularly well-suited for analyzing longitudinal data with repeated measures, especially when there is substantial missing data, which was a notable limitation in this study. Despite this, ANOVA models were selected because of their simplicity and interpretability, aligning with the exploratory nature of the research. Implementing LMMs would have increased the complexity of the analysis, requiring more advanced statistical assumptions and a larger sample size, which was not feasible for this pilot study.

LISREL, a structural equation modeling tool, could have been used if the study aimed to model latent constructs related to voice performance. However, this was not applicable, as the focus was on directly measured acoustic features without an underlying theoretical framework involving latent variables. Given the limited existing research on the impact of dance on vocal features in PD, ANOVA and mixed-effect ANOVA were deemed appropriate for this preliminary investigation. Future studies may benefit from more complex statistical models as the field evolves.

When considering the potential effects of dance on these voice features, the lack of significant post-dance improvements in either F0SD or IntSD for the PD group contrasts with previous studies suggesting that dance can promote neuroplasticity and improve motor symptoms (Bearss & DeSouza, 2021). While the dance intervention may have provided some benefits, these effects may have been too subtle to detect with the speech parameters measured or the duration of the intervention. Furthermore, the variability within the PD group and the observational nature of the study may have limited the ability to detect more subtle improvements in vocal features. Future studies with longer intervention periods and additional speech parameters are needed to fully understand the impact of dance on speech in PD.

Alternatively, the effects of dance on speech may require a longer duration or more intensive interventions to become apparent. Given the significant role that speech impairment plays in the quality of life for individuals with PD, these findings highlight the need for further research into non-pharmacological interventions that could help preserve or improve communication abilities in this population.

Conclusion

This study aimed to investigate the effects of Parkinson's disease and a dance intervention on two critical voice features: F0SD and IntSD. The results indicate that PD influences these features, as evidenced by the significant interaction between group and time for F0SD.

Additionally, the calculation of Cohen's d revealed moderate effect sizes for both F0SD (0.54) and IntSD (0.57), suggesting that while there are noticeable differences between the PD and healthy control groups, the individual variability within each group likely limited the ability to detect statistically significant differences. These moderate effect sizes are clinically meaningful, indicating that even moderate changes in speech features could be important for tracking PD progression or developing interventions.

The changes observed did not differ significantly between the PD and healthy control groups in terms of intensity standard deviation, indicating that voice intensity may be similarly affected by aging in both groups. However, the moderate effect size for IntSD suggests that vocal intensity may still be impacted by PD. The absence of significant post-dance improvements could also suggest that the dance intervention was either not long enough or not specifically targeted to address speech-related symptoms. Extending the duration of interventions or incorporating additional therapeutic approaches may yield more observable changes in vocal intensity.

Although no significant post-dance improvements were observed in either group, this study contributes to the growing body of literature on the use of speech features as biomarkers for PD and how interventions like dance may influence these features over time. Future research should focus on larger sample sizes, longer intervention periods, and the inclusion of additional speech parameters such as articulation rate, speech rhythm, and voice tremor to capture a

more comprehensive picture of voice changes in individuals with PD. Incorporating neuroimaging techniques alongside speech analysis may also help uncover the neural mechanisms underlying these changes.

These findings underscore the critical need for early detection and intervention for voice impairments in PD. Given that speech features like F0SD and IntSD are often affected early in the disease, they represent valuable biomarkers for both diagnosis and tracking therapeutic outcomes. Early interventions, particularly non-pharmacological ones like dance or speech therapy, may help mitigate the progression of speech impairments and improve the quality of life for individuals with PD. The moderate effect sizes observed in this study provide a foundation for future research aimed at refining and expanding the use of voice features in clinical practice, particularly for early diagnosis and intervention in PD. Future studies should consider pairing dance interventions with targeted speech therapy or vocal exercises to determine if combined therapeutic approaches can better address the speech impairments observed in PD.

LIMITATIONS AND FUTURE WORK

Limitations

While this study provides valuable insights into the effects of Parkinson's disease (PD) and dance on vocal features, several limitations must be acknowledged.

First, the study is exploratory in nature and observational, conducted in a community dance class. It was not a randomized controlled trial, and as such, corrections for multiple comparisons were not applied. The lack of randomization may introduce confounding variables and limit the generalizability of the findings. Factors such as disease progression, changes in medication, and variability in individual responses may have influenced the outcomes independently of the intervention. Future studies should consider applying multiple comparison corrections where appropriate to reduce the risk of Type I errors, especially in observational studies where variability is high. Additionally, factors like medication changes or cognitive declines over time may have introduced variability, limiting the ability to isolate the effects of the intervention on speech.

Second, the sample size may have limited the statistical power of the analyses. With 29 participants in each group, the study may not have had sufficient power to detect smaller but

meaningful differences between the PD and healthy control groups or subtle effects of the dance intervention on speech features.

Increasing the amount of data in future studies could significantly enhance the reliability and generalizability of findings on the effects of dance on vocal features in individuals with Parkinson's Disease (PD). In this study, a total of 266 audio files from 29 individuals with PD and 29 healthy controls were analyzed, with recordings spanning five years. Despite the longitudinal nature of the dataset, several factors limited its overall size, including participant drop-out, missing data due to technical issues, and incomplete post-dance recordings.

A. Enhancing Statistical Power:

A larger dataset would increase statistical power, allowing for the detection of smaller, more subtle effects that may have been masked due to high within-group variability observed in measures like F0SD and IntSD. Given the moderate effect sizes (Cohen's d : 0.54 for F0SD, 0.57 for IntSD), a larger sample would increase confidence in detecting meaningful changes with greater precision.

B. Reducing Bias from Missing Data:

The inclusion of more data could mitigate the impact of missing data points caused by participant drop-out or incomplete post-dance sessions. Advanced statistical models, such as Linear Mixed-Effects Models (LMMs) or Generalized Estimating Equations (GEEs), could be more effectively applied if a larger dataset were available, allowing for better handling of missing records while preserving the integrity of longitudinal analyses.

C. Capturing Disease Progression:

A more extensive dataset would enable better tracking of **disease progression** by capturing more frequent speech assessments over time. This could provide insights into whether speech features like F0SD and IntSD change gradually or exhibit sudden shifts in response to the progression of PD or the intensity of dance interventions.

D. Improving Generalizability:

Including data from a more diverse participant pool with different PD severity levels, ages, and genders would improve the external validity and generalizability of the findings. This would allow future research to explore how factors such as disease stage or baseline vocal characteristics affect treatment outcomes.

E. Exploring Additional Speech Features:

With a larger dataset, future analyses could expand beyond F0SD and IntSD to include other critical speech features such as articulation rate, phonation time, speech rhythm, and voice tremor. This would provide a more comprehensive understanding of how PD affects speech production and how interventions like dance may mitigate these effects.

F. Incorporating Advanced Analyses:

A more extensive dataset would support applying machine learning algorithms for automated classification tasks, enabling prediction models for disease severity or progression. Additionally, incorporating neuroimaging data alongside

speech features could reveal how dance-induced neural changes influence vocal outcomes in PD.

Third, the variability within groups was substantial, particularly in both the fundamental frequency and intensity standard deviations. This intra-group variability likely reduced the ability to detect significant effects in the post hoc analyses, as the wide range of speech characteristics in both the PD and healthy control groups may have masked more subtle group differences. The moderate effect sizes suggest that while there is a measurable impact of PD on speech features, this variability limited the study's ability to detect stronger statistical differences.

Fourth, the duration and intensity of the dance intervention may not have been sufficient to elicit detectable improvements in speech features. While dance has been shown to have therapeutic benefits for motor symptoms in PD, the effects on speech may require a longer or more intensive intervention to become evident. Additionally, the lack of significant post-dance improvements could indicate that the dance sessions used in this study were not optimized to target speech-related symptoms.

Fifth, A key limitation of this study is the lack of matching participants based on age, sex, or disease severity levels within the Parkinson's Disease (PD) group. Although efforts were made to include similar numbers of male and female participants, the groups were not fully matched for demographic variables such as age or disease progression. This could have introduced confounding variables that influenced the results.

Additionally, the analysis did not account for the stages of Parkinson's Disease, which likely varied among participants due to the community-based nature of the study. The lack of clinical

staging data, such as the Hoehn and Yahr scale or Unified Parkinson's Disease Rating Scale (UPDRS) scores, limited the ability to assess whether differences in speech features were related to disease severity or progression. Including this information could have strengthened the analysis by enabling subgroup comparisons based on disease stage or severity, offering more precise insights into how speech features evolve in PD.

Sixth, speech data collection and measures were limited to specific parameters (F0SD and IntSD). While these features are known to be affected in PD, they may not fully capture the complexity of speech impairments in the disease. Other features, such as articulation rate, speech rhythm, or voice tremor, could provide a more comprehensive picture of how PD affects communication. Additionally, the study relied on pre- and post-dance measurements, which may not fully capture the day-to-day variability in speech production for PD patients.

Finally, the longitudinal nature of the study presents challenges, as some participants may have experienced disease progression or changes in medication that could have influenced their speech patterns independently of the dance intervention. Without accounting for changes in disease severity or treatment over time, it is difficult to isolate the specific effects of the intervention on speech.

Future Directions

Future research on vocal changes in PwPD could benefit from the application of more complex statistical and machine learning models, incorporating non-linear effects and additional covariates. While this study used linear ANOVA models to evaluate the effects of dance intervention on F0SD and IntSD, several promising directions could further enhance understanding of vocal changes over time.

1. Modeling Non-linear Effects:

Given that disease progression in PD often follows a non-linear trajectory, future studies could explore statistical models that capture these complex dynamics. Generalized Additive Models (GAMs) or non-linear mixed-effects models (NLMMs) could account for potential non-linear changes in vocal features due to disease progression, dance intervention intensity, or participant-specific factors. These models could also detect threshold effects where improvements in vocal features occur only after reaching a specific intervention intensity or time point.

2. Incorporating Additional Covariates:

Future models could include relevant covariates such as:

- A. Demographic Variables: Age, gender, and years since PD diagnosis.
- B. Clinical Data: Hoehn and Yahr stages, medication regimens, or UPDRS scores.
- C. Intervention-Related Data: Frequency and intensity of dance participation, session attendance, and engagement level.

Including these covariates in models such as Hierarchical Bayesian Models or Multivariate, Mixed-Effects Models could help identify individual-level responses and refine predictive models for vocal feature changes.

3. Machine Learning and Deep Learning Models:

The development of machine learning models, including Random Forests, Support Vector Machines (SVMs), or Recurrent Neural Networks (RNNs), could allow for more precise prediction of disease progression from longitudinal speech data. Long Short-Term Memory (LSTM) networks could model time-dependent changes by leveraging sequential audio features.

4. Multimodal Integration:

Combining speech features with neuroimaging data (e.g., fMRI, EEG) could enable a deeper understanding of the relationship between brain activity and vocal function. Advanced models could integrate data from multiple sources through multimodal deep learning frameworks, offering a holistic view of the effects of PD on speech production.

5. Time-Series and Survival Analysis:

Given the longitudinal structure of the dataset, time-series models like autoregressive integrated moving averages (ARIMA) or survival models could predict the likelihood of significant vocal changes over time or identify the critical points when such changes become statistically detectable.

BIBLIOGRAPHY

- Abdul, Z. K. & A. K. Al-Talabani, A. K. (2022). Mel Frequency Cepstral Coefficient and its Applications: A Review. *IEEE Access*, 10, 122136–122158.
<https://doi.org/10.1109/ACCESS.2022.3223444>
- Abdurrahman, G., & Sintawati, M. (2020). Implementation of xgboost for classification of parkinson's disease. *Journal of Physics: Conference Series*, 1538(1), 012024.
<https://doi.org/10.1088/1742-6596/1538/1/012024>
- Alvargonzález, D. (2011). Multidisciplinarity, Interdisciplinarity, Transdisciplinarity, and the Sciences. *International Studies in the Philosophy of Science*, 25(4), 387–403.
<https://doi.org/10.1080/02698595.2011.623366>
- Arora, S., Visanji, N. P., Mestre, T. A., Tsanas, A., AlDakheel, A., Connolly, B. S., Gasca-Salas, C., Kern, D. S., Jain, J., & Slow, E. J. (2018). Investigating voice as a biomarker for leucine-rich repeat kinase 2-associated Parkinson's disease. *Journal of Parkinson's Disease*, 8(4), 503–510.
- Azadi, H., Akbarzadeh-T, M.-R., Shoeibi, A., & Kobrafi, H. R. (2021). Evaluating the effect of Parkinson's disease on jitter and shimmer speech features. *Advanced Biomedical Research*, 10(1), 54.
- Bar, R. J., & DeSouza, J. F. X. (2016). Tracking Plasticity: Effects of Long-Term Rehearsal in Expert Dancers Encoding Music to Movement. *PLOS ONE*, 11(1), e0147731.
<https://doi.org/10.1371/journal.pone.0147731>
- Barnstaple, R. E., Bearss, K., Bar, R. J., & Joseph F DeSouza, J. F. X. (2022). Weekly dance training

- over eight months reduces depression and correlates with fMRI brain signals in subcallosal cingulate gyrus (SCG) for people with Parkinson's Disease: An observational study. *bioRxiv*, 2022.10.14.512180. <https://doi.org/10.1101/2022.10.14.512180>
- Bearss, K. A., & DeSouza, J. F. X. (2021). Parkinson's Disease Motor Symptom Progression Slowed with Multisensory Dance Learning over 3-Years: A Preliminary Longitudinal Investigation. *Brain Sciences*, 11(7). <https://doi.org/10.3390/brainsci11070895>
- Bearss, K. A., McDonald, K. C., Bar, R. J., & DeSouza, J. F. (2017). Improvements in balance and gait speed after a 12 week dance intervention for Parkinson's disease. *Advances in Integrative Medicine*, 4(1), 10–13.
- Benba, A., Jilbab, A., & Hammouch, A. (2016). Analysis of multiple types of voice recordings in cepstral domain using MFCC for discriminating between patients with Parkinson's disease and healthy people. *International Journal of Speech Technology*, 19, 449–456.
- Benba, A., Jilbab, A., Hammouch, A., & Sandabad, S. (2015). Voiceprints analysis using MFCC and SVM for detecting patients with Parkinson's disease. *2015 International Conference on Electrical and Information Technologies (ICEIT)*, 300–304. <https://doi.org/10.1109/EITech.2015.7163000>
- Boersma, P. (2011). Praat: Doing phonetics by computer [Computer program]. [Http://Www.Praat.Org/](http://www.Praat.Org/).
- Celik, E. & Omurca, S.I. (2019). Improving Parkinson's Disease Diagnosis with Machine Learning Methods. *2019 Scientific Meeting on Electrical-Electronics & Biomedical Engineering and Computer Science (EBBT)*, 1–4. <https://doi.org/10.1109/EBBT.2019.8742057>
- Dashtipour, K., Tafreshi, A., Lee, J., & Crawley, B. (2018). Speech disorders in Parkinson's disease:

- Pathophysiology, medical management and surgical approaches. *Neurodegenerative Disease Management*, 8(5), 337–348. <https://doi.org/10.2217/nmt-2018-0021>
- Dauer, W., & Przedborski, S. (2003). Parkinson's Disease: Mechanisms and Models. *Neuron*, 39(6), 889–909. [https://doi.org/10.1016/S0896-6273\(03\)00568-3](https://doi.org/10.1016/S0896-6273(03)00568-3)
- El Naqa, I., & Murphy, M. J. (2015). What Is Machine Learning? In I. El Naqa, R. Li, & M. J. Murphy (Eds.), *Machine Learning in Radiation Oncology: Theory and Applications* (pp. 3–11). Springer International Publishing. https://doi.org/10.1007/978-3-319-18305-3_1
- Feinberg, D. (2022). *Parselmouth Praat Scripts in Python*. <https://doi.org/10.17605/OSF.IO/6DWR3>
- Fradkov, A. L. (2020). Early History of Machine Learning. *21st IFAC World Congress*, 53(2), 1385–1390. <https://doi.org/10.1016/j.ifacol.2020.12.1888>
- Galaz, Z., Mekyska, J., Zvoncak, V., Mucha, J., Kiska, T., Smekal, Z., Eliasova, I., Mrackova, M., Kostalova, M., & Rektorova, I. (2018). Changes in phonation and their relations with progress of Parkinson's disease. *Applied Sciences*, 8(12), 2339.
- Gaskin, J., Gomes, J., Darshan, S., & Krewski, D. (2017). Burden of neurological conditions in Canada. *NeuroToxicology*, 61, 2–10. <https://doi.org/10.1016/j.neuro.2016.05.001>
- Giannakopoulou, K.-M., Roussaki, I., & Demestichas, K. (2022). Internet of Things Technologies and Machine Learning Methods for Parkinson's Disease Diagnosis, Monitoring and Management: A Systematic Review. *Sensors*, 22(5). <https://doi.org/10.3390/s22051799>
- Gillivan-Murphy, P., Miller, N., & Carding, P. (2019). Voice Tremor in Parkinson's Disease: An Acoustic Study. *Journal of Voice*, 33(4), 526–535. <https://doi.org/10.1016/j.jvoice.2017.12.010>

- Goetz, C. G., Tilley, B. C., Shaftman, S. R., Stebbins, G. T., Fahn, S., Martinez-Martin, P., Poewe, W., Sampaio, C., Stern, M. B., Dodel, R., Dubois, B., Holloway, R., Jankovic, J., Kulisevsky, J., Lang, A. E., Lees, A., Leurgans, S., LeWitt, P. A., Nyenhuis, D., ... LaPelle, N. (2008). Movement Disorder Society-sponsored revision of the Unified Parkinson's Disease Rating Scale (MDS-UPDRS): Scale presentation and clinimetric testing results. *Movement Disorders*, 23(15), 2129–2170. <https://doi.org/10.1002/mds.22340>
- Grabski, K., Lamalle, L., Vilain, C., Schwartz, J.-L., Vallée, N., Tropres, I., Baciú, M., Le Bas, J.-F., & Sato, M. (2012). Functional MRI assessment of orofacial articulators: Neural correlates of lip, jaw, larynx, and tongue movements. *Human Brain Mapping*, 33(10), 2306–2321. <https://doi.org/10.1002/hbm.21363>
- Harel, B., Cannizzaro, M., & Snyder, P. J. (2004). Variability in fundamental frequency during speech in prodromal and incipient Parkinson's disease: A longitudinal case study. *Brain and Cognition*, 56(1), 24–29.
- Hermansky, H., Hanson, B., & Wakita, H.. (1985). Perceptually based linear predictive analysis of speech. *ICASSP '85. IEEE International Conference on Acoustics, Speech, and Signal Processing*, 10, 509–512. <https://doi.org/10.1109/ICASSP.1985.1168384>
- Hackney, M. E., & Earhart, G. M. (2009). Health-related quality of life and alternative forms of exercise in Parkinson disease. *Parkinsonism & Related Disorders*, 15(9), 644–648.
- Heiberger, L., Maurer, C., Amtage, F., Mendez-Balbuena, I., Schulte-Mönting, J., Hepp-Reymond, M.-C., & Kristeva, R. (2011). Impact of a weekly dance class on the functional mobility and on the quality of life of individuals with Parkinson's disease. *Frontiers in Aging Neuroscience*, 3, 14.

- Holmes, R. J., M. Oates, J. J. Phyland, D., & J. Hughes, A. (2000). Voice characteristics in the progression of Parkinson's disease. *International Journal of Language & Communication Disorders*, 35(3), 407–418. <https://doi.org/10.1080/136828200410654>
- Jadoul, Y., Thompson, B., & de Boer, B. (2018). Introducing Parselmouth: A Python interface to Praat. *Journal of Phonetics*, 71, 1–15. <https://doi.org/10.1016/j.wocn.2018.07.001>
- Jankovic, J. (2008). Parkinson's disease: Clinical features and diagnosis. *Journal of Neurology, Neurosurgery & Psychiatry*, 79(4), 368. <https://doi.org/10.1136/jnnp.2007.131045>
- Jiang, J. J., & Zhang, Y. (2002). Nonlinear dynamic analysis of speech from pathological subjects. *Electronics Letters*, 38(6), 1–2.
- Jiménez-Jiménez, F. J., Gamboa, J., Nieto, A., Guerrero, J., Orti-Pareja, M., Molina, J. A., García-Albea, E., & Cobeta, I. (1997). Acoustic voice analysis in untreated patients with Parkinson's disease. *Parkinsonism & Related Disorders*, 3(2), 111–116. [https://doi.org/10.1016/S1353-8020\(97\)00007-2](https://doi.org/10.1016/S1353-8020(97)00007-2)
- KILIÇ, M., Oguz, H., & şafak, M. A. (2011). Comparison of results in two acoustic analysis programs: Praat and MDVP. *Turkish Journal of Medical Sciences*, 41, 835–841. <https://doi.org/10.3906/sag-0909-290>
- Kitajima, K., & Fujita, F. (1990). Estimation of Subglottal Pressure with Intraoral Pressure. *Acta Oto-Laryngologica*, 109(5–6), 473–478. <https://doi.org/10.3109/00016489009125172>
- Knight, R.-A., & Setter, J. (Eds.). (2021). *The Cambridge Handbook of Phonetics*. Cambridge University Press; Cambridge Core. <https://doi.org/10.1017/9781108644198>
- Kononenko, I. (2001). Machine learning for medical diagnosis: History, state of the art and perspective. *Artificial Intelligence in Medicine*, 23(1), 89–109.

[https://doi.org/10.1016/S0933-3657\(01\)00077-X](https://doi.org/10.1016/S0933-3657(01)00077-X)

Kowalska-Taczanowska, R., Friedman, A., & Kozirowski, D. (2020). Parkinson's disease or atypical parkinsonism? The importance of acoustic voice analysis in differential diagnosis of speech disorders. *Brain and Behavior*, 10(8), e01700.

<https://doi.org/10.1002/brb3.1700>

Lees, A. J., Hardy, J., & Revesz, T. (2009). Parkinson's disease. *The Lancet*, 373(9680), 2055–2066.

[https://doi.org/10.1016/S0140-6736\(09\)60492-X](https://doi.org/10.1016/S0140-6736(09)60492-X)

Asgari, M. & Shafran, I.. (2010). Predicting severity of Parkinson's disease from speech. 2010 *Annual International Conference of the IEEE Engineering in Medicine and Biology*, 5201–5204. <https://doi.org/10.1109/IEMBS.2010.5626104>

Ma, A., Lau, K. K., & Thyagarajan, D. (2020). Voice changes in Parkinson's disease: What are they telling us? *Journal of Clinical Neuroscience*, 72, 1–7.

<https://doi.org/10.1016/j.jocn.2019.12.029>

Mahesh, B. (2020). Machine learning algorithms-a review. *International Journal of Science and Research (IJSR).[Internet]*, 9(1), 381–386.

Malek, N. (2019). Deep Brain Stimulation in Parkinson's Disease. *Neurology India*, 67(4).

https://journals.lww.com/neur/fulltext/2019/67040/deep_brain_stimulation_in_parkinson_s_disease.4.aspx

Maslan, J., Leng, X., Rees, C., Blalock, D., & Butler, S. G. (2011). Maximum Phonation Time in Healthy Older Adults. *Journal of Voice*, 25(6), 709–713.

<https://doi.org/10.1016/j.jvoice.2010.10.002>

Mathew, M. M., & Bhat, J. S. (2009). Soft phonation index—A sensitive parameter? *Indian*

- Journal of Otolaryngology and Head & Neck Surgery*, 61(2), 127–130.
- <https://doi.org/10.1007/s12070-009-0050-4>
- McFee, B., Raffel, C., Liang, D., Ellis, D. P., McVicar, M., Battenberg, E., & Nieto, O. (2015). *librosa: Audio and music signal analysis in python*. 18–24.
- Michaelis, D., Gramß, T., & Strube, H. W. (1997). Glottal-to-Noise Excitation Ratio—A New Measure for Describing Pathological Voices. *Acustica*, 83, 700–706.
- Moro-Velazquez, L., Gomez-Garcia, J. A., Arias-Londoño, J. D., Dehak, N., & Godino-Llorente, J. I. (2021). Advances in Parkinson’s Disease detection and assessment using voice and speech: A review of the articulatory and phonatory aspects. *Biomedical Signal Processing and Control*, 66, 102418. <https://doi.org/10.1016/j.bspc.2021.102418>
- Moro-Velázquez, L., Gómez-García, J. A., Dehak, N., & Godino-Llorente, J. I. (2019). Analysis of phonatory features for the automatic detection of Parkinson’s disease in two different corpora. *Models and Analysis of Vocal Emissions for Biomedical Applications (MAVEBA)*, 33.
- Nagel, T. (1989). *The view from nowhere*. oxford university press.
- Naranjo, L., Perez, C. J., Campos-Roca, Y., & Martin, J. (2016). Addressing voice recording replications for Parkinson’s disease detection. *Expert Systems with Applications*, 46, 286–292.
- Nasteski, V. (2017). An overview of the supervised machine learning methods. *Horizons. b*, 4, 51–62.
- O’Shaughnessy, D. (1988). Linear predictive coding. *IEEE Potentials*, 7(1), 29–32.
- <https://doi.org/10.1109/45.1890>

- Orozco-Arroyave, J. R., Hönig, F., Arias-Londoño, J., Vargas-Bonilla, J., Daqrouq, K., Skodda, S., Rusz, J., & Nöth, E. (2016). Automatic detection of Parkinson's disease in running speech spoken in three different languages. *The Journal of the Acoustical Society of America*, 139(1), 481–500.
- Ongsulee, P.. (2017). Artificial intelligence, machine learning and deep learning. *2017 15th International Conference on ICT and Knowledge Engineering (ICT&KE)*, 1–6.
<https://doi.org/10.1109/ICTKE.2017.8259629>
- Pappas, G. S. (1979). *Justification and Knowledge: New Studies in Epistemology* (Vol. 17). Springer Science & Business Media.
- Pauwels, E. K. J., & Boer, G. J. (2023). PARKINSON'S DISEASE; A TALE OF MANY PLAYERS. *Medical Principles and Practice : International Journal of the Kuwait University, Health Science Centre*. <https://api.semanticscholar.org/CorpusID:259110363>
- Poewe, W., Seppi, K., Tanner, C. M., Halliday, G. M., Brundin, P., Volkman, J., Schrag, A.-E., & Lang, A. E. (2017). Parkinson disease. *Nature Reviews Disease Primers*, 3(1), 17013.
<https://doi.org/10.1038/nrdp.2017.13>
- Prashanth, R., Roy, S. D., Mandal, P. K., & Ghosh, S. (2014). *Parkinson's disease detection using olfactory loss and REM sleep disorder features*. 5764–5767.
- Quan, C., K. Ren, & Z. Luo. (2021). A Deep Learning Based Method for Parkinson's Disease Detection Using Dynamic Features of Speech. *IEEE Access*, 9, 10239–10252.
<https://doi.org/10.1109/ACCESS.2021.3051432>
- Rahn, D. A., Chou, M., Jiang, J. J., & Zhang, Y. (2007). Phonatory Impairment in Parkinson's Disease: Evidence from Nonlinear Dynamic Analysis and Perturbation Analysis. *Journal of*

- Voice*, 21(1), 64–71. <https://doi.org/10.1016/j.jvoice.2005.08.011>
- Rayan, Z., Alfonse, M., & Salem, A.-B. M. (2019). Machine learning approaches in smart health. *Procedia Computer Science*, 154, 361–368.
- Revilla, F. J., & Shukla, A. (2014). *Understanding Postural Response of Parkinson's Subjects Using Nonlinear Dynamics and Support Vector*.
<https://api.semanticscholar.org/CorpusID:111010395>
- Rosenblatt, F. (2021). *The Perceptron: A Probabilistic Model for Information Storage and Organization (1958)*.
- Rustempasic, I., & Can, M. (2013). Diagnosis of Parkinson's Disease using Fuzzy C-Means Clustering and Pattern Recognition. *SOUTHEAST EUROPE JOURNAL OF SOFT COMPUTING*, 2. <https://doi.org/10.21533/scjournal.v2i1.44>
- Rusz, J., Cmejla, R., Ruzickova, H., & Růžička, E. (2011). Quantitative acoustic measurements for characterization of speech and voice disorders in early untreated Parkinson's disease. *The Journal of the Acoustical Society of America*, 129 1, 350–367.
- Rusz, J., Tykalová, T., Novotný, M., Zogala, D., Růžička, E., & Dušek, P. (2022). Automated speech analysis in early untreated Parkinson's disease: Relation to gender and dopaminergic transporter imaging. *European Journal of Neurology*, 29(1), 81–90.
- Sandoval, S., Berisha, V., Utianski, R. L., Liss, J. M., & Spanias, A. (2013). Automatic assessment of vowel space area. *The Journal of the Acoustical Society of America*, 134(5), EL477–EL483. <https://doi.org/10.1121/1.4826150>
- Sapir, S., Fox, C., Spielman, J., & Ramig, L. (2011). Acoustic metrics of vowel articulation in Parkinson's disease: Vowel space area (VSA) vs. Vowel articulation index (VAI). *Acoustic*

Metrics of Vowel Articulation in Parkinson's Disease: Vowel Space Area (VSA) vs. Vowel Articulation Index (VAI), 173–175.

Sapir Shimon, Ramig Lorraine O., Spielman Jennifer L., & Fox Cynthia. (2010). Formant Centralization Ratio: A Proposal for a New Acoustic Measure of Dysarthric Speech. *Journal of Speech, Language, and Hearing Research*, 53(1), 114–125.
[https://doi.org/10.1044/1092-4388\(2009/08-0184\)](https://doi.org/10.1044/1092-4388(2009/08-0184))

Schalling, E., Johansson, K., & Hartelius, L. (2018). Speech and Communication Changes Reported by People with Parkinson's Disease. *Folia Phoniatrica et Logopaedica*, 69(3), 131–141. <https://doi.org/10.1159/000479927>

Silveira-Moriyama, L., Carvalho, M., Katzenschlager, R., Petrie, A., Ranvaud, R., Barbosa, E., & Lees, A. (2008). The Use of Smell Identification Tests in the Diagnosis of Parkinson's Disease in Brazil. *Movement Disorders : Official Journal of the Movement Disorder Society*, 23, 2328–2334. <https://doi.org/10.1002/mds.22241>

Simon, J. R., Bek, J., Ghanai, K., Bearss, K., Barnstaple, R., Bar, R. J., & DeSouza, J. F. (2023). *Neural effects of multisensory dance training in Parkinson's disease: A longitudinal neuroimaging case study*.

Skodda, S. (2011). Aspects of speech rate and regularity in Parkinson's disease. *Seventh Congress of Mental and Other Non-Motor Dysfunctions in Parkinson's Disease*, 310(1), 231–236. <https://doi.org/10.1016/j.jns.2011.07.020>

Skodda, S., Rinsche, H., & Schlegel, U. (2009). Progression of dysprosody in Parkinson's disease over time—A longitudinal study. *Movement Disorders*, 24(5), 716–722.
<https://doi.org/10.1002/mds.22430>

- Skodda, S., Visser, W., & Schlegel, U. (2011). Vowel Articulation in Parkinson's Disease. *Journal of Voice*, 25(4), 467–472. <https://doi.org/10.1016/j.jvoice.2010.01.009>
- Smith, K. M., & Caplan, D. N. (2018). Communication impairment in Parkinson's disease: Impact of motor and cognitive symptoms on speech and language. *Brain and Language*, 185, 38–46. <https://doi.org/10.1016/j.bandl.2018.08.002>
- Statistics Canada. (2017). *Population estimates on July 1, by age and gender* [dataset]. [object Object]. <https://doi.org/10.25318/1710000501-ENG>
- Suppa, A., Costantini, G., Asci, F., Di Leo, P., Al-Wardat, M. S., Di Lazzaro, G., Scalise, S., Pisani, A., & Saggio, G. (2022). Voice in Parkinson's Disease: A Machine Learning Study. *Frontiers in Neurology*, 13. <https://www.frontiersin.org/journals/neurology/articles/10.3389/fneur.2022.831428>
- Teixeira, J. P., & Fernandes, P. O. (2014). Jitter, Shimmer and HNR Classification within Gender, Tones and Vowels in Healthy Voices. *CENTERIS 2014 - Conference on ENTERprise Information Systems / ProjMAN 2014 - International Conference on Project MANagement / HCIST 2014 - International Conference on Health and Social Care Information Systems and Technologies*, 16, 1228–1237. <https://doi.org/10.1016/j.protcy.2014.10.138>
- Teixeira, J. P., Oliveira, C., & Lopes, C. (2013). Vocal Acoustic Analysis – Jitter, Shimmer and HNR Parameters. *Procedia Technology*, 9, 1112–1122. <https://doi.org/10.1016/j.protcy.2013.12.124>
- Thomas, A. & Gopinath, D. P. (2012). Analysis of the chaotic nature of speech prosody and music. *2012 Annual IEEE India Conference (INDICON)*, 210–215.

<https://doi.org/10.1109/INDCON.2012.6420617>

- Tsanas, A., Little, M. A., Fox, C., & Ramig, L. O. (2013). Objective automatic assessment of rehabilitative speech treatment in Parkinson's disease. *IEEE Transactions on Neural Systems and Rehabilitation Engineering*, 22(1), 181–190.
- Tsanas, A., Little, M. A., McSharry, P. E., Spielman, J., & Ramig, L. O. (2012). Novel speech signal processing algorithms for high-accuracy classification of Parkinson's disease. *IEEE Transactions on Biomedical Engineering*, 59(5), 1264–1271.
- Upadhyaya, S. S., Cheeran, A. N., & Nirmal, J. H. (2017). Statistical comparison of Jitter and Shimmer voice features for healthy and Parkinson affected persons. *2017 Second International Conference on Electrical, Computer and Communication Technologies (ICECCT)*, 1–6. <https://doi.org/10.1109/ICECCT.2017.8117853>
- Vikas & R. K. Sharma. (2014). Early detection of Parkinson's disease through Voice. *2014 International Conference on Advances in Engineering and Technology (ICAET)*, 1–5. <https://doi.org/10.1109/ICAET.2014.7105237>
- Viswanathan, R., Arjunan, S. P., Bingham, A., Jelfs, B., Kempster, P., Raghav, S., & Kumar, D. K. (2019). Complexity measures of voice recordings as a discriminative tool for Parkinson's disease. *Biosensors*, 10(1), 1.
- Westheimer, O. (2008). Why Dance for Parkinson's Disease. *Topics in Geriatric Rehabilitation*, 24(2). https://journals.lww.com/topicsingeriatricrehabilitation/fulltext/2008/04000/why_dance_for_parkinson_s_disease.5.aspx

Wong, S., Gilmour, H., & Ramage-Morin, P. (2014). Parkinson's Disease: Prevalence, diagnosis and impact. *Health Reports / Statistics Canada, Canadian Centre for Health Information* = *Rapports Sur La Santé / Statistique Canada, Centre Canadien d'information Sur La Santé*, 25, 10–14. <https://doi.org/10.13140/2.1.4842.9767>

Yang, Y., Yuan, Y., Zhang, G., Wang, H., Chen, Y.-C., Liu, Y., Tarolli, C. G., Crepeau, D., Bukartyk, J., Junna, M. R., Videnovic, A., Ellis, T. D., Lipford, M. C., Dorsey, R., & Katabi, D. (2022). Artificial intelligence-enabled detection and assessment of Parkinson's disease using nocturnal breathing signals. *Nature Medicine*, 28(10), 2207–2215. <https://doi.org/10.1038/s41591-022-01932-x>

APPENDIX-

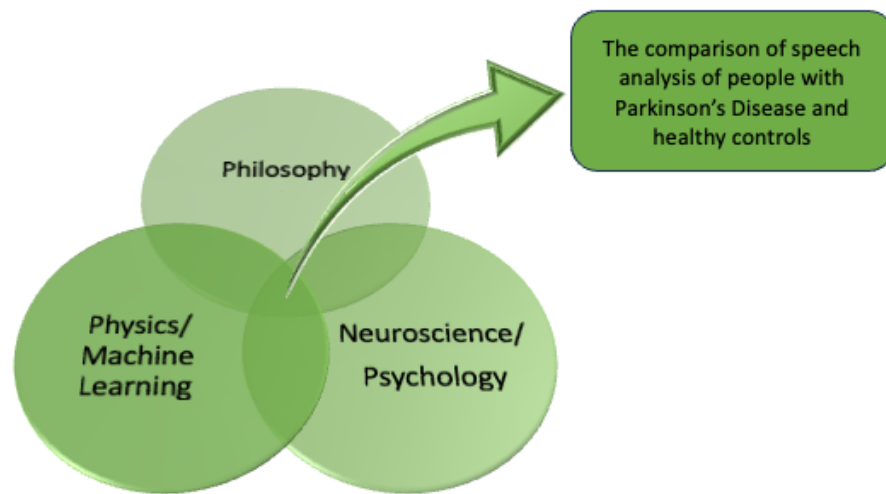
NOTES, CODES AND FORMS

A. Notes

1. A NOTE ON INTERDISCIPLINARITY

The term “discipline” in “interdisciplinary” refers to a branch of knowledge, teaching, education, or learning. Interdisciplinarity occurs when two or more disciplines converge to address a specific problem (Alvargonzález, 2011). In reality, most problems benefit from an interdisciplinary approach, as nature itself operates as an interconnected system. The categorization of science into different disciplines was created to provide clarity in the study of nature, even though nature itself is not divided in such a way. Utilizing knowledge from various disciplines to investigate a problem is highly advantageous.

In this study, the primary disciplines involved include neuroscience/psychology, physics, machine learning, and philosophy. The investigation of speech analysis in people living with Parkinson’s Disease (PD) draws on these disciplines to generate and analyze meaningful data.



Venn diagram of the project's disciplines

B. PYTHON CODES FOR EXTRACTING VOICE FEATURES

1. Measuring Pitch and HNR

```
In [ ]: pip install praat-parselmouth
```

```
In [ ]: #Measure pitch of all wav files in directory
import glob
import numpy as np
import pandas as pd
import parselmouth
from parselmouth.praat import call
```

```
In [ ]: # This is the function to measure voice pitch
def measurePitch(voiceID, f0min, f0max, unit):
    sound = parselmouth.Sound(voiceID) # read the sound
    pitch = call(sound, "To Pitch", 0.0, f0min, f0max) #create a praat pitch object
    meanF0 = call(pitch, "Get mean", 0, 0, unit) # get mean pitch
    stdevF0 = call(pitch, "Get standard deviation", 0, 0, unit) # get standard deviation
    harmonicity = call(sound, "To Harmonicity (cc)", 0.01, 75, 0.1, 1.0)
    hnr = call(harmonicity, "Get mean", 0, 0)
    return meanF0, stdevF0, hnr
```

```

In [ ]: # create lists to put the results
file_list = []
mean_F0_list = []
sd_F0_list = []
hnr_list = []

# Go through all the wave files in the folder and measure pitch
for wave_file in glob.glob("/Users/ashkan/Downloads/updrsa/*.wav"):
    sound = parselmouth.Sound(wave_file)
    (meanF0, stdevF0, hnr) = measurePitch(sound, 75, 500, "Hertz")
    file_list.append(wave_file) # make an ID list
    mean_F0_list.append(meanF0) # make a mean F0 list
    sd_F0_list.append(stdevF0) # make a sd F0 list
    hnr_list.append(hnr)

df = pd.DataFrame(np.column_stack([file_list, mean_F0_list, sd_F0_list, hnr_list]),
                  columns=['voiceID', 'meanF0Hz', 'stdevF0Hz', 'HNR']) #add these lists to

# Write out the updated dataframe
df.to_csv("processed_results_pitch_HNR.csv", index=False)

```

2. Measuring Jitter and Shimmer and their variants

```
In [ ]: #Measure pitch of all wav files in directory
import glob
import numpy as np
import pandas as pd
import parselmouth

from parselmouth.praat import call
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
```

```
In [ ]: # This is the function to measure voice pitch
def measurePitch(voiceID, f0min, f0max, unit):
    sound = parselmouth.Sound(voiceID) # read the sound
    pitch = call(sound, "To Pitch", 0.0, f0min, f0max) #create a praat pitch object
    meanF0 = call(pitch, "Get mean", 0, 0, unit) # get mean pitch
    stdevF0 = call(pitch, "Get standard deviation", 0, 0, unit) # get standard deviation
    harmonicity = call(sound, "To Harmonicity (cc)", 0.01, 75, 0.1, 1.0)
    hnr = call(harmonicity, "Get mean", 0, 0)
    pointProcess = call(sound, "To PointProcess (periodic, cc)", f0min, f0max)
    localJitter = call(pointProcess, "Get jitter (local)", 0, 0, 0.0001, 0.02, 1.3)
    localabsoluteJitter = call(pointProcess, "Get jitter (local, absolute)", 0, 0, 0.0001, 0.02, 1.3)
    rapJitter = call(pointProcess, "Get jitter (rap)", 0, 0, 0.0001, 0.02, 1.3)
    ppq5Jitter = call(pointProcess, "Get jitter (ppq5)", 0, 0, 0.0001, 0.02, 1.3)
    ddpJitter = call(pointProcess, "Get jitter (ddp)", 0, 0, 0.0001, 0.02, 1.3)
    localShimmer = call([sound, pointProcess], "Get shimmer (local)", 0, 0, 0.0001, 0.02, 1.3, 1.6)
    localdbShimmer = call([sound, pointProcess], "Get shimmer (local_dB)", 0, 0, 0.0001, 0.02, 1.3, 1.6)
    apq3Shimmer = call([sound, pointProcess], "Get shimmer (apq3)", 0, 0, 0.0001, 0.02, 1.3, 1.6)
    apq5Shimmer = call([sound, pointProcess], "Get shimmer (apq5)", 0, 0, 0.0001, 0.02, 1.3, 1.6)
    apq11Shimmer = call([sound, pointProcess], "Get shimmer (apq11)", 0, 0, 0.0001, 0.02, 1.3, 1.6)
    ddaShimmer = call([sound, pointProcess], "Get shimmer (dda)", 0, 0, 0.0001, 0.02, 1.3, 1.6)

    return meanF0, stdevF0, hnr, localJitter, localabsoluteJitter, rapJitter, ppq5Jitter, ddpJitter, localShimmer, localdbShimmer, apq3Shimmer, apq5Shimmer, apq11Shimmer, ddaShimmer
```

```
In [ ]: def runPCA(df):
    #Z-score the Jitter and Shimmer measurements
    features = ['localJitter', 'localabsoluteJitter', 'rapJitter', 'ppq5Jitter', 'ddpJitter',
                'localShimmer', 'localdbShimmer', 'apq3Shimmer', 'apq5Shimmer', 'apq11Shimmer', 'ddaShimmer']
    # Separating out the features
    x = df.loc[:, features].values
    # Separating out the target
    #y = df.loc[:,['target']].values
    # Standardizing the features
    x = StandardScaler().fit_transform(x)
    #PCA
    pca = PCA(n_components=2)
    principalComponents = pca.fit_transform(x)
    principalDf = pd.DataFrame(data = principalComponents, columns = ['JitterPCA', 'ShimmerPCA'])
    principalDf
    return principalDf
```

```
In [ ]: # create lists to put the results
file_list = []
mean_F0_list = []
sd_F0_list = []
hnr_list = []
localJitter_list = []
localabsoluteJitter_list = []
rapJitter_list = []
ppq5Jitter_list = []
ddpJitter_list = []
localShimmer_list = []
localdbShimmer_list = []
apq3Shimmer_list = []
apq5Shimmer_list = []
apq11Shimmer_list = []
ddaShimmer_list = []

# Go through all the wave files in the folder and measure pitch
for wave_file in glob.glob("audio/*.wav"):
    sound = parselmouth.Sound(wave_file)
    (meanF0, stdevF0, hnr, localJitter, localabsoluteJitter, rapJitter, ppq5Jitter, ddpJitter, localShimmer)
    file_list.append(wave_file) # make an ID list
    mean_F0_list.append(meanF0) # make a mean F0 list
    sd_F0_list.append(stdevF0) # make a sd F0 list
    hnr_list.append(hnr)
```

```

localJitter_list.append(localJitter)
localabsoluteJitter_list.append(localabsoluteJitter)
rapJitter_list.append(rapJitter)
ppq5Jitter_list.append(ppq5Jitter)
ddpJitter_list.append(ddpJitter)
localShimmer_list.append(localShimmer)
localdbShimmer_list.append(localdbShimmer)
apq3Shimmer_list.append(apq3Shimmer)
apq5Shimmer_list.append(apq5Shimmer)
apq11Shimmer_list.append(apq11Shimmer)
ddaShimmer_list.append(ddaShimmer)
df = pd.DataFrame(np.column_stack([file_list, mean_F0_list, sd_F0_list, hnr_list, localJitter_list, localabsoluteJitter_list, rapJitter_list, ppq5Jitter_list, ddpJitter_list, localShimmer_list, localdbShimmer_list, apq3Shimmer_list, apq5Shimmer_list, apq11Shimmer_list, ddaShimmer_list],
                                columns=['voiceID', 'meanF0Hz', 'stdevF0Hz', 'HNR', 'localJitter', 'localabsoluteJitter', 'rapJitter', 'ppq5Jitter', 'ddpJitter', 'localShimmer', 'localdbShimmer', 'apq3Shimmer', 'apq5Shimmer', 'apq11Shimmer', 'ddaShimmer'])) #add these lists to pandas in the
pcaData = runPCA(df)

df = pd.concat([df, pcaData], axis=1)

# Write out the updated dataframe
df.to_csv("processed_results.csv", index=False)

```

3. Measure Pitch, HNR, Jitter, Shimmer, Formants and estimate VTL

Measure Pitch, HNR, Jitter, Shimmer, Formants, and Estimate VTL

Import the external modules

```
In [ ]: pip install praat-parselmouth
```

```
In [ ]: #!/usr/bin/env python3
import glob
import numpy as np
import pandas as pd
import parselmouth
import statistics

from parselmouth.praat import call
from scipy.stats.mstats import zscore
from sklearn.decomposition import PCA
from sklearn.preprocessing import StandardScaler
```

This function measures duration, pitch, HNR, jitter, and shimmer

```
In [ ]: # This is the function to measure source acoustics using default male parameters.

def measurePitch(voiceID, f0min, f0max, unit):
    sound = parselmouth.Sound(voiceID) # read the sound
    duration = call(sound, "Get total duration") # duration
    pitch = call(sound, "To Pitch", 0.0, f0min, f0max) #create a praat pitch object
    meanF0 = call(pitch, "Get mean", 0, 0, unit) # get mean pitch
    stdevF0 = call(pitch, "Get standard deviation", 0, 0, unit) # get standard deviation
    harmonicity = call(sound, "To Harmonicity (cc)", 0.01, f0min, 0.1, 1.0)
    hnr = call(harmonicity, "Get mean", 0, 0)
    pointProcess = call(sound, "To PointProcess (periodic, cc)", f0min, f0max)
    localJitter = call(pointProcess, "Get jitter (local)", 0, 0, 0.0001, 0.02, 1.3)
    localabsoluteJitter = call(pointProcess, "Get jitter (local, absolute)", 0, 0, 0.0001, 0.02, 1.3)
    rapJitter = call(pointProcess, "Get jitter (rap)", 0, 0, 0.0001, 0.02, 1.3)
    ppq5Jitter = call(pointProcess, "Get jitter (ppq5)", 0, 0, 0.0001, 0.02, 1.3)
    ddpJitter = call(pointProcess, "Get jitter (ddp)", 0, 0, 0.0001, 0.02, 1.3)
    localShimmer = call([sound, pointProcess], "Get shimmer (local)", 0, 0, 0.0001, 0.02, 1.3, 1.6)
    localdbShimmer = call([sound, pointProcess], "Get shimmer (local_db)", 0, 0, 0.0001, 0.02, 1.3, 1.6)
    apq3Shimmer = call([sound, pointProcess], "Get shimmer (apq3)", 0, 0, 0.0001, 0.02, 1.3, 1.6)
    apq5Shimmer = call([sound, pointProcess], "Get shimmer (apq5)", 0, 0, 0.0001, 0.02, 1.3, 1.6)
    apq11Shimmer = call([sound, pointProcess], "Get shimmer (apq11)", 0, 0, 0.0001, 0.02, 1.3, 1.6)
    ddaShimmer = call([sound, pointProcess], "Get shimmer (dda)", 0, 0, 0.0001, 0.02, 1.3, 1.6)

    return duration, meanF0, stdevF0, hnr, localJitter, localabsoluteJitter, rapJitter, ppq5Jitter, ddpJitter
```

This function measures formants at each glottal pulse

Puts, D. A., Apicella, C. L., & Cárdenas, R. A. (2012). Masculine voices signal men's threat potential in forager and industrial societies. *Proceedings of the Royal Society of London B: Biological Sciences*, 279(1728), 601-609.

Adapted from: DOI 10.17605/OSF.IO/K2BHS

```
In [ ]: # This function measures formants using Formant Position formula

def measureFormants(sound, wave_file, f0min, f0max):
    sound = parselmouth.Sound(sound) # read the sound
    pitch = call(sound, "To Pitch (cc)", 0, f0min, 15, 'no', 0.03, 0.45, 0.01, 0.35, 0.14, f0max)
    pointProcess = call(sound, "To PointProcess (periodic, cc)", f0min, f0max)

    formants = call(sound, "To Formant (burg)", 0.0025, 5, 5000, 0.025, 50)
```

```

numPoints = call(pointProcess, "Get number of points")

f1_list = []
f2_list = []
f3_list = []
f4_list = []

# Measure formants only at glottal pulses
for point in range(0, numPoints):
    point += 1
    t = call(pointProcess, "Get time from index", point)
    f1 = call(formants, "Get value at time", 1, t, 'Hertz', 'Linear')
    f2 = call(formants, "Get value at time", 2, t, 'Hertz', 'Linear')
    f3 = call(formants, "Get value at time", 3, t, 'Hertz', 'Linear')
    f4 = call(formants, "Get value at time", 4, t, 'Hertz', 'Linear')
    f1_list.append(f1)
    f2_list.append(f2)
    f3_list.append(f3)
    f4_list.append(f4)

f1_list = [f1 for f1 in f1_list if str(f1) != 'nan']
f2_list = [f2 for f2 in f2_list if str(f2) != 'nan']
f3_list = [f3 for f3 in f3_list if str(f3) != 'nan']
f4_list = [f4 for f4 in f4_list if str(f4) != 'nan']

# calculate mean formants across pulses
f1_mean = statistics.mean(f1_list)
f2_mean = statistics.mean(f2_list)
f3_mean = statistics.mean(f3_list)
f4_mean = statistics.mean(f4_list)

# calculate median formants across pulses, this is what is used in all subsequent calculations
# you can use mean if you want, just edit the code in the boxes below to replace median with mean
f1_median = statistics.median(f1_list)
f2_median = statistics.median(f2_list)
f3_median = statistics.median(f3_list)
f4_median = statistics.median(f4_list)

return f1_mean, f2_mean, f3_mean, f4_mean, f1_median, f2_median, f3_median, f4_median

```

This function runs a 2-factor Principle Components Analysis (PCA) on Jitter and Shimmer

```
In [ ]: def runPCA(df):  
        # z-score the Jitter and Shimmer measurements  
        measures = ['localJitter', 'localabsoluteJitter', 'rapJitter', 'ppq5Jitter', 'ddpJitter',  
                    'localShimmer', 'localdbShimmer', 'apq3Shimmer', 'apq5Shimmer', 'apq11Shimmer', 'ddaShimmer']  
        x = df.loc[:, measures].values  
        x = StandardScaler().fit_transform(x)  
        # PCA  
        pca = PCA(n_components=2)  
        principalComponents = pca.fit_transform(x)  
        principalDf = pd.DataFrame(data = principalComponents, columns = ['JitterPCA', 'ShimmerPCA'])  
        principalDf  
        return principalDf
```

This block of code runs the above functions on all of the '.wav' files in the /audio folder

```
In [ ]: # create lists to put the results  
file_list = []  
duration_list = []  
mean_F0_list = []  
sd_F0_list = []  
hnr_list = []  
localJitter_list = []  
localabsoluteJitter_list = []  
rapJitter_list = []  
ppq5Jitter_list = []  
ddpJitter_list = []  
localShimmer_list = []  
localdbShimmer_list = []  
apq3Shimmer_list = []  
apq5Shimmer_list = []  
apq11Shimmer_list = []  
ddaShimmer_list = []  
f1_mean_list = []
```

```

f2_mean_list = []
f3_mean_list = []
f4_mean_list = []
f1_median_list = []
f2_median_list = []
f3_median_list = []
f4_median_list = []

# Go through all the wave files in the folder and measure all the acoustics
for wave_file in glob.glob("/Users/ashkan/Downloads/1/*.wav"):
    sound = parselmouth.Sound(wave_file)
    (duration, meanF0, stdevF0, hnr, localJitter, localabsoluteJitter, rapJitter, ppq5Jitter, ddpJitter,
     localShimmer, localdbShimmer, apq3Shimmer, aqpq5Shimmer, apq11Shimmer, ddaShimmer) = measurePitch(
        sound, 75, 300, "Hertz")
    (f1_mean, f2_mean, f3_mean, f4_mean, f1_median, f2_median, f3_median, f4_median) = measureFormants(
        sound, wave_file, 75, 300)
    file_list.append(wave_file) # make an ID list
    duration_list.append(duration) # make duration list
    mean_F0_list.append(meanF0) # make a mean F0 list
    sd_F0_list.append(stdevF0) # make a sd F0 list
    hnr_list.append(hnr) #add HNR data

    # add raw jitter and shimmer measures
    localJitter_list.append(localJitter)
    localabsoluteJitter_list.append(localabsoluteJitter)
    rapJitter_list.append(rapJitter)
    ppq5Jitter_list.append(ppq5Jitter)
    ddpJitter_list.append(ddpJitter)
    localShimmer_list.append(localShimmer)
    localdbShimmer_list.append(localdbShimmer)
    apq3Shimmer_list.append(apq3Shimmer)
    aqpq5Shimmer_list.append(aqpq5Shimmer)
    apq11Shimmer_list.append(apq11Shimmer)
    ddaShimmer_list.append(ddaShimmer)

    # add the formant data
    f1_mean_list.append(f1_mean)
    f2_mean_list.append(f2_mean)
    f3_mean_list.append(f3_mean)
    f4_mean_list.append(f4_mean)
    f1_median_list.append(f1_median)
    f2_median_list.append(f2_median)
    f3_median_list.append(f3_median)

```

```
f4_median_list.append(f4_median)
```

This block of code adds all of that data we just generated to a Pandas data frame

```
In [ ]: # Add the data to Pandas
df = pd.DataFrame(np.column_stack([file_list, duration_list, mean_F0_list, sd_F0_list, hnr_list,
    localJitter_list, localabsoluteJitter_list, rapJitter_list,
    ppq5Jitter_list, ddpJitter_list, localShimmer_list,
    localdbShimmer_list, apq3Shimmer_list, apq5Shimmer_list,
    apq11Shimmer_list, ddaShimmer_list, f1_mean_list,
    f2_mean_list, f3_mean_list, f4_mean_list,
    f1_median_list, f2_median_list, f3_median_list,
    f4_median_list]),
    columns=['voiceID', 'duration', 'meanF0Hz', 'stdevF0Hz', 'HNR',
        'localJitter', 'localabsoluteJitter', 'rapJitter',
        'ppq5Jitter', 'ddpJitter', 'localShimmer',
        'localdbShimmer', 'apq3Shimmer', 'apq5Shimmer',
        'apq11Shimmer', 'ddaShimmer', 'f1_mean', 'f2_mean',
        'f3_mean', 'f4_mean', 'f1_median',
        'f2_median', 'f3_median', 'f4_median'])

#pcaData = runPCA(df) # Run jitter and shimmer PCA
#df = pd.concat([df, pcaData], axis=1) # Add PCA data
# reload the data so it's all numbers
df.to_csv("processed_results.csv", index=False)
df = pd.read_csv('processed_results.csv', header=0)
df.sort_values('voiceID').head(20)
```

Next we calculate the vocal-tract length estimates

Formant position

Puts, D. A., Apicella, C. L., & Cárdenas, R. A. (2012). Masculine voices signal men's threat potential in forager and industrial societies. *Proceedings of the Royal Society of London B: Biological Sciences*, 279(1728), 601-609.

```
In [ ]: df['pF'] = (zscore(df.f1_median) + zscore(df.f2_median) + zscore(df.f3_median) + zscore(df.f4_median)) /
```

Formant Dispersion

Fitch, W. T. (1997). Vocal tract length and formant frequency dispersion correlate with body size in rhesus macaques. The Journal of the Acoustical Society of America, 102(2), 1213-1222.

```
In [ ]: df['fdisp'] = (df['f4_median'] - df['f1_median']) / 3
```

Fn (Average Formant)

Pisanski, K., & Rendall, D. (2011). The prioritization of voice fundamental frequency or formants in listeners' assessments of speaker size, masculinity, and attractiveness. The Journal of the Acoustical Society of America, 129(4), 2201-2212.

```
In [ ]: df['avgFormant'] = (df['f1_median'] + df['f2_median'] + df['f3_median'] + df['f4_median']) / 4
```

MFF

Smith, D. R., & Patterson, R. D. (2005). The interaction of glottal-pulse rate and vocal-tract length in judgements of speaker size, sex, and age. The Journal of the Acoustical Society of America, 118(5), 3177-3186.

```
In [ ]: df['mff'] = (df['f1_median'] * df['f2_median'] * df['f3_median'] * df['f4_median']) ** 0.25
```

Fitch VTL

Fitch, W. T. (1997). Vocal tract length and formant frequency dispersion correlate with body size in rhesus macaques. The Journal of the Acoustical Society of America, 102(2), 1213-1222.

```
In [ ]: # reload the data again
df.to_csv("processed_results.csv", index=False)
df = pd.read_csv('processed_results.csv', header=0)

df['fitch_vtl'] = ((1 * (35000 / (4 * df['f1_median']))) +
                  (3 * (35000 / (4 * df['f2_median']))) +
                  (5 * (35000 / (4 * df['f3_median']))) +
                  (7 * (35000 / (4 * df['f4_median'])))) / 4
```

ΔF

Reby,D,& McComb,K.(2003). Anatomical constraints generate honesty: acoustic cues to age and weight in the roars of red deer stags. Animal Behaviour, 65, 519e-530.

```
In [ ]: xysum = (0.5 * df['f1_median']) + (1.5 * df['f2_median']) + (2.5 * df['f3_median']) + (3.5 * df['f4_median'])
xsquaredsum = (0.5 ** 2) + (1.5 ** 2) + (2.5 ** 2) + (3.5 ** 2)
df['delta_f'] = xysum / xsquaredsum
```

VTL(ΔF)

Reby,D,&McComb,K.(2003).Anatomical constraints generate honesty: acoustic cues to age and weight in the roars of red deer stags. Animal Behaviour, 65, 519e-530.

```
In [ ]: df['vtl_delta_f'] = 35000 / (2 * df['delta_f'])
```

Save the final data

```
In [ ]: # Write out the final dataframe
df.to_csv("processed_results_finalhc.csv", index=False)
```

Run this to tell you when it's done

```
In [ ]: print("finished")
```

4. Intensity Standard Deviation Extraction from the Audio Files

```
In [ ]: pip install librosa numpy
```

```
In [ ]: import os
import librosa
import numpy as np

def extract_intensity_std(file_path):
    # Load the audio file
    y, sr = librosa.load(file_path)

    # Extract intensity (amplitude) envelope
    envelope = np.abs(librosa.amplitude_to_db(librosa.stft(y), ref=np.max))

    # Calculate standard deviation of intensity
    intensity_std = np.std(envelope)

    return intensity_std

# Folder path containing all voice WAV files
folder_path = "/Users/ashkan/Downloads/pd-post/others"

# Get a list of all WAV files in the folder
wav_files = [os.path.join(folder_path, file) for file in os.listdir(folder_path) if file.endswith(".wav")]

# Process each WAV file
for file in wav_files:
    intensity_std = extract_intensity_std(file)
    print(f"Intensity Std for {file}: {intensity_std}")
```

C. Sample Part of MDS-UPDRS Questionnaire

2142

C.G. GOETZ ET AL.

_____ Patient Name or Subject ID	_____ Site ID	____-____-_____ (mm-dd-yyyy) Assessment Date	_____ Investigator's Initials
-------------------------------------	------------------	--	----------------------------------

MDS UPDRS

Part I: Non-Motor Aspects of Experiences of Daily Living (nM-EDL)

Part 1A: Complex behaviors: [completed by rater]

Primary source of information:

☐ Patient
 ☐ Caregiver
 ☐ Patient and Caregiver in Equal Proportion

To be read to the patient: I am going to ask you six questions about behaviors that you may or may not experience. Some questions concern common problems and some concern uncommon ones. If you have a problem in one of the areas, please choose the best response that describes how you have felt MOST OF THE TIME during the PAST WEEK. If you are not bothered by a problem, you can simply respond NO. I am trying to be thorough, so I may ask questions that have nothing to do with you.

1.1 COGNITIVE IMPAIRMENT

Instructions to examiner: Consider all types of altered level of cognitive function including cognitive slowing, impaired reasoning, memory loss, deficits in attention and orientation. Rate their impact on activities of daily living as perceived by the patient and/or caregiver.

Instructions to patients [and caregiver]: Over the past week have you had problems remembering things, following conversations, paying attention, thinking clearly, or finding your way around the house or in town? [If yes, examiner asks patient or caregiver to elaborate and probes for information]

0: Normal:	No cognitive impairment.
1: Slight:	Impairment appreciated by patient or caregiver with no concrete interference with the patient's ability to carry out normal activities and social interactions.
2: Mild:	Clinically evident cognitive dysfunction, but only minimal interference with the patient's ability to carry out normal activities and social interactions.
3: Moderate:	Cognitive deficits interfere with but do not preclude the patient's ability to carry out normal activities and social interactions.
4: Severe:	Cognitive dysfunction precludes the patient's ability to carry out normal activities and social interactions.

SCORE

3.1 SPEECH <u>Instructions to examiner:</u> Listen to the patient's free-flowing speech and engage in conversation if necessary. Suggested topics: ask about the patient's work, hobbies, exercise, or how he got to the doctor's office. Evaluate volume, modulation (prosody) and clarity, including slurring, palilalia (repetition of syllables) and tachyphemia (rapid speech, running syllables together). 0: Normal: No speech problems. 1: Slight: Loss of modulation, diction or volume, but still all words easy to understand. 2: Mild: Loss of modulation, diction, or volume, with a few words unclear, but the overall sentences easy to follow. 3: Moderate: Speech is difficult to understand to the point that some, but not most, sentences are poorly understood. 4: Severe: Most speech is difficult to understand or unintelligible.	SCORE
3.2 FACIAL EXPRESSION <u>Instructions to examiner:</u> Observe the patient sitting at rest for 10 seconds, without talking and also while talking. Observe eye-blink frequency, masked facies or loss of facial expression, spontaneous smiling and parting of lips. 0: Normal: Normal facial expression. 1: Slight: Minimal masked facies manifested only by decreased frequency of blinking. 2: Mild: In addition to decreased eye-blink frequency, Masked facies present in the lower face as well, namely fewer movements around the mouth, such as less spontaneous smiling, but lips not parted. 3: Moderate: Masked facies with lips parted some of the time when the mouth is at rest. 4: Severe: Masked facies with lips parted most of the time when the mouth is at rest.	

Part IV: Motor Complications

Overview and Instructions: In this section, the rater uses historical and objective information to assess two motor complications, dyskinesias and motor fluctuations that include OFF-state dystonia. Use all information from patient, caregiver, and the examination to answer the six questions that summarize function over the past week including today. As in the other sections, rate using only integers (no half points allowed) and leave no missing ratings. If the item cannot be rated, place UR for Unable to Rate. You will need to choose some answers based on percentages, and therefore you will need to establish how many hours generally are awake hours and use this figure as the denominator for "OFF" time and Dyskinesias. For "OFF dystonia", the total "Off" time will be the denominator. Operational definitions for examiner's use.

Dyskinesias: Involuntary random movements

Words that patients often recognize for dyskinesias include "irregular jerking", "wiggling", "twitching". It is essential to stress to the patient the difference between dyskinesias and tremor, a common error when patients are assessing dyskinesias.

Dystonia: contorted posture, often with a twisting component:

Words that patients often recognize for dystonia include "spasms", "cramps", "posture".

Motor fluctuation: Variable response to medication:

Words that patients often recognize for motor fluctuation include "wearing out", "wearing off", "roller-coaster effect", "on-off", "uneven medication effects".

OFF: Typical functional state when patients have a poor response in spite of taking medication or the typical functional response when patients are on NO treatment for parkinsonism. Words that patients often recognize include "low time", "bad time", "shaking time", "slow time", "time when my medications don't work."

ON: Typical functional state when patients are receiving medication and have a good response:

Words that patients often recognize include "good time", "walking time", "time when my medications work."

A . DYSKINESIAS [exclusive of OFF-state dystonia]

4.1 TIME SPENT WITH DYSKINESIAS

Instructions to examiner: Determine the hours in the usual waking day and then the hours of dyskinesias. Calculate the percentage. If the patient has dyskinesias in the office, you can point them out as a reference to ensure that patients and caregivers understand what they are rating. You may also use your own acting skills to enact the dyskinetic movements you have seen in the patient before or show them dyskinetic movements typical of other patients. Exclude from this question early morning and nighttime painful dystonia.

Instructions to patient [and caregiver]. Over the past week, how many hours do you usually sleep on a daily basis, including nighttime sleep and daytime napping? Alright, if you sleep ____ hrs, you are awake ____ hrs. Out of those awake hours, how many hours in total do you have wiggling, twitching or jerking movements? Do not count the times when you have tremor, which is a regular back and forth shaking or times when you have painful foot cramps or spasms in the early morning or at nighttime. I will ask about those later. Concentrate only on these types of wiggling, jerking and irregular movements. Add up all the time during the waking day when these usually occur. How many hours ____ (use this number for your calculation).

0: Normal: No dyskinesias.

1: Slight: ≤ 25% of waking day.

2: Mild: 26 - 50% of waking day.

3: Moderate: 51 - 75% of waking day.

4: Severe: > 75% of waking day.

1. Total Hours Awake: _____

2. Total Hours with Dyskinesia: _____

3. % Dyskinesia = $((2/1) \times 100)$: _____

SCORE



Copyright © 2008 Movement Disorder Society. All rights reserved.

This chart may not be copied, distributed or otherwise used in whole or in part without prior written consent of the Movement Disorder Society.

D. Parkinson Disease: Feature Selections (Google Colab)

4/20/24, 8:30 AM

Parkinson_voice_All.ipynb - Colab

```
1 from google.colab import drive
2 drive.mount('/content/drive')

1 #Author: Maheshwor Tiwari
2 # Parkinson Disease: Feature Selections
3
4 """ Data Loading """
5 import numpy as np
6 import pandas as pd
7 df = pd.read_csv('/content/drive/My Drive/All_subjects2.csv')
8
9
10 # finding number of rows and columns
11 df.shape
12 #Show first 5 rows of the dataset
13 df.head()
14 # Display basic information about the dataset
15 print(df.info())
16 # Check for any missing values in the entire dataset
17 print(df.isnull().sum().sum())
18 # Check for duplicate rows in the dataset
19 duplicate_rows = df[df.duplicated()]
20 print("Number of duplicate rows:", duplicate_rows.shape[0])

1 """ Bar Diagram: PD Indicator """
2
3 import seaborn as sns
4 import matplotlib.pyplot as plt
5 sns.set(style="whitegrid")
6 plt.figure(figsize=(6, 4))
7
8 ax = sns.countplot(x='Group', data=df, palette=["#1f77b4", "#ff7f0e"])
9 plt.xlabel('Group')
10 plt.ylabel('Count')
11 plt.title('Distribution of Group')
12 plt.xticks([0, 1], ['Healthy', 'PD'])
13
14 # Adding integer count numbers on top of the bars
15 for p in ax.patches:
16     ax.annotate(f'{int(p.get_height())}', (p.get_x() + p.get_width() / 2., p.get_height()),
17               ha='center', va='center', fontsize=10, color='black', xytext=(0, 5),
18               textcoords='offset points')
19
20 plt.show()

1 """ Divide the dataset into two groups based on Group """
2
3 df1 = df[df["Group"] == 0]
4 df2 = df[df["Group"] == 1]
5 print(df1)
6 print(df2)
7 df1.shape
8 df2.shape
9 # Calculate summary statistics for the DataFrame
10 df1.describe()
11 df2.describe()
```

<https://colab.research.google.com/drive/19Jup8q8dh-7s6xiko3neLkjllyUrglBd#scrollTo=4dbe295f-531f-4d5a-85d4-7410c8193e54&printMode=true>

1/5

```

1 """Central Tendencies and Difference between them """
2 # Select the columns for comparison (excluding "Subject_ID" and "PD Indicator")
3 columns_to_compare = df1.columns.difference(["duration", "Group", "IntSD", "F0SD"])
4 # Calculate the differences between describe statistics for df2 and df1
5 differences = df2[columns_to_compare].describe() - df1[columns_to_compare].describe()
6 # Extract the desired statistics (mean, median, std, min, max) from the differences DataFrame
7 desired_statistics = ["mean", "50%", "std"]
8 differences = differences.loc[desired_statistics]
9 # Transpose the differences DataFrame for desired display format
10 differences = differences.transpose()
11 differences
12
13 # Display the differences
14 print("Differences between central tendencies of df2 and df1:")
15 print(differences)
16 # Calculate the absolute differences
17 absolute_differences = differences.abs()
18
19 # Sort the absolute differences DataFrame by mean values in descending order
20 sorted_absolute_differences = absolute_differences.sort_values(by=["mean"], ascending=False)
21
22 # Get the indices of the top 10 absolute differences
23 top_10_indices = sorted_absolute_differences.head(10).index
24
25 # Display the top 10 absolute differences with the original sign
26 print("Top 10 Absolute Differences between central tendencies \n of df2 and df1 by Mean:")
27 print(differences.loc[top_10_indices])

1 """ Histogram Plotting """
2 import matplotlib.pyplot as plt
3 import seaborn as sns
4 # Select numeric columns for histograms
5 numeric_columns = df1.select_dtypes(include=['float64', 'int64']).columns
6
7 # Exclude specific columns
8 columns_to_exclude = ["Group", "duration"]
9 numeric_columns = numeric_columns.difference(columns_to_exclude)
10
11 # Set up the Seaborn style
12 sns.set(style="whitegrid")
13
14 # Define custom color palette for histograms
15 custom_color_palette = sns.color_palette(["#1f77b4", "#ff7f0e"]) # Blue and orange
16
17 # Define hatch patterns for healthy and unhealthy individuals
18 hatch_patterns = [None, "////"] # No hatch for healthy, hatch for unhealthy
19
20 # Function to plot side-by-side histograms with hatch patterns
21 def plot_side_by_side_histograms(dataframe1, dataframe2, title):
22     plt.figure(figsize=(40, 30))
23     for i, column in enumerate(numeric_columns, start=1):
24         plt.subplot(6, 5, i)
25         sns.histplot(dataframe1[column], bins=10, kde=True, color=custom_color_palette[0], hatch=hatch_patterns[0])
26         sns.histplot(dataframe2[column], bins=10, kde=True, color=custom_color_palette[1], hatch=hatch_patterns[1])
27         plt.title(column, fontsize=25) # Set individual histogram title font size
28         plt.xlabel("Value", fontsize=25)
29         plt.ylabel("Number of files", fontsize=25)
30         plt.legend(labels=["Healthy", "PD"])
31
32     plt.tight_layout()
33     plt.suptitle(f"Histogram Comparison for {title}", fontsize=30)
34     plt.subplots_adjust(top=0.92)
35     plt.show()
36
37 # Plot side-by-side histograms for df1 (healthy) and df2 (unhealthy)
38 plot_side_by_side_histograms(df1, df2, "Healthy vs PD")

```

4/20/24, 8:30 AM

Parkinson_voice_All.ipynb - Colab

```
1 """ Box Plotting """
2 import matplotlib.pyplot as plt
3 import seaborn as sns
4
5 # Select numeric columns for box plots
6 numeric_columns = df1.select_dtypes(include=['float64', 'int64']).columns
7
8 # Exclude specific columns
9 columns_to_exclude = ["Group", "duration"]
10 numeric_columns = numeric_columns.difference(columns_to_exclude)
11
12 # Set up the Seaborn style
13 sns.set(style="whitegrid")
14
15 # Create a 6 by 5 grid of axes for the box plots
16 fig, axes = plt.subplots(6, 5, figsize=(40, 30))
17 axes = axes.flatten()
18
19 # Create a box plot for each numeric column in df1 and df2
20 for i, column in enumerate(numeric_columns):
21     sns.boxplot(data=df1, x="Group", y=column, ax=axes[i], color="blue")
22     sns.boxplot(data=df2, x="Group", y=column, ax=axes[i], color="orange")
23
24     # Add hatches for the boxes
25     for patch in axes[i].artists:
26         patch.set_hatch('/')
27
28     axes[i].set_title(column, fontsize=20)
29     axes[i].set_xlabel("Group", fontsize=15)
30     axes[i].set_ylabel("Value", fontsize=15)
31     axes[i].tick_params(axis="both", labelsize=12)
32
33 plt.tight_layout()
34 plt.suptitle("Box Plot Comparison for Healthy and PD Individuals", fontsize=30)
35 plt.subplots_adjust(top=0.92)
36 plt.legend(labels=["Healthy", "PD"])
37 plt.show()
```

```

1 """ Confidence Interval """
2 import pandas as pd
3 import numpy as np
4 from scipy.stats import t
5 # List of features/columns in your dataset
6 features = df1.columns.difference(["Group", "duration"])
7
8 # Initialize empty lists to store results
9 selected_features = []
10 mean_differences = []
11 confidence_intervals = []
12 absolute_mean_differences = [] # New list to store absolute mean differences
13
14 # Loop through each feature
15 for feature in features:
16     # Calculate mean and standard error for each group
17     mean_healthy = df1[feature].mean()
18     mean_unhealthy = df2[feature].mean()
19     std_error_healthy = df1[feature].std() / np.sqrt(len(df1))
20     std_error_unhealthy = df2[feature].std() / np.sqrt(len(df2))
21
22     # Calculate the t-statistic
23     t_statistic = (mean_unhealthy - mean_healthy) / np.sqrt(std_error_healthy**2 + std_error_unhealthy**2)
24
25     # Calculate degrees of freedom for the t-distribution
26     dof = len(df1) + len(df2) - 2
27
28     # Calculate the critical value for the t-distribution
29     t_critical = t.ppf(0.975, dof) # 95% confidence level
30
31     # Calculate the margin of error
32     margin_of_error = t_critical * np.sqrt((std_error_healthy**2 + std_error_unhealthy**2) / 2)
33
34     # Calculate the confidence interval
35     ci_lower = (mean_unhealthy - mean_healthy) - margin_of_error
36     ci_upper = (mean_unhealthy - mean_healthy) + margin_of_error
37
38     # Check if confidence intervals do not overlap
39     if ci_lower > 0 or ci_upper < 0:
40         selected_features.append(feature)
41         mean_difference = mean_unhealthy - mean_healthy
42         mean_differences.append(mean_difference)
43         confidence_intervals.append((ci_lower, ci_upper))
44         absolute_mean_differences.append(abs(mean_difference)) # Add the absolute mean difference
45
46 # Create a DataFrame to store the results
47 feature_selection_results = pd.DataFrame({
48     'Feature': selected_features,
49     'Mean Difference': mean_differences,
50     'Confidence Interval': confidence_intervals,
51     'Absolute Mean Difference': absolute_mean_differences # Add the absolute mean difference column
52 })
53
54 # Sort features based on larger absolute mean differences and narrower CIs
55 sorted_results = feature_selection_results.sort_values(by=['Absolute Mean Difference', 'Confidence Interval'], ascending=[False, True])
56
57 # Drop the "Absolute Mean Difference" column
58 sorted_results = sorted_results.drop(columns='Absolute Mean Difference')
59
60 # Print the sorted results with formatting
61 pd.options.display.float_format = '{:.3f}'.format
62 print(sorted_results.to_string(index=False))
63
64
65 # Define the file path where you want to save the top 10 results
66 output_file_path = '/content/drive/My Drive/sorted_results_All.csv'
67
68 # Save the top 10 rows of the sorted results to a CSV file
69 top_10_sorted_results = sorted_results.head(10)
70 top_10_sorted_results.to_csv(output_file_path, index=False)
71
72 print("Top 10 results saved to", output_file_path)

```

4/20/24, 8:30 AM

Parkinson_voice_All.ipynb - Colab

```
1 """ Hypothesis Testing """
2 import numpy as np
3 from scipy.stats import norm
4 # List of features/columns in your dataset
5 features = df1.columns.difference(["Group"])
6 # Set the significance level
7 alpha = 0.05
8 # Initialize empty lists to store results
9 reject_results = []
10 fail_to_reject_results = []
11 # Loop through each feature
12 for feature in features:
13     # Calculate sample means and standard deviations
14     mean_healthy = df1[feature].mean()
15     mean_unhealthy = df2[feature].mean()
16     std_healthy = df1[feature].std()
17     std_unhealthy = df2[feature].std()
18     n_healthy = len(df1)
19     n_unhealthy = len(df2)
20     # Calculate the pooled standard error
21     pooled_std = np.sqrt((std_healthy**2 / n_healthy) + (std_unhealthy**2 / n_unhealthy))
22     # Calculate the z-score
23     z_score = (mean_unhealthy - mean_healthy) / pooled_std
24     # Calculate the critical z-value for two-tailed test
25     critical_z = norm.ppf(1 - alpha / 2)
26     # Perform the hypothesis test
27     result_dict = {
28         "Feature": feature,
29         "Z-Score": z_score,
30         "Critical Z-Value": critical_z,
31         "Result": "Reject H0" if np.abs(z_score) > critical_z else "Fail to reject H0"
32     }
33     # Store the results in the appropriate list
```

E. T-test Python code

```
In [ ]: import pandas as pd
        from scipy.stats import ttest_ind

        def perform_t_test(csv_file, group_column, value_column):
            # Read the CSV file into a pandas DataFrame
            data = pd.read_csv(csv_file)

            # Split data into two groups based on the specified column
            group1 = data[data[group_column] == 'PD'][value_column]
            group2 = data[data[group_column] == 'HC'][value_column]

            # Perform t-test
            t_statistic, p_value = ttest_ind(group1, group2)

            return p_value

        # Example usage
        csv_file = '/Users/ashkan/Downloads/Monoloudnesschange_fort-test-2014-2019.csv'
        group_column = 'Group'
        value_column = 'Value'

        p_value = perform_t_test(csv_file, group_column, value_column)
        print("P-value:", p_value)
```

F. Plotting Python code

```
In [ ]: import pandas as pd
import matplotlib.pyplot as plt

# Read the data from CSV
data = pd.read_csv('/Users/ashkan/Downloads/Plotting/monoloudness-plotting-post.csv')

# Separate data for each group
group1_data = data[data['Group'] == 'PD']
group2_data = data[data['Group'] == 'HC']

# Extract time points and measurements for each group
time_points = ['TimeA', 'TimeB', 'TimeC', 'TimeD']
group1_measurements = group1_data[time_points].mean(axis=0)
group2_measurements = group2_data[time_points].mean(axis=0)

# Plotting
plt.plot(time_points, group1_measurements, label='PD')
plt.plot(time_points, group2_measurements, label='HC')

plt.xlabel('Time Points')
plt.ylabel('Mean IntSD')
plt.title('HC and PD Groups IntSD after Dance session')

plt.legend()
plt.grid(True)

# Save the plot as PNG
plt.savefig('intsd-hc-pd-post.png', dpi=300) # specify the file name and dpi

plt.show()
```

```

In [ ]: import pandas as pd
import matplotlib.pyplot as plt

# Read the data from CSV
data = pd.read_csv('/Users/ashkan/Downloads/Plotting/monoloudness-plotting.csv')

# Separate data for each group
group1_data = data[data['Group'] == 'PD']
group2_data = data[data['Group'] == 'HC']

# Extract time points and measurements for each group
time_points = ['TimeA', 'TimeB', 'TimeC', 'TimeD']
group1_measurements = group1_data[time_points]
group2_measurements = group2_data[time_points]

# Calculate mean and percentiles for each group
group1_mean = group1_measurements.mean()
group2_mean = group2_measurements.mean()
group1_25th_percentile = group1_measurements.quantile(0.25)
group2_25th_percentile = group2_measurements.quantile(0.25)
group1_75th_percentile = group1_measurements.quantile(0.75)
group2_75th_percentile = group2_measurements.quantile(0.75)

# Plotting
plt.plot(time_points, group1_mean, label='PD', color='blue')
plt.plot(time_points, group2_mean, label='HC', color='orange')

# Fill between the 25th and 75th percentiles
plt.fill_between(time_points, group1_25th_percentile, group1_75th_percentile, color='blue', alpha=0.2)
plt.fill_between(time_points, group2_25th_percentile, group2_75th_percentile, color='orange', alpha=0.2)

plt.xlabel('Time Points')
plt.ylabel('Mean IntSD')
plt.title('HC and PD Groups IntSD before Dance session')

plt.legend()
plt.grid(True)

# Save the plot as PNG
plt.savefig('intsd-hc-pd-pre2.png', dpi=300) # specify the file name and dpi

plt.show()

```

Tables

[illegible]

2. Processed audio files for healthy controls before the dance session

processed results All subjects per HC																																		
visit	duration	mean(fHz)	std(fHz)	HRV	locality	localization	quality	pre(fHz)	delta(fHz)	localization	localization	quality	R mean	R median	R mean	R median	R mean	R median	R mean	R median	R mean	R median	R mean	R median	R mean	R median	R mean	R median	R mean	R median	R mean	R median	R mean	R median
Arnsjohann/DanishLysen_3_hc_well01	25.42579166667	17.951604861	5.54509122101	7.1171-4940336	0.02943402558	0.001574743824	0.015134820394	0.70071895315	0.046434079690	0.167007185139	1.673108139775	0.046234519464	0.133333333333	0.225491954897	0.547762926307	0.121308384705	0.19134657789170	0.259238366408	0.1751433271121	0.4515841914408	0.1657491250370	0.244306393600	0.1761177741000	0.0716391836980	0.1104171608738	0.1912177693719	0.1674705319116	0.1769063961960	0.1711534266100	0.1837399194101	0.1837399194101	0.1837399194101	0.1837399194101	
Arnsjohann/DanishLysen_3_hc_well02	9.04403333333	17.94116841000	5.54509122101	7.1171-4940336	0.02943402558	0.001574743824	0.015134820394	0.70071895315	0.046434079690	0.167007185139	1.673108139775	0.046234519464	0.133333333333	0.225491954897	0.547762926307	0.121308384705	0.19134657789170	0.259238366408	0.1751433271121	0.4515841914408	0.1657491250370	0.244306393600	0.1761177741000	0.0716391836980	0.1104171608738	0.1912177693719	0.1674705319116	0.1769063961960	0.1711534266100	0.1837399194101	0.1837399194101	0.1837399194101	0.1837399194101	
Arnsjohann/DanishLysen_3_hc_well03	13.38851666667	19.17411684100	5.54509122101	7.1171-4940336	0.02943402558	0.001574743824	0.015134820394	0.70071895315	0.046434079690	0.167007185139	1.673108139775	0.046234519464	0.133333333333	0.225491954897	0.547762926307	0.121308384705	0.19134657789170	0.259238366408	0.1751433271121	0.4515841914408	0.1657491250370	0.244306393600	0.1761177741000	0.0716391836980	0.1104171608738	0.1912177693719	0.1674705319116	0.1769063961960	0.1711534266100	0.1837399194101	0.1837399194101	0.1837399194101	0.1837399194101	
Arnsjohann/DanishLysen_3_hc_well04	11.45201666667	18.13876116841	5.54509122101	7.1171-4940336	0.02943402558	0.001574743824	0.015134820394	0.70071895315	0.046434079690	0.167007185139	1.673108139775	0.046234519464	0.133333333333	0.225491954897	0.547762926307	0.121308384705	0.19134657789170	0.259238366408	0.1751433271121	0.4515841914408	0.1657491250370	0.244306393600	0.1761177741000	0.0716391836980	0.1104171608738	0.1912177693719	0.1674705319116	0.1769063961960	0.1711534266100	0.1837399194101	0.1837399194101	0.1837399194101	0.1837399194101	
Arnsjohann/DanishLysen_3_hc_well05	16.42004333333	18.55007168410	5.54509122101	7.1171-4940336	0.02943402558	0.001574743824	0.015134820394	0.70071895315	0.046434079690	0.167007185139	1.673108139775	0.046234519464	0.133333333333	0.225491954897	0.547762926307	0.121308384705	0.19134657789170	0.259238366408	0.1751433271121	0.4515841914408	0.1657491250370	0.244306393600	0.1761177741000	0.0716391836980	0.1104171608738	0.1912177693719	0.1674705319116	0.1769063961960	0.1711534266100	0.1837399194101	0.1837399194101	0.1837399194101	0.1837399194101	
Arnsjohann/DanishLysen_3_hc_well06	6.67116666667	19.03860370000	5.54509122101	7.1171-4940336	0.02943402558	0.001574743824	0.015134820394	0.70071895315	0.046434079690	0.167007185139	1.673108139775	0.04623																						

On 11/15/2015, the following information was received from the following source:

[illegible]

		processed_results_A1 Subjects_top_PC																			
visit		duration	meanPC	stdPC	HR	localizer	localizer_hispanic	regtype	pepdir	distdir	applied_apriori	mean	z_mean	z_mean	mean	z_mean	mean	z_mean	mean	z_mean	mean
ArmsJenkinDownloadTop, visitNo18-2	27.308033000000	25.8242224600	43.7579420000	8.61786762200e	0.173399317890	0.391789748600	0.073308189070	0.073308189070	0.211006983210	0.138114974400	1.283287101400	0.154142028100	0.147371000600	0.118049121600	0.140366386000	0.211006983210	0.138114974400	0.154142028100	0.147371000600	0.118049121600	0.140366386000
ArmsJenkinDownloadTop, visitNo18-2	18.916986880000	17.770902119000	41.4874400000	4.958081481700	0.041494453810	0.002011841540	0.002011841540	0.002011841540	0.002011841540	0.002011841540	0.002011841540	0.002011841540	0.002011841540	0.002011841540	0.002011841540	0.002011841540	0.002011841540	0.002011841540	0.002011841540	0.002011841540	
ArmsJenkinDownloadTop, visitNo18-2	19.264830000000	18.165187700000	30.7606000000	7.027603200000	0.021891620000	0.001492250000	0.001492250000	0.001492250000	0.001492250000	0.001492250000	0.001492250000	0.001492250000	0.001492250000	0.001492250000	0.001492250000	0.001492250000	0.001492250000	0.001492250000	0.001492250000	0.001492250000	
ArmsJenkinDownloadTop, visitNo18-2	14.535000000000	13.182266000000	27.218821700000	5.808333411200	0.020000017470	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	
ArmsJenkinDownloadTop, visitNo18-2	24.866700000000	23.782713521000	27.1280000000	6.868657296000	0.017077604020	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	
ArmsJenkinDownloadTop, visitNo18-2	10.170700000000	11.861727588000	26.3846100000	5.662571538120	0.022274465770	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	
ArmsJenkinDownloadTop, visitNo18-2	1.86153419990000	1.270359358000	5.141742847000	0.002159627600	0.004866717000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	
ArmsJenkinDownloadTop, visitNo18-2	7.14317943700000	6.184749300000	23.414534740000	4.243453474000	0.024464174340	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	
ArmsJenkinDownloadTop, visitNo18-2	20.810470000000	17.412475800000	38.498317300000	6.947167112600	0.014861144000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	0.000000000000	
ArmsJenkinDownloadTop, visitNo18-2	24.8740																				