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Influence of Creative Engagement in Parkinson's Disease:
A Quantitative Image Property and Machine Learning Analysis

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Using Machine Learning to Understand Parkinson's Disease and its Impact on Creativity

"While I wouldn't wish a Parkinson's diagnosis on anyone, it has brought with it gifts that I'm truly grateful for."

-Yo Jalden, during the 'Year of Yes' Interview about her Diagnosis (bliss, 2022)

Parkinson's disease is considered one of the most debilitating and wide-reaching neurological disorders (Gadhave et al., 2024), with its global impact expected to rise significantly in the coming decades. Epidemiological predictions estimate that by 2040, approximately 0.6% of the world's population will be affected (Dorsey et al., 2018). At present, around 3% of individuals aged 65 years and older already live with the condition, highlighting both its prevalence in aging populations and its growing relevance as life expectancy continues to increase (Gillies et al., 2014; Mhyre et al., 2012; *WHO Factsheet*, 2023).

The primary mechanism believed to underlie the pathogenesis of Parkinson's disease is the progressive degeneration of dopamine-producing neurons starting in the substantia nigra, a region of the midbrain crucial for motor control and reward processing, and over time impacting the whole brain (Boot et al., 2017; Cameron et al., 2010; Lauring et al., 2019; Sveinbjornsdottir, 2016). As these neurons die, dopamine levels in the brain decline, leading to an imbalance in the delicate neurochemical networks responsible for movement, cognition, and emotion (Khalil et al., 2019). This imbalance gives rise to a broad spectrum of symptoms and behavioural changes that remain only partially understood. Common manifestations include motor impairments such as tremors, rigidity, bradykinesia, and postural instability, alongside non-motor symptoms including depression, anxiety, cognitive decline, sleep disturbances, autonomic dysfunction, and profound alterations in motivation and personality (Chaudhuri et al., 2005, 2006; Lauring et al., 2019; Pelowski et al., 2022; Spee, Crone, et al., 2025; Sveinbjornsdottir, 2016).

The growing prevalence of Parkinson's disease, driven largely by the aging global population, has spurred intensive research into both therapeutic strategies and diagnostic innovations (Bloem et al., 2015). Current treatments primarily aim to manage symptoms (Fox et al., 2018; Sveinbjornsdottir, 2016), often through pharmacological approaches such as dopamine replacement therapy (Chaudhuri et al., 2006; Fox et al., 2018). Meanwhile, there is increasing recognition of the urgent need for earlier, cheaper, and more accessible diagnostic tools (Chaudhuri et al., 2006). Detecting the disease at its earliest stages could enable more effective interventions, potentially slowing disease progression and improving quality of life (R. Cools et al., 2007).

An intriguing yet understudied aspect that could benefit the detection of Parkinson's disease in patients are unexpected and sometimes considerable changes in artistic drive, creativity, and self-expression (Chatterjee et al., 2006; Kulisevsky et al., 2009; Lauring et al., 2019,

2019; Lhommée et al., 2014; Pelowski et al., 2022; Spee, Crone, et al., 2025). There is evidence that those changes affect up to 41 percent of the Parkinson patients population (Joutsa et al., 2012; Spee, Crone, et al., 2025). Patients may experience either a sudden increase or a significant decline in their motivation to create art, as well as noticeable transformations in their "artistic signature" (Pelowski et al., 2022). These shifts may illustrate how the disease affects not only movement and cognition, but also the subtler realms of personality, emotional life, and human creativity, underscoring the complex and multifaceted nature of Parkinson's disease. This research is especially important if cognitive changes and in particular art-related changes can already be observed and detected during the pre-diagnostic stage of the disease, which may occur 10–20 years before it is currently identified (Braak et al., 2003; Goetz et al., 2008; Lauring et al., 2019; Pelowski et al., 2022; Ramaker et al., 2002; Schrag et al., 2015; Sveinbjornsdottir, 2016; *WHO Factsheet*, 2023).

Art as a Golden Bullet

As mentioned, there is evidence by recent studies that creativity and other cognitive areas that influences artistic expression are among the areas affected by Parkinson's disease (Spee, Crone, et al., 2025). Within this framework, creativity specifically can be connected to dopaminergic differences through the dual pathway model (Baas et al., 2008; Boot et al., 2017). At the same time, artistic expression which is closely associated with creativity and is a fundamental element of producing art (Pelowski et al., 2019), can be understand through the lens of aesthetic theory (Chatterjee & Vartanian, 2014; Cropley & Cropley, 2011). Aesthetics unites the processes of dopaminergic changes during PD and producing art, serving as the cornerstone of this work. Using artistic expression to understand changes in Patients with PD seem therefore a logical step.

Since the turn of the century, there has been a renewed increase in empirical investigations examining artistic changes in Parkinson's disease (Pelowski et al., 2019). These reports have suggested recurring features, including shifts toward increased detail or repetition, alterations in compositional structure, changes in colour usage (Lauring et al., 2019; Lhommée et al., 2014; Pelowski et al., 2022), and in some cases heightened artistic productivity following dopaminergic treatment (Boot et al., 2017; C. I. Cools et al., 2020; Faust-Socher et al., 2014).

However, when examining papers regarding art-related changes in individuals with Parkinson's disease, a number of methodological limitations emerge. A primary issue is that many studies are based on very small sample sizes (Lauring et al., 2019; Lhommée et al., 2014) or anecdotal evidence (Chaudhuri et al., 2006), reducing the reliability and generalizability of their findings. It is evident that other research endeavours have placed significant reliance on subjective interpretations of artworks. While such approaches can generate meaningful insights, they tend to be time-intensive, resource-heavy, and challenging to replicate in larger or cross-study comparisons (Pelowski et al., 2019).

Additionally, the diversity of artistic media examined in this field ranging from but not exclusive writing, sculpting, casting and painting makes methodological comparison even more difficult (Lhommée et al., 2014). A further complicating factor in this field is the difficulty of conducting a comparison of data sets due to inconsistent methodologies applied after data collection (Redies et al., 2025).

The present thesis attempts to address some of the aforementioned limitations. This is achieved by synthesizing the approaches of Pelowski et al. (2019) and Redies et al. (2025) and by focusing on the objectively quantifiable properties of images, with the goal of establishing a standardized, cost-effective and efficient method for analysing artworks.

To achieve this goal, the present study narrows its focus specifically to drawings, both for practical and theoretical reasons. Drawings are relatively straightforward to operationalize, making them more suitable for systematic comparison. Moreover, this choice is informed by the precedent set by Pelowski et al. (2019), who elected to utilise drawings as their medium for examining artistic expression in Parkinson's disease due to a controllable paradigm, with specific outcome and time limit. Artistic changes in style, emotion, and personal expression encompass many facets, some of which can be rendered more visible through systematic extraction of quantifiable image properties from artworks (Aks & Sprott, 1996; Redies, 2008; Redies et al., 2025). An especially promising development is the use of directly quantifiable features of artworks as empirical evidence. Redies et al. (2025), introduced a toolbox designed to facilitate the efficient extraction of such properties, opening new possibilities for a more replicable analysis.

The analysis employs a machine-learning approach, specifically a Gradient Boosted Decision Tree, to evaluate whether a modern non-linear model can accurately distinguish patients with Parkinson's disease from unaffected individuals. Crucially, the thesis examines the stability of the results and assesses whether they are influenced by extraneous factors such as time cues or intervention group, using complementary linear modelling techniques.

The present work is based on data collected from two primary sources. The first source consists of data obtained from patients diagnosed with Parkinson's disease at the Radboud University Medical Center (Radboudumc) in Nijmegen, which generously provided access to their patient data for the purposes of this research. The second source of data consists of data gathered from healthy control participants, namely students from the University of Vienna, who participated in the study from Pelowski et al. (2019). This interdisciplinary team, composed of neuroscientists, medical doctors, and art therapists, was established with the support of the FWF – der Wissenschaftsfonds (Austrian Science Fund). Their research focuses on exploring the connection between Parkinson's disease and artistic expression. The project forms the broader scientific framework within which the present thesis is situated (Unlocking the Muse, 2025).

In essence, the objective of the present study is to ascertain whether a machine learning algorithm possesses the capability to reliably differentiate between the quantitative image

properties of artistic creations executed by individuals living with Parkinson's disease and those of non-affected individuals. Those differentiate capabilities will be examined to see if those effects are stable over time and different cues. Also, the potential effect of engagement with artistic activities on creative output will be a consideration in the study's design. This investigation constitutes a component of a more extensive research project encompassing the domain of art therapy. The potential effect of engagement with artistic activities on creative output will be a consideration in the study's design.

Ultimately, the present study aims to deepen the understanding of the relationship between creative expression, art, and PD, while also offering new insights into how machine learning tools can be used to evaluate the artistic engagement of Parkinson's patients and what broader implications this has.

1. Theoretical Background

A disturbance in the brain physiology due to its delicate and complex nature is one of the challenging problems researchers can solve about human health. Neurodegenerative diseases describe a cluster of ailments that are exactly that. Alzheimer's disease, Multiple sclerosis, Parkinson's disease, Amyotrophic lateral sclerosis and Huntington's disease make up the bulk of global prevalence in this group (Gadhave et al., 2024).

Alzheimer's might be the best known and is in fact the disease out of this cluster with the most affected individuals with 83.6% of the global prevalence in all major neurodegenerative diseases and 10 million deaths associated (Ding et al., 2022; Gadhave et al., 2024; Huang et al., 2023). Following that, Parkinson’s disease (PD) remains the second largest neurodegenerative ailment with an estimated share of 12.3% of the global prevalence of major neurodegenerative diseases (Gadhave et al., 2024). PD is also among the fastest growing neurological disorders, driven in part by population aging and increased life expectancy. Current estimates suggest that approximately 8.5 million people, or about 0.3% of the global population, are living with the disease with numbers expected to double by 2040 (Dorsey et al., 2018). This results in 6.2 million disability adjusted life years (DALYs) (Ding et al., 2022). DALYs reflect overall disease burden in terms of years of healthy life lost due to illness, disability, or premature death. Beyond its high prevalence and DALYs, PD is associated a significantly impairment of quality of life (QoL), placing an increasing burden on patients, caregivers, and healthcare systems worldwide (Ding et al., 2022; Gadhave et al., 2024; Gillies et al., 2014; *WHO Factsheet*, 2023).

1.1. Parkinson’s Disease

Despite this early clinical characterization (Parkinson, 2002), an effective treatment did not emerge until 75 years ago, with the introduction of the first L-dopa injections. Building on this groundbreaking work of Arvid Carlsson, Oleh Hornykiewicz, a Viennese pharmacologist,

demonstrated that the highly localized production of dopamine in specific brain regions was directly linked to parkinsonism. This discovery was pivotal in elucidating the complex yet crucial role of dopamine in the origin and progression of the disease. The first consistent clinical results of L-dopa therapy were later observed under the work of George C. Cotzias. These achievements laid the foundation for modern symptomatic treatment and inspired generations of researchers worldwide to continue investigating the underlying mechanisms and improved therapies for PD (Fahn, 2015).

1.1.1. Life with Parkinsons: Pathogenesis and Pathophysiology

PD is typically recognized only after motor symptoms, for example bradykinesia or tremor, becomes apparent (Hughes et al., 1992; Sveinbjornsdottir, 2016). The primary tool used for PD diagnosis is the Unified Parkinson's Disease Rating Scale (UPDRS), or with its revised version, the MDS-UPDRS (Goetz et al., 2003, 2008; Ramaker et al., 2002; Sveinbjornsdottir, 2016). This scale not only helps establish the presence of PD but also provides a standardized framework for categorizing disease severity. In combination with the Hoehn and Yahr scale (Hoehn & Yahr, 1967), it enables reliable classification of disease progression. Diagnosis requires exclusion of differential diagnoses such as repeated head trauma or a history of encephalitis (see Table 1; Hughes et al., 1992; Sveinbjornsdottir, 2016).

However, the neurodegenerative process often begins much earlier: pathological changes may be present ten, and in some cases even twenty, years before the first motor signs (Lauring et al., 2019; Pelowski et al., 2022; Sveinbjornsdottir, 2016; WHO Factsheet, 2023). Braak and colleagues support this view, arguing that pathology originating in the olfactory system and lower brainstem can be detectable during preclinical stages, they classify these early changes as Braak stage 1 (Braak et al., 2003; Braak & Tredici, 2010; Lauring et al., 2019). At 13 to 6 years before diagnosis a wide range of non-motor symptoms has been associated with the Braak stage 2 phase of PD, including neuropsychiatric symptoms (depression, anxiety), sleep disturbances, gastrointestinal problems (nausea, reflux), and sensory symptoms (for a more complete list see Table 2). These findings indicate that non-motor manifestations frequently affect individuals long before a formal diagnosis is made, supporting the hypothesis that behavioural and cognitive changes occur prior to clinical diagnosis (Chaudhuri et al., 2006).

These symptoms persist and continue to evolve with age. With 10 years or less until diagnosis usually the first tremors are usually detectable (Lauring et al., 2019; Schrag et al., 2015). With disease progression and the involvement of the substantia nigra and other midbrain nuclei (see Figure 1), the first clear clinical symptoms of PD emerge (Chaudhuri et al., 2006; Sveinbjornsdottir, 2016). This is the time usually the disease gets diagnosed (Braak stage 3; Hoehn and Yahr (HY) stage 1). The median age of diagnosis is 60 years, and at this time, further cognitive changes due to impairment of dopaminergic pathways also become apparent (Lee & Gilbert, 2016).

The post diagnostic disease starts to affect areas linked to the dopaminergic pathways and especially the ventral substantia nigra pars compacta (vSNc) where synthesizing of Dopamine takes place. The main symptoms of diagnosed PD, which stem from the lack of dopamine in the brain, are tremors, bradykinesia, rigidity, and postural instability (Lauring et al., 2019; Pelowski et al., 2022). The most characteristic feature bradykinesia is described as a slowness in initiating voluntary movement, accompanied by a progressive reduction in the speed and amplitude of repetitive actions. It is typically the key criterion for clinical diagnosis (Hughes et al., 1992). The late motor symptoms are due to the ability of the brain to substitute a loss of up to 80% of the dopaminergic neurons in the substantia nigra leading to patients only showing symptoms in the case of severe and irreversible loss of neurons in the dopaminergic system (Chung et al., 2001; Lauring et al., 2019; Sveinbjornsdottir, 2016).

Between approximately four and nine years after the initial diagnosis, which corresponds to Braak stage 4 and Hoehn and Yahr stage 2, the disease typically shows a notable progression. During this phase, it begins to extend beyond its early motor symptoms and increasingly affects a wide range of functional domains, including cognitive abilities, emotional regulation, autonomic control, somatomotor coordination, and even oculomotor performance (Schrag et al., 2015).

As the condition advances into Braak stage 5 or HY stage 3–4, generally occurring around 10 to 16 years after diagnosis, the impairments become more severe and life-altering. Patients at this stage frequently develop significant difficulties with balance, which contributes to instability and increases the risk of falls. In addition, vital autonomic processes such as heart rate regulation, blood pressure control, and respiratory function begin to deteriorate. From about 17 years after the initial diagnosis severe complications such as immobilization, repeated falls, gait freezing, choking episodes, and the appearance of hallucinations are common (Braak et al., 2003; Lauring et al., 2019; Schrag et al., 2015). Around this same time, dementia is usually diagnosed, reflecting the extensive involvement of higher brain regions and the marked deterioration of cognitive capacities. The median survival time following a dementia diagnosis is 4.5 years (Lauring et al., 2019; Lim et al., 2009).

Table 1
UK Parkinson's Disease Society Brain Bank clinical diagnostic criteria

Step	Diagnostic category	Criteria
1	Diagnosis of parkinsonian syndrome	Mandatory criterion: Bradykinesia (slowness of initiation of voluntary movement with progressive reduction in speed and amplitude of repetitive actions). At least one of the following must be present: muscular rigidity; 4–6 Hz rest tremor; postural instability not caused by primary visual, vestibular, cerebellar, or proprioceptive dysfunction.
2	Exclusion criteria for Parkinson's disease	History of repeated strokes with stepwise progression of parkinsonian features; history of repeated head injury; history of definite encephalitis; oculogyric crises; neuroleptic treatment at onset of symptoms; more than one affected relative; sustained remission; strictly unilateral features after three years; supranuclear gaze palsy; cerebellar signs; early severe autonomic involvement; early severe dementia with disturbances of memory, language, and praxis; Babinski sign; presence of cerebral tumour or communicating hydrocephalus on CT scan; negative response to large doses of levodopa (if malabsorption is excluded); MPTP exposure.
3	Supportive prospective positive criteria for Parkinson's disease (Three or more required for diagnosis of definite Parkinson's disease)	unilateral onset; rest tremor present; progressive disorder; persistent asymmetry affecting the side of onset most; excellent response (70–100%) to levodopa; severe levodopa-induced chorea; levodopa response for five years or more; clinical course of ten years or more.

Note. Diagnostic criteria are presented according to a three-step framework including mandatory features, exclusion criteria, and supportive prospective features. CT = computed tomography; MPTP = 1-methyl-4-phenyl-1,2,3,6-tetrahydropyridine. Source*:* Hughes et al. (1992).

1.1.2. Treatment

Although Levodopa, also known as L-dopa the precursor of Dopamine, has long been considered the "gold standard" for treating PD due to the early recognition and its ability to cross the blood-brain barrier (Gadhave et al., 2024; Nagatsu & Sawada, 2009), it has been gradually supplemented or replaced in recent years by new treatment options (Lane, 2019). One such addition to the treatment arsenal is the use of dopamine agonists (DA), which offsets the diminished Dopamine production by directly stimulating the dopamine receptors in neurons (Jankovic & Stacy, 2007). DA work either as a standalone therapy or in combination with Levodopa. This shift comes as a response to drawbacks associated with long-term Levodopa use, such as Levodopa-induced dyskinesia (LID) (Jankovic & Stacy, 2007; Lane, 2019; Nagatsu & Sawada, 2009). Further treatment options are for example with MAO-B Inhibitors or Adenosine antagonists (Fox et al., 2018; Jankovic & Stacy, 2007).

The primary focus of treatment can be divided into the management and stabilisation of motor symptoms and dyskinesia, as well as the prevention or delay of disease progression (Fox et

al., 2018). Although Parkinson's disease is associated with a wide range of non-motor symptoms, these are frequently under-recognised and undertreated. This phenomenon, Chaudhuri et al. (2005, 2006) argue constitutes a major contributor to mortality among patients with PD. Despite ongoing therapeutic advances and active research efforts, no curative treatment has yet been identified.

1.1.3. Associated Diseases and non-Motor Effects

Due to ongoing research, there is no definitive evidence as to whether associated symptoms are intrinsic features of PD or co-occurring conditions. Nevertheless, Chaudhuri et al. (2005) made a significant contribution by proposing a classification of the complex spectrum of non-motor symptoms related to PD (Table 2). These diverse symptoms have been shown to exert a substantial impact on the QoL of individuals with PD (Grandas & Iranzo, 2004; Slaughter et al., 2001). Beyond the economic burden, the effects of PD on mood, emotional functioning, and cognition have been consistently linked to the disease. Examples include mood swings, dementia, reduced capacity to process emotional information, language impairments, and apathy, all of which illustrate the broad neuropsychiatric impact of PD (Chatterjee et al., 2006; Chaudhuri et al., 2005, 2006; C. I. Cools et al., 2020; Drijgers et al., 2012; Faust-Socher et al., 2014; Inzelberg, 2013; Lauring et al., 2019). Furthermore, evidence indicates that some patients with PD treated with DA may develop dysfunctional obsessive–compulsive behaviours, such as pathological gambling (Chatterjee et al., 2006; Dodd et al., 2005). As discussed later (Chapter 1.4) some of these symptoms might be crucial for artistic expression and therefore shared denominators between changes in PD and artistic expression.

Table 2
Non-motor and neuropsychiatric symptoms associated with Parkinson's disease

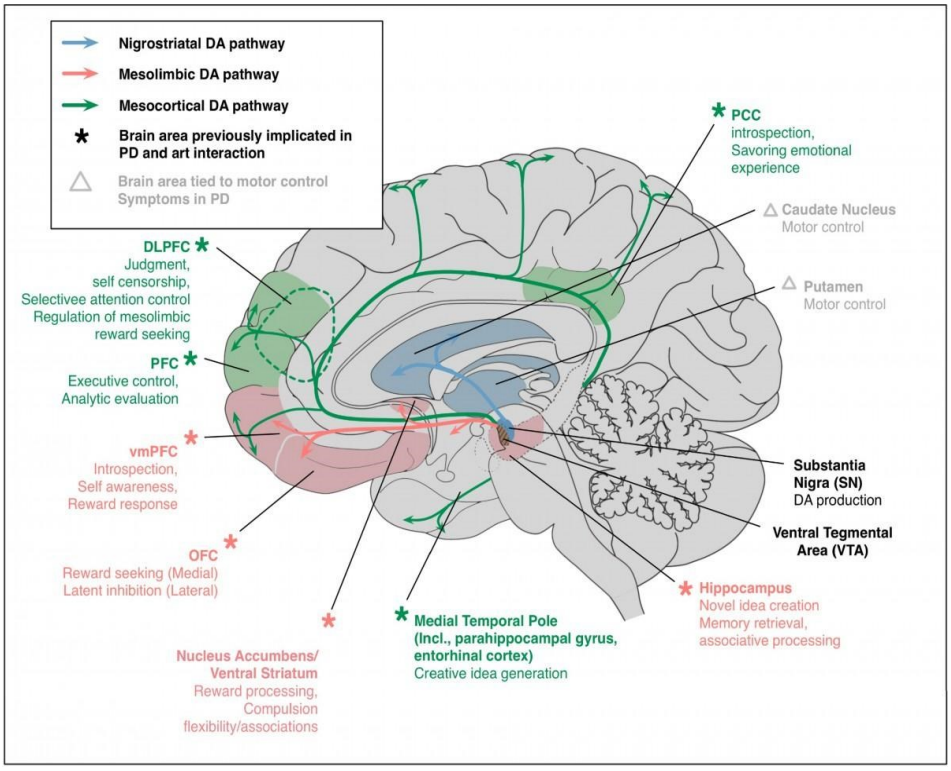
Neuropsychiatric symptoms	Sleep disorders	Autonomic symptoms	Gastrointestinal symptoms	Sensory symptoms	Other symptoms
Anhedonia	Excessive daytime somnolence	Bladder disturbances	Ageusia	Olfactory disturbance	Blurred vision
Anxiety	Insomnia	Coat-hanger pain	Choking	Pain	Diplopia
Apathy	Non-REM sleep-related movement disorders	Dry eyes	Constipation	Paraesthesia	Fatigue
Attention deficit	Periodic limb movements	Erectile impotence	Dribbling of saliva		Seborrhoea
Confusion	REM sleep behaviour disorder	Falls related to orthostatic hypotension	Dysphagia		Weight gain
Delirium (DI*)	REM sleep without atonia	Frequency	Faecal incontinence		Weight loss
Delusions	Restless legs	Hypersexuality	Nausea		
Dementia	Sleep-disordered breathing	Nocturia	Reflux		
Hallucinations (DI*)	Vivid dreaming	Orthostatic hypotension	Unsatisfactory bowel emptying		
Illusions		Sexual dysfunction	Vomiting		
Obsessional behaviour (DI*)		Sweating			
Panic attacks		Urgency			
Repetitive behaviour		Xerostomia			

Note. DI* = symptoms that may be drug induced Source: Chaudhuri et al. (2006)

1.2. Neurotransmitters

Dopamine neurotransmission plays a central role in the execution of various cognitive functions. Processes such as reward, addiction, attention, and compulsions are all at least partially regulated by dopamine (Khalil et al., 2019). The majority of dopamine is synthesized in the brainstem specifically in the ventral substantia nigra pars compacta (vSNc) and subcortical ventral tegmental area (VTA) (Boot et al., 2017; Lauring et al., 2019; Pelowski et al., 2022). Dopamine affects nearly every region of the brain through distinct neural pathways, which themselves regulate activity via reciprocal connections and inhibitory autoreceptors (Alexander et al., 1986; Boot et al., 2017; Khalil et al., 2019). As shown in Figure 1**,** these pathways can be classified into the mesocortical, nigrostratial, and mesolimbic pathway (Lauring et al., 2019). The pathways, in combination with the various dopaminergic receptors, enable precise and regulated delivery of dopamine to different brain regions. Given the widespread influence of dopamine in the brain, this thesis provides only a brief introduction to the implications most relevant to PD.

Figure 1
Sche*matic overview of the Dopaminergic Pathways*



Note. Lauring et al. (2019)

1.2.1. Dopaminergic Pathways

The mesocortical pathway, for example, targets the prefrontal cortex (PFC), where it influences working memory and supports sustained attention. Dopamine in the PFC is therefore essential for cognitive control and managing distractibility (Boot et al., 2017; Flaherty, 2005).

The nigrostriatal pathway plays a central role in controlling dopamine activity in the basal ganglia, particularly in the dorsal striatum. The basal ganglia comprise a network of subcortical nuclei including the striatum (caudate nucleus and putamen), substantia nigra, and subthalamic nucleus. This network is essential for action selection, habit learning, and the regulation of motor and premotor functions. Dopamine transfer within this system is crucial for mechanisms such as shifting attention and integrating new information (Boot et al., 2017; Grahn et al., 2008; Lauring et al., 2019).

Using spontaneous eye-blink rates, mesolimbic dopamine has been associated with motivation, reward prediction (Boot et al., 2017) and creative drive in humans (Flaherty, 2005) as novelty-seeking behaviour in animals (Khalil et al., 2019).

As mentioned, the specificity and function of dopamine are strongly influenced by the type of receptors present in the brain. Boot et al. (2017) describe a trade-off between cognitive flexibility and persistence. Higher dopamine levels in the PFC are typically associated with lower dopaminergic activity in the striatum (Cools et al., 2007; Lhommée et al., 2014; Nijstad et al.,

2010). This antagonistic balance is partly shaped by the distribution of dopamine receptor subtypes. D1-type receptors, which are the most abundant in the PFC, are linked to cognitive persistence, whereas D2-type receptors, which occur at levels up to eleven times higher in the striatum compared to the PFC, are associated with cognitive flexibility (Boot et al., 2017; Camps et al., 1989; Lhommée et al., 2014). The broader implications of this trade-off will be addressed later in the discussion of the dual pathway model.

While dopamine is the neurotransmitter system most affected by PD, other neurotransmitter systems in conjunction or by direct influence from dopamine are also believed to be impacted by the disease (Chaudhuri et al., 2006).

For example, sleep may be affected by abnormalities in the sleep–wake cycle pathway that regulates thalamocortical arousal, involving brainstem nuclei such as the raphe nucleus (serotonin), locus coeruleus (norepinephrine), and pedunculopontine nucleus. Additionally, these regions are implicated in the development of visual hallucinations and rapid eye movement (REM) sleep behaviour disorder in PD (Chatterjee et al., 2006; Chaudhuri et al., 2005, 2006).

To summarize, dopamine, through its various pathways and receptors, influences motor and premotor functions (Boot et al., 2017; Grahn et al., 2008; Lauring et al., 2019); cognition, including cognitive control, flexibility, persistence, and attention; the management of distractibility (Boot et al., 2017; Flaherty, 2005); motivation and reward prediction (Boot et al., 2017); action selection and habit learning; creative drive (Flaherty, 2005); and novelty-seeking behaviour (Khalil et al., 2019). These functions are all directly or indirectly linked to creative output. As the primary neurological feature of PD is dopamine loss, alterations in these systems and pathways can lead to profound changes in human cognition and subjective experience for example change in art style.

1.2.2. Parkinson's Disease Medication

While there seems to be a direct influence of PD through dopamine on creativity and therefore art style another strong influence modulating this connection is Parkinson medication (Boot et al., 2017; R. Cools et al., 2001; Drijgers et al., 2012; Faust-Socher et al., 2014; Inzelberg, 2013)

The destruction of dopamine producing cells during PD is a slow process (Hughes et al., 1992; Sveinbjornsdottir, 2016). The function of dopamine agonists and Levodopa is to stabilize dopamine activity in the brain by binding to and stimulating dopamine receptors, primarily those on postsynaptic neurons, to compensate for diminished natural dopamine production and activity (R. Cools et al., 2001; Jankovic & Stacy, 2007). A recent review by Lauring et al. (2019) suggests, that specifically DA, play a key role in creativity-related changes in PD, based on case literature and general discussion on creativity and dopamine processes (e.g. Boot et al., 2017; Cools et al., 2007).

This theory rests on the finding that the mesolimbic pathway, also called the reward pathway, is typically left largely intact at the beginning of a PD diagnosis and therefore a DA

therapy (R. Cools et al., 2001; Lauring et al., 2019), when there is already noticeable damage to the nigrostriatal pathway (most notably to the putamen and dorsal caudate nucleus). Dopamine receptivity is then not only increased in the earlier degenerated areas of the nigrostriatal pathway but also in regions of the mesolimbic pathway. This means, that while dopamine function is sufficiently restored in affected areas, it can become excessive in the less affected mesolimbic pathway leading to the aforementioned creativity changes (Lauring et al., 2019).

1.3. Conceptual Foundations of Creativity in Artistic Expression

Creativity one of the key aspects of artistic expression and itself is a concept that intrigues researchers since the beginning of science history (Simonton, 1997). Creativity plays a huge role in problem solving (Mumford & Gustafson, 1988) but encompasses more than that. The capacity to adapt creatively has been instrumental in enabling humanity to gain advantages in every era of its existence, representing a fundamental driving force behind human development (Runco, 2004). Creativity is described as the production of original or novel but at the same time useful outcomes (Lhommée et al., 2014; Runco & Jaeger, 2012; Sternberg, 1998). It is operationalized through different outputs. Measurements include fluency, originality and flexibility (De Dreu et al., 2008).

The mechanism of creative expression like creating art is a complex interaction of different cognitive processes (divert thinking and accessing remote associations) (Baas et al., 2008, 2016), exogenous factors (extrinsic rewards and time pressure) (Boot et al., 2017; Sternberg, 1998) and characteristics of the person itself (e.g.: intelligence, openness to experience and vulnerability to psychopathology) (Boot et al., 2017; Runco, 2004; Sternberg, 1998).

In literature (Boot et al., 2017; Gardner, 1993; Kaufman & Beghetto, 2009; Nijstad et al., 2010; Runco & Jaeger, 2012), creativity is often divided into two distinctive categories. The ‘big C’ refers to groundbreaking contributions made by exceptional individuals such as philosophers, (e.g. Hypatia of Alexandria and Simone de Beauvoir) scientists (e.g. Marie Curie and Rosalind Franklin), and artists (e.g. Frida Kahlo and Artemisia Gentileschi).

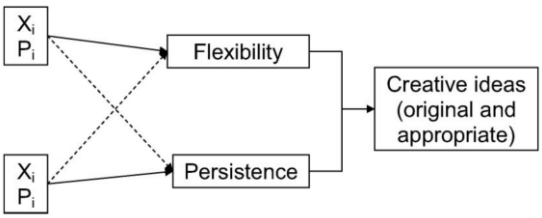
In comparison ‘little c’ creativity describes the day-to-day achievements like combining food ideas, adapt to changing life circumstances or create new opportunities. This reveals that creativity while still a broad concept still has use as categorizable and measurable instrument in human cognition.

1.3.1. The Dual Process and Dual Pathway Model

Creativity has been strongly associated with Dopamine (Baas et al., 2008; Boot et al., 2017; Faust-Socher et al., 2014; Khalil et al., 2019; Lhommée et al., 2014; Nijstad et al., 2010). One of the first attempts that connects ‘small c’ creativity with dopamine has been first proposed by Baas et al. (2008). They link the motivational system of approach and avoidance to creativity through psychopathologies that have a disturbance in dopamine levels.

The ‘dual-process’ model by Nijstad et al. (2010), which was developed on the basis of the research findings of Bass et al. (2008) adds the dimensions of cognitive flexibility and rigidity. It posit that creativity requires sufficient flexibility in the thought process to enable divergent thinking and associations, on the one hand, and sufficient stability to implement these new associations, on the other (Baas et al., 2008; De Dreu et al., 2008).

Figure 2
The “dual process” to creativity model



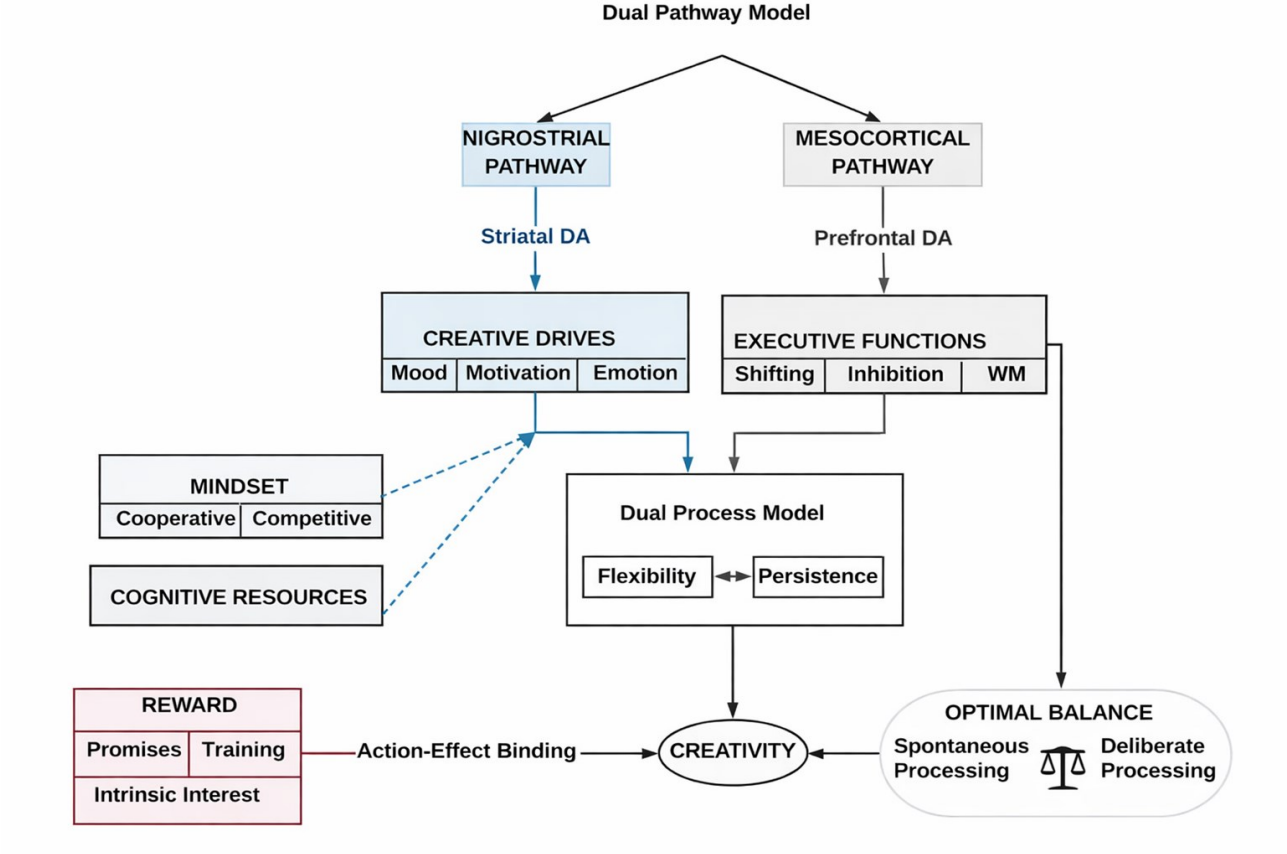
Note. Nijstad et al. (2010)

Boot et al., (2017) linked the “dual process” model in the similar named “dual pathway” model with the underlying interplay between the nigrostratial and mesocortical dopaminergic pathway. As mentioned above the nigrostratial pathway is the primary neuronal structure for mood, motivation and emotions and besides mindset and cognitive resources (see Figure 1) the main reason for flexibility in the “dual process” model (Cassotti et al., 2016; Khalil et al., 2019). Similarly, the mesocortical pathway has a crucial role in the regulation of the executive functions of the PFC like shifting focus, inhibition of new thoughts and working memory (WM). They are in turn key parts in the persistence part of the “dual process” model. Boot et al., (2017) argue that not the excess (or lack) of Dopamine is crucial but rather the right quantity is paramount for creative outcomes.

Both the “dual process” model and the “dual pathway” model are strongly influenced by mood and motivation (Khalil et al., 2019). Relating to works of earlier “dual system” models (De Neys et al., 2013; Houdé, 1997; Kahneman, 2011) Cassotti et al., (2016) explained that for ideal conditions of creativity in the “dual process” model System 1 (flexibility) and System 2 (persistence) have to work together to create the most optimal solution by optimally disregarding spontaneous, fast but ultimately wrong ideas while at the same time not fixating on typical but non ideal solutions.

So, as Boot et al., (2017) concludes the “dual process” model which is guided by the “dual pathway” model has to have the optimal amount of dopamine to achieve optimal creative output. Important to notice here is that every person has a different baseline and threshold of dopamine in their system so the optimal amount of dopamine is highly subjective (Boot et al., 2017; Khalil et al., 2019). Essentially, the models posit that an adequate level of dopamine is required for the generation of creative outputs, which, as will be elaborated later, play a key role in artistic change.

Figure 3
The "dual pathway" Model



Note. Adapted from Boot et al. (2017)

1.4. Parkinson's Disease and Changes in Creativity

Based on this knowledge, it is hardly surprising that it had been shown that influences such as the dopaminergic loss during a progressing PD can lead to creative outbursts, a creative loss or a general change towards creative behaviour and creative output (Pelowski et al., 2022; Spee, Crone, et al., 2025). For example, Spee et al. (2025) analysed cross-sectional survey data from a large Dutch cohort of people with Parkinson's disease (N = 793) and found that 41% reported changes in creativity after diagnosis, with 12% reporting an increase, 22% a decrease, and 7% fluctuations. Longer disease duration and use of dopamine agonists were significantly associated with increased creativity, whereas older age and higher levels of creative engagement before diagnosis were associated with a greater likelihood of decreased creativity. Changes were most commonly reported in everyday 'small c' creativity, sports/movement, and fine art/design domains.

These findings highlight that Parkinson's disease does not affect creativity uniformly but instead produces individually variable changes. This variability raises important questions about how such alterations manifest specifically in artistic production.

1.4.1. Parkinson's Disease and Artistic Production

One way to better understand these reported shifts in artistic creativity, is to examine artistic production more closely and consider the cognitive and neural mechanisms that underlie it. When examining art, and artistic production in particular, a complex interplay of multiple cognitive, perceptual, and neural systems becomes evident (Pelowski et al., 2019). Although this procedure of artistic creation especially in drawing has been the focus of numerous scientific investigations (Anastasi & Schaefer, 1971; Cavanagh, 2005; Pelowski et al., 2017; Zaidel et al., 2013), the underlying processes remain only partially understood. Nevertheless, several theoretical and empirical attempts have been made to address this knowledge gap. For example a few of the main drivers of art production that could be recognized are artistic creativity, motivation and ability (Lauring et al., 2019; Pelowski et al., 2019). While these mechanisms are still complex systems themselves, Lauring et al. (2019) postulates that they are heavily linked to the dopaminergic system. While research on drivers of art production is heavily grounded in case studies of paintings, there are documented examples of various artistic creations that demonstrate a similar correlation (see (Lhommée et al., 2014).

Although the direction and precise nature of creativity changes in individuals with PD still have to be determined (Spee, Crone, et al., 2025) the PD patients who get influenced a significant change in art style could be seen. Pelowski et al. (2022) describe these as "artistic signatures" that appear in connection with PD. This phenomenon is hypothesized to result from changes in the brain's neural structure, particularly in dopaminergic systems affected by the disease and its treatment. These changes, although diverse, can be observed in various aspects of creative expression, including style, technique, and even in the choice of art form. As such, they provide a potential entry point for systematically investigating PD-related neural and behavioural interactions (Pelowski et al., 2019, 2022; Spee, Stap, et al., 2025).

For example, a noticeable area of change is the engagement with Art. Some people with PD even appear to develop addictive-like behaviour, forgoing sleep and food in order to devote themselves to their art or, as in a particular case study, to embellish walls, tables, and the washing machine (Lhommée et al., 2014). Particularly striking is the fact that such changes occur not only in artists with PD, but also in individuals who were previously far removed from art and who suddenly display newly discovered artistic interests (Inzelberg, 2013; Lauring et al., 2019; Pelowski et al., 2022).

Artistic changes in PD may be traced to dopaminergic depletion by considering creativity as pre-diagnostic and earliest domains affected by neuronal alterations. In this view, creativity functions as a conceptual link between dopaminergic dysfunction and the observable modifications in artistic style associated with PD (Chaudhuri et al., 2006). However, creativity should be understood as a theoretical intermediary rather than a direct explanatory mechanism, linking dopaminergic dysfunction to the measurable transformations in artistic production observed in PD.

1.5. How to Measure Change

Starting with the question: How to collect art pieces that could detect such artistic changes in PD patients, Pelowski et al. (2019) developed a study setup which tries to encompass the challenges associated with reliable art production. In their review, they argue that prior research has focused predominantly on realistic copying rather than on the creation of actual artworks, thereby limiting conclusions about artistic ability. To overcome this, they introduced a cued-drawing task in which participants were instructed to “make a work of art” using predefined visual stimuli, enabling the assessment of artistic quality, creativity, realism, and liking**.** Building on this framework may represent an initial step toward establishing a standardized yet ecologically valid approach for systematically comparing art pieces.

One way to quantify those creative expression in art pieces is through aesthetics. (Cropley & Cropley, 2011; Wassiliwizky & Menninghaus, 2021). Because aesthetics emerges from creative engagement, it can serve as a valuable tool for measuring. While aesthetics is subjective and relative, it has a close relationship with creativity. As Cropley and Cropley (2011, P. 24) put it:

“There is a considerable overlap between aesthetics and creativity. Indeed, in everyday discussions creativity is often treated as almost synonymous with beauty, and thus aesthetics, although scholarly definitions give more emphasis to novelty and effectiveness.”

The “aesthetic triad” describes a concept in psychology that tries to encompass the aesthetic experience, which arises when engagement with art happens (Chatterjee & Vartanian, 2014). Knowledge-meaning, emotion-valuation and sensory-motor make up the three main drivers for said aesthetic experience. This concept helped to shape the neuroaesthetic field and therefore is a major framework when researching art making in psychology. Identifying visual properties is a key factor in understanding aesthetic experience through the sensory-motor neuronal system. While this process is heavily reliant on individual perception and thus inherently subjective, quantitative image properties (QIPs) might provide a more objective perspective on the subject of aesthetics (Redies et al., 2025).

1.6. Quantifiable Image Properties

As mentioned, artistic expression encompasses a wide range of forms, including but not exclusively paintings, dance, architectural works, sculptures, and films (Christensen & Calvo-Merino, 2013; Joye, 2007; Pelowski et al., 2022; Redies et al., 2025; Vukadinović & Marković, 2012). Additionally, artistic expression involves diverse changes in style, emotional content, and individual interpretation, which manifest across multiple dimensions and aspects. In this context, QIPs offers a means to analyse aesthetics through objective, quantifiable features, complementing the inherently subjective nature of human aesthetic experience.

When it comes to analysing QIPs, research on three-dimensional and dynamic stimuli like videos remains limited, making it difficult to perform direct comparisons or classifications within

those studies (Redies et al., 2025; Vukadinović & Marković, 2012). Consequently, paintings are often the preferred medium for investigation. This preference is primarily because paintings allow for the systematic and straightforward extraction of QIPs, offering a more accessible and analysable foundation for research (Aks & Sprott, 1996; Redies, 2008; Redies et al., 2025).

1.7. Aesthetics Toolbox

Multiple strategies to obtain QIPs have been explored, but an especially promising development is the work of Redies et al. (2025). They recently introduced a toolbox designed to facilitate the efficient extraction of such properties, opening new possibilities for a more straight forward and replicable analysis.

While the process of extracting image properties is commonplace with computer technology today most researchers are using or have been using different approaches and software to analyse their respective visual art (Redies et al., 2025). Redies et al., (2025) created one of the first open-source toolboxes, to achieve a more standardized and reliable process (but also see: Mayer & Landwehr, 2018; Walther et al., 2023). They compiled an easily accessible way to extract QIPs for 2D drawings, by focusing on the most prevalent features in experimental aesthetics.

Table 2
Overview of Quantitative Image Properties used

Domain	Quantitative image properties
Image dimensions	Image size; aspect ratio
Contrast & complexity	RMS contrast; lightness entropy; HOG-based complexity; edge density
Colour	Channel means; channel variability; colour entropy
Balance & symmetry	Balance (APB); center-of-mass deviation (DCM); mirror symmetry; CNN-based symmetry
Scale invariance	Fourier slope; Fourier sigma; 2D and 3D fractal dimension
Self-similarity	PHOG self-similarity; CNN self-similarity
Distribution & entropy	Homogeneity; anisotropy; edge-orientation entropy
Sparseness & variability	CNN feature variance

Note. QIPs quantify low- and mid-level visual characteristics of images across spatial, chromatic, and structural domains. Detailed definitions and computational procedures are provided in Table 3. RMS = root mean square; HOG = histogram of oriented gradients; PHOG = pyramid histogram of oriented gradients; CNN = convolutional neural network.

1.7.1. Benefits of QIPs

The Aesthetics Toolbox includes 24 QIPs (see Table 2) that capture a wide range of visual characteristics. Human aesthetic judgment is widely assumed to rely on low- and mid-level visual features, which can be operationalized using the QIPs provided by the Aesthetics Toolbox (Datta et al., 2006; Farzanfar & Walther, 2023; Graham & Redies, 2010; Redies, 2015). In line with this view, previous research has shown that subjective aesthetic judgments can be partially predicted from quantitative image properties. This relationship has been demonstrated for judgments such as liking, interest, and beauty, including in the domain of artworks (Leder et al., 2004; Taylor et al., 2011).

Although aesthetics can be assessed using subjective methods, such as standardized rating tasks with human observers (Drago et al., 2006, 2009), these methods as discussed above seem to be unreliable and resource intense. Here the value of QIPs lies in their ability to provide a systematic and objective analysis of visual stimuli, thereby complementing the inherently subjective nature of aesthetic perception. Because QIPs are mathematically defined and computationally extracted, analyses can be reproduced across studies and datasets using identical procedures. By translating visual characteristics such as colour distribution, contrast, spatial structure, and complexity into measurable features, QIPs offer a common framework for comparing images across different artworks, styles, cultural contexts, and experimental conditions. This standardization is particularly important in interdisciplinary research, where comparability across diverse methodological traditions is essential (Redies et al., 2025).

A further advantage of QIPs is their suitability for statistical modelling and machine learning approaches. Quantitative features can be directly integrated into predictive models or, as in the present study, computed in advance and used as model inputs.

Overall, QIPs provide a robust analytical foundation for the study of visual aesthetics by increasing objectivity, enabling reproducibility, and supporting advanced data-driven analyses. While it is still a new tool it could prove valuable for comparativeness in this thesis and thus is part of it.

1.8. Machine Learning

While linear models have historically provided a strong framework for capturing psychological and medical information, recent advances have led to an increased use of complex machine learning models to detect non-linear interrelations relevant to prediction. This methodological evolution, becoming progressively more sophisticated and widely applied, offers a valuable pathway for new discoveries (Dwyer et al., 2018; Qiu et al., 2022).

1.8.1. Gradient Boosted Decision Trees

Machine learning encompasses a broad range of computational methods aimed at learning patterns and generating predictions from empirical data. Deep learning, for example, has had a

substantial impact on the training of image, language, and even audio datasets (Grinsztajn et al., 2022). However, as noted by Grinsztajn et al. (2022), decision tree models continue to represent the primary methodological choice for many researchers. They emphasize that datasets characterized by small sample sizes, extreme values, or heterogeneous features are still most effectively handled using decision tree–based approaches. Consequently, decision tree classifiers are widely regarded as one of the most well-established and prominent methods for data classification and the representation of classifiers (Charbuty & Abdulazeez, 2021).

A typical analytical approach generally involves three main steps: training prediction models, testing their generalizability, and analysing the resulting models.

One decision tree–based method that is characterized by particularly high accuracy and computational efficiency is the Gradient Boosted Decision Tree (GBDT) model (Zeggio et al., 2025). One of its primary advantages lies in its ability to capture not only nonlinear associations but also interactions between variables, which makes it an especially suitable choice for prediction model training in the context of QIPs. Another important advantage is its robustness to multicollinearity and the presence of outliers within the data (Zeggio et al., 2025).

To prevent overfitting and thereby ensure the ability of a model to generalize beyond the training data, nested cross-validation is commonly employed as an evaluation strategy (Cawley & Talbot, 2010; Zeggio et al., 2025).

Following these three steps, the GBDT model can be used to predict the classification of pictures between groups and to evaluate the model's ability to generalize beyond the training data.

1.8.2. SHapley Additive exPlanations

SHapley Additive exPlanations (SHAP) is a model-agnostic approach used to evaluate the contribution of individual predictors to a model's predictions. The model-agnostic nature of SHAP implies that it does not require knowledge of the internal structure or parameters of the model being evaluated (Molnar et al., 2020). SHAP is an interpretable machine learning method grounded in cooperative game theory, in which feature contributions are quantified using Shapley values. A key advantage of SHAP lies in its ability to provide a detailed and consistent assessment of the relative importance and direction of predictor effects in regression tasks (Lundberg & Lee, 2017; Zeggio et al., 2025).

In conjunction with the predictive performance of the GBDT model, SHAP enables a detailed characterization of predictive QIPs, thereby facilitating feature selection and reducing the amount of data required to distinguish between PD patients and healthy controls (HC).

Overall, the combination of Gradient Boosted Decision Tree models and SHAP demonstrates how machine learning can support the differentiation and classification between pictures while retaining interpretability of the underlying QIPs.

1.9. ANOVA and Reliability

Although machine learning models provide powerful tools for prediction and the detection of complex, non-linear relationships (Grinsztajn et al., 2022), they do not replace traditional inferential statistics. Predictive accuracy does not automatically imply statistical reliability. Therefore, complementary statistical analyses like Analysis of Variance (ANOVA) are used to validate whether identified differences are robust and systematically present across groups (Thakur et al., 2022).

This provides an important benchmark for evaluating whether model-identified features reflect stable population differences rather than sample-specific patterns. Establishing reliability is essential to ensure that findings are reproducible and not driven by measurement error. Together, ANOVA and reliability testing serve as validation steps, strengthening the interpretability and robustness of the machine learning results.

1.10. Synapsis

In essence, dopamine plays a central role in cognition, motivation, and creative behaviour, all of which are affected by PD (Boot et al., 2017; Flaherty, 2005; Khalil et al., 2019). As PD is fundamentally characterized by dopamine loss, early dopaminergic imbalance particularly between the nigrostriatal and mesolimbic pathways may therefore influence perception and creative expression before classical motor symptoms dominate (R. Cools et al., 2001; Lauring et al., 2019). One of the theories like the dual pathway and dual process models suggest that optimal cognitive and creative functioning, which are fundamental for artistic expression, depends on a balanced dopaminergic system, yet this balance is vulnerable to disruption in PD (Boot et al., 2017; Khalil et al., 2019).

While the direction of creativity-related changes in PD is not yet fully understood, some patients show pronounced alterations in artistic expression, described as distinct “artistic signatures,” likely reflecting dopaminergic and treatment-related neural changes (Pelowski et al., 2019, 2022, 2024; Spee, Crone, et al., 2025).

In this context, the aesthetic triad provides a useful framework for artistic changes by understanding how sensory-motor, emotional, and meaning-related processes contribute to creative creation and therefore artistic signatures (Chatterjee & Vartanian, 2014). While aesthetic responses to art are inherently subjective, QIPs provide an objective and reproducible way to characterize aesthetic features that may reflect disease-related changes (Redies et al., 2025).

Machine learning approaches offer promising means of integrating QIPs to identify subtle and non-linear patterns that may not be detectable using traditional analytical methods (Lundberg & Lee, 2017; Zeggio et al., 2025). Together, these theoretical models and computational tools point toward the potential of streamlined, data-driven diagnostic approaches, addressing the growing need for earlier detection of PD and improved QoL for patients (Chaudhuri et al., 2006; R. Cools et

al., 2007). Complementary analyses using linear models such as ANOVA could provide an additional statistical validation and strengthen the robustness of machine learning results.

1.11. Research Questions and Hypotheses

In line with current research, the present study examines whether QIPs extracted from drawings can be used to distinguish between individuals with PD and HC using machine learning techniques and if this is influenced by passing of time. In addition, conventional inferential statistics are employed to characterize systematic effects of group membership, engagement in an art-based intervention, time, and task cue on these image properties. Machine learning constitutes the primary approach for classification, whereas linear modelling serves to validate and contextualize the underlying classification performance.

1.11.1. Research Question 1

How do group membership **(H1a)**, engagement in an art-based intervention **(H1b)**, time **(H1c)**, and drawing cue **(H1a)** influence quantitative image properties of drawings?

H1a – Group x Cue:

At the pre-intervention, quantitative characteristics of drawings differ between individuals with Parkinson's disease and healthy controls, and this difference depends on the drawing cue used.

H1b – Intervention:

Within the PD group, quantitative image properties differ as a function of engagement in the art-based intervention and time, with differential changes between intervention and non-intervention subgroups.

H1c – Temporal Aspects:

Within the PD non-intervention group, quantitative image properties differ across pre-intervention, post-intervention, and follow-up assessments.

1.11.2. Research Question 2

Can a machine learning algorithm distinguish between drawings produced by individuals with Parkinson's disease and healthy controls based on quantitative image properties and is this classification reliable over time?

H1:

A machine learning algorithm will classify drawings from PD patients and healthy controls with accuracy exceeding chance level based on quantitative image properties.

H2:

The classification accuracy of a machine learning algorithm distinguishing drawings from Parkinson's disease patients and healthy controls based on quantitative image properties does not differ from chance level across different time points.

2. Methods

2.1. Framework

This work is part of a larger research project developed by the University of Vienna entitled “Unlocking the Muse: Transdisciplinary Approaches to Understanding the Intersection of Artistic Creativity and Parkinson’s Disease.” This Project is founded by the FWF der Wissenschaftsfond, #ConnectingMinds (CM1100-B). The aim of this project is to found a large-scale, systematic and collaborative series of studies, and why the relationship between art and creativity is changing in Parkinson's patients.

The project is led by Assoz.-Prof. Dr. Matthew Pelowski (University of Vienna, Faculty of Psychology, Department of Cognition, Emotion, and Methods in Psychology), in collaboration with Dr. Julia Crone (University of Vienna, Vienna Cognitive Science Hub) and Dr. B.T.M. Spee, Mag. (Center of Expertise for Parkinson & Movement Disorders, Radboud university medical center, Department of Neurology Nijmegen, The Netherlands). The project further benefits from the generous support and data provided by researchers at Radboud University Medical Center (Radboudumc) and the Donders Institute for Brain, Cognition and Behaviour, Netherlands. Calculations related to the machine learning model results were conducted in collaboration with Dipl.-Ing. Dr. techn. David Steyrl (University of Vienna, Institute of Psychology of Cognition, Emotion, and Methods).

2.1.1. Associated Studies

Looking at the PD data from the Netherlands, the project “The Art’s CAP Study” (Artistic Creativity & Anxiety in Parkinson’s Disease) focused on transformative learning combined with arts-based approaches to reduce anxiety. Arts-based interventions can engage physical, cognitive, and emotional processes through person-centred and self-empowering methodologies (Osman et al., 2018; Van Lith & Ettenberger, 2023). They focused on anxiety because in a pilot study it was identified as the primary outcome affected by the intervention (Spee, Stap, et al., 2025). The current project aimed to establish the relationship between anxiety reduction and improvements in general health-related QoL and well-being.

The researchers conducted a mixed-methods randomized controlled trial. Following an initial screening to determine eligibility based on predefined inclusion and exclusion criteria, which are described later, blinded assessors carried out evaluations at baseline, mid-intervention, post-intervention, and at an eight-week follow-up. Assessments employed validated questionnaires, experience sampling methods, and semi-structured interviews to evaluate adherence and study outcomes. Outcome measures included, but were not limited to, depression, Parkinson’s disease specific anxiety, self-efficacy, well-being, self-management, cognitive flexibility, and visual art cueing, as well as data obtained through semi-structured interviews. Participants assigned to the

control group, who did not receive the Art's CAP intervention, were offered an alternative online visual arts course upon completion of all assessments.

Participants in the intervention group completed a structured 10-week program comprising weekly creative sessions facilitated by trained creative therapists. Sessions were conducted in a "creative playground" and art studio environment specifically designed to support individualized creative expression and exploration. The program encouraged engagement in a range of artistic activities, fostering autonomy in creative choice while addressing the specific challenges and interests of individuals with PD.

2.2. Participants

The study used data from individuals diagnosed with idiopathic PD who were under the care of Radboud University Medical Center (Radboudumc) and the Expertise Centre for Parkinson and Movement Disorders in Nijmegen, the Netherlands. The data for the Healthy controls are from Students from the University of Vienna, participating in exchange for course credit.

2.2.1. Inclusion and Exclusion Criteria

Participants were eligible if they had a confirmed diagnosis of idiopathic PD, were 18 years of age or older, demonstrated adequate global cognitive functioning (Montreal Cognitive Assessment (MoCA) score > 24), and had sufficient motor mobility (Hoehn & Yahr stage < 5) to complete all study procedures. Eligibility further required willingness to participate in the intervention program and to attend all scheduled assessment sessions.

Participants were excluded if they were legally incapable of providing informed consent or managing their own affairs, were classified as Hoehn & Yahr stage 5 even during optimal periods of the day, exhibited severe cognitive impairment (MoCA score < 24), required full-time nursing care, or failed to provide written informed consent.

2.2.2. Sample Size

Data were collected from 63 PD patients in Nijmegen (42 women mean age = 66.13 years, SD = 9.26), of whom 42 were women. Data collection for the PD sample spanned a six-month period. Seven participants dropped out or had missing data at the post-intervention assessment, with one additional dropout at the follow-up. Half of the PD participants were assigned to an arts therapy intervention group, while the remaining participants formed a non-intervention control group. The intervention group completed the drawing task adapted from Pelowski et al. (2019) at baseline, at the end of the three-month therapy period, and again approximately three months later. The non-intervention group completed the same drawing task at three comparable time points, each separated by approximately three months.

The HC group consisted of 57 psychology students from the University of Vienna, Faculty of Psychology (47 women; mean age = 31.3 years, SD = 3.9, range = 18–36). All HC participants

were novice art-makers, reporting little to no formal artistic training and no regular engagement in visual design hobbies, as assessed via a post-study questionnaire. All participants provided written informed consent, and the study was approved by the Ethics Committee of the University of Vienna (Pelowski et al., 2019).

After accounting for dropouts, the final dataset comprised 680 drawings, including 510 drawings from PD participants (265 from the intervention group and 245 from the non-intervention group) and 170 drawings from HC participants. Across both groups, 224 drawings corresponded to cue 1, 228 to cue 2, and 228 to cue 3. With respect to assessment time points, 358 drawings were collected at baseline (HC and PD), 169 at post-intervention, and 153 at follow-up (both PD only), with declining numbers reflecting participant dropouts.

2.2.3. Power Analysis

This study was exploratory in nature and was conducted in the absence of prior evidence that would allow for a formal power analysis. Accordingly, the sample size was determined by data availability. General methodological guidelines indicate that meaningful machine learning analyses typically require between 10 and 20 observations per predictor, or at least a minimum of 50 observations overall. An alternative, and more debated, perspective proposes a requirement of 10–20 observations per degree of freedom (i.e., per predictor), which would correspond to an estimated sample size of approximately 200–400 observations for the present study (Pedregosa et al., 2011; Zeggio et al., 2025). However, establishing an adequate sample size for non-linear machine learning models remains challenging, as no widely accepted standards exist for high-dimensional, multivariable analyses.

As a rough post hoc approximation, a conventional power analysis was conducted in G*Power for an independent-samples t-test (two-tailed, $\alpha = .05$), assuming a small effect size (Cohen's $d = 0.2$) and based on the number of independent participants rather than the total number of drawings or cue-specific observations (PD: $n = 63$; HC: $n = 57$). This analysis yielded an achieved power of 0.29, indicating limited sensitivity to detect small group differences and supporting the exploratory nature of the present study (Faul et al., 2007, 2009).

2.3. Design

This study capitalized on the aforementioned research design by inviting participants from both the intervention and non-intervention groups to take part in an additional task at baseline, post-intervention, and at the eight-week follow-up. Participants were asked whether they were willing to complete a drawing task at each assessment point (see Figure 4).

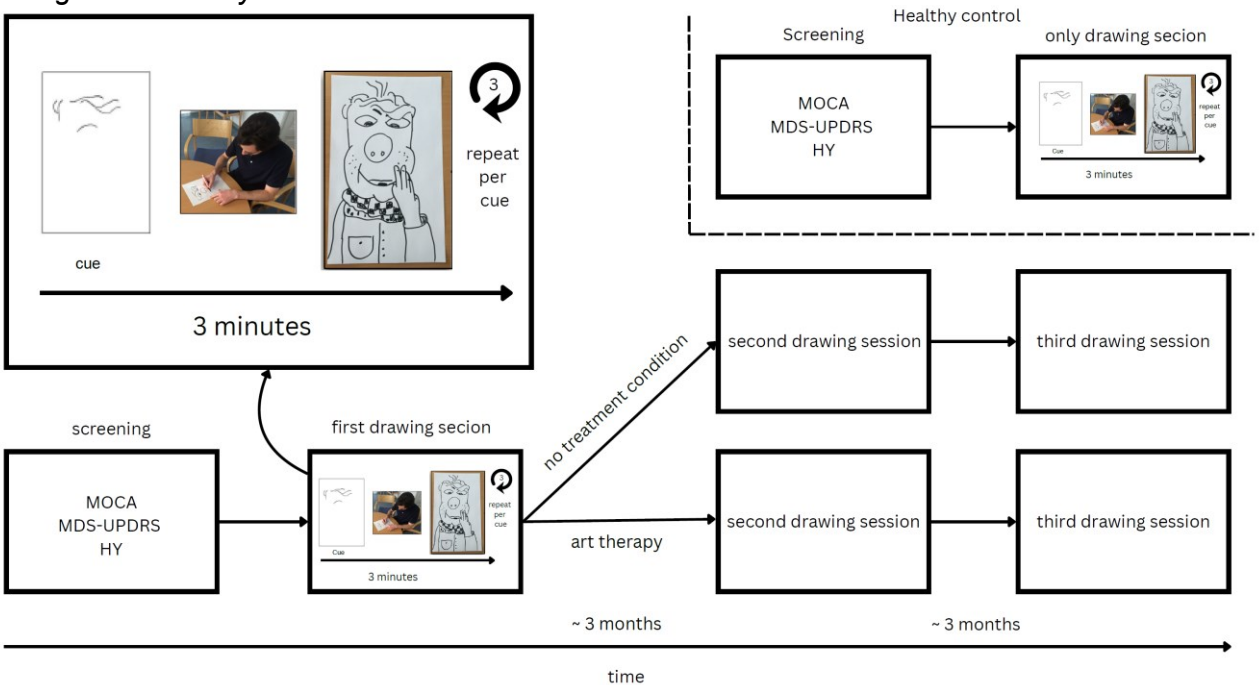
The drawing task was adapted from Pelowski et al. (2019) and was specifically designed to generate artistic outputs that could be meaningfully compared both across individual participants and between different task prompts. As noted by Pelowski et al. (2019), the task was "...developed

with the goal of… elicit art products that can be generalized across both subjects and between cues themselves."

Drawings produced by both Parkinson's disease patients and healthy controls were subsequently pre-processed and analysed using the Aesthetics Toolbox developed by Reddies et al. (2025). This toolbox enabled the systematic extraction of QIPs from visual artworks and provided a robust analytical framework for the examination of the collected drawings.

Finally, the extracted QIPs were used to train a machine learning algorithm in order to evaluate whether these features could successfully discriminate between PD patients and HC.

Figure 4
Design of this study



2.3.1. Drawings

The 'Cued, Free Drawing' task provides a structured way to assess an individual's capacity for spontaneous artistic creation, while still leaving participants a large degree of freedom in how they approach the task (Pelowski et al., 2019). It aims to capture a range of artistic qualities, including technical skill, creativity, aesthetic appeal, and overall execution, all of which can vary considerably between individuals. Participants are encouraged to choose any artistic style they prefer whether abstract or representational and they are allowed to use the entire page as they wish.

In the original study, the pictures produced during the task were assessed by human raters in order to generate evaluations on several dimensions (Pelowski et al., 2019). These included creativity, technical execution, emotional expression, overall quality, aesthetic pleasantness, symbolism, the extent of page usage, degree of abstractness, and the affective tone of the artwork

(e.g., whether it appeared more positive or negative, as measured by the Art Attributes Scale; Chatterjee, 2010). In the present study, however, these same factors are not directly applied in the same way. This is because the artworks will not be rated by human judges but instead will be categorized by a machine learning algorithm, which takes over the task of analysing the produced drawings and further tries to categorize between PD and HC and the stability of this effects over time.

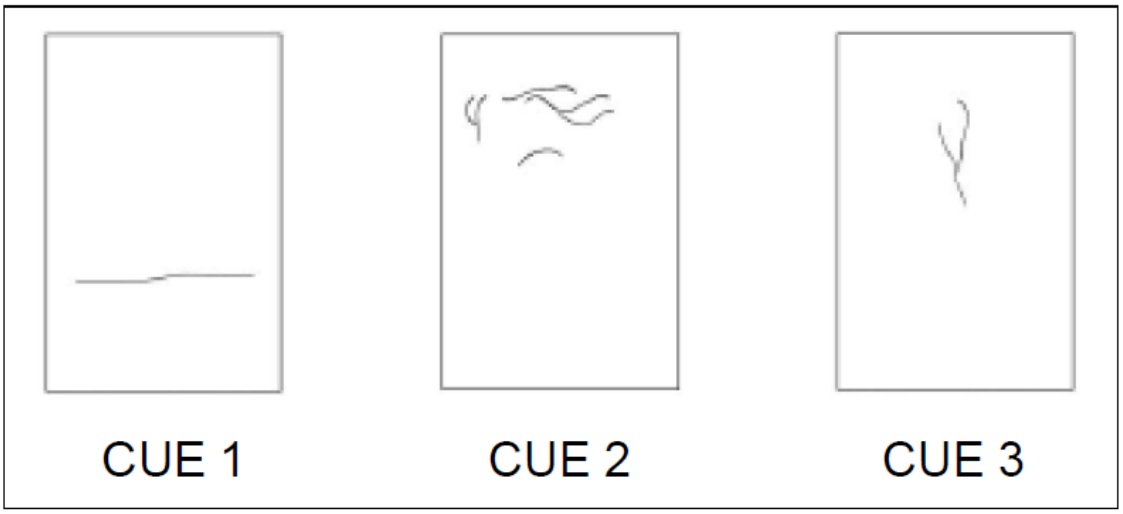
2.3.2. Cued Art Making

The task from Pelowski et al. (2019) itself requires only very minimal materials. These include a black 1 mm ‘Edding’ 400 permanent marker, as well as three sheets of white A4 paper, each of which contains a preprinted cue in black (Figure 5).

This design choice was implemented to “limit focus on formal depiction without added variables of colour or obvious shading and in order to disallow erasing” (Pelowski et al., 2019). Participants are informed beforehand that they will be given a sheet of paper and asked to “make an artwork” incorporating the cue, using only the black pen that is provided. Each sheet of paper is placed face down on the desk at a 45° angle to test whether the participants will prefer to use the sheet in a vertical or horizontal orientation. Participants are instructed that they may draw freely and spontaneously, but at the same time they are told to treat the exercise as if they were creating a finished artwork of sufficient quality that one might expect to encounter in a museum. Furthermore, they are explicitly told that their artwork does not have to be realistic or representational, so they are free to interpret the task in any style or manner they wish. They were told that if they made a mistake, they should continue with the artwork and either incorporate or adapt the mistake into their work. Once the participants have confirmed that they clearly understand the instructions, they are allowed to begin by turning the page over and starting the drawing.

Each visual cue is given a fixed time limit of three minutes, and this time frame is also communicated in advance to the participants. After each cue has been completed, a new sheet is provided for the next trial. In total, the task is repeated three times, one for each cue, which results in a total drawing duration of nine minutes (see Figure 4). A verbal reminder is provided after two minutes, following the protocol that had already been established in pilot testing (Pelowski et al., 2019). To ensure comparability between participants, all cues are chosen to have a comparable level of complexity, and they are specifically designed to avoid overly suggestive or stereotypical shapes that might lead to predictable responses (for example, a simple square that could easily be turned into a house).

Figure 5
"Make an artwork" visual cues



Note. Adapted from Pelowski et al. (2019)

2.4. Data Processing and Analysis Plan

All images were either collected in Vienna (HC) or sent to Vienna (PD), scanned using a Canon scanner (imageRUNNER Advance DX C5735i), and converted to JPEG format. This resulted in Pictures with the dimensions of 3507x2480 Pixels (Broad x Hight) and 300x300 dpi. To ensure maximum accuracy with the Aesthetic Toolbox, the data had to be free of digital artefacts that may have arisen during transport or the scanning process. Accordingly, the images were manually cleaned using MS Paint. This primarily involved redrawing the grey borders of the images, which resulted from incomplete scanning of the original paper.

2.4.1. Aesthetic Toolbox Processing

After the drawings were scanned and cleaned the Aesthetics Toolbox version 1.0.2 (Redies et al., 2025) was used to extract the QIP's of the images. The toolbox is a free to use Python 3 (*Python*, 2026) based Code available on GitHub (Bartho, 2024/2025). The Python 3 script was run on anaconda (Advance AI with Open Source | Anaconda, 2026) a free to use Python environment. Here all QIPs from the toolbox except for the image dimensions were calculated (Table 3).

Methodologically, the Aesthetics Toolbox provides a standardized framework for computing objective low- and mid-level image properties relevant to empirical aesthetics (Graham & Redies, 2010; Redies, 2008, 2015; Redies et al., 2025). It includes automated preprocessing steps (e.g., resizing, colour space conversion, grayscale transformation or binarization where required) to ensure comparability across images. The toolbox extracts a broad set of features, including contrast and complexity metrics (e.g., RMS contrast, HOG-based complexity, edge density), colour statistics (channel means, standard deviations, colour entropy), balance and symmetry measures (pixel-based balance, deviation of center of mass, mirror symmetry, CNN-based symmetry), scale-

invariant properties (Fourier spectrum slope and sigma, 2D and 3D fractal dimension), as well as self-similarity and entropy-based measures. For a detailed description of the parameters see the Table 3.

Overall, the toolbox operationalizes theoretical constructs from empirical aesthetics into standardized computational metrics, enabling systematic, reproducible quantification of structural image properties.

Table 3

Quantitative Image Properties and Short Explanations

Type	QIP	Short explanation
Image dimensions	Image size	Overall image extent measured as the sum of width and height.
	Aspect ratio	Ratio of image width to height describing image proportions.
Contrast & complexity	RMS contrast	Standard deviation of luminance values, indicating global image contrast.
	Lightness entropy	Shannon entropy of luminance values, reflecting randomness in brightness distribution.
	Complexity (HOG)	Mean gradient strength derived from histograms of oriented gradients.
	Edge density	Amount and strength of edges computed using Gabor filter responses.
Colour	Channel means	Average colour values across RGB, HSV, and L*a*b* colour channels.
	Channel SD	Variability (standard deviation) of colour values within each channel.
	Colour entropy	Hue diversity quantified using Shannon entropy.
Balance & symmetry	Balance (APB)	Difference in visual mass across paired image regions.
	DCM	Distance between the perceptual center of mass and the geometric image center.
	Mirror symmetry	Degree of reflectional symmetry across horizontal and vertical axes.
	CNN symmetry	Symmetry estimated from early convolutional neural network feature responses.
Scale invariance	Fourier slope	Scaling relationship of spatial frequencies in the Fourier domain.
	Fourier sigma	Deviation from an ideal power-law distribution of spatial frequencies.
	2D fractal dimension	Geometric complexity derived from binarized image structures.
	3D fractal dimension	Grayscale surface complexity estimated from intensity variations.
Self-similarity	PHOG self-similarity	Repetition of gradient structures across spatial scales based on PHOG descriptors.
	CNN self-similarity	Feature-based repetition across image regions derived from CNN activations.
Distribution & entropy	Homogeneity	Degree of uniformity in pixel intensity distribution.
	Anisotropy	Directional bias in image gradient orientations.
	Edge-orientation entropy	Randomness of edge orientation distributions.
Sparseness & variability	CNN feature variance	Variability of activation responses across CNN feature maps.

Note. QIP = quantitative image property; RMS = root mean square; HOG = histogram of oriented gradients; PHOG = pyramid histogram of oriented gradients; CNN = convolutional neural network; DCM = deviation of center of mass.

2.4.2. Machine Learning

This study employed an interpretable machine-learning approach, specifically a Gradient Boosted Decision Tree model, to examine whether drawing-based features could successfully discriminate between individuals with PD and HC, in line with the research questions. The multivariable statistical analyses were implemented in Python (version 3.11) using the scikit-learn library (version 1.4.84). QIPs derived from the drawings served as predictor variables, while diagnostic group (PD vs. HC) was used as the classification target (Pedregosa et al., 2011; Zeggio et al., 2025).

Model generalizability was evaluated using a nested cross-validation procedure with participant-wise splits. In the outer loop, 5-fold cross-validation was applied to estimate out-of-sample performance, ensuring that all observations from a given participant were confined to either the training or test set. Hyperparameters were optimized via random search in the inner loop (column subsampling per tree: 0.1–1; extra trees: true/false; path smoothing: 1–100, log-scale), while learning rate (0.01), number of leaves (100), and boosting rounds (1000) were held constant. The best-performing parameter configuration was then applied in the outer loop. Model performance was quantified using balanced accuracy for classification and the coefficient of determination (R^2) and mean absolute error (MAE) for regression analyses (Cawley & Talbot, 2010).

2.4.3. Model Analysis

The importance of individual predictors was assessed using SHAP, an interpretable machine-learning method grounded in cooperative game theory. SHAP quantifies each predictor's contribution to the model's predictions, thereby providing a detailed and transparent assessment of feature relevance. Beyond offering insights into the multivariate machine-learning model, the SHAP results were used to guide subsequent linear analyses by identifying a reduced set of influential QIPs, thereby complementing the machine-learning approach with focused inferential statistics (Lundberg & Lee, 2017; Molnar et al., 2020).

2.4.4. Linear Model Testing

To validate and contextualize the machine-learning findings, analyses of variance (ANOVAs) were conducted on the QIPs. First, baseline group- and task-related effects were examined using a mixed-design ANOVA restricted to T0 data, with Group (PD vs. HC) as a between-subject factor and Cue (C1–C3) as a within-subject factor, including the Group × Cue interaction. Second, within the PD cohort, a mixed-design ANOVA was performed with Treatment (intervention vs. non-intervention) as a between-subject factor and Time (T0, T1) as a within-

subject factor. Third, within the PD non-intervention group, a one-way repeated-measures ANOVA with Time (T0, T1, T2) was conducted to examine the temporal stability of QIP changes.

Table 4
Overview of ANOVAs Conducted on Quantitative Image Properties

Comparison Category	ANOVA Type	Sample	Timepoints Included	Cues Included	Effects / Interactions Tested
Baseline group and cue effects	Mixed-design ANOVA	PD, HC	Pre-intervention only	Cue 1-3	Group, Cue, Group × Cue
Intervention effects within PD	Mixed-design ANOVA	PDT, PDN	Before and after intervention	All cues combined	Treatment, Time, Treatment × Time
Longitudinal effects within intervention group	One-way repeated-measures ANOVA	PDN	All Three Timepoints	All cues combined	Time

Note. PD = Parkinson's disease; PDT = PD patients with art intervention; PDN = PD patients without intervention; HC = healthy control participants. The mixed-design ANOVA examining group and cue effects was restricted to the initial assessment to ensure a comparable data structure between PD and HC groups.

Normality of residuals was assessed using visual inspection of Q–Q plots and formally tested using the Shapiro–Wilk test (Shapiro & Wilk, 1965). Homogeneity of variances for between-subject factors was examined using Levene's test (Levene, 1960). For repeated-measures factors, the assumption of sphericity was assessed using Mauchly's test and when violated, Greenhouse Geisser corrected degrees of freedom were reported. In cases of minor deviations from normality, ANOVAs were retained due to their robustness under balanced or moderately unbalanced designs. Outliers were inspected using standardized residuals and influence diagnostics and were retained unless they reflected clear data recording errors.

3. Results

3.1. Machine Learning

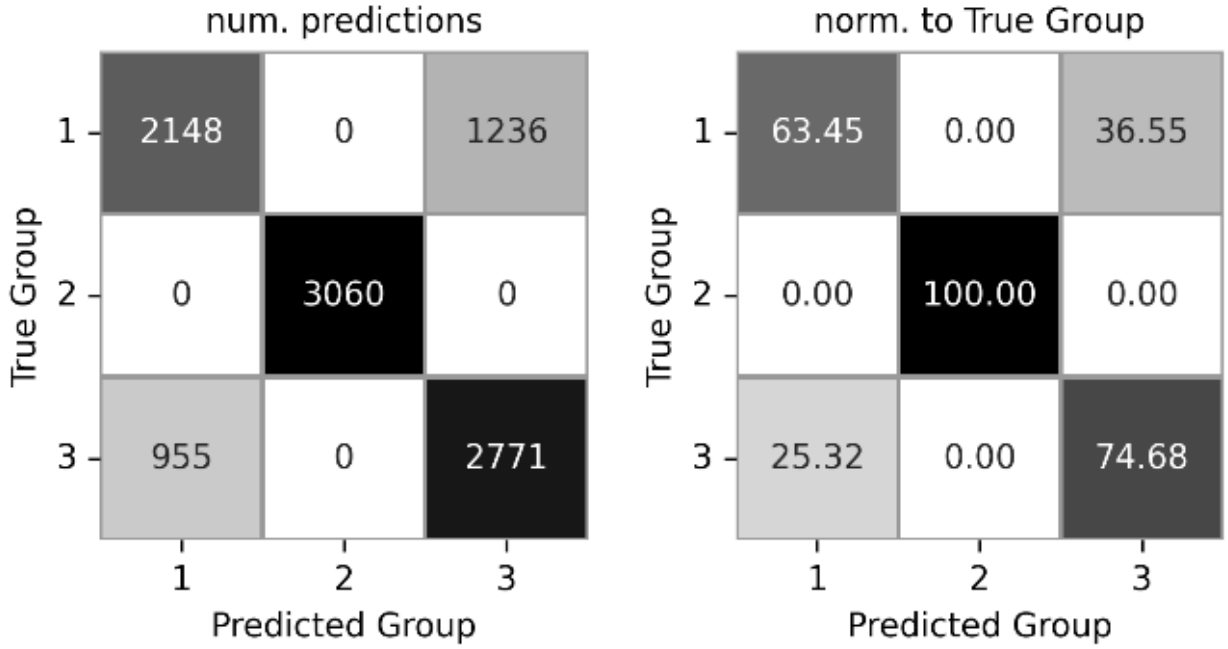
The results of the models are based on the mean predictive value of the PD group (group setting) and T0 (time setting), respectively. Statistical significance was assessed using the coefficient of determination (R^2) by comparing model predictions against shuffled labels.

3.1.1. Gradient Boosted Decision Tree Model for Group

The first GBDT model was trained using three groups, as defined by the overall project design. Group 3 consisted of an age-matched cohort (matched to the PD patients) from Vienna, who completed the task in the same experimental setting as the healthy control group.

The model achieved a coefficient of determination (R^2) of 0.79 ± 0.04. When compared with shuffled labels, the corresponding p-value was < 0.001, indicating that the model explained 79% of the variance and performed well above chance level (shuffled labels: R^2 = 0.34 ± 0.06).

Figure 6
Predictions of the Machine learning Model for Group

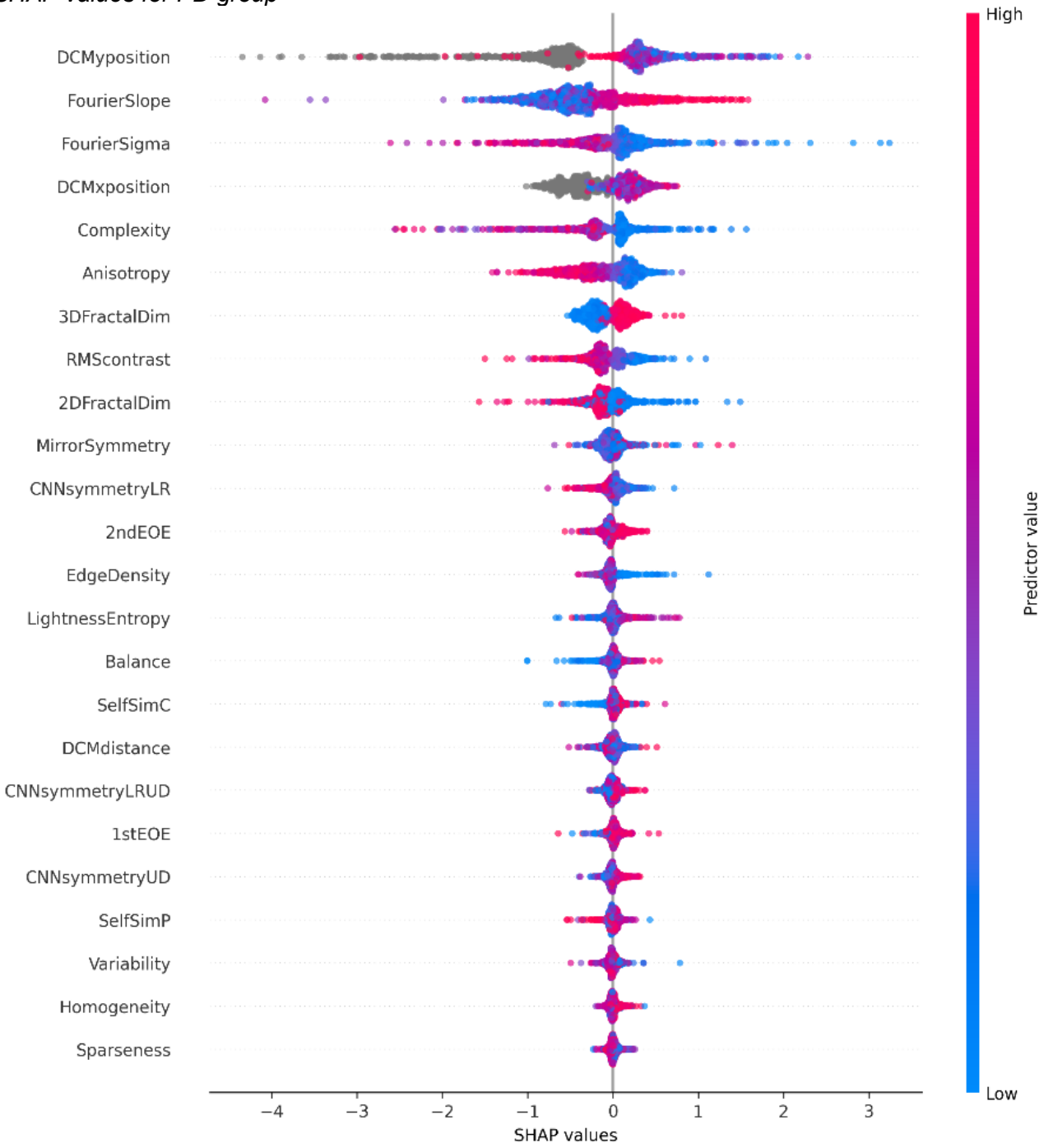


Note. Displays the classification performance of the model across the three groups. The left panel shows the total number of predictions, and the right panel shows the percentage of correct predictions. Group labels: 1 = PD group, 2 = HC, 3 = age-matched group (from a different study).

3.1.2. SHAP Values for Group

SHAP values (Figure 7) illustrate the importance of individual QIPs for predicting group membership. The values indicate both the direction and magnitude of each predictor's contribution to the model output.

Figure 7
SHAP values for PD group



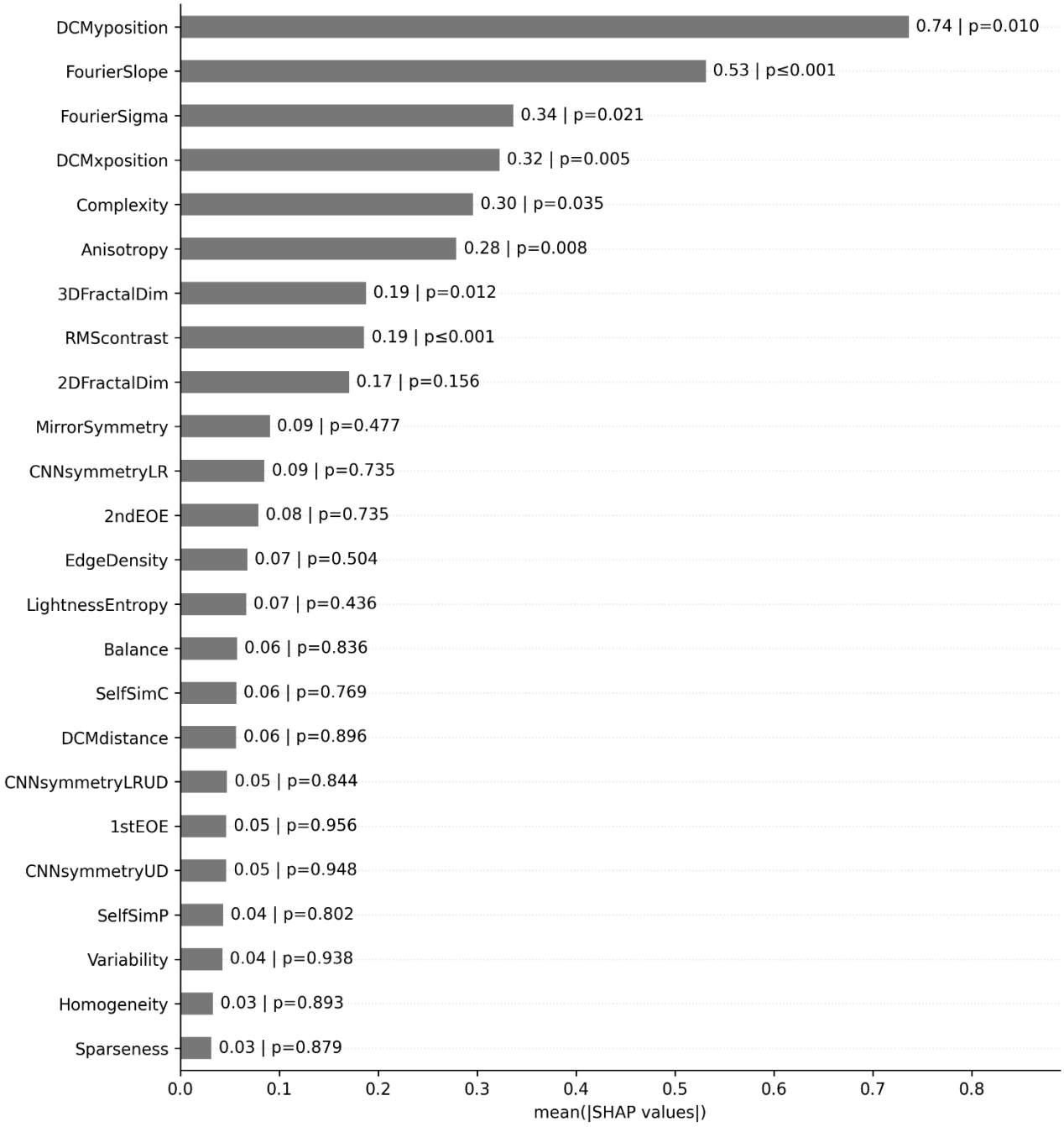
Note. Shows SHAP values for each QIP. Red indicates high predictor values and blue indicates low predictor values. The x-axis represents SHAP values, reflecting the contribution of each predictor to the model prediction.

Figure 8 presents the rank-based predictor importance derived from the mean absolute SHAP values for each factor. The most influential predictors were DMC y-position, Fourier slope, Fourier sigma, DMC x-position, complexity anisotropy, 3D fractal dimension, and RM contrast.

Mean absolute SHAP deviation values for these QIPs ranged from 0.74 to 0.28. The mean SHAP deviation of the expected value across all groups was −1.97.

Figure 8

SHAP effects for PD group



Note. Importance of predictor based on mean absolute SHAP-value for PD group. Predictions of the Machine learning Model for Group

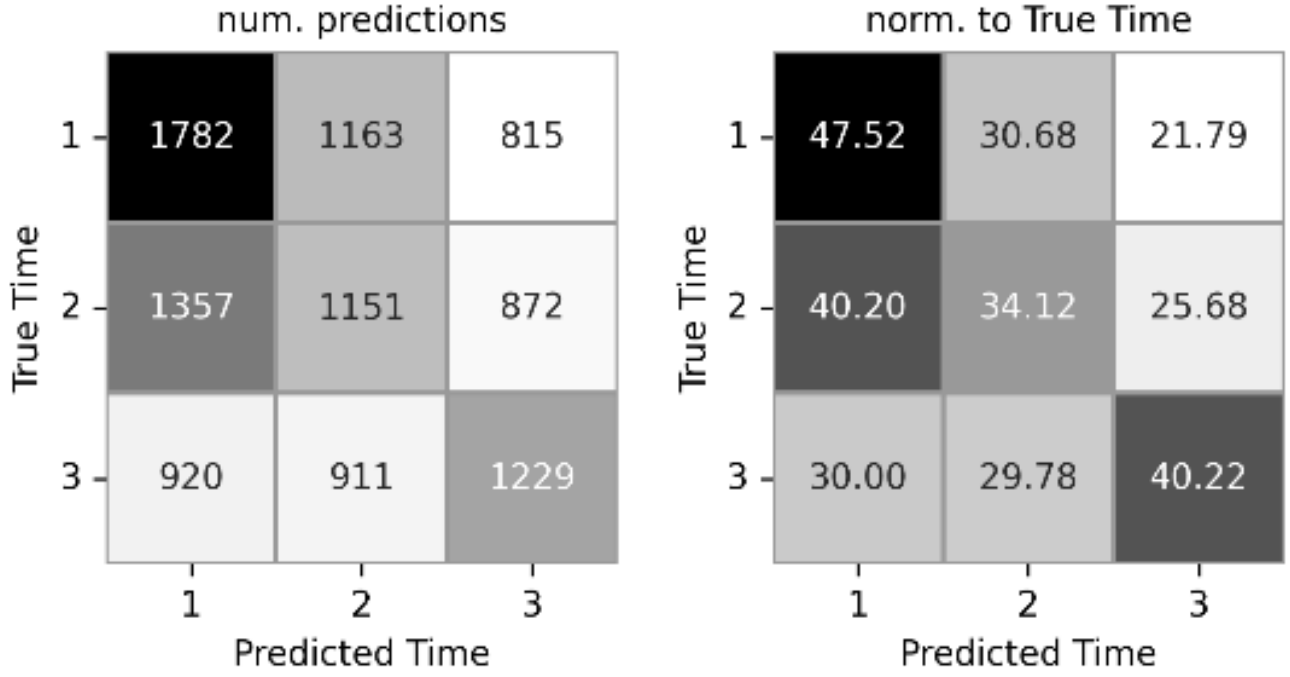
3.1.3. Gradient Boosted Decision Tree Model for Time

A second GBDT model was trained using three time points within the PD group. Only images from PD participants were included in this analysis.

The model achieved an R^2 of 0.40 ± 0.05, with a corresponding p-value of 0.01 when compared with shuffled labels. This indicates that the model explained 40% of the variance and performed slightly above chance level (shuffled labels: R^2 = 0.33 ± 0.05).

Figure 9

Predictions of the Machine learning Model for Time



Note. Displays model performance across the three time points. The left panel shows the total number of predictions, and the right panel shows the percentage of correct predictions. Labels 1–3 correspond to baseline, post-intervention, and follow-up measurements.

3.1.4. SHAP Values for Time

Figure 10 shows the rank-based predictor importance based on mean absolute SHAP values for each factor. Anisotropy was the only predictor with a significant contribution, with a mean absolute SHAP deviation value of 0.48. The mean SHAP deviation of the expected value across all time points was −1.43

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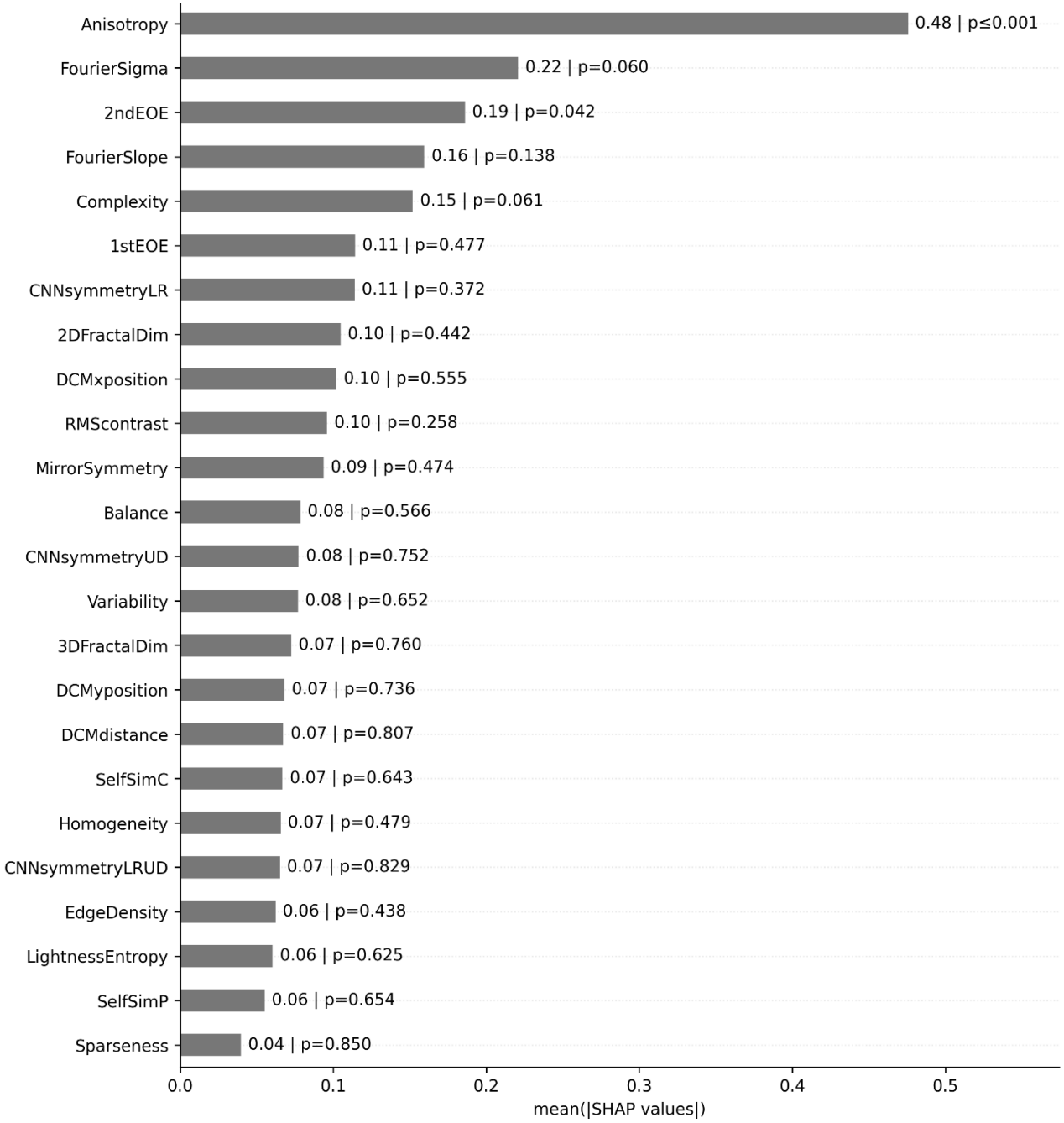
Figure 10

SHAP effects for PD over Time



Note. Importance of predictor based on mean absolute SHAP-value for Timepoint T0.

3.2. Descriptive Statistics

Statistical analysis of data was reduced to the top 5 most important SHAP values calculated for the Parkinson pictures for group.

Table 5
Descriptive statistics (Mean, SD, 95% CI) -Complexity

group	time	N	Mean	SD	CI_low	CI_high
HC	T0	170	7.58	3.51	7.05	8.11
PD	T0	188	1.78	0.88	1.65	1.90
PD	T1	169	1.90	1.17	1.72	2.08
PD	T2	153	1.90	1.13	1.72	2.08

HC showed substantially higher Complexity values (M = 7.58, SD = 3.51, 95% CI [7.05, 8.11]) than participants with PD at T0 (PD; M = 1.78, SD = 0.88, 95% CI [1.65, 1.90]). Across time, PD Complexity values increased slightly from T0 to T1 (M = 1.90, SD = 1.17) and remained stable at T2 (M = 1.90, SD = 1.13). However, PD values remained markedly lower than HC baseline levels at all time points and confidence intervals overlapped strongly across T0, T1, and T2, suggesting no change over time.

Table 6
Descriptive statistics (Mean, SD, 95% CI) - DCM x position

group	time	N	Mean	SD	CI_low	CI_high
PD	T0	188	-0.0033	0.081	-0.0150	0.0083
PD	T1	169	0.0039	0.078	-0.0079	0.0160
PD	T2	153	0.0048	0.075	-0.0072	0.0170

Note. HC was not calculated due to missing Data

In the PD group, mean DCM x position values were close to zero at all time points (T0–T2), with very small variability (SD ≈ 0.08). Confidence intervals overlapped strongly across T0, T1, and T2, suggesting no change over time.

Table 7
Descriptive statistics (Mean, SD, 95% CI) - DCM y position

group	time	N	Mean	SD	CI_low	CI_high
PD	T0	188	-0.00330	0.095	-0.0170	0.010
PD	T1	169	0.00089	0.100	-0.0140	0.016
PD	T2	153	0.00520	0.094	-0.0098	0.020

Note. HC was not calculated due to missing Data

In the PD group, mean values were approximately zero across all time points, with small standard deviations (SD ≈ 0.09–0.10). Confidence intervals overlapped strongly across T0, T1, and T2, suggesting no change over time.

Table 8
Descriptive statistics (Mean, SD, 95% CI) - Fourier sigma

group	time	N	Mean	SD	CI_low	CI_high
HC	T0	170	0.046	0.023	0.042	0.049
PD	T0	188	0.056	0.040	0.051	0.062
PD	T1	169	0.047	0.032	0.042	0.052
PD	T2	153	0.050	0.036	0.044	0.055

HC showed a mean Fourier sigma of 0.046 (SD = 0.023, 95% CI [0.042, 0.049]). PD participants exhibited slightly higher mean values at T0 (M = 0.056, SD = 0.04), followed by a small reduction at T1 (M = 0.047, SD = 0.037) and relative stability at T2 (M = 0.05, SD = 0.036). Overall, group differences were small, and confidence intervals overlapped across groups and time points.

Table 9
Descriptive statistics (Mean, SD, 95% CI) - Fourier slope

group	time	N	Mean	SD	CI_low	CI_high
HC	T0	170	-2.34	0.18	-2.36	-2.31
PD	T0	188	-1.66	0.22	-1.69	-1.63
PD	T1	169	-1.68	0.29	-1.72	-1.63
PD	T2	153	-1.66	0.23	-1.69	-1.62

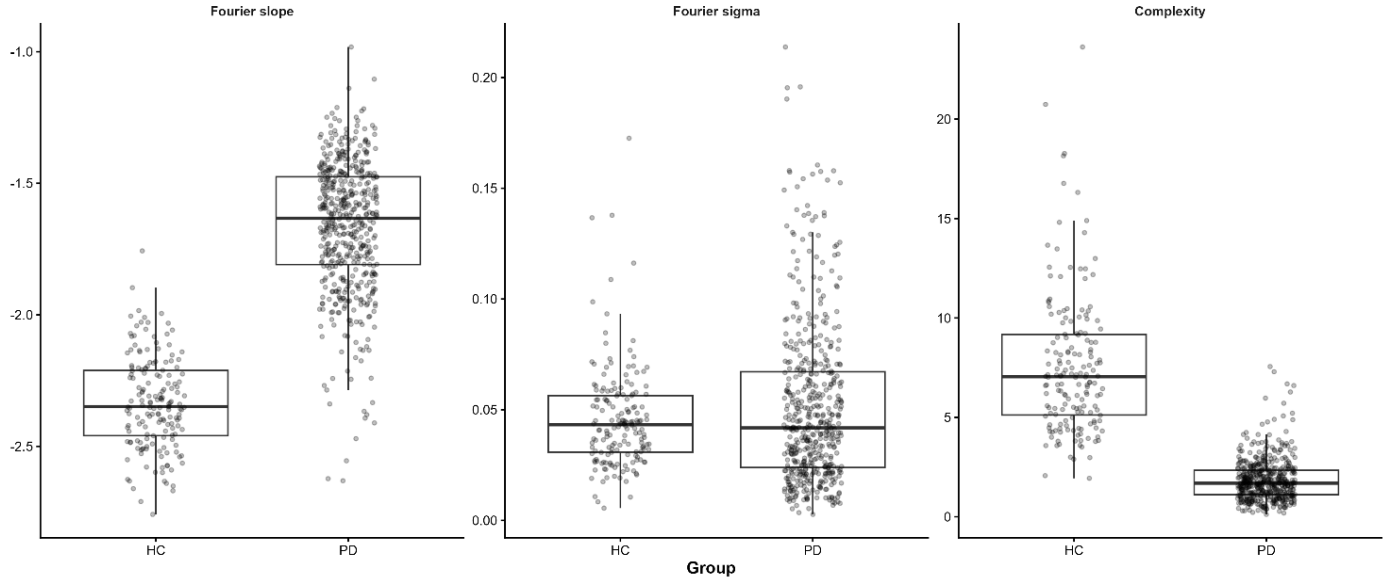
Fourier slope differed clearly between groups at baseline. HC showed more negative slopes (M = −2.34, SD = 0.18, 95% CI [−2.36, −2.31]) than PD participants at T0 (M = −1.66, SD = 0.22). Across time, PD Fourier slope values showed minimal change, with means remaining between −1.66 and −1.68 from T0 to T2 and overlapping confidence intervals, indicating temporal stability.

Descriptive analyses revealed group differences for Complexity and Fourier slope at baseline, with healthy controls exhibiting higher Complexity and more negative Fourier slope values compared to participants with PD. In contrast, Fourier sigma showed only small group differences and substantial overlap in confidence intervals across groups and time points.

Within the PD group, Complexity demonstrated a modest increase from baseline to post-intervention assessments, whereas Fourier slope, Fourier sigma, and DCM-based positional measures remained largely stable across time. Overall, the descriptive patterns suggest stable spatial balance measures over time in PD, alongside persistent group differences in global image structure measures such as Complexity and Fourier slope.

Figure 11 illustrates the group differences between HC and participants with PD patients using boxplots. Given the relevance of the group comparison, only this boxplot is presented in the main text, and all remaining boxplots are reported in the Appendix. Clear group differences are evident for Fourier slope and Complexity, whereas no apparent difference is observed for Fourier sigma. Due to missing data, there is no comparison for DCM x position and DCM y position.

Figure 11
Boxplot of group differences



Note. Boxplots for Fourier slope, Fourier sigma and Complexity comparing PD and HC group.

3.3. ANOVA Results

Statistical analysis of data was reduced to the top 5 most important SHAP values calculated for the Parkinson pictures for group. Detailed descriptions of all analyses conducted in this chapter, including assumption checks and corresponding values, together with the R script and data required to compute all additional QIPs, are provided in the Appendix.

3.4. ANOVA 1 - Baseline (T0): Group × Cue

Because the assumption of sphericity was violated for the within-subject factor Cue, Greenhouse–Geisser–corrected degrees of freedom were applied for all baseline mixed-design ANOVAs (see Table 13). Baseline ANOVAs for DCM x position and DCM y position were not estimable due to the absence of baseline data for the healthy control group and are therefore not reported. Mixed-design ANOVAs were conducted at baseline (T0) with Group (PD vs. HC) as a between-subject factor and Cue (C1–C3) as a within-subject factor Table 10.

Table 10
Mixed-Design ANOVA Results at Baseline (T0)

QIP	Effect	F(df)	p	η²p
Fourier slope	Group	489.00 (1, 114)	< .001	.81
	Cue	6.06 (1.91, 218.00)	.003	.05
	Group × Cue	4.97 (1.91, 218.00)	.009	.04
Fourier sigma	Group	4.30 (1, 114)	.040	.04
	Cue	10.50 (1.94, 221.00)	< .001	.09
	Group × Cue	2.00 (1.94, 221.00)	.140	.02
Complexity	Group	220.00 (1, 114)	< .001	.66
	Cue	1.82 (1.98, 226.00)	.164	.02
	Group × Cue	1.68 (1.98, 226.00)	.188	.02

Note. Mixed-design ANOVAs were conducted with Group (PD vs. HC) as a between-subject factor and Cue (C1–C3) as a within-subject factor at baseline (T0). Greenhouse–Geisser corrected degrees of freedom are reported where applicable. η²p = partial eta squared. Baseline ANOVAs for DCM x position and DCM y position were not estimable and are therefore not reported.

3.4.1. Fourier Slope

The analysis revealed a significant main effect of Group, $F(1, 114) = 489.00$, $p < .001$, $\eta^2p = .81$, indicating overall differences between PD and HC. A significant main effect of Cue was also observed, $F(1.91, 218.00) = 6.06$, $p = .003$, $\eta^2p = .05$. Importantly, the Group × Cue interaction was significant, $F(1.91, 218.00) = 4.97$, $p = .009$, $\eta^2p = .04$.

Follow-up analyses showed that, collapsed across groups, Fourier slope differed between Cue 1 and Cue 2, whereas comparisons involving Cue 3 were not significant. Simple-effects analyses indicated that within the HC group, significant differences were present between Cue 1 and Cue 2 as well as between Cue 2 and Cue 3, while no difference was observed between Cue 1 and Cue 3. In contrast, within the PD group, a significant difference emerged only between Cue 1 and Cue 3. Group comparisons conducted separately for each cue revealed significant differences between PD and HC for all three cue conditions.

3.4.2. Fourier Sigma

For Fourier sigma, there was a significant main effect of Group, $F(1, 114) = 4.30$, $p = .040$, $\eta^2p = .04$, and a significant main effect of Cue, $F(1.94, 221.00) = 10.50$, $p < .001$, $\eta^2p = .09$. The Group × Cue interaction was not significant, $F(1.94, 221.00) = 2.00$, $p = .140$, $\eta^2p = .02$.

Pairwise comparisons collapsed across groups indicated that Cue 3 differed significantly from both Cue 1 and Cue 2, whereas Cue 1 and Cue 2 did not differ from each other. Follow-up comparisons within groups showed no significant cue differences in the HC group. In the PD group, significant differences were observed between Cue 3 and both Cue 1 and Cue 2.

3.4.3. Complexity

For Complexity, a significant main effect of Group was found, $F(1, 114) = 220.00$, $p < .001$, $\eta^2p = .66$. Neither the main effect of Cue, $F(1.98, 226.00) = 1.82$, $p = .164$, $\eta^2p = .02$, nor the Group × Cue interaction, $F(1.98, 226.00) = 1.68$, $p = .188$, $\eta^2p = .02$, reached significance.

3.4.4. ANOVA 2 - PD Only: Intervention × Time (T0–T1)

No violations of model assumptions were observed for the mixed-design ANOVAs conducted within the PD cohort therefore, standard ANOVA procedures were applied (see Table 13). Within the PD cohort, mixed-design ANOVAs were conducted with Intervention (PDT vs. PDN) as a between-subject factor and Time (T0 vs. T1) as a within-subject factor (Table 11).

Table 11
Mixed-Design ANOVA Results in PD (Intervention × Time)

QIP	Effect	F(df)	p	η²p
DCM y position	Intervention	0.58 (1, 55)	.448	.01
	Time	0.26 (1, 55)	.610	.01
	Intervention × Time	0.35 (1, 55)	.560	.01
DCM x position	Intervention	0.00 (1, 55)	.960	<.001
	Time	0.73 (1, 55)	.397	.01
	Intervention × Time	0.01 (1, 55)	.920	<.001
Fourier slope	Intervention	0.46 (1, 55)	.502	.01
	Time	0.06 (1, 55)	.804	<.001
	Intervention × Time	1.53 (1, 55)	.221	.03
Fourier sigma	Intervention	0.11 (1, 55)	.739	<.01
	Time	8.31 (1, 55)	.006	.13
	Intervention × Time	8.49 (1, 55)	.005	.13
Complexity	Intervention	0.00 (1, 55)	.947	<.001
	Time	0.45 (1, 55)	.507	.01
	Intervention × Time	0.03 (1, 55)	.875	<.001

Note. Mixed-design ANOVAs were conducted within the PD cohort with Intervention (PDT vs. PDN) as a between-subject factor and Time (T0, T1) as a within-subject factor. η²p = partial eta squared.

3.4.5. Fourier Sigma

The analysis revealed a significant main effect of Time, $F(1, 55) = 8.31$, $p = .006$, $\eta^2p = .13$, as well as a significant Intervention × Time interaction, $F(1, 55) = 8.49$, $p = .005$, $\eta^2p = .13$. The main effect of Intervention was not significant, $F(1, 55) = 0.11$, $p = .739$, $\eta^2p < .01$.

Follow-up analyses indicated that Fourier sigma changed significantly from T0 to T1 in the PDT group, whereas no change over time was observed in the PDN group. Comparisons between intervention groups at each time point did not reach significance at either T0 or T1.

3.4.6. Other QIPs

For DCM x position, DCM y position, Fourier slope, and Complexity, no significant main effects of Intervention or Time and no Intervention × Time interactions were observed (all $p \geq .221$, all $\eta^2p \leq .03$).

3.5. ANOVA 3 - PD non-Intervention: Time (T0–T2)

Repeated-measures ANOVAs were conducted within the PD non-intervention group to examine changes across Time (T0–T2). Because the assumption of sphericity was violated for the within-subject factor Time (see Table 13) Greenhouse–Geisser–corrected degrees of freedom were applied for all repeated-measures ANOVAs in the PD non-intervention group (Table 12).

Table 12
Repeated-Measures ANOVA Results in PD Non-Intervention Group

QIP	Effect	F(df)	p	η^2p
DCM y position	Time	0.43 (1.81, 39.80)	.631	.02
DCM x position	Time	0.86 (1.82, 40.00)	.421	.04
Fourier slope	Time	0.63 (1.90, 41.90)	.531	.03
Fourier sigma	Time	0.01 (1.65, 36.40)	.986	<.001
Complexity	Time	0.29 (1.78, 39.30)	.724	.01

Note. Mixed-design ANOVAs tested the effects of Intervention (PDT vs. PDN) and Time (T0, T1) within the PD cohort. Values represent F(df), exact p values, and partial eta squared (η^2p).

No significant main effects of Time were observed for any QIP, including DCM x position, DCM y position, Fourier slope, Fourier sigma, or Complexity (all $p \geq .421$, all $\eta^2p \leq .04$), indicating stability of these measures across the three time points in the PD non-intervention group.

4. Discussion

4.1. General Caveat

A major limitation of the present work concerns the missing data for the QIPs DCM x position and DCM y position. Due to an error during data acquisition, these two datasets were not available for the HC group by the time of final submission. This limitation is particularly relevant, as DCM x position and DCM y position were identified as two of the five most influential QIPs for distinguishing between PD and HC groups. Given the homogenous nature of these measures, their classification power for group affiliation is not unexpected. Consequently, the absence of these variables restricts the interpretability of the current findings and renders the results only partially conclusive.

However, an age-matched dataset, originating from a separate study and analysed using the same model for group classification, was available. This dataset remained significantly distinguishable from the PD group, suggesting that systematic differences between PD and non-

PD populations persist even in the absence of the missing QIPs. On this basis, the present study is able to draw limited conclusions regarding group differences.

Nevertheless, a complete and robust interpretation of the results requires a recalculation of the analyses using the full and correct dataset, including the missing QIPs for the HC group. Accordingly, the findings reported here should be interpreted with caution and with explicit consideration of this methodological limitation.

4.2. Interpretation of Results

Machine learning analyses demonstrated a clear capacity to distinguish between participant groups based on quantitative image properties. The GBDT model trained to predict group membership differentiated individuals with Parkinson's disease from healthy controls and an age-matched comparison group, performing well above chance. Model interpretation using SHAP values indicated that spatial balance measures and global image structure metrics were the most influential predictors. In particular, positional measures derived from the drawing center of mass, Fourier-based descriptors, complexity-related indices, and texture contrast contributed most strongly to group classification. These findings indicate that Parkinson's disease is associated with systematic alterations in multiple, partly independent visual features.

In contrast, the model trained to predict time points within the Parkinson's disease group showed only modest performance. Although it exceeded chance level, its explanatory power was substantially lower than that of the group model. SHAP analyses revealed that anisotropy was the only feature with a meaningful contribution to time prediction, suggesting that longitudinal changes were subtle and limited to specific aspects of image structure.

Descriptive analyses supported the machine learning results. At baseline, healthy controls showed markedly higher visual complexity and more pronounced global structural organization than participants with Parkinson's disease. These group differences persisted across all assessed time points. Within the Parkinson's disease group, complexity showed a small increase following intervention but remained substantially below healthy control levels, while Fourier-based and positional measures were largely stable over time. Overall, descriptive patterns pointed to robust between-group differences alongside minimal within-group temporal change.

Baseline mixed-design ANOVAs confirmed strong group effects for complexity and Fourier slope, indicating consistent differences between healthy controls and participants with Parkinson's disease. Cue-related effects were present for Fourier-based measures, with evidence that cue manipulation influenced visual output differently across groups, particularly for Fourier slope. In contrast, complexity was unaffected by cue condition, suggesting that this measure reflects a stable group characteristic rather than task-specific modulation. Meaning that cues do not influence outcomes and rather the group specific variance is the reason for these findings.

Intervention analyses within the Parkinson's disease cohort revealed limited effects. A change over time was observed only for Fourier sigma, with evidence that this change was driven

by the intervention group rather than the non-intervention group. All other measures, including complexity, Fourier slope, and positional indices, showed no meaningful intervention-related or temporal effects. Repeated-measures analyses in the non-intervention group further supported the temporal stability of all examined features.

Taken together, the results indicate that machine learning models robustly capture group-specific visual characteristics associated with Parkinson's disease, primarily driven by global image structure and spatial organization. Longitudinal and intervention-related changes were comparatively small, suggesting that these quantitative image properties are stable markers of group differences rather than sensitive indicators of short-term change, intervention or cue specificality.

4.3. Synopsis of Interpretation

This master's thesis investigated whether a standardized, computerized approach can serve as a reliable method for distinguishing individuals with PD from HC. To address this aim, three complementary methodological approaches were applied: the Cued Drawing Task (Pelowski et al., 2019), the Aesthetic Toolbox (Redies et al., 2025), and a machine learning–based classification approach using gradient boosted decision trees (Zeggio et al., 2025). All three parts combined allowed in unison for a quick and reliable distinguishing between HC and PD.

The Cued Drawing Task provided a reliable and highly standardized framework for data acquisition. Supported by a linear analytical approach (ANOVAs), the cue conditions did not differ significantly from one another, indicating that the task design itself did not introduce systematic bias. This supports the suitability of the task for consistent and comparable data collection across participants.

The Aesthetic Toolbox proved to be an efficient and methodologically accessible tool for the standardized extraction of QIPs. While the extraction of QIPs is not novel in itself, the ability to compute a broad range of such measures within a single, unified toolbox represents a substantial methodological gain. The results gathered from this toolbox could be crucial in facilitating interdisciplinary research and could enhance comparability across studies by providing a common quantitative framework for the analysis of future drawing data.

Finally, the gradient boosted decision tree model demonstrated potential as a valid method for extracting diagnostically relevant information and constructing a classification model. Despite being trained on incomplete data, as discussed earlier, the model yielded meaningful results, suggesting that machine learning approaches are well suited for capturing complex, multivariate patterns in QIP based data.

4.4. Study Limitations

In addition to the limited interpretability of the data resulting from the missing predictors in the HC group, several further limitations must be considered. Owing to the data structure, which

includes only a single time point for the HC group, more detailed longitudinal analyses and comparisons across time are not possible or at least limited in their interpretability. This constraint reduces the generalizability of the findings. Moreover, the relatively small number of participants, in combination with the results of the G*Power analysis, suggests that the significant effect sizes observed may be overestimated and potentially not replicable.

Another important limitation concerns the origin of the datasets. The PD sample was collected in the Netherlands, whereas the HC sample originated from Austria. This discrepancy introduces the possibility that some of the detected differences reflect country- or culture-specific factors rather than disease-related effects. Additionally, the mean age difference between the groups represents a potential confounding variable that may have influenced the results.

With respect to the PD group, although participation in art therapy was documented, no reliable information was available regarding participants' drawing experience at the start of data collection. As a result, the potential influence of prior drawing experience cannot be adequately assessed. Furthermore, information on medication status, particularly regarding dopaminergic medication, was not available due to confidentiality constraints. Consequently, the potential impact of medication on drawing behaviour and the extracted measures remains unknown.

Finally, although ANOVAs are widely used in psychological research (Rouder et al., 2023), their capacity to validate non-linear approaches is inherently limited. Attempting to substantiate a non-linear classification approach using primarily linear statistical methods therefore has restricted explanatory power. In light of these limitations, the overall interpretative strength of the present findings is limited, and the results should primarily be viewed as a basis for a methodologically more rigorous replication of the experimental setup.

Lastly, the exclusive use of QIPs represents only one perspective on aesthetics and therefore creative expression. As such, this approach may not fully capture differences in creative output and may instead reflect related but distinct constructs.

4.5. Strengths

Nevertheless, this initial exploration highlights the potential of an automated, systematic, and quantitative approach. The operational costs of such a methodology are practically negligible, and, if reproducible, it could provide an efficient means of distinguishing individuals with PD from HC. Beyond this application, the approach may also be extended to investigate whether other neurodegenerative diseases can be reliably differentiated using similar methods (Pelowski et al., 2022).

In addition, machine learning enables a more holistic analytical perspective by leveraging the full multivariate structure of the data. Rather than evaluating individual QIPs in isolation, the algorithm simultaneously incorporates information from all available features, thereby reducing the risk of selective reporting, biased interpretation, or misestimation associated with simple univariate comparisons. In future iterations, this approach may further reveal that a reduced subset of QIPs is

sufficient for reliable group classification, which would enhance both the interpretability and practical applicability of the method.

4.6. Future Research

Future research should address the limitations identified in the present study through several methodological refinements. First, sample sizes should be increased in accordance with the results of the power analysis to ensure sufficient statistical power and more stable effect size estimates. In addition, participants should be matched with respect to age and gender, and recruited from the same country, in order to minimize potential biases related to demographic and cultural differences.

Further studies should also systematically document the status of DA medication, given its substantial influence on the dopaminergic system, which forms the theoretical foundation of the present work.

Moreover, future approaches could benefit from the digitalization of the drawing process itself. Providing participants with tablets for the drawing task would eliminate several preprocessing steps required for scanned images and further streamline the analytical pipeline.

4.7. Conclusion

The present study aimed to validate the combined use of these methodological approaches and to identify systematic patterns in the data that might influence interpretation, thereby clarifying whether the observed classification results can be attributed to genuine differences between PD and HC or to other confounding factors. Within the scope of this study, it is not possible to determine the reliability or validity of each individual tool in isolation. However, the findings support the notion that the integration of these approaches constitutes a reliable and valid framework for addressing the question of whether PD and HC can be differentiated.

Identifying reliable patterns between PD and HC may contribute to a more robust understanding of the underlying neurobiological alterations associated with PD (Khalil et al., 2019; Kulisevsky et al., 2009; Lauring et al., 2019). Moreover, such patterns could form the basis for a standardized diagnostic procedure that is easy to administer, cost-effective, and reliable. In light of proposed early changes in creativity-related processes in PD, this approach may further support the development of classification tools capable of identifying PD at a pre-diagnostic stage, as suggested by previous research (Chaudhuri et al., 2006).

The contribution of this work lies in advancing the understanding of the interplay between creativity, PD, and neurobiological processes. Although the underlying mechanisms remain incompletely understood, the association between these domains appears robust. By combining standardized behavioural tasks, quantitative feature extraction, and machine learning–based classification, this study represents an initial step toward identifying stable patterns within a complex, multifaceted research domain. While these findings are preliminary, they underscore the

potential of systematic, data-driven classification approaches. Further research with larger and more comprehensive datasets is required to validate, refine, and generalize the results.

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6. Abbreviations

ABBREVIATION	DEFINITION
ANOVA	Analyses of variance
CAP	Artistic Creativity & Anxiety in Parkinson's Disease
DA	Dopamine agonist
DALY	Disability adjusted life years
GBDT	Gradient boosted Decision tree
HC	Healthy Controls
HY	Hoehn and Yahr
LID	Levodopa-induced dyskinesia
MAO-B	Monoaminooxidase B
MOCA	Montreal Cognitive Assesment
PD	Parkinson's Disease
PDN	Parkinson's Patients without intervention
PDT	Parkinson's Patients with intervention
PVC	Prefrontal cortex
QIP	Quantitative Image Property
QIP	Quantitative image properties
QOL	Quality of life
REM	Rapid eye movement
SHAP	Shapley Additive exPlanations
UPDRS	Unified Parkinson's disease rating scale
VSNC	ventral substantia nigra pars compacta
VTA	subcortical ventral tegmental area

7. Table of Tables

8. Table of Figures

9. Appendix

APENDIX A – Abstract

9.1. Abstract ENG

Parkinson’s disease is a progressive neurodegenerative disorder associated not only with motor impairments but also with cognitive, emotional, and creativity-related changes. Emerging evidence suggests that alterations in artistic expression may constitute an early and underexplored marker of the disease. The primary aim of the present master’s thesis was to validate a standardized, quantitative, and reproducible methodological pipeline for analysing art-related changes in Parkinson’s disease. Specifically, the study evaluated whether the combined use of a controlled drawing task, objective image feature extraction, and machine learning–based classification constitutes a valid framework for distinguishing individuals with Parkinson’s disease from healthy controls.

The machine learning model reliably distinguished Parkinson’s disease participants from healthy controls well above chance, with classification driven by multiple independent quantitative

image properties rather than isolated features. Importantly, cue conditions did not systematically bias results, and longitudinal as well as intervention-related effects were minimal, supporting the temporal stability of the extracted measures. Together, these findings indicate that the observed group differences are attributable to robust visual characteristics rather than task artifacts or short-term fluctuations.

Despite limitations related to missing predictors and sample heterogeneity, the results support the validity of the proposed end-to-end approach as a standardized, cost-effective, and scalable framework for future research. This work demonstrates that integrating controlled drawing task, quantitative image analysis, and machine learning provides a methodologically sound basis for investigating art-related changes in Parkinson's disease and lays the groundwork for more rigorous replication and potential pre-diagnostic applications.

9.2. Abstract DEU

Die Parkinson-Krankheit ist eine progressive neurodegenerative Erkrankung, die nicht nur mit motorischen Beeinträchtigungen, sondern auch mit kognitiven, emotionalen und kreativitätsbezogenen Veränderungen einhergeht. Zunehmende empirische Evidenz deutet darauf hin, dass Veränderungen im künstlerischen Ausdruck einen frühen und bislang wenig erforschten Marker der Erkrankung darstellen könnten. Das primäre Ziel der vorliegenden Masterarbeit bestand darin, eine standardisierte, quantitative und reproduzierbare methodische Pipeline zur Analyse kunstbezogener Veränderungen bei der Parkinson-Krankheit zu validieren. Konkret wurde untersucht, ob die kombinierte Anwendung einer kontrollierten Zeichenaufgabe, objektiver Bildmerkmalextraktion und maschineller Klassifikationsverfahren ein valides Rahmenkonzept zur Unterscheidung von Personen mit Parkinson-Krankheit und gesunden Kontrollpersonen darstellt.

Das eingesetzte Machine-Learning-Modell unterschied zuverlässig zwischen Teilnehmenden mit Parkinson-Krankheit und gesunden Kontrollen deutlich über dem Zufallsniveau, wobei die Klassifikation durch mehrere unabhängige quantitative Bildeigenschaften und nicht durch einzelne isolierte Merkmale bestimmt wurde. Von besonderer Bedeutung ist, dass Cue-Bedingungen die Ergebnisse nicht systematisch verzerrten und sowohl longitudinale als auch interventionsbezogene Effekte gering ausfielen, was die zeitliche Stabilität der extrahierten Maße unterstützt. Ultimativ sprechen diese Befunde dafür, dass die beobachteten Gruppenunterschiede auf robuste visuelle Charakteristika zurückzuführen sind und nicht auf Aufgabenartefakte oder kurzfristige Schwankungen.

Trotz bestehender Limitationen, insbesondere im Hinblick auf fehlende Prädiktoren und Stichprobenheterogenität, stützen die Ergebnisse die Validität des vorgeschlagenen End-to-End-Ansatzes als standardisiertes, kosteneffizientes und skalierbares Framework für zukünftige Forschung. Die Arbeit zeigt, dass die Integration einer kontrollierten Zeichenaufgabe, quantitativer Bildanalyse und maschinellen Lernens eine methodisch fundierte Grundlage zur Untersuchung

kunstbezogener Veränderungen bei der Parkinson-Krankheit bietet und den Weg für Replikationsstudien sowie potenzielle prädiagnostische Anwendungen ebnet.

APENDIX B-Statistic

Table 13
Assumption Checks for All ANOVAs (Baseline, PD Intervention, PD Non-Intervention)

ANOVA	QIP	Normality	Homogeneity of Variance (Levene)	Sphericity	Correction
1 (T0 Group × Cue)	Fourier slope	Assumed	Assumed	Violated	Greenhouse–Geisser
	Fourier sigma	Assumed	Assumed	Violated	Greenhouse–Geisser
	Complexity	Assumed	Assumed	Violated	Greenhouse–Geisser
2 (PD Intervention × Time)	DCM y position	Assumed	Assumed	Not applicable	None
	DCM x position	Assumed	Assumed	Not applicable	None
	Fourier slope	Assumed	Assumed	Not applicable	None
	Fourier sigma	Assumed	Assumed	Not applicable	None
	Complexity	Assumed	Assumed	Not applicable	None
3 (PDN RM Time)	DCM y position	Assumed	Not applicable	Violated	Greenhouse–Geisser
	DCM x position	Assumed	Not applicable	Violated	Greenhouse–Geisser
	Fourier slope	Assumed	Not applicable	Violated	Greenhouse–Geisser
	Fourier sigma	Assumed	Not applicable	Violated	Greenhouse–Geisser
	Complexity	Assumed	Not applicable	Violated	Greenhouse–Geisser

Note. Normality was assessed using Shapiro–Wilk tests on model residuals. Homogeneity of variance was evaluated using Levene's test (ANOVA 1: tested per cue; ANOVA 2: tested on participant-level means collapsed across time). Sphericity was assessed using Mauchly's test for within-subject factors with more than two levels (Cue in ANOVA 1; Time in ANOVA 3). Where sphericity was violated, Greenhouse–Geisser–corrected degrees of freedom were used. Sphericity is not applicable for ANOVA 2 because Time has two levels. Baseline ANOVAs for DCM x position and DCM y position were not estimable due to missing baseline data for the HC group; therefore, assumption tests were not applicable for these variables.

9.3. ANOVA 1

9.3.1. Fourier Slope

Table 14
Fourier slope: Tukey-adjusted pairwise cue comparisons (collapsed across Group)

Contrast	Estimate	SE	df	t	p
C1 − C2	0.0582	0.0185	114	3.153	.0058*
C1 − C3	0.0356	0.0154	114	2.316	.0576
C2 − C3	−0.0227	0.0166	114	−1.364	.3632

Note. Tukey adjustment for the family of 3 cue comparisons. p values are adjusted. p < .05 marked with *.

Table 15
Fourier slope: Tukey-adjusted pairwise cue comparisons within Group
Group = HC

Contrast	Estimate	SE	df	t	p
C1 − C2	0.0937	0.0266	114	3.528	.0017*
C1 − C3	0.0191	0.0221	114	0.863	.6649
C2 − C3	−0.0747	0.0239	114	−3.125	.0063*

Group = PD

Contrast	Estimate	SE	df	t	p
C1 − C2	0.0227	0.0257	114	0.885	.6507
C1 − C3	0.0521	0.0213	114	2.440	.0426*
C2 − C3	0.0294	0.0231	114	1.272	.4141

Note. Tukey adjustment applied within each group (family of 3 cue comparisons per group). p < .05 marked with *.

Table 16
Fourier slope: Group contrasts within each Cue

Cue	Contrast	Estimate	SE	df	t	p
C1	HC − PD	−0.666	0.0350	114	−19.020	< .0001*
C2	HC − PD	−0.737	0.0393	114	−18.762	< .0001*
C3	HC − PD	−0.633	0.0346	114	−18.329	< .0001*

Note. These are simple contrasts of Group within each cue (no multiple-comparison correction was shown in this output; with only two groups, the contrast is unique per cue). p < .05 marked with *.

9.3.2. Fourier Sigma

Table 17
Fourier sigma: Tukey-adjusted pairwise cue comparisons (collapsed across Group)

Contrast	Estimate	SE	df	t	p
C1 − C2	0.00134	0.00225	114	0.595	.8229
C1 − C3	−0.00910	0.00253	114	−3.591	.0014*
C2 − C3	−0.01044	0.00262	114	−3.988	.0003*

Note. Tukey adjustment for the family of 3 cue comparisons. p values are adjusted. p < .05 marked with *.

Table 18
Fourier sigma: Tukey-adjusted pairwise cue comparisons within Group
Group = HC

Contrast	Estimate	SE	df	t	p
C1 − C2	−0.00172	0.00324	114	−0.531	.8564
C1 − C3	−0.00727	0.00364	114	−1.994	.1182

Contrast	Estimate	SE	df	t	p
C2 − C3	−0.00555	0.00376	114	−1.473	.3075

Group = PD

Note. Tukey adjustment applied within each group (family of 3 cue comparisons per group). p < .05 marked with *.

Contrast	Estimate	SE	df	t	p
C1 − C2	0.00440	0.00313	114	1.406	.3411
C1 − C3	−0.01092	0.00352	114	−3.104	.0068*
C2 − C3	−0.01533	0.00364	114	−4.214	.0001*

9.4. ANOVA 2

9.4.1. Fourier Sigma

Table 19

Fourier sigma: Time contrasts (T0 − T1) within Intervention

Intervention	Contrast	Estimate	SE	df	t	p
PDN	T0 − T1	−0.000119	0.00545	55	−0.022	.9826
PDT	T0 − T1	0.022520	0.00554	55	4.063	.0002*

Note. Pairwise comparisons of Time within each Intervention (2-level factor → single contrast per group). p < .05 marked with *.

Table 20

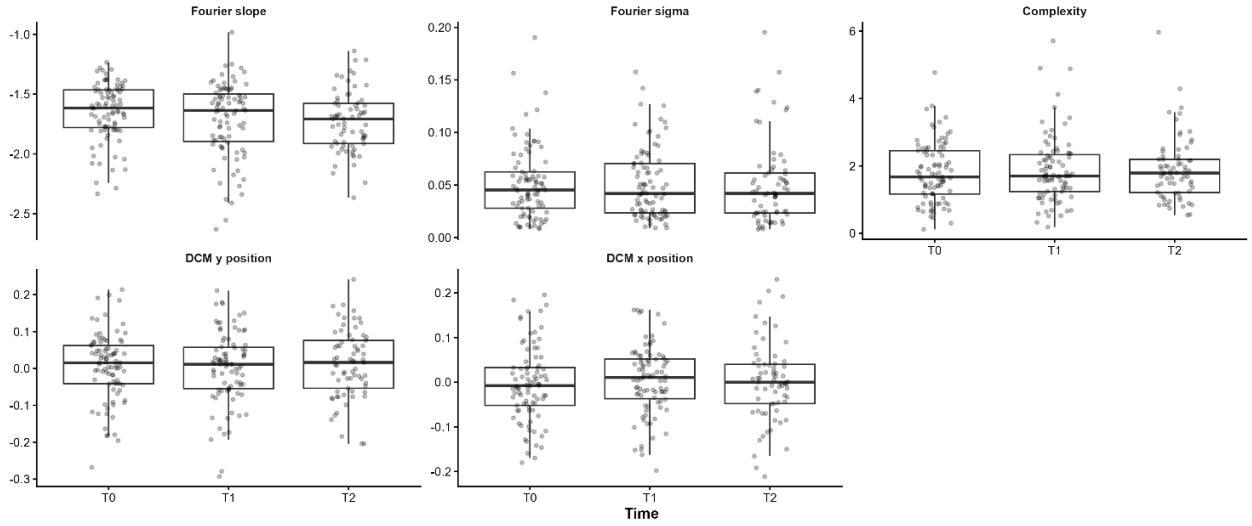
Fourier sigma: Intervention contrasts (PDN − PDT) within Time

Time	Contrast	Estimate	SE	df	t	p
T0	PDN − PDT	−0.01393	0.00982	55	−1.419	.1616
T1	PDN − PDT	0.00871	0.00746	55	1.167	.2484

Note. Pairwise comparisons of Intervention within each Time (two groups).

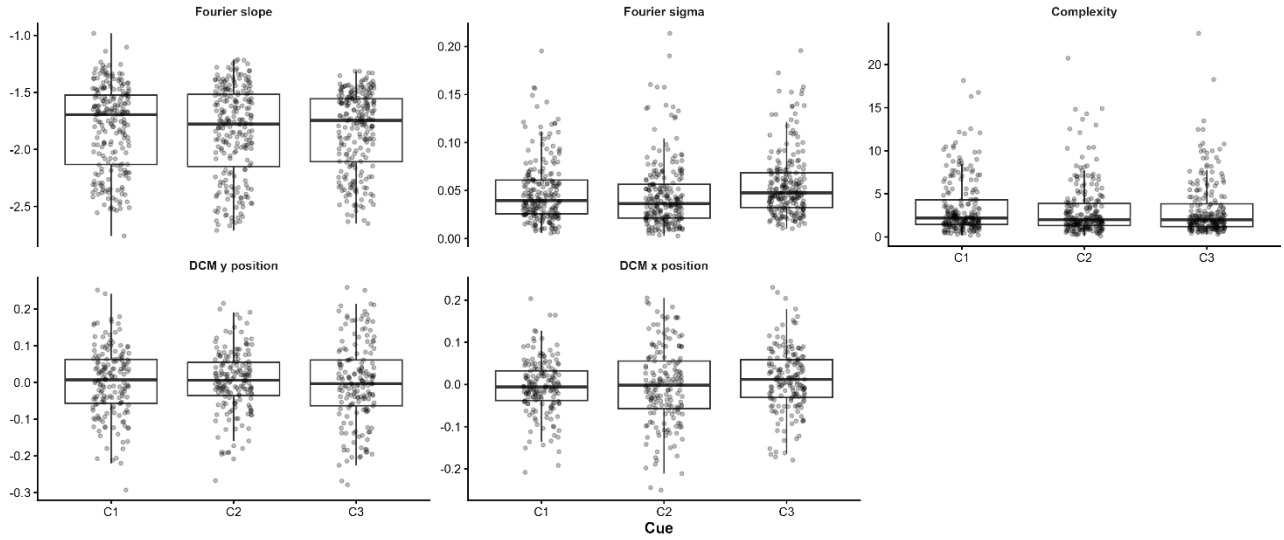
9.5. Descriptive Data

Figure 12
Boxplot of Time differences



Note. Boxplots for Fourier slope, Fourier sigma, Complexity, DCM y position and DCM x position for PD group over time.

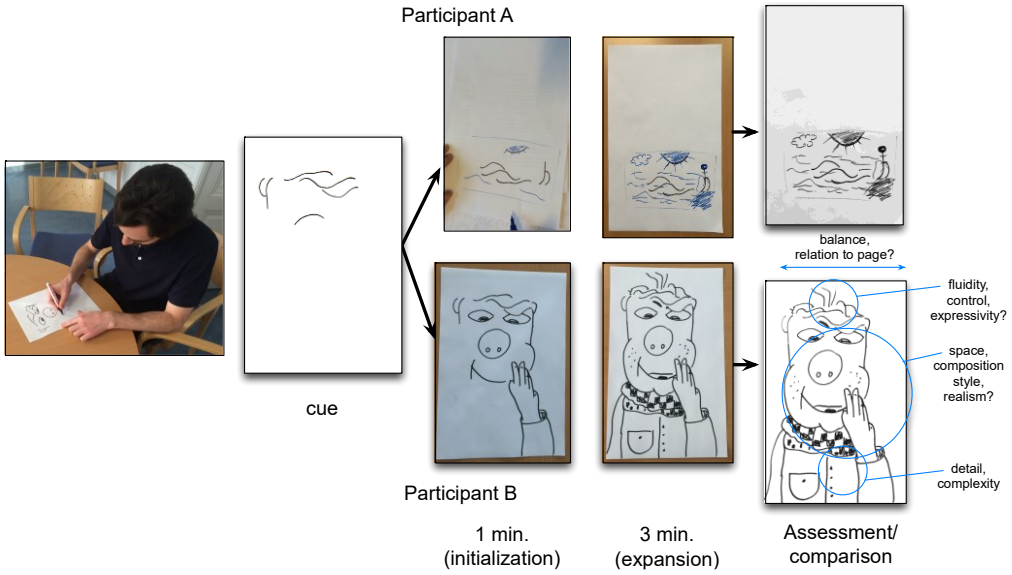
Figure 13
Boxplot of cue differences



Note. Boxplots for Fourier slope, Fourier sigma, Complexity, DCM y position and DCM x position for PD group split for each cue.

APENDIX C – Additional Figures and Tables

Figure 14



Note: Sketching procedure 'Cued, Drawing Task' from Pelowski et al. (2019)

9.5.1. R-Version Number

R version 4.3.3 (2024-02-29 ucrt) -- "Angel Food Cake"

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Platform: x86_64-w64-mingw32/x64 (64-bit)