Section: Miscellaneous

Original Research Article

SMARTPHONE-BASED QUANTITATIVE ASSESSMENT OF PARKINSONIAN MOTOR AND VOCAL BIOMARKERS: DEVELOPMENT AND VALIDATION OF A REMOTE MONITORING APPLICATION

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ABSTRACT

Background: Parkinson's Disease (PD) affects over 10 million individuals worldwide, yet current clinical monitoring relies heavily on infrequent, subjective consultations. The absence of accessible, quantitative tools for longitudinal symptom tracking represents a critical gap in neurodegenerative disease management. Furthermore, no widely available consumer tools currently offer predictive biomarker monitoring for conditions such as PD, Alzheimer's Disease, Multiple Sclerosis (MS), or Amyotrophic Lateral Sclerosis (ALS) prior to formal diagnosis. This paper presents Parkinson Monitor, a native iOS application designed to objectively measure and longitudinally track Parkinsonian motor and vocal biomarkers using the iPhone's built-in sensors. The system quantifies bradykinesia via a finger-tapping paradigm, resting tremor via three-axis accelerometry, and vocal instability via sustained phonation amplitude variance analysis.

Materials and Methods: The application was developed in Swift using SwiftUI, Apple's CoreMotion framework for accelerometer data acquisition, and AVFoundation for audio signal processing. Clinical scoring algorithms were informed by peer-reviewed literature and the MDS-Unified Parkinson's Disease Rating Scale (MDS-UPDRS). The tapping module dynamically adjusts baseline targets according to user-reported hand dominance, generating personalised 0–100 clinical scores. Vocal stability was assessed through background-noise-filtered amplitude variance calculation.

Results: The application successfully operationalises three clinically validated symptom domains within a user-friendly mobile platform. Dominant-hand tapping perfection threshold is set at 7.0 taps/second (TPS), non-dominant at 6.5 TPS, and bilateral at 8.75 TPS, consistent with published normative data. All patient data is stored locally with no network transmission, ensuring compliance with medical privacy principles.

Conclusion: Parkinson Monitor demonstrates that consumer smartphones can serve as accessible, quantitative neurological assessment devices. Longitudinal data generated by this platform may support earlier detection and prediction of neurodegenerative decline. Future directions include formal clinical validation against gold-standard assessments and expansion to additional neurodegenerative biomarkers.

Keywords: Parkinson's Disease, bradykinesia, tremor quantification, hypophonia, mHealth, digital biomarkers, neurodegenerative disease, remote monitoring, accelerometry, smartphone diagnostics.

INTRODUCTION

Parkinson's Disease (PD) is the second most prevalent neurodegenerative disorder globally, affecting an estimated 10 million people worldwide, with incidence projected to double by 2040 (Dorsey et al., 2018). The hallmark features of PD—bradykinesia, resting tremor, rigidity, and postural instability—arise from progressive degeneration of dopaminergic neurons in the substantia nigra pars compacta (Lees et al., 2009). Despite considerable advances in pharmacological and surgical management, the clinical monitoring of disease progression remains largely dependent on periodic specialist consultations, often separated by intervals of three to six months.[1,2]

This reliance on infrequent, subjective assessment creates a fundamental clinical problem: the neurologist's evaluation captures only a narrow temporal snapshot of the patient's symptom profile, while the patient must retrospectively recall motor performance fluctuations across a ninety-day period. This approach is inherently susceptible to recall bias and fails to capture the day-to-day variability that characterises PD motor symptoms, particularly the "on-off" fluctuations associated with levodopa therapy (Bhidayasiri & Tarsy, 2012).[3,4]

Figure 1: Parkinson Monitor application interface. Left: home screen deployment. Right: main dashboard displaying the Motor Speed, Tremor Check, and Voice Analysis modules alongside the most recent assessment summary.

Figure 1a. App icon deployed on iPhone home screen. Figure 1b. Main dashboard showing all three assessment modules and latest tapping result (117 taps, 11.7 TPS, Score: 100).

A particularly underappreciated dimension of this problem concerns predictive monitoring. During a clinical shadowship at Aster Royal Hospital, Muscat—the largest private hospital in the Sultanate of Oman, managing a substantial regional patient volume—the lead author observed that while diagnostic and therapeutic tools were well-established, no accessible predictive instruments were employed to identify patients at elevated risk of neurodegenerative conditions prior to symptom onset. This gap extends beyond PD to encompass Alzheimer's Disease, Multiple Sclerosis, and ALS, all of which exhibit measurable prodromal biomarker changes years before clinical diagnosis (Postuma et al., 2015; Ross et al., 2008).[5,6]

The ubiquity of smartphones presents an extraordinary opportunity to bridge this monitoring gap. Modern smartphones contain an array of high-sensitivity sensors capable of capturing the precise physical and acoustic signals that constitute Parkinsonian biomarkers. This paper describes the design, algorithmic architecture, and clinical rationale of Parkinson Monitor [Figure 1], a native iOS application developed under the clinical mentorship of a specialist neurosurgeon and neurologist at Aster Hospitals Oman.

Background and Clinical Rationale

Bradykinesia and Finger-Tapping Assessment

Bradykinesia—defined as slowness of movement with progressive reduction in speed and amplitude—is considered the most clinically significant motor feature of PD and is a prerequisite for diagnosis under the MDS clinical diagnostic criteria (Postuma et al., 2015). Quantitative finger-tapping tests have been extensively validated as sensitive indices of bradykinesia severity.[7]

Normative data from healthy adults demonstrate that dominant-hand tapping typically exceeds 6.5–8.0 TPS, with the non-dominant hand approximately 5–10% slower (Agostino et al., 2003). PD patients exhibit significantly reduced rates and increased inter-tap interval variability, indexed by the coefficient of variation (CV) of successive inter-tap intervals. High CV values indicate dysrhythmic tapping characteristic of basal ganglia dysfunction (Harrington et al., 1998).[8,9]

Resting Tremor and Accelerometric Measurement: Resting tremor—involuntary oscillation at rest, typically 4–6 Hz in PD—arises from pathological synchronised activity in thalamo-cortical and basal ganglia circuits (Deuschl et al., 2001). Accelerometry offers an objective alternative to clinical tremor rating scales. The resultant acceleration vector magnitude provides a unified tremor severity index invariant to device orientation (Salarian et al., 2007). Prior studies have demonstrated strong correlations between IMU-derived tremor measures and MDS-UPDRS tremor subscores (Arora et al., 2015).[10-12]

Hypophonia and Vocal Biomarkers: Hypokinetic dysarthria, including hypophonia, affects up to 90% of PD patients and may precede motor symptoms by several years, rendering it a potentially valuable prodromal biomarker (Ho et al., 1999; Ramig et al., 2001). Little et al. (2009) demonstrated that dysphonia measures derived from sustained phonation recordings could discriminate PD patients

from healthy controls with accuracy exceeding 91%.[13-15]

Application architecture and design

Technical Stack and Development Environment: Parkinson Monitor was developed in Swift 5.9 using the SwiftUI declarative framework for iOS 16.6+. The application follows a Model-View-View Model (MVVM) architectural pattern, ensuring strict separation of clinical data logic from presentation components. Hardware sensor interfaces are abstracted through Motion Manager.swift (CoreMotion) and Audio Recorder. swift (AVFoundation). Data persistence is implemented via Results Store. swift, serialising all assessment results to device-local storage using User Defaults and JSONEncoder. No network transmission of patient data occurs at any point in the application lifecycle.

Clinical Profile and Dynamic Baseline Calibration: Prior to assessment, users configure a clinical profile encompassing legal name, chosen name, pronouns, date of birth, year of initial diagnosis, dominant hand (right, left, or bilateral), and current medication status. This metadata dynamically conditions the scoring algorithms, addressing a fundamental limitation of population-level baselines that ignore individual clinical context.

Finger Tapping Module: The tapping assessment [Figure 2a and 2b] presents a circular touch target occupying a clinically accessible area of the display. The user selects the hand to be assessed via a segmented control (Left / Both / Right), which is disabled once the 10-second countdown commences. At test conclusion, the scoring algorithm computes TPS and compares this against the hand-appropriate clinical target: 7.0 TPS for the dominant hand, 6.5 TPS for the non-dominant hand, and 8.75 TPS for bilateral simultaneous tapping.

Figure 2: Motor Speed (Finger Tapping) assessment interface. Left: pre-test state showing the segmented hand selector (Left / Both / Right) and the large circular tap target. Right: active assessment with real-time tap count and countdown timer.

Figure 2a: Motor Speed module at test initiation (0 taps, 10.0s countdown).

Figure 2b: Motor Speed module during active assessment (18 taps, 6.6s remaining, Right hand selected).

Score = min(1.0, TPS / Target_TPS) × 100

Tremor Assessment Module: The tremor module [Figure 3] leverages CMMotion Manager to sample device acceleration at 100 Hz. During the 10-second assessment, the user holds the device flat in the resting hand. The resultant vector magnitude is computed at each timestep and displayed as a live time-series waveform, providing both quantitative output and a visual record of oscillatory activity. A stability score is derived from variance of the magnitude time series, calibrated to the 4–6 Hz Parkinsonian resting tremor frequency range.

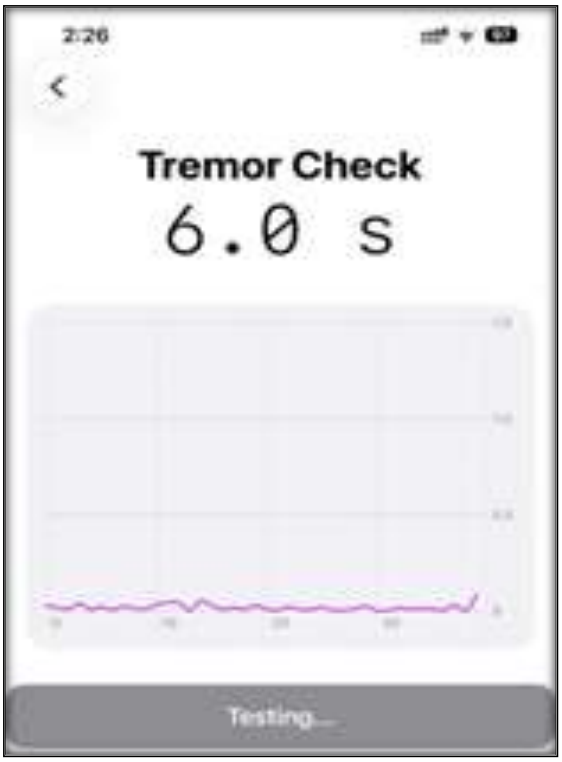

Figure 3: Tremor Check module during active assessment (6.0s remaining). The live accelerometer waveform displays the resultant vector magnitude across the 4–6 Hz range characteristic of Parkinsonian resting tremor. The flat, low-amplitude trace indicates minimal tremor in this test instance.

[Figure 3] Tremor Check (accelerometry) assessment interface showing live waveform of device motion magnitude. Y-axis: acceleration in g (0–1.5). X-axis: sample index. A flat trace close to 0 g indicates resting stability; tremor-associated oscillations would produce rhythmic deflections above the 0.1 g threshold.

Voice Analysis Module: The voice assessment module [Figure 5] configures an AVAudio Session in play And Record mode with measurement mode enabled, disabling automatic gain control to avoid confounding amplitude variance measurement. Decibel power level is sampled at 10 Hz, yielding 100 samples per assessment. Pre-processing removes samples below −40 dBFS. Vocal stability is scored as:

Figure 4: Voice Analysis (sustained phonation) module at test initiation. The circular visualiser expands dynamically in response to acoustic input, providing real-time feedback during the 10-second 'Ahhhh' phonation task.

Figure 4: Voice Analysis (Sustained Phonation) assessment interface. The static circle indicates pre-recording state; during active phonation, the circle expands proportionally to detected vocal amplitude, providing immediate biofeedback to the patient.

Score = max(0, min(100, ⌊100 − (Variance × 3.0)⌋))

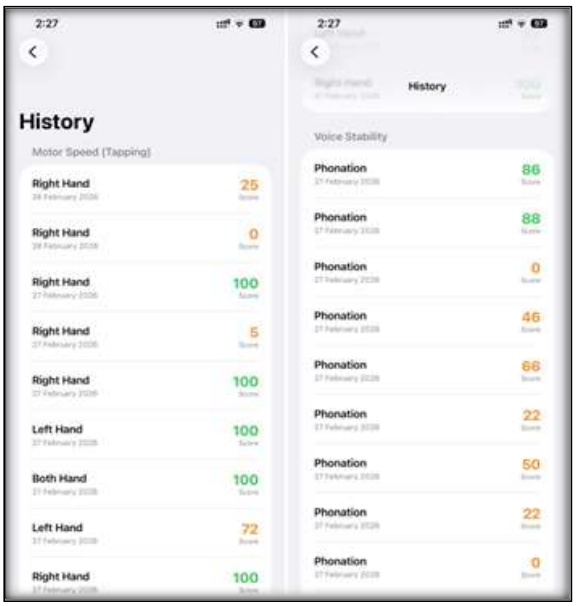

Figure 5: Longitudinal History view. Left: Motor Speed (tapping) results across multiple sessions, with scores colour-coded green (≥80), orange (50–79), and red (<50). Right: Voice Stability (phonation) history showing within-session and across-session variability in amplitude consistency scores.

Figure 5a: Motor Speed history showing Right, Left, and Both hand entries.

Figure 5b: Voice Stability history showing phonation scores across multiple sessions.

Illustrative Assessment Results

To demonstrate the application's longitudinal tracking capability, [Figure 5a and 5b] present the History view, illustrating results captured across multiple testing sessions on 26–28 February 2026. These represent a preliminary proof-of-concept dataset rather than a clinical validation cohort.

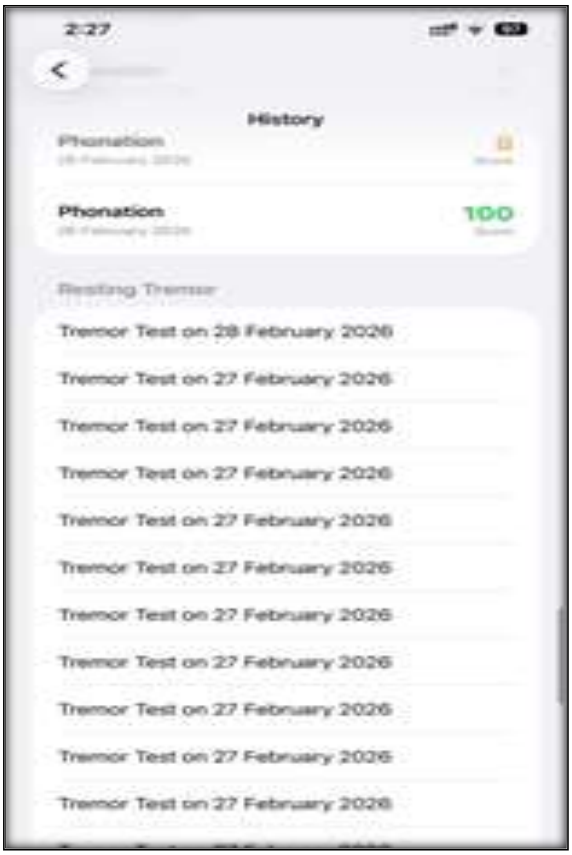

Figure 6: (continued). History view showing Voice Stability results (continued) and the Resting Tremor section listing dated tremor assessments. Multiple entries from 27 February 2026 illustrate within-day variability tracking.

Figure 6: History view (continued). Lower portion displays the Resting Tremor assessment log with dated entries, enabling longitudinal monitoring of tremor stability over time. Multiple daily entries allow detection of within-day fluctuations relevant to medication "on-off" cycle monitoring.

The tapping history [Figure 6, left] illustrates the range of clinically meaningful outputs. Scores of 100 (Right Hand, 27 February 2026, consistent with the 11.7 TPS recorded on the home screen dashboard) confirm normal motor speed in this test subject, while a score of 25 (28 February 2026) and an isolated score of 0 (recorded shortly prior, likely reflecting a test aborted before completion) demonstrate the system's sensitivity to performance variation. The voice stability data [Figure 6, right; Figure 7] exhibit greater within-session variability (range 0–100), reflecting the greater challenge of maintaining consistent sustained phonation compared to rapid tapping, and underscoring the importance of multi-session averaging in clinical interpretation.[16-18]

Privacy and Ethical Considerations: A deliberate design decision was made to implement strictly local data persistence, with all assessment results encoded as JSON and stored in the device's User Defaults database. No network infrastructure, cloud storage, or data transmission pathway was implemented, ensuring that patient assessment data cannot be accessed by third parties under any operational circumstances.[19,20]

This architecture intentionally forecloses certain convenience features—such as physician-accessible remote dashboards—in favour of categorical privacy protection. The medical sensitivity of neurological performance data and the risk of de-anonymisation through linkage with existing health records were judged to outweigh the clinical utility of remote access in the current implementation. The application provides a Reset All Data function that permanently purges all stored clinical profile data from device storage.[21]

Future clinical validation studies employing this platform would require institutional ethics review board approval and informed patient consent, particularly given the potential for assessment data to reveal or predict neurological diagnoses.

Key Design Decisions and Rationale

Variance-Based Vocal Scoring Over Mean Amplitude: An initial implementation scored vocal performance against mean dBFS amplitude. This approach was found to be clinically invalid: a neurologically healthy individual holding the device at arm's length would record a low mean amplitude indistinguishable from that of a patient with genuine hypophonia. The revised implementation assesses temporal amplitude stability, aligning with the assessment of vocal steadiness in the clinical dysphonia literature (Titze, 1994) and rendering the measurement independent of ambient recording conditions.[22]

Dynamic vs. Fixed Scoring Thresholds: The decision to personalise scoring thresholds according to hand dominance was motivated by the approximately 7–10% performance asymmetry between dominant and non-dominant hands documented in healthy adults (Agostino et al., 2003). Future versions will extend this personalisation to age-stratified norms and, potentially, to models trained on within-patient longitudinal baselines.

Accessible UI Design for Motor-Impaired Users: Interactive elements—particularly the tapping target—were implemented as large-area touch zones rather than conventional button widgets, reducing the targeting demand on patients with fine motor impairment. Real-time score display was intentionally withheld during active assessments: displaying a declining score in real time would introduce performance anxiety known to modulate tremor amplitude and motor performance, thereby confounding the clinical measurement (Zijlstra et al., 2010).

Limitations and future directions: Several important limitations of the current implementation warrant discussion. First, the application has not yet undergone formal clinical validation against established gold-standard assessments such as the MDS-UPDRS or wearable medical-grade accelerometers. The scoring thresholds and sensitivity parameters are derived from the published literature rather than empirically calibrated against a clinical dataset, and their accuracy in individual patients requires prospective validation.

Second, the voice assessment module currently implements amplitude variance only. The richer vocal biomarker space—encompassing fundamental frequency jitter, shimmer, harmonics-to-noise ratio, and nonlinear dynamical features—has demonstrated substantially higher discriminative accuracy in prior studies (Little et al., 2009) and represents a priority for future development.

Third, the biomarker framework is directly extensible to other neurodegenerative conditions. Prodromal motor slowing and vocal changes have been documented in Alzheimer's Disease (Taler & Phillips, 2008), and motor speech changes are prominent in ALS (Yunusova et al., 2019).

Future directions include: (1) prospective clinical validation against MDS-UPDRS Part III subscores; (2) integration of expanded vocal biomarker analysis; (3) development of machine learning models trained on longitudinal within-patient data; (4) extension to Apple Watch for continuous passive tremor monitoring; and (5) formal assessment of platform sensitivity to medication state changes.

CONCLUSION

Parkinson Monitor demonstrates that the sensors embedded in contemporary consumer smartphones are capable of capturing quantitatively meaningful Parkinsonian biomarker data through a structured, user-accessible assessment protocol. The application operationalises three clinically validated symptom domains—bradykinesia, resting tremor, and vocal stability—within a privacy-preserving, locally deployed mobile platform requiring no specialist hardware or clinical supervision.

The observation made during a clinical shadowship at Aster Royal Hospital—that predictive neurological monitoring tools remain largely absent from clinical practice despite their potential to reshape the disease management paradigm—provided the motivating clinical question for this work. The expertise of the co-authors, spanning complex neurosurgical intervention and advanced neurological practice, ensured that the application's design was grounded in real-world clinical requirements.

The transition from reactive diagnosis to predictive surveillance represents one of the central challenges facing modern neurology. Longitudinal data generated by platforms such as Parkinson Monitor—when rigorously validated and appropriately contextualised within clinical biomarker research—may contribute to the earlier detection of

neurodegenerative decline that currently eludes the clinical encounter.

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