Longitudinal Quantification of Parkinsonian Gait Using Apple HealthKit: A Single-Subject Digital Phenotyping Study

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Abstract

Background

Parkinsonian gait is traditionally assessed using subjective clinical scales such as the Hoehn–Yahr classification and MDS-UPDRS, which lack temporal granularity and sensitivity to daily fluctuations. Advances in smartphone-based sensing now allow continuous, real-world gait quantification.

Objective

To determine whether Apple HealthKit gait metrics can detect year-to-year progression, daily variability, and gait-component contributions to walking-speed decline in a single individual with Parkinson's disease (PD).

Methods

A 77-year-old male with PD was monitored continuously from January 2024 to December 2025. HealthKit metrics included walking speed, step length, step count, double-support time, gait asymmetry, and walking steadiness. Weekly and daily patterns were compared across years.

Results

Walking speed declined by 14.3% from 2024 to 2025. Step length decreased by 31%. Step count also declined (69% relative contribution in decomposition analysis), although this metric reflects free-living walking activity and may be influenced by reduced walking opportunity rather than intrinsic gait alteration. The decline in walking speed may be partly attributable to reduced step length. Walking asymmetry showed variable data acquisition patterns that were not solely explained by walking volume.

Conclusion

Smartphone-derived gait metrics provide objective, sensitive detection of PD gait progression and daily motor fluctuations. These findings demonstrate the potential of pervasive digital monitoring to complement traditional clinical assessments and support individualized disease management.

Introduction

Parkinson's disease (PD) is a progressive neurodegenerative disorder characterized by bradykinesia, rigidity, tremor, and postural instability. Among these features, gait impairment is one of the most functionally disabling symptoms, leading to reduced mobility, increased fall risk, and loss of

independence. Despite its clinical importance, the assessment of gait disturbance in PD remains predominantly subjective and dependent on clinician observation.[1]

The most widely used clinical measures, including the Hoehn–Yahr (H–Y) staging system[2] and the Movement Disorder Society–Unified Parkinson's Disease Rating Scale (MDS-UPDRS)[3], offer only coarse, semi-quantitative descriptions of gait. For example, the distinction between "mild–moderate" impairment (H–Y stage 3) and "severe" gait disability (stage 4) is not defined by objective thresholds. Likewise, MDS-UPDRS Part III Item 11 ("Walking") assigns scores from 0 to 4 based on vague descriptors such as "mild," "moderate," or "severe," without specifying quantitative criteria for gait speed, stride length, cadence, stability, or freezing episodes[4,5.] As a result, inter-rater variability is substantial, and brief in-clinic evaluations fail to capture the pronounced intra-day and day-to-day fluctuations that characterize PD motor function.

With the increasing availability of smartphone-based sensors, continuous and passive gait quantification in real-world environments has become feasible[6-8]. Apple's HealthKit framework provides daily and weekly gait metrics—including walking speed, step length, step count, double-support time, gait asymmetry, and walking steadiness—derived from inertial sensors in standard consumer devices. These digital biomarkers offer objective, high-resolution, longitudinal measures of gait that may overcome the limitations of clinic-based assessments.

However, few studies have examined long-term within-subject gait dynamics in PD using consumer-grade devices. In particular, it remains unclear whether smartphone-derived gait measures can detect year-to-year progression, quantify daily variability, or decompose gait-speed decline into changes in stride length versus cadence.

In the present case, gait symptoms were relatively mild and stable during 2024, despite a confirmed diagnosis of PD. In contrast, clear clinical worsening—including increased freezing of gait, reduced stride amplitude, and greater difficulty with postural control—emerged during 2025, particularly after April. This natural progression provided an opportunity to examine whether digital gait metrics could sensitively capture functional decline. Therefore, we compared gait measures collected between January and December of 2024 and 2025, corresponding to a period of relative stability followed by clinically evident deterioration.

However, interpretation of digital gait metrics is not always straightforward. Some parameters, particularly those derived from proprietary algorithms, may depend on specific conditions for data acquisition. As disease severity progresses, changes in walking patterns may alter the likelihood that certain metrics are recorded, potentially leading to misinterpretation if acquisition mechanisms are not considered.

Therefore, in addition to longitudinal changes in conventional gait parameters, we examined the conditions under which walking asymmetry percentage was acquired, focusing on the relationship

between step count and data availability. This approach aimed to clarify whether changes in asymmetry metrics reflect true functional improvement or limitations in algorithm-dependent measurement.

To address these gaps, we conducted a single-subject, longitudinal digital phenotyping study using Apple HealthKit data collected over two years. We compared weekly gait metrics between 2024 and 2025, analyzed daily variability, and quantified the relative contributions of step length and step count to walking-speed decline. We further examined weekly walking steadiness scores to assess long-term stability of gait. Finally, we propose that within-subject longitudinal monitoring—rather than cross-sectional comparison—offers a more precise approach to evaluating gait impairment in PD.

Methods

A summary of the study design and analytical framework is presented in Table 1.

1. Participant and Clinical Background

A 77-year-old male with Parkinson's disease (PD) participated in this longitudinal digital gait monitoring study. PD was diagnosed in May 2021 based on clinical presentation and DAT-SPECT imaging showing reduced striatal dopamine transporter uptake (specific binding ratio: right 1.96, left 1.90). At diagnosis, the Hoehn–Yahr (H–Y) stage was 2; during the study period, symptoms progressed to H–Y stage 3, with increasing freezing of gait, stooped posture, and difficulty with prolonged ambulation. Motor symptoms retrospectively traceable to 2016 included diurnal stooping, followed by left-hand tremor in 2018. Pharmacological management consisted of levodopa (titrated from 200 mg/day to 600 mg/day by 2025) and a rotigotine transdermal patch (up to 13.5 mg/day). The participant attended outpatient rehabilitation twice weekly beginning in March 2024, targeting muscle tightness in the gastrocnemius–soleus complex, hamstrings, iliopsoas, and external oblique muscles. All data were self-collected and anonymized.

2. Data Sources and Digital Gait Metrics

Daily gait metrics were passively collected using Apple's HealthKit framework[9,10] on an iPhone carried in the participant's front pocket during normal daily activities. Apple HealthKit derives gait parameters using onboard accelerometer and gyroscope sensors, applying proprietary algorithms validated in healthy adults and populations with mobility impairment.

The following gait metrics were analyzed:

- Walking speed (km/h)
- Step length (cm)
- Step count (steps/day)
- Double-support time (% of gait cycle)
- Walking asymmetry (%)

- Walking steadiness (dimensionless 0–1 scale)

Walking steadiness is a composite metric provided by Apple, where lower values indicate poorer dynamic stability.

Raw XML files containing timestamped entries for each metric were exported from the Health app and parsed using custom scripts (Python 3.11, Pandas 2.2).

Example of Raw HealthKit XML Record (Walking Speed)

<Record type="HKQuantityTypeIdentifierWalkingSpeed" sourceName="iPhone 15 plus ky" sourceVersion="17.5.1" device="<<HKDevice: 0x81a1f92c0>, name:iPhone, manufacturer:Apple Inc., model:iPhone, hardware:iPhone15,5, software:17.5.1, creation date:2024-06-06 14:30:11 +0000>" unit="km/hr" creationDate="2024-09-01 09:24:03 +0900" startDate="2024-09-01 09:13:45 +0900" endDate="2024-09-01 09:13:53 +0900" value="3.816"/>

Interpretation:

- type indicates the gait metric (here, WalkingSpeed).
- unit describes the measurement scale (e.g., km/hr).
- startDate and endDate specify the time window over which Apple's algorithm computed the gait parameter.
- value represents the measured gait variable (e.g., 3.816 km/hr).

Study Periods

Two 12-month intervals were compared:

• January 1 to December 31, 2024 — period of relatively mild gait impairment

• January 1 to December 31, 2025 — period with clinically evident worsening, especially after April

Weekly and daily analyses were performed using data within these intervals.

- Data Preprocessing
- Weekly Aggregation

Metrics logged at irregular intervals (e.g., walking speed, step length) were aggregated into weekly means, corresponding to HealthKit's standard Sunday-to-Sunday reporting. Two anomalous overlapping weeks in February–March 2024 (Feb 20–27 and Feb 27–Mar 5), caused by a HealthKit transition in week-boundary definitions, were excluded to avoid double counting.

2. Normalization

To compare patterns across years within the same individual, all analyses used raw, unnormalized HealthKit values.

3. Outcome Measures

    1. Primary outcomes:

• Difference in weekly walking speed between 2024 and 2025.

• Relative contributions of step length and step count to walking-speed change (qualitative interpretation; no differential equation used).

2. Secondary outcomes:

• Changes in double-support time.

• Changes in gait asymmetry.

• Changes in weekly walking steadiness.

4. Statistical Analysis

Weekly 2024 and 2025 data were compared using two-tailed t-tests (paired when appropriate), effect sizes (Cohen's d), and percent change values for clinical interpretability. All statistical analyses were performed in Python (SciPy 1.12) and R (4.3). Significance was defined as $p < 0.05$.

4. Sensitivity analysis

Sensitivity analyses were performed using alternative temporal aggregation windows (days 1–10, 11–20, and 21–end of month) to confirm robustness of the main findings.

5. Ethical Considerations

This study analyzed anonymized self-collected gait data from a single individual. No intervention was performed. The participant provided informed consent for the use and publication of these data. According to institutional guidelines, analysis of de-identified self-tracked data does not require IRB approval.

RESULTS

Year-to-year changes in primary gait parameters

Between January–December 2024 and January–December 2025, walking speed, step length, and step count all declined (Figure 1). Weekly walking speed was consistently lower in 2025, with reductions of approximately 15–25% in most weeks.

Reductions in step length were observed across most weeks. Step count also declined during 2025; however, because step count reflects free-living daily activity, this decrease may partly represent reduced walking opportunity rather than intrinsic gait alteration.

Decomposition of walking-speed decline

Joint comparison of step length and step count suggested that both factors were associated with walking-speed reduction. Because step count in this context represents total daily steps rather than cadence, its contribution should be interpreted cautiously.

Longitudinal changes in gait stability metrics

Walking steadiness declined markedly from 2024 to 2025 (Figure 2). Values shifted from predominantly within higher categories in 2024 to lower categories in 2025. Double-support time increased during 2025.

Walking asymmetry percentage showed substantial variability and did not consistently increase in parallel with other deterioration metrics.

Variability in acquisition of walking asymmetry percentage

Walking asymmetry values were frequently unavailable despite ongoing walking activity (Figure 3). In October 2025, asymmetry values were not recorded on 19 of 31 days (61.3%), and the minimum daily step count on days with recorded asymmetry was 38 (most commonly >91) (Figure 3A). In November 2025, asymmetry values were not recorded on 23 of 30 days (76.7%), with a minimum daily step count of 109 on days with recorded asymmetry (Figure 3B). In December 2025, asymmetry values were not recorded on 20 of 31 days (64.5%), with a minimum daily step count of 23 on days with recorded asymmetry (Figure 3C).

In contrast, in a health control subject (November 2025), asymmetry values were missing on only 3 of 30 days (10.0%), and the minimum daily step count on days with recorded asymmetry was 32. (Figure 3D) These findings indicate variability in asymmetry data acquisition that is not explained by walking volume alone.

Falls

Falls occurred on November 3, 17, and 29 and December 8, 2025. These events were annotated without exclusion from analysis.

DISCUSSION

Overall longitudinal progression

This longitudinal single-participant study demonstrates that smartphone-derived gait metrics can sensitively capture progressive deterioration of Parkinsonian gait over two years. Continuous passive monitoring revealed quantitative declines in walking speed and stability that paralleled clinical worsening.

Digital monitoring versus conventional assessment

Traditional clinical scales provide episodic and semi-quantitative evaluation of gait. In contrast, smartphone-based monitoring enables continuous real-world quantification. The observed reductions in walking speed and marked decline in walking steadiness illustrate the sensitivity of digital metrics to gradual disease progression.

Differential contributions of step length and step count

Reductions in step count were observed alongside reductions in step length. Because step count reflects overall daily stepping activity rather than pure cadence, its contribution should be interpreted cautiously.

Gait stability as a sensitive indicator

Walking steadiness declined more prominently than other parameters and was accompanied by increased double-support time. These findings suggest that stability-related metrics may provide early and sensitive indicators of functional deterioration.

Interpretation of walking asymmetry percentage

Walking asymmetry percentage did not consistently increase with clinical worsening. Further analysis demonstrated substantial variability in asymmetry data availability. Acquisition of asymmetry values appeared to depend not only on walking volume but also on conditions likely required by proprietary algorithms.

As gait instability progresses, walking may become fragmented or irregular, potentially reducing the likelihood that asymmetry values are generated. Therefore, absence or reduction of asymmetry data should not be interpreted as improvement. Careful interpretation of algorithm-dependent metrics is essential.

Falls within the trajectory of decline

Falls occurred during the period of declining gait stability. Rather than representing isolated events, they appeared within a broader trajectory of progressive instability. Continuous digital monitoring may help contextualize fall risk within ongoing functional decline.

Limitations

This study involves a single participant and therefore has limited generalizability. HealthKit algorithms are proprietary and not specifically optimized for Parkinsonian gait. Environmental and activity-related factors may influence measurements. Nevertheless, consistency across multiple independent metrics and alignment with clinical progression support the internal validity of the findings.

Conclusion

Smartphone-derived gait metrics provide objective longitudinal insight into Parkinsonian gait progression in daily life. Integration of multiple digital parameters, including stability measures and data availability patterns, offers a nuanced framework for monitoring disease evolution. The approach presented here may contribute to the development of more objective longitudinal evaluation of gait in Parkinson's disease.

Declarations

Author contributions

K.Y. developed the research concept and wrote the paper.

Z.L., J.S. curated the data.

J.S., H.I. performed formal analysis.

Z.L. edited the manuscript.

All authors approved the final manuscript.

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Competing interests

The authors declare no competing interests.

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Tables

Table 1. Study design and longitudinal digital gait monitoring framework

Component	Description
Study design	Single-subject longitudinal digital phenotyping study
Observation period	January 1–December 31, 2024 (relatively mild gait impairment); January 1–December 31, 2025 (clinically evident worsening)
participant	77-year-old male with Parkinson's disease (H–Y stage 2 → 3 during study period)
Devise and platform	iPhone carried in front pocket; Apple HealthKit framework
Gait metrics analyzed	Walking speed (km/h); step length (cm); step count (steps/day); double-support time (% gait cycle); walking asymmetry (%); walking steadiness (0–1 scale)
Primary analysis	Weekly comparison of gait metrics between 2024 and 2025
Secondary analyses	(1) Qualitative decomposition of walking-speed decline into step length and step count components; (2) longitudinal changes in stability metrics; (3) evaluation of walking asymmetry data acquisition patterns
Sensitivity analysis	Alternative temporal aggregation windows (days 1–10, 11–20, 21–end of month)
Clinical event annotation	Falls in November–December 2025; included without data exclusion

Figures

Figure 1. Weekly gait metrics in 2024 and 2025.

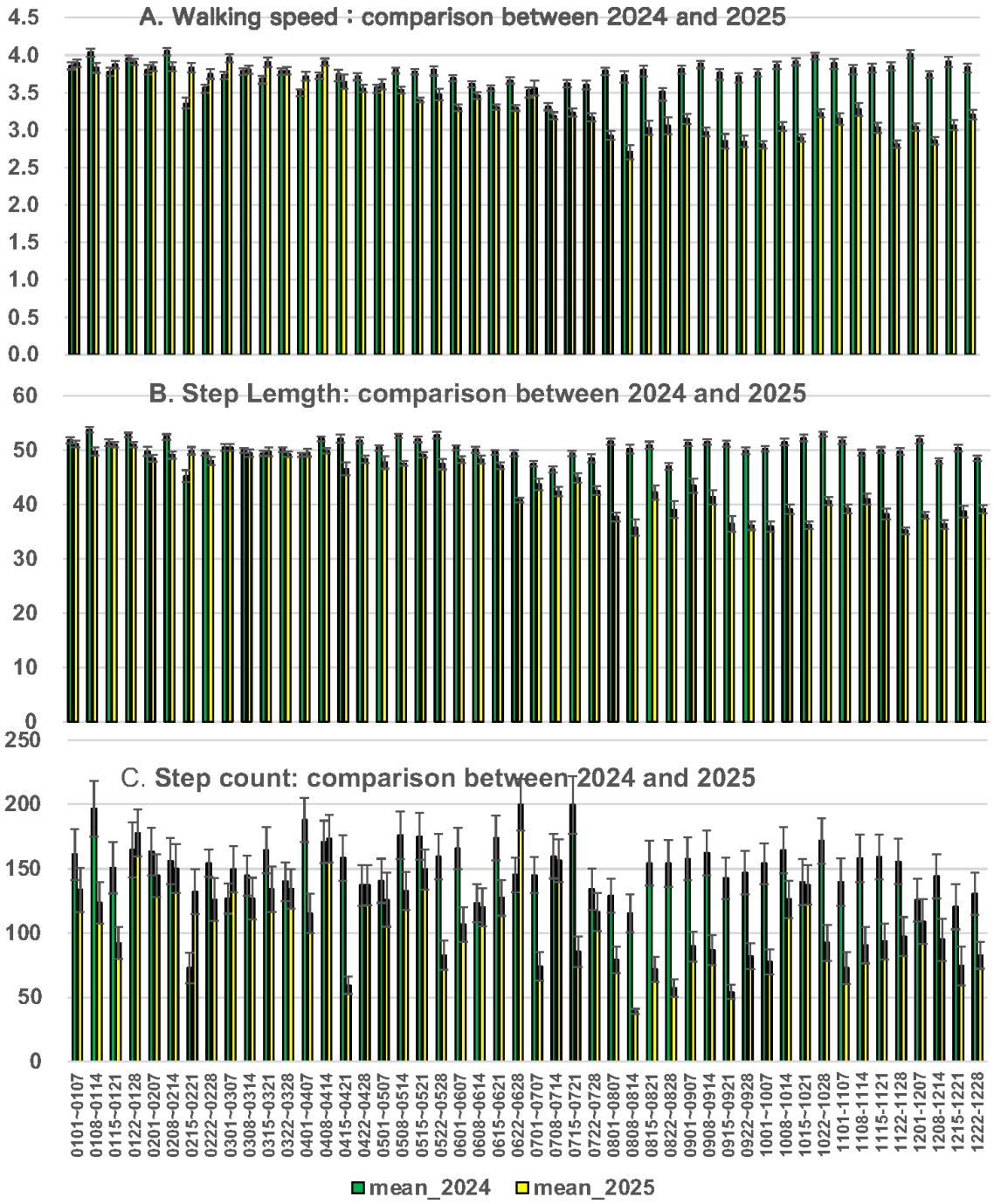

Figure 1

Weekly gait metrics in 2024 and 2025

Weekly mean walking speed (A), step length (B), and step count (C) were derived from Apple HealthKit data between January and December of 2024 and 2025. Values represent weekly averages of passively collected measurements during daily activities. Compared with 2024, all three metrics showed lower

values in 2025, with progressive divergence observed after spring. Shaded areas indicate standard error of the mean.

Figure 2. Longitudinal changes in gait stability–related metrics.

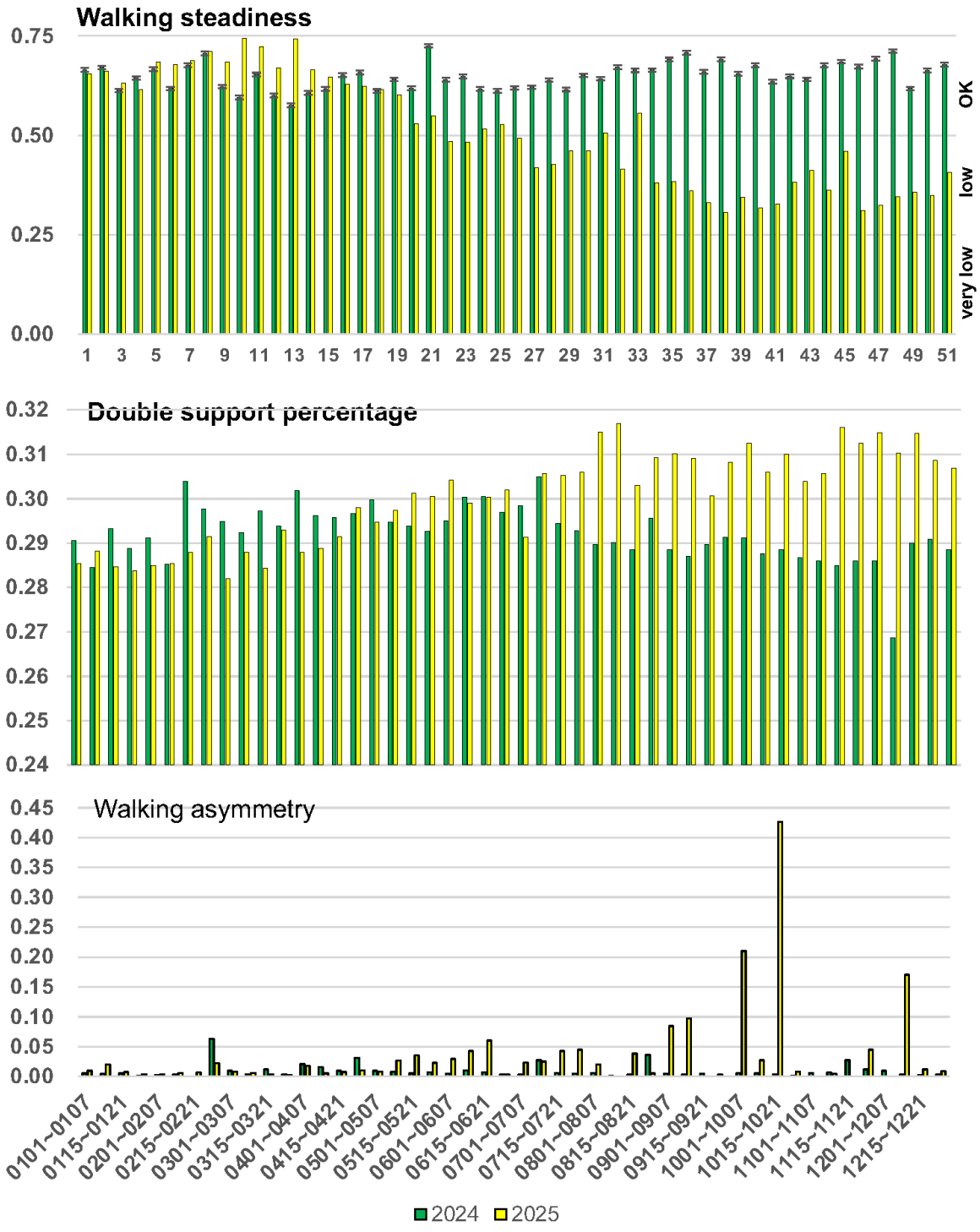

Figure 2

Longitudinal changes in gait stability–related metrics.

Weekly walking steadiness, double-support time, and walking asymmetry percentage are shown for

January–December 2024 and January–December 2025. Values represent weekly averages derived from passive HealthKit recordings during daily activities.

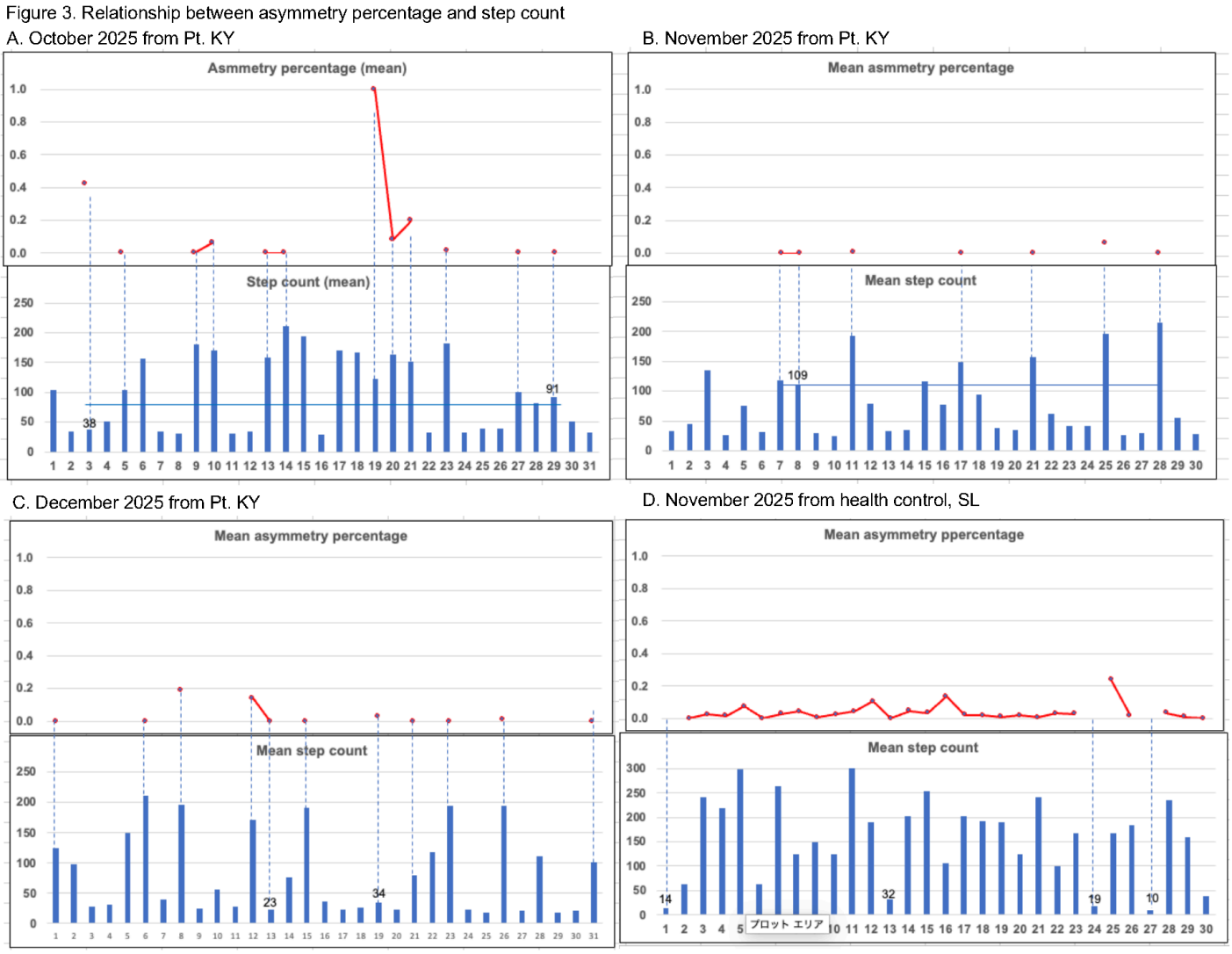

Figure 3

Relationship between walking asymmetry percentage and daily step count.

Daily step count and availability of walking asymmetry percentage are shown for October–December 2025 in the PD participant (Panels A–C) and for November 2025 in a health control subject (Panel D). Days without recorded asymmetry values are indicated.