MOBILE & WIRELESS HEALTH

Gait and Balance Assessments using Smartphone Applications in Parkinson's Disease: A Systematic Review

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Abstract

Gait dysfunctions and balance impairments are key fall risk factors and associated with reduced quality of life in individuals with Parkinson's Disease (PD). Smartphone-based assessments show potential to increase remote monitoring of the disease. This review aimed to summarize the validity, reliability, and discriminative abilities of smartphone applications to assess gait, balance, and falls in PD. Two independent reviewers screened articles systematically identified through PubMed, Web of Science, Scopus, CINAHL, and SportDiscuss. Studies that used smartphone-based gait, balance, or fall applications in PD were retrieved. The validity, reliability, and discriminative abilities of the smartphone applications were summarized and qualitatively discussed. Methodological quality appraisal of the studies was performed using the quality assessment tool for observational cohort and cross-sectional studies. Thirty-one articles were included in this review. The studies present mostly with low risk of bias. In total, 52% of the studies reported validity, 22% reported reliability, and 55% reported discriminative abilities of smartphone applications to evaluate gait, balance, and falls in PD. Those studies reported strong validity, good to excellent reliability, and good discriminative properties of smartphone applications. Only 19% of the studies formally evaluated the usability of their smartphone applications. The current evidence supports the use of smartphone to assess gait and balance, and detect freezing of gait in PD. More studies are needed to explore the use of smartphone to predict falls in this population. Further studies are also warranted to evaluate the usability of smartphone applications to improve remote monitoring in this population.
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Keywords Smartphone · Parkinson's Disease · Gait · Postural control · mHealth

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Introduction

Parkinson's disease (PD) is the second most common neurodegenerative disorder in the United States of America behind Alzheimer's disease [1]. It is associated with 4 cardinal well-known motor symptoms: resting tremor, bradykinesia, postural instability, and musculoskeletal stiffness [2]. These motor symptoms lead to gait dysfunctions and balance impairments which have been linked to an increased risk of falls [3], mortality, and morbidity in individuals diagnosed with PD [4]. Due to the consequences associated with gait dysfunctions and balance impairments within individuals with PD, accurate assessments widely available to a variety of clinicians and healthcare providers is critical for monitoring the overall progression of the disease and providing targeted care.

Significant effort by clinicians and researchers has focused on the accurate and valid measurement of gait and

balance in individuals with PD. Performance-based clinical measures commonly used include the Timed Up and Go (TUG) test, Berg Balance Scale (BBS), Mini Balance Evaluation Systems Test (Mini-BESTest), and Functional Gait Assessment (FGA) [5–7]. These clinical outcomes are quick, easy to administer, and suitable for clinical practice. However, the clinical test's scoring criteria are often subjective, and it is recommended that trained healthcare professionals such as physical and occupational therapists administer the tests [8]. In addition, clinical outcomes are often insensitive to subtle dysfunctional changes and have poor reliability [9]. Within a laboratory-based setting, gait alterations and balance impairments have been accurately evaluated using motion capture, wearable sensor systems, or force plate [10–12]. These advanced technologies require specialized equipment and advanced knowledge to interpret their results. Due to their excessive cost and the requirement of specialized training before implementation and interpretation of the data, they are not always suitable for clinical practice [8, 13]. Additionally, clinical and laboratory-based assessments require in-person contact which is not possible during a global health crisis such as the COVID-19 pandemic [14].

With the progress of technology, smartphones can serve as an alternative to the use of the aforementioned expensive and complex technologies. Smartphones are ubiquitous, portable, and affordable. Smartphones also offer the potential to perform remote assessments in home environments to gather more insight into an individual's true functional abilities and limitations. Smartphones are equipped with triaxial accelerometers and gyroscopes that use applications that can be installed on smartphones. This technology has been used to assess gait and balance in various clinical populations including older adults [15], non-ambulatory individuals [16], individuals with traumatic brain injury [17], and people with multiple sclerosis [18]. Previous systematic reviews by Linares-Del Rey et al. [19] and Zapata et al. [20] indicated that smartphone and mHealth applications presented with potential to be used to monitor medication and provide PD-related information. However, these reviews did not synthetize the validity, reliability, and discriminative abilities of smartphone applications to assess gait and balance in this population. Therefore, the primary purpose of this systematic review was to synthetize the current state of smartphone applications to evaluate gait and balance in individuals with PD. Specifically, this review summarized the validity, reliability, and discriminative abilities of smartphone applications in PD. As a secondary aim, due to relationship between gait, balance, and falls, this review also aimed to report on smartphone applications ability to predict future falls in PD.

Methods

Review Protocol and Registration

The systematic review was conducted in accordance with the Cochrane Handbook [21]. The reporting of the study followed the instructions suggested by the Preferred Reporting Items for Systematic Reviews and Meta-Analysis (PRISMA) [22]. The review protocol was pre-registered with PROS-PERO, the International prospective register of systematic review (CRD: 42020198510).

Data Sources and Searches

The following databases search were searched from inception to February 2021: PubMed/Medline, Scopus, Web of Science, CINAHL, and SportDiscuss. The search strategies were adjusted for the various databases and filters were added to exclude studies such as animal studies. The search algorithm included possible combinations of "smartphone", or "cell phone", or "mobile phone", and "gait", or "ambulation", or "standing" or "fall", or "postural control", or "balance", and "Parkinson's Disease". The search strategies developed for each database are presented in Appendix A.

(EW) and (SMD) independently examined title and abstract of articles retrieved from the databases to identify potential articles for this review. They each compiled a list of potentially eligible studies. The full papers on both lists were retrieved and both review authors independently culled on the basis of the full text articles. A manual search in the reference lists (forward and backward searches) of included articles was conducted to identify other relevant studies. Any discrepancies were discussed until consensus was reached with a third author (LA).

Study Selection

Studies meeting the eligibility criteria were included in the systematic review. The eligibility criteria were developed based on the populations, interventions or exposures, comparators, outcomes, and study designs (PICOS). Participants: adults (over the age of 18 years) with the diagnosis of Parkinson's Disease; Interventions or Exposures: not applicable; Comparators: data collected with a smartphone and compared with any clinical gait and balance outcome measures or with any validated technology such as standalone accelerometer, inertial measurement unit (IMU), 3-D motion capture, or force plate; Outcomes: gait measures such as 10-m Walking Test (10MWT), Freezing of Gait (FoG) measure, TUG; balance measures such as BBS and Mini-BESTest; and prospective falls; Study designs: cross-sectional and prospective cohort observational studies and intervention studies. Studies were

excluded if they were non-human trials, reviews, abstracts, conference proceedings, case–control studies, and protocol papers without data collection. Studies published in languages other than English, French, Spanish, Italian, and Portuguese were intended to be excluded due to the inability of the research team to fully understand the content of these eventual studies.

Data Extraction and Analysis

Two review authors (EW) and (JP) independently extracted the following data: authors, publication year, study design, participant characteristics (Hoehn and Yahr, percentage of males, and duration of disease), mean age of participants, sample size, smartphone outcome measures, and types of smartphone, gait and balance outcome measures, measure of validity, reliability, sensitivity, and specificity, main results, smartphone wear site, intended user (i.e., clinicians or individuals with PD) and locations of assessment. Different smartphone applications based on accelerometers and gyroscopes were extracted. Any discrepancies between the authors during data extraction were resolved through discussion with a third author (LA).

Methodological Quality Assessment

The methodological quality assessment of the included studies was performed independently by two review authors (JP) and (RA) using the Quality Assessment Tool for Observational Cohort and Cross-sectional Studies developed by the National Institute of Health-NIH [23]. This tool includes 14 criteria that are rated according to 3 responses: Yes, No, or Other (cannot determine, not reported, or not available). The 14 criteria are listed and defined in Appendix B. Overall, the studies are rated as good, fair, or poor methodological quality [23]. Studies with 8 or more than 50% of the total applicable questions responded as "yes" were considered "good quality," studies with 5–7 or less than 50% of the total applicable questions responded as "yes" were considered "fair quality." Studies with < 5 questions responded as "yes" were considered "low quality" [24]. Any discrepancies between the authors during methodological quality assessment were resolved through discussion with a third author (LA).

Results

Study Selection

The databases search yielded a total of 376 articles and 4 articles were found following forward and backward searches. After removing duplicates, 252 articles underwent title and abstract screening. Following initial screening, 71 articles were retrieved for full text review. A total

of 40 articles were excluded after the full text review due to the following reason: did not use a smartphone to assess fall, gait, or balance (n = 19), did not include individuals with PD (n = 17), and protocol papers (n = 4). Finally, 31 articles were included in this review. Figure 1 presents a detailed illustration of the study selection in accordance with PRISMA guidelines.

Study Analysis

Table 1 presents the characteristics of the studies included in this review. Sample size varied from 9 to 334 participants among the included studies. Nine studies were prospective cohort, and the remaining 22 studies were cross-sectional including individuals with PD. The mean age of participants varied from 50.7 to 77.0 years old. Hoehn and Yahr (H&Y) scale evaluating the level of disability and how the symptoms of PD progress varied from 1 to 4 across the studies. Ten studies did not report the level of disability of their participants. Most participants with PD in the studies were males. Percentage of males varied from 43 to 86%. Six studies did not provide information about the gender of the participants. The mean duration of disease varied from 3.5 to 15.5 years. Seven studies did not report the mean duration of PD.

Table 2 presents the details of the smartphone outcome measures, models of smartphone used, gait and balance outcome measures, measures of validity, reliability, sensitivity, and specificity of the smartphone measures, the main results, as well as the intended users of the smartphone, and locations of assessment. Only one of the included studies used a smartphone application to specifically predict future falls among individuals with PD [8], four studies used smartphone applications to specifically evaluate balance impairments [25–28], and 13 studies used smartphone applications to specifically assess gait including freezing of gait (FoG) [9, 29–40]. In addition, 11 studies used smartphone applications to assess gait and balance simultaneously [41–51] and two studies used smartphone applications to assess gait, balance, and predict future falls among individuals with PD [52, 53].

Gait and balance measurements trough clinical and biomechanics outcomes differed greatly between the studies. The most common gait and balance outcome measures included the gait, FoG, and postural stability items of the Unified Parkinson's Disease Rating Scale-III (UPDRS-III), FoG, TUG, 10MWT, and Six-Minute Walking Test (6MWT). Seventeen studies (55%) completed the smartphone assessments in laboratory settings, ten studies (32%) completed the assessments in home settings, and four (13%) completed the assessments in both home and laboratory settings. Smartphone models also varied greatly from iOS to Android OS across the studies reviewed. iOS models included iPod Touch 4th and 5th generation, iPhone

Fig. 1 PRISMA flow chart
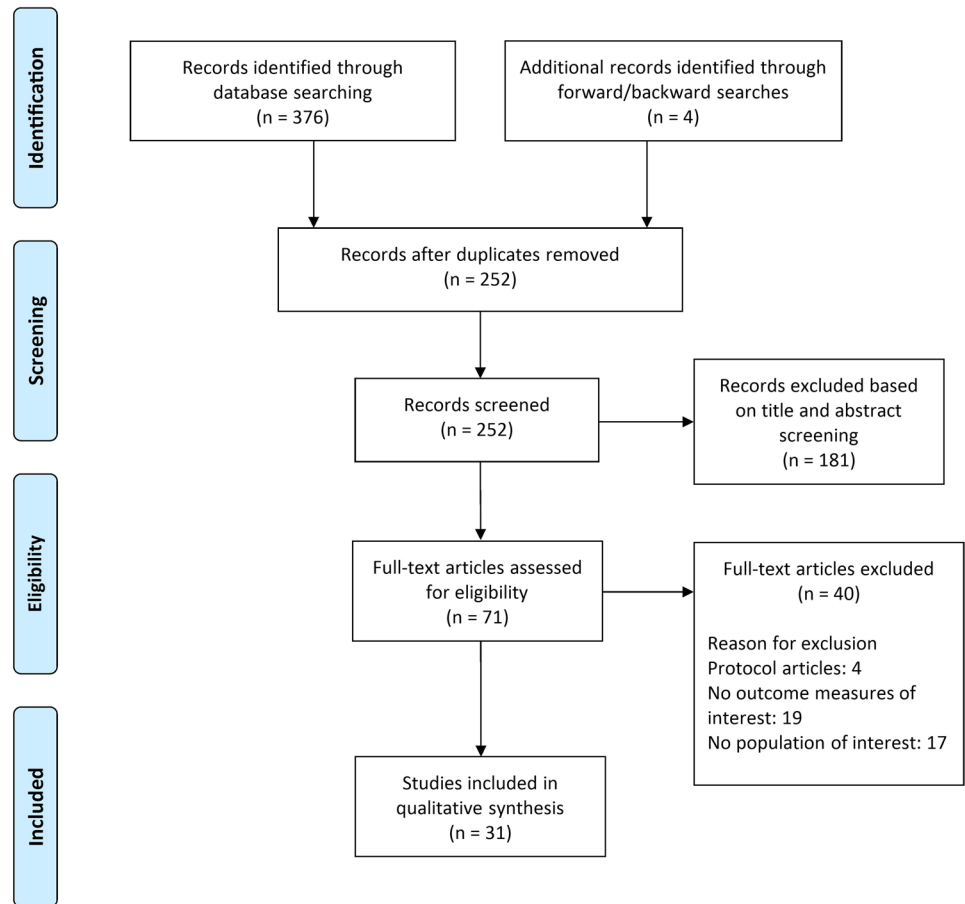
5, 6, and 6 plus and Android OS models included Samsung S3, S5, S8, J7, LG, LG Optimus, Sony Xperia, Google Nexus, Huawei Ascend, and Moto G4. Six studies did not specify the smartphone models used [26, 28, 34, 38, 50, 51]. Nineteen (61%) out the 31 studies included in this review reported individuals with PD as their intended users, seven (23%) reported clinicians as intended users, and five (16%) reported both individuals with PD and clinicians as their intended users. Although most of the studies mentioned their intended users, only six out the 31 included studies formally evaluated the usability, feasibility, or satisfaction of their smartphone applications [27, 35, 38, 44, 46, 50]. Also, smartphone wear site during gait and balance assessments differed greatly among the studies and included the device secured to the chest, placed in front pocket, or mounted at the hip, navel, ankle, thigh, and lower back. Two studies did not specify the smartphone wear site during their assessments [29, 46].

Validity and Reliability of Smartphone Applications

Sixteen (52%) out of the 31 studies included in this review evaluated the validity of smartphone assessments by comparing their results to gait and balance clinical tests, standalone accelerometers, or force plate (See Table 2). Fiems et al. [8, 25] reported concurrent validity through significant correlations between an assessment performed with the Sway Balance™ smartphone application (balance and fall protocols) and IMUs placed at pelvic and thoracic regions ($\rho = -0.61$ to -0.92, $p < 0.001$). Su et al. [9] found significant correlations between a customized smartphone application and mobility laboratory measures, including stride time and stride variability, and total UPDRS-III ($r = 0.98 - 0.99$, $p < 0.001$ and $\beta = 0.37 - 0.39$, $p < 0.001$). Similarly, Borzì et al. [41] reported significant correlations between a smartphone derived quality of movement (QoM) index, 6MWT, and gait and postural stability items of the UPDRS III ($r = 0.4 - 0.61$, $p < 0.0001$). Ellis et al. [36] reported concurrent validity of the SmartMOVE application with step durations and step displacements. Also, Capecci et al. [37] reported significant correlations between a FoG detection smartphone application and step cadence. Chen et al. [43] and Lipsmeier et al. [45] reported that the Roche PD application significantly correlated with gait and postural stability items of UPDRS ($r = 0.54$, $p < 0.001$) for severity of gait and balance assessments. Additionally, Clavijo-Buendía et al. [44] reported construct validity of the RUNZI application for gait measurements but not for balance assessments

Table 1 Characteristics of the included studies

Author's name and year of publication	Design	Participant's characteristics	Age (years)	Sample size
Fiems et al. 2018 [25]	Cross-sectional	**.** H & Y: 1–3 **.** % Male: 43% **.** Chronicity: 5.8 ± 4.3	69.2 ± 7.4	30
Fiems et al. 2020 [8]	Prospective cohort	**.** H & Y: 1–4 **.** % Male: NA **.** Chronicity - Recurrent fallers: 8.1 (5.9 – 11.5) - Nonrecurrent fallers: 4.5 (1.5 – 6.8)	- Recurrent fallers: 69.5 (65.5 – 76.5) - Nonrecurrent fallers: 69.5 (60 – 74)	59
Su et al. 2021 [9]	Cross-sectional	**.** H & Y: NA **.** % Male: 63% **.** Chronicity: 6.4 ± 3.8	63 ± 10	52
Pepa et al. 2020 [39]	Cross-sectional	**.** H & Y: median 4 **.** % Male: NA **.** Chronicity: 12.7 ± 7.4	68.02 ± 8.3	44
Borzì et al. 2020 [41]	Cross-sectional	**.** H & Y: 2.14 ± 0.8 **.** % Male: 63% **.** Chronicity: 6.7 ± 5.3	69.2 ± 10.2	59
Bayés et al. 2018 [38]	Prospective cohort	**.** H & Y: 3 (2.5 – 4) **.** % Male: 68.3% **.** Chronicity: 11.3 ± 0.9	71.3 ± 7.3	41
Capecci et al. 2016 [37]	Cross-sectional	**.** H & Y: 3.6 ± 0.8 **.** % Male: 75% **.** Chronicity: 15.5 ± 6.6	67.6 ± 9.1	20
Ellis et al. 2015 [36]	Cross-sectional	**.** H & Y: 2.63 ± 0.61 **.** % Male: 58.3% **.** Chronicity: 5.50 ± 3.42	64.96 ± 8.41	12
Mazilu et al. 2015 [35]	Cross-sectional	**.** H & Y: 2.44 ± 0.52 **.** % Male: 78% **.** Chronicity: 12.8 ± 8.5	68.38 ± 10.7	9
Pepa et al. 2015 [34]	Cross-sectional	**.** H & Y: 3.4 ± 1.1 **.** % Male: 72.2% **.** Chronicity: 14.1 ± 4.6	69.0 ± 9.7	18
Chomiak et al. 2019 [33]	Cross-sectional	**.** H & Y: NA **.** % male: NA **.** Chronicity: (range: 4–14)	Range: 18–77	21
Orozco-Arroyave et al. 2020 [42]	Cross-sectional	**.** H & Y: NA **.** % Male: 47.8% **.** Chronicity: 9.7 ± 9.3	68.6 ± 11.3	23
Chen et al. 2020 [43]	Prospective Cohort	**.** H & Y: NA **.** % male: NA **.** Chronicity: NA	NA	37
Clavijo-Buendía et al. 2020 [44]	Cross-sectional	**.** H & Y: 1.87 ± .71 **.** % Male: 50% **.** Chronicity: 10.2 ± 3.1	71.70 ± 5.1	30
Arora et al. 2015 [32]	Prospective Cohort	**.** H & Y: NA **.** % Male: 70% **.** Chronicity: NA	65.1 ± 9.8	10
Lipsmeier et al. 2018 [45]	Prospective Cohort	**.** H & Y: 1.91 ± 0.48 **.** % Male: 81% **.** Chronicity: 3.51 ± 2.86	57.5 ± 8.45	43
Elm et al. 2019 [46]	Prospective Cohort	**.** H & Y: 2.0 ± 0.4 **.** % Male: 57% **.** Chronicity: 7.1 ± 4.8	61.9 ± 10.5	51

Table 1 (continued)

Author's name and year of publication	Design	Participant's characteristics	Age (years)	Sample size
Tang et al. 2020 [40]	Cross-sectional	. H & Y: 3.2 (2–4) . % Male: 55% . Chronicity: 15.3 (4–25)	72.6 (54–86)	20
Borzì et al. 2019 [31]	Cross-sectional	. H & Y: 2.3 (1–4) (LA) 2.5 (2–4) (FOG) . % Male: 70% (LA) 75% (FOG) . Chronicity: 9.0 ± 6.5 (LA) 9 ± 4.8 (FOG)	. 69 ± 10 (LA) . 70.7 ± 8.2 (FOG)	. 97 (LA) . 38 (FOG)
Abujrida et al. 2020 [47]	Cross-sectional	. H & Y: NA . % Male: NA . Chronicity: NA	NA	152
Lo et al. 2019 [52]	Prospective Cohort	. H & Y: NA . % Male: 69% (Fall), 61% (FOG), 86% (PI) . Chronicity: 4.1 ± 1.9 (Falls), 4.0 ± 2.2 (FOG), 4.2 ± 1.8 (PI)	. 71.9 ± 8.5 (Fall) . 69.9 ± 9.4 (FOG) . 74 ± 7.7 (PI)	. 39 (Fall) . 41 (FOG) . 21 (PI)
Yahalom et al. 2020 [48]	Cross-sectional	. H & Y: 2.0 (IQR: 0.5) . % Male: 55.6% . Chronicity: 6.7 ± 4.5	50.7 ± 8.8	18
Ferreira et al. 2015 [50]	Prospective Cohort	. H & Y: 2.0 (0.5) . % Male: 64% . Chronicity: 6.7 ± 4.5	NA	22
Yahalom et al. 2020 [49]	Cross-sectional	. H & Y: NA . % Male: 52.4% (PD-NPT), 56.5% (PD-APT) . Chronicity: 6.6 ± 3.9 (PD-NPT), 8.7 ± 5.0 (PD-APT)	. 67.3 ± 6.8 (PD-NPT) . 67.8 ± 6.9 (PD-APT)	. 21 (PD-NPT) . 23 (PD-APT)
Arora et al. 2018 [53]	Prospective Cohort	. H & Y: 1.8 ± 0.5 . % Male: 63 . Chronicity: NA	66.1 ± 9.0	334
Borzì et al. 2020 [26]	Cross-sectional trial	. H & Y: 2.3 ± 0.6 . % Male: 73.8% . Chronicity: 10.3 ± 6.6	68.6 ± 10.7	42
Kim et al. 2015 [30]	Cross-sectional	. H & Y: NA . % Male: 46.7% . Chronicity: NA	NA	15
Fung et al. 2018 [27]	Cross-sectional	. H & Y: 3.0 ± 0.67 . % Male: 50% . Chronicity: NA	70.7 ± 7.89	10
Ozinga et al. 2017 [28]	Cross-sectional	. H & Y: 2.4 ± 0.5 . % Male: 50% . Chronicity: 5.6 ± 3.2	62.9 ± 8.3	14
Zhan et al. 2018 [29]	Cross-sectional	. H & Y: 2.1 ± 0.7 . % Male: 62% (Smartphone users) 57.4% (Development cohort) 52% (Clinic cohort with PD) . Chronicity: 4.4 ± 4.9 (Smartphone users) 4.3 ± 4.4 (Development cohort) 7.0 ± 4.1 (Clinic cohort with PD)	. 57.2 ± 9.4 (Smartphone users) . 58.7 ± 8.6 (Development cohort) . 65.6 ± 11.5 (Clinic cohort with PD)	. 250 (smartphone users) . 129 (development cohort) . 23 (clinic cohort with PD)
Serra-Añó et al. 2020 [51]	Cross-sectional	. H & Y: NA . % Male: NA . Chronicity: NA	68.9 ± 8.98	29

H & Y Hoehn and Yahr, *IQR* Interquartile range, *LA* Leg agility, *PI* Postural Instability, *PD-NPT* PD patients with normal pull test, *PD-APT* PD patients with abnormal pull test, *RAS* Rhythmic Auditory Stimulation

Table 2 Summary of smartphone outcome measures, validity, reliability, discriminative ability, and main results of the included studies

Author's name and year of publication	Smartphone outcome measures and model of smartphone	Gait, balance, or fall measures	Validity and Reliability	Main results	Sensitivity, specificity, and cut-off	Smartphone wear site	Intended user and test location
Fiems et al. 2018 [25]	. Smartphone App (Sway Balance™) based on accelerometer to assess postural sway . iPod Touch 5th generation	. Modified clinical test of sensory integration and balance . Fall protocol: Romberg, semi-tandem, tandem, and single leg stance	Validity - Concurrent validity of Sway Balance™ with pelvic and thoracic IMU ($\rho=-0.82$ to -0.92, $p<0.001$) - Concurrent validity of Sway Balance™ fall protocol with pelvic and thoracic IMU ($\rho=-0.61$ to -0.77, $p<0.001$) . Reliability High test–retest reliability of the balance assessment with the Sway Balance™ (ICC$=0.92$, 95% CI$=0.84-0.97$)	. Sway Balance™ demonstrated high test–retest reliability and strong concurrent validity with IMUs for measurement of postural sway during quiet stance in people with PD . Sway Balance™ showed limited ability to predict early H&Y levels of PD	. Accuracy of the Sway Balance™ to predict H&Y level is 56.7% . Sway Balance™ fall protocol to differentiate H&Y levels: Se$=0\%$ Sp$=100\%$	iPod touch secured in a chest harness	. Clinicians . Laboratory based assessment
Fiems et al. 2020 [8]	. Smartphone App (Sway Balance™) based on accelerometer to assess postural sway . iPod Touch 5th generation	. Prospective 6-month fall tracking . MDS-UPDRS motor examination, Mini-BESTest, ABC scale . Sway: Romberg, semi-tandem, tandem, and single leg stance	Previously reported in Fiems et al. 2018	. Sway Balance mobile App does not offer an improved alternative in fall prediction in individuals with PD compared with the ABC scale, Mini-BESTest, or an individual's fall history	Accuracy to detect fallers: Sway$=0.65$ ABC$=0.76$ Mini-BESTest$=0.72$ MDS-UPDRS$=0.66$ Fall history$=0.83$	iPod touch secured in a chest harness	. Clinicians . Laboratory based assessment
Su et al. 2021 [9]	. Smartphone App based on accelerometer and gyroscope to assess gait . iPhone iOS platform	. 10-m walking test . Gait kinematics . UPDRS III	Validity . Correlation between smartphone App and Mobility lab measures: - Stride time ($r=0.99$, $p<0.001$) for single-task and dual-task - Stride time variability ($r=0.99$, $p<0.001$ for single-task and $r=0.98$, $p<0.001$ for dual-task) . Correlation between smartphone App and clinical status: - Stride time variability ($\beta=0.39$, $p<0.001$ for single-task and $\beta=0.37$, $p<0.001$ for dual-task)	Individuals with PD can use a smartphone App by themselves to accurately assess gait during single-task and cognitive dual-task walking conditions	NA	Placed in the front pocket	. Individuals with PD . Laboratory based assessment

Table 2 (continued)

Author's name and year of publication	Smartphone outcome measures and model of smartphone	Gait, balance, or fall measures	Validity and Reliability	Main results	Sensitivity, specificity, and cut-off	Smartphone wear site	Intended user and test location
Pepa et al. 2020 [39]	. Smartphone accelerometer-based App using Fuzzy logic algorithm to assess FoG . iPhone 5 and 6	. FoG	NA	. The fuzzy logic is one of the most reliable and ecological objective tools for quantifying the FoG in individuals with PD	To detect FoG . Se: 84.9% . Sp: 95.2% . AUC: 0.99	Right or left side of the hip	. Individuals with PD . Laboratory and home-based assessments
Borzi et al. 2020 [41]	. Smartphone-based accelerometer and gyroscope to determine QoM index (motor impairment level) . Samsung S5	. 6MWT . UPDRS	. Correlation between QoM and 6MWT ($r=0.61$, $p<0.0001$) . Moderate correlation between QoM and postural stability item of UPDRS and UPDRS-III ($r=0.4 - 0.5$, $p<0.0001$)	. The QoM is suitable for an implementation in a domestic, unsupervised environment and able to distinguish mild vs moderate/severe motor impairment in PD	NA	3rd lumbar vertebrae	. Individuals with PD . Laboratory-based assessment
Bayés et al. 2018 [38]	. Smartphone-based accelerometer to determine motor state estimation as part of REMPARK system . NA	. UPDRS-III . ON–OFF Diaries	NA	. The motor state estimation device showed to be valid for 5 h. The device is accurate in determining ON–OFF states . Good SUS score for usability and user satisfaction of the system	To recognize on–off motor-states . Se: 97% . Sp: 88%	Worn near iliac crest inside bio-compatible belt	. Individuals with PD . Home-based assessment
Capecci et al. 2016 [37]	. Smartphone App based on acceleration to detect and quantify FoG . iPhone 5	. TUG without dual tasking . Cognitive dual task TUG . Manual dual task TUG	. Clinical FoG detection and smartphone measurement of FoG including step cadence proved to be significantly correlated ($p=0.01$)	. The application accurately predicted 92.86% FoG events	Algorithm 1 and 2: . Se: 70.11- 87.57% . Sp: 87.57- 94.97% . AUC: 0.81- 0.90 . Turning Se: 80.63- 94.87% . Turning Se: 75.87- 90.33%	Smartphone attached to elastic belt at hip joint	. Individuals with PD . Laboratory-based assessment
Ellis et al. 2015 [36]	. Acceleration and gyroscope measures embedded into Smart-MOVE app . Apple iPod Touch	. FoG questionnaire . Step time . step length	Concurrent validity of SmartMOVE with walking patterns	. SmartMOVE offers moderate-to-high accuracy in characterizing gait differences between individuals with PD and healthy subjects, and also in characterizing changes in gait outcome measures	NA	Smartphone attached to participant navel using elastic strap	. Clinicians and researchers . Laboratory-based assessment

Table 2 (continued)

Author's name and year of publication	Smartphone outcome measures and model of smartphone	Gait, balance, or fall measures	Validity and Reliability	Main results	Sensitivity, specificity, and cut-off	Smartphone wear site	Intended user and test location
Mazilu et al. 2015 [35]	. GaitAssist app based on 3D acceleration, 3D gyroscope, and 3D magnetometer to detect number and duration of FoG detected . Android API (Samsung S3)	FoG	NA	. GaitAssist can be efficiently used by people with PD as an unobstructive assistive device during their daily life activities in habitual settings and received a good acceptance . GaitAssist is able to detect FoG episodes during training	NA	Two IMUs attached around the ankles	. Individuals with PD and clinicians . Laboratory and home-based assessments
Pepa et al. 2015 [34]	. Acceleration integrated in a smartphone for FoG detection . NA	. Standard TUG . Cognitive Dual Task TUG . Manual Dual Task TUG	NA	The smartphone application detected 72/73 (98.6%) FOG events	Algorithm 1 and 2 Se: 74.02 – 88.31% . Sp: 85.46 – 94.72% (A1)	Smartphone held in an elastic belt with a socket in the right side of hip	. Individuals with PD . Laboratory-based assessment
Chomiak et al. 2019 [33]	. GaitReminder™ App connected to a sensor based on gyroscope and 3-axis accelerations . iPod touch 4th generation	. Gait cycle breakdown . FoG	. NA	. Free-D was effective at detecting dynamic gait instability, gait-cycle breakdown, and FoG	To discriminate gait and FoG . Se: 100% . Sp: 100%	The sensor device is placed in thigh band just above patellofemoral joint line	Individuals with PD . Laboratory-based assessment
Orozco-Arroyave et al. 2020 [42]	*Apkinson* App based on sensors embedded in a smartphone (microphone, gyroscope, and accelerometer) to detect FoG, number of steps and postural stability . Android operating systems	. 4×10 m walking test . Standing task . 2MWT	NA	. Preliminary evidence shows that *Apkinson* App can be used for monitoring individuals with PD . Significant difference in discriminating between patients and controls related to postural stability but not for freeze index	NA	Smartphone in pocket	. Individuals with PD and clinicians . Home-based assessment

Table 2 (continued)

Author's name and year of publication	Smartphone outcome measures and model of smartphone	Gait, balance, or fall measures	Validity and Reliability	Main results	Sensitivity, specificity, and cut-off	Smartphone wear site	Intended user and test location
Chen et al. 2020 [43]	. Roche PD App based on sensors embedded in a smartphone (microphone, gyroscope, and accelerometer) to estimate severity of PD (dexterity, gait, postural tremor, balance, and rest tremor features) . Samsung Galaxy S3 mini	MDS-UPDRS III (motor examination)	PD severity assessment observed scores correlated with MDS-UPDRS total scores ($r = 0.54$, $p < 0.001$)	Gait, dexterity, rest tremor, postural tremor, and balance features are reliable in evaluating PD severity	To discriminate PD severity Se: 0.973 Sp: 0.971 Accuracy: 0.972	Smartphone placed in pouch on belt	. Individuals with PD . Home-based assessment
Clavijo-Buendía et al. 2020 [44]	. RUNZI App based on accelerometer data to measure number of steps, time, walking speed, cadence, stride length . Samsung Galaxy S8	. 10 MWT . TUG . Tinetti Scale . BBS	- Construct validity between RUNZI App and 10 MWT . Steps: $r = 0.78$, (CS), $r = 0.88$ (FS) . Walking Speed: $r = 0.94$ (CS), $r = 0.96$ (FS) . Cadence: $r = 0.42$ (CS) $r = 0.59$ (FS) . Stride Length: $r = 0.76$ (CS), $r = 0.82$ (FS) - Construct validity between RUNZI App and TUG: . Walking speed $r = -0.59$ (CS), $r = -0.63$ (FS) . Number of steps: $r = 0.57$ (FS) . Stride length ($r = -0.53$) - Poor correlation between RUNZI App and Tinetti and BBS, $r \leq 0.49$ - Good to excellent test–retest reliability of the App, ICC = 0.82 – 0.98	. Moderate to excellent construct validity between RUNZI App and 10 MWT and TUG . No correlation between RUNZI App and balance measures (BBS and Tinetti) . Good to excellent test–retest reliability was for RUNZI parameters . RUNZI is feasible for spatio-temporal gait analysis in people with mild to moderate PD	NA	Strapped to Anterior aspect of thigh of more affected side	. Individuals with PD . Laboratory-based assessment

Table 2 (continued)

Author's name and year of publication	Smartphone outcome measures and model of smartphone	Gait, balance, or fall measures	Validity and Reliability	Main results	Sensitivity, specificity, and cut-off	Smartphone wear site	Intended user and test location
Arora et al. 2015 [32]	. Smartphone- based 3D acceleration to measure posture test (Stand upright unaided) and gait test (Walk 20 steps and return) . LG Optimus S smartphones (Android OS)	. Motor portion of the UPDRS	NA	Smartphone-based assessment can be used to accurately differentiate gait severity between individuals with PD and age-matched control and potentially predict disease severity. This assessment could also be used to monitor disease progression	To discriminate PD and control . Se: 96.2% . Sp: 96.9%	Hip	. Individuals with PD . Home-based assessment
Lipsmeier et al. 2018 [45]	. Roche PD App based on sensors embedded in a smartphone (microphone, gyroscope, and accelerometer) to estimate severity of PD (dexterity, gait, postural tremor, balance, and rest tremor features) . Samsung Galaxy S3 mini	. UPDRS	- All active tests significantly correlated to UPDRS -Test–retest reliability of Roche PD App: . Balance, ICC = 0.80 . Gait, ICC = 0.88	. Roche PD App showed moderate to excellent reliability . All active tests and passive monitoring with Roche PD App discriminated gait and balance of PD from control subjects	. Active tests showed greater sensitivity than UPDRS	Smartphone placed in belt pocket	. Individuals with PD . Home-based assessment
Elm et al. 2019 [46]	. *Fox Wearable Companion App* (FWC App) based on accelerometer embedded in a smartphone . Apple iPhone 5 or newer running iOS 10.0 or higher	. UPDRS	. Validity Correlation between measures of FWC App and balance/walking: $r = 0.43 - 0.54$, p's < 0.01	. Remote data collection with FWC App is feasible for people with PD	NA	NA, phone just needed to be paired with an Apple Watch	. Individuals with PD and clinicians . Home-based assessment

Table 2 (continued)

Author's name and year of publication	Smartphone outcome measures and model of smartphone	Gait, balance, or fall measures	Validity and Reliability	Main results	Sensitivity, specificity, and cut-off	Smartphone wear site	Intended user and test location
Tang et al. 2020 [40]	. Smartphone-based accelerometer and gyroscope to estimate gait pace, rhythm, variability, asymmetry, postural control, FoG . Sony Xperia XZ F8331	. TUG	. Validity: - High degree of consistency between gait analysis obtained using the smartphone and the Xsens TM MTw Awinda (ICC = 0.84, r = 0.86, ρ = 0.85) - High degree of consistency between clinicians FoG detection and the smartphone (ICC = 0.97, r = 0.97, ρ = 0.94) . Reliability FoG detection: ICC > 0.82	The convenience of using a smartphone has the potential of enhancing the frequency of gait assessment and FoG detection	The Smartphone detected 89.7% of FoG	Elastic band attached smartphone adjacent to center of body mass, behind the navel against the second lumbar spine (L2)	. Individuals with PD . Laboratory-based assessment
Borzi et al. 2019 [31]	. Smartphone-based accelerometer and gyroscope to assess Leg agility and FoG . Samsung S5 mini	. UPDRS – III . 6MWT	NA	. The results show that PD motor fluctuations can be estimated in domestic environment using a smartphone-based assessment	Neural Network model for leg agility: . Se: 58.7% . Sp: 80.0% . AUC: 0.92 FOG: . Se: 81.2% . Sp: 98.7% . AUC: 97.5%	Leg agility – individual' thigh right above knee with y-axis parallel to the femur direction FOG – waist, at lower back level	. Individuals with PD and clinicians . Laboratory-based assessment
Abujrida et al. 2020 [47]	. Smartphone-based accelerometer and gyroscope to assess walking balance, shaking Tremor, and FoG . iPhone 5 s, 5, 6, 6 Plus	. UPDRS . Walking activities	NA	. The automatic patient classification based on smartphone sensor data can be used to objectively infer PD severity and gait anomalies	. Random Forest model for walking balance: Pre: 92% Acc: 93% AUC: 0.97 . Bagged Trees model for shaking tremor: Pre: 95% Acc: 95% AUC: 0.92 . Bagged Trees model for FoG: Pre: 96% Acc: 98% AUC: 0.98 . Random Forest for Discriminating PD and healthy control: Pre: 95% Acc: 94% AUC: 0.99	Smartphone in pants front pocket	. Clinicians . Home-based assessment

Table 2 (continued)

Author's name and year of publication	Smartphone outcome measures and model of smartphone	Gait, balance, or fall measures	Validity and Reliability	Main results	Sensitivity, specificity, and cut-off	Smartphone wear site	Intended user and test location
Lo et al. 2019 [52]	. Smartphone-based falls, FoG, and postural instability. LG, Moto G4, Samsung Galaxy, Huawei Ascend, Sony Xperia	. Fall questionnaire. FoG Questionnaire. Hoehn and Yahr for postural instability	NA	. Baseline smartphone tests predicted new onset of falls, Fog, and postural instability	. Random Forest model for falls, FoG, and postural instability: AUC = 0.94, 0.95, and 0.9, respectively. Random Forest model for future FoG, and postural instability: AUC = 0.77 and 0.76, respectively	Phone is trouser pocket or arm band	. Individuals with PD. Laboratory and home-based assessments
Yahalom et al. 2020 [48]	. EncephaLog App based on tri-axial accelerometer, gyroscope, and magnetometer embedded in standard smartphones. iPhone 6	. 3 m-TUG. 10 m-TUG. UPDRS	. Validity. Difference in all EncephaLog measures between individuals with PD and healthy control except ML say, ($F = 4.4 – 25.4$, $p < 0.05$)	Smartphone-based assessment may offer more sensitive and quantitative tool than standard clinical ratings for gait and balance	NA	Smartphone attached to their chest at level of sternum	. Individuals with PD. Laboratory-based assessment
Ferreira et al. 2015 [50]	. SENSE-PARK App. NA	Balance tests	NA	The SENSE-PARK System is highly feasible and easy to use as a home-based gait and balance assessment in PD	NA	When awake, small sensor on wrist and leg of most affected side and lower back. When asleep, user wore one sensor on lower back	. Individuals with PD. Laboratory and home-based assessment
Yahalom et al. 2020 [49]	. EncephaLog App based on tri-axial accelerometer, gyroscope, and magnetometer embedded in standard smartphones. iPhone 6	. 3-m TUG. 10-m TUG. UPDRS	. Validity: - High correlation between EncephaLog app measures and 4-axial motor UPDRS and UPDRS items arising from chair, posture, and gait ($r = 0.14 – 0.46$, $p < 0.05$) - Marginal correlation between EncephaLog app measures and UPDRS item pull test ($r = 0.10 – 0.11$, $p < 0.05$) - Significant difference in EncephaLog measures between individuals with PD with postural instability and without and healthy control	. Motion sensor data from smartphone can detect difference in gait balance measures between PD with and without postural instability and healthy control	NA	Smartphone attached to chest at sternal level with adjustable elastic strap	. Clinicians. Laboratory-based assessment

Table 2 (continued)

Author's name and year of publication	Smartphone outcome measures and model of smartphone	Gait, balance, or fall measures	Validity and Reliability	Main results	Sensitivity, specificity, and cut-off	Smartphone wear site	Intended user and test location
Arora et al. 2018 [53]	. Smartphone- based 3D acceleration to measure posture test (Stand upright unaided) and gait test (Walk 20 steps and return) . LG Optimus S smartphones (Android OS)	. FoG . Falling	NA	. Consumer grade smartphones can differentiate gait and balance dysfunctions between controls and individuals with PD patients	Discrimination between PD control: . Se: 84.6% . Sp: 88.3%	Smartphone in pocket	. Individuals with PD . Home-based assessment
Borzì et al. 2020 [26]	. SensorLog App based on tri-axial accelerometer and gyroscope embedded in commercial smartphones . NA	. MDS-UPDRS	Validity: High correlation between SVM model and clinical score ($r = 0.76$, $p < 0.0001$)	. The smartphone-based App was able to differentiate individuals with PD with mild postural instability from those with severe postural instability and from healthy controls with 100% accuracy	.Discrimination between Control vs PD: Se = 100% Sp = 86%–100% .Discrimination between PD with different levels of postural stability: Se = 63.6%–100% Sp = 78.6%–100%	Smartphone inside elastic band secured to lower back at L3-L5 level	. Individuals with PD . Laboratory-based assessment
Kim et al. 2015 [30]	. Smartphone-based tri-axial accelerometer and gyroscope to assess FoG . Google Nexus 5	. Self-reported FoG	NA	. The best FoG classification results was obtained using a smartphone on the waist of participants . The pocket placement does not seem to decrease the efficacy of smartphone to recognize gait characteristics and FoG	Discriminate FoG Ankle: . Se = 81% . Sp = 92% Pocket: . Se = 84% . Sp = 93% Waist: . Se = 86% . Sp = 92%	In ankle, pockets of trouser, pockets of shirt, waist	. Clinicians . Home-based assessment
Fung et al. 2018 [27]	. SBS Smartphone-based accelerometer, magnetometer, and gyroscope to assess dynamic balance . Samsung J7	LOS	NA	This longitudinal study showed the efficacy, usability, and feasibility of smartphone-based balance rehabilitation in PD	NA	IMU worn on belt positioned at the L5/S1 vertebra, iPhone mounted on walker	. Individuals with PD . Laboratory-based assessment

Table 2 (continued)

Author's name and year of publication	Smartphone outcome measures and model of smartphone	Gait, balance, or fall measures	Validity and Reliability	Main results	Sensitivity, specificity, and cut-off	Smartphone wear site	Intended user and test location
Ozinga et al. 2017 [28]	. Mobile device COM acceleration . NA	. SOT . NeuroCom equilibrium scores	Validity High agreement between Mobile device measures and NeuroCom force platform measures with difference close to 0 . Good to excellent test–retest reliability of mobile device measurements, (ICC = 0.64 –0.92)	. Mobile device COM acceleration differentiates postural instability between PD subjects and healthy subjects . Mobile device is equally or more reliable than the NeuroCom and provides better discriminative properties than the NeuroCom equilibrium scores	NA	iPad fixed to waist at the sacrum level	. Clinicians . Laboratory-based assessment
Zhan et al. 2018 [29]	. mPDS derived from a smartphone HopkinsPD App . Android smartphones	. MDS-UPDRS . TUG	Validity Correlation between mPDS and: . MDS-UPDRS III ($r=0.88$, $P<0.001$); . TUG test ($r=0.72$, $P=0.002$);. H & Y ($r=0.91$, $P<0.001$)	The mPDS is a measure that provides rapid, remote, frequent, and objective assessment of PD symptom severity on widely used smartphones	NA	NA	. Individuals with PD . Home-based assessment
Serra-Añó et al. 2020 [51]	. FallSkip system based on 3-axis acceleration, 3-axis gyroscope, and a Digital Motion Processor . NA	. Postural control . Gait . Turn-to-sit and getting up from a chair . Reaction time	Good reliability for postural control variables (ICC = 0.62–0.71) and excellent for gait (ICC = 0.89– 0.92)	FallSkip is able to distinguish functional differences between PD subjects and healthy subjects	NA	Smartphone attached horizontally and just below posterior superior iliac crests	. Clinicians and Individuals with PD . Laboratory-based assessment

TUG Timed Up & Go Test, *CS* Comfortable Speed, *FS* Fast speed, *BBS* Berg Balance Scale, *SWS* shoulder-width stance, *FTS* feet-together stance, *STS* semi-tandem stance, *EO* eyes open, *EC* eyes closed, *ABC* Activities-specific balance confidence scale, *DGI* Dynamic Gait Index, *FSST* Four Square Step Test, *FAC* Functional Ambulation Category, *10MWT* 10 m walking test, *LOS* Limit of support, *WSBE* dynamic weight shifting balance exercise, *mPDS* mobile Parkinson score, *H&Y* Hoehn and Yahr stage, *COM* Center of mass, *FT5TS* Five-Times Sit-to-Stand test, *UPDRS* Unified Parkinson's Disease Rating Scale, *6MWT* Six-Minute Walking Test, *TUG* Timed Up and Go, *PD* Parkinson's Disease, *HC* Healthy Controls, *ICC* Interclass Correlation Coefficient, *Se* Sensitivity, *Sp* Specificity, *AUC* Area Under Curve, *AP* Anterior–Posterior, *ML* Mediolateral, *COP* Center of pressure, *SBS* Smarter Balance System

($p > 0.05$). Elm et al. [46] found significant correlations between the *Fox Wearable Companion* (FWC) application paired with a smartwatch and balance and walking items of UPDRS ($r = 0.43 – 0.54$, p's < 0.01). Tang et al. [40] reported strong correlation between a customized smartphone application and a research-grade accelerometer measuring gait and FoG detection ($r = 0.86 – 0.97$, $p < 0.05$). Yahalom et al. [48, 49] reported discriminant validity between individuals with PD and healthy control using the EncephaLog application measures. In addition, the authors reported high correlation between EncephaLog application measures and 4-axial motor UPDRS and UPDRS items arising from chair, posture, and gait measures ($r = 0.14 – 0.46$, $p < 0.05$) [49]. Borzì et al. [26] reported high correlation between a SensorLog application and UPDRS postural instability clinical score ($r = 0.76$, $p < 0.0001$). Similarly, Ozinga et al. [28] reported a high agreement between a mobile device center of mass (COM) acceleration and NeuroCom force plate measures with a difference close to 0. Finally, Zhan et al. [29] reported correlation between the Hopkins PD application and UPDRS, TUG Test, and H & Y ($r = 0.72 – 0.91$, p's < 0.01).

Seven (22%) out of the 31 studies included in this review evaluated some measure of reliability using a smartphone. Fiems et al. [8, 25], Clavijo-Buendía et al. [44], Lipsmeier et al. [45], Ozinga et al. [28] reported good to excellent test–retest reliability (ICC = $0.64 – 0.98$) of smartphone applications (Sway Balance™, RUNZI application, Roche PD application, mobile device COM acceleration) to assess gait and balance in individuals with PD. Additionally, Tang et al. [40] reported good reliability in detecting FoG (ICC = 0.82) using a customized smartphone-based assessment. Finally, Serra-Añó et al. [51] reported good reliability for postural control (ICC = $0.62 – 0.71$) and excellent for gait (ICC = $0.89 – 0.92$) using the FallSkip application.

Discriminative abilities of Smartphone Applications

Seventeen (55%) out of the 31 studies included in this review evaluated some discriminative ability of smartphone applications to assess falls, gait, and/or balance among individuals with PD. Fiems et al. [8] indicated that the Sway Balance™ smartphone application showed an accuracy of 0.65 to predict future falls. This prediction performance is lower than the prediction performance of the ABC (0.76), Mini-BESTest (0.72), MDS-UPDRS (0.66), and fall history (0.83) [8]. In contrast, Lo et al. [52] reported a high accuracy of 0.94 of a customized smartphone-based assessment to predict future falls. Lo et al. [52] also reported an accuracy of 0.95 and 0.9 to predict FoG and postural instability in individuals with PD. Similarly, Pepa et al. [34, 39], Borzì et al. [31], Capecci et al. [37], Tang et al. [40], Abujrida et al. [47], and Kim et al. [30] reported good predictive abilities of smartphone applications to detect FoG

(sensitivity: 0.70—0.96, specificity, 0.85—0.99, and accuracy: 0.81—0.99).

Additionally, Borzì et al. [41], Arora et al. [32, 53], Abujrida et al. [47], reported good to excellent ability of smartphone applications to discriminate gait and postural instability between individuals with PD and healthy controls (sensitivity: 0.85–1, specificity: 0.88–1). Also, Borzi et al. [31, 41], Chomiak et al. [33], Chen et al. [43], Lipsmeier et al. [45], and Abujrida et al. [47] indicated good to excellent ability of smartphone applications to discriminate between individuals with PD with different levels of postural stability, dynamic gait instability, gait cycle breakdown, resting tremor, dexterity, and leg dexterity (sensitivity: 0.58–1, specificity: 0.79–1, accuracy: 0.92 – 0.97). Finally, Fiems et al. [25] and Bayés et al. [38] reported moderate to good ability of smartphone applications to predict H & Y levels (sensitivity: 0, specificity: 1, accuracy: 0.57) and to recognize on–off motor states (sensitivity: 97% and specificity: 88%), respectively.

Methodological Quality Assessment

Appendix C presents the details of the methodological quality assessment of the included studies. Twenty-eight (90%) out the 31 studies presented with good methodological quality indicating a low risk of bias. Different levels of exposure and blinding of outcome measures were not applicable to any of the included studies and were not accounted in the overall quality rating. Lack of sample size justification was the most common deficiency reported in the included studies.

Discussion

The purpose of this study was to synthesize the current evidence of smartphone applications to assess gait, balance, and falls among individuals with PD. Smartphone-based assessments may be an appropriate alternative to conventional gait and balance analysis methods when such methods are cost prohibitive or not possible. In addition, the importance of remote monitoring and assessments have become clear in light of the COVID-19 pandemic. As a result of this systematic review, smartphone applications have shown to present with strong validity, reliability, and discriminative abilities to evaluate gait and balance and detect FoG among individuals with PD. The ability of smartphone applications to predict future falls in this population is inconclusive and deserves further exploration.

Within this review, sixteen studies evaluated the validity of smartphone applications against clinical and biomechanics measures to assess gait and balance in individuals with PD. The

results indicate strong concurrent and discriminant validities of smartphone applications in detecting FoG, gait alterations, and postural instability in this population. Also, the results indicate that smartphone applications are valid to differentiate gait and postural instability between healthy control and individuals with PD. Only one study reported low correlations between cadence derived from the EncephaLog application and arising and gait axial motor UPDRS measures [49]. These low correlations may be explained by the measurement errors of the EncephaLog application that needs to be refined to appropriately reflect gait constructs in individuals with PD. The EncephaLog application was not fully automated and some human preprocessing before every measurement was still required prior to analysis [49]. In summary, the validity of 13 smartphone applications to evaluate gait and/or balance in PD has been reported in the literature. Sway Balance™ [8, 25], SensorLog application [26], and a smartphone-based accelerometer application without a specific name [28] have been validated to assess postural instability in PD. Also, SmartMOVE application [36], RUNZI application [44], Hopkins PD application [29], a Fuzzy logic algorithm embedded in a smartphone [39], and two other smartphone-based accelerometer applications without specific names [9, 40] have been validated to assess gait alterations and FoG in PD. While Roche PD application [43, 45], Fox Wearable Companion application [46], EncephaLog application [49], and a FallSkip system based on accelerometer and gyroscope [51] have been validated to evaluate both gait and postural instability in this population.

Similar to the validity of smartphone applications, the seven studies that evaluated the reliability of smartphone applications indicated good to excellent reliability to assess gait and balance, and in detecting FoG among individuals with PD. Although the studies reported high reliability of smartphone applications which minimizes the measurement errors between assessments, only 22% of the included studies in this review evaluated reliability. This is similar to the results of previous reviews indicating that the reliability of smartphone applications was only evaluated among few studies including older adults [15] and people with multiple sclerosis [18]. To increase the use of smartphone applications within clinical settings and provide an appropriate remote monitoring of gait and balance in individuals with PD, more studies are warranted to explore the reliability of smartphone applications in PD.

Additionally, smartphone applications showed good to excellent abilities to discriminate gait and postural instability between healthy controls and individuals with PD. Also, several of the included studies reported the ability of smartphone applications to appropriately discriminate between individuals with PD with different levels of postural stability, dynamic gait instability, gait cycle breakdown, rest tremor, dexterity, and leg dexterity. These results are also consistent with the results reported in older adults [15] and people with

multiple sclerosis [18] indicating that smartphone applications are sensitive, specific, and accurate in discriminating gait and postural control within subgroups of individuals with PD and between healthy control and individuals with PD. However, the discriminative ability of smartphone applications to predict falls is inconclusive. While Fiems et al. [8] indicate that the Sway Balance™ mobile application is not as accurate as history of falls and other clinical measures including ABC and Mini-BESTest in predicting falls and should not be used as alternative, Lo et al. [52] reported a high accuracy of a customized smartphone-based assessment to predict future falls. This contradictory result should be further clarified by using smartphone applications to track falls in prospective studies. Gait dysfunctions, FoG, and balance impairments are the main fall risks among individuals with PD [54] and therefore, their relationship should be explored using smartphone-based assessments. This will increase the clinical use of smartphone applications among people with PD.

The type of smartphone applications (i.e., RUNZI, EncephaLog, Roche PD, FWC) and model of smartphones (i.e., iOS-based and Android-based smartphones) differed greatly among the studies included in this review. This may influence the results of the validity, reliability, and discriminative properties described in this study. While no comparisons can be made based on the studies included in this review because of the different conditions of data collection, future studies should investigate the differences between smartphone applications and/or smartphone models. Also, the smartphone wear sites while evaluating gait and balance varied greatly among the studies reviewed. In most studies, participants carried smartphones in their front pant pocket or secured at the chest or waist. Smartphone placement has been reported as an important factor during gait and balance assessments in people with multiple sclerosis [55]. In individuals with PD, Kim et al. [30] compared different smartphone placements during FoG detection and reported that location of smartphone did not influence the results. The authors furthermore reported that smartphones mounted at ankle, waist, or pocket provided similar FoG detection results in this population [30]. Since only one study has investigated the influence of different smartphone locations on gait and balance assessments in PD, this topic also deserves further exploration.

Lastly, only 19% of the included studies formally evaluated the usability, feasibility, or satisfaction of their smartphone applications and 32% completed the assessments in home settings. In general, the studies reported feasibility, good acceptability, and high satisfaction of the smartphone applications in unsupervised home settings [27, 35, 38, 44, 46, 50]. However, in individuals with advanced PD, common motor features including tremor, bradykinesia, rigidity, and postural instability [2] are likely to be exacerbated which may lead to an

increased difficulty using smartphone technology. Due to the importance of the intended users in the development of smartphone applications for remote monitoring [20], more studies are needed to investigate the usability of smartphone applications to assess gait and balance in individuals with PD. Adaptations of smartphone applications based on user's needs may help to overcome the challenge of incorporating smartphone applications into clinical practice and clinical decision making.

Limitations

They are some limitations associated with this systematic review that should be taken into consideration when interpretating the results presented. First, the results of validity and discriminative abilities reported in this review are based on only approximately 50% of the total number of studies included. The other 50% did not report any results of validity and discriminative abilities of smartphone applications. Similarly, approximately 80% of the included studies did not report any results of reliability of smartphone applications in PD. Given the importance of the psychometric properties of an outcome measures regarding measurement errors and measurement construct, the results presented may be overstated. It is essential that more studies compare smartphone application outcomes with clinical outcomes and/or biomechanics measures to corroborate the results presented in this review. Additionally, none of the included studies performed a sample size calculation before recruiting participants. This is a crucial limitation as the power of the analysis in the included studies may be hindered. Finally, our review did not specify which smartphone applications are more appropriate to assess gait and balance according to the stage and severity of PD. This was mainly because most of the studies included in this review did not focus on differentiating gait and balance assessments based on participant's characteristics using smartphone applications. We recommend that future studies explore the differences between the various stages and severity of PD using smartphone applications to facilitate their incorporation into clinical decision making.

Conclusion

This review provides strong evidence regarding the potential use of smartphone applications to assess gait and balance among individuals with PD in the home or laboratory. The results indicate that smartphone applications present with strong validity, reliability, and discriminative abilities to monitor gait dysfunctions and balance impairments and to detect FoG in individuals with PD. This review also highlights the need for further use of smartphone applications to monitor fall risk factors in this population. Additionally, most studies did not formally investigate the usability

of smartphone applications. Due to the importance of the acceptability and satisfaction of smartphone applications in these assessments, further studies are warranted to investigate the usability of smartphone applications to assess gait and balance in PD. This will help to efficiently use smartphone applications as an unobstructive technology for gait and balance assessments during individuals with PD daily life activities in habitual setting. Consequently, remote monitoring of PD will help provide targeted care to individuals with PD.

Author's Contributions LA was responsible for designing the study, protocol registration, mediating any data screening and extraction discrepancies, interpreting the results, and writing the initial manuscript. JP, EW, SMD, and RA were responsible for screening the studies, extracting the data, and assessing the methodological quality assessment of the included studies at different levels. JJS and LAR contributed to the study design and provided feedback on the initial review protocol and the manuscript.

Availability of Data and Material Not applicable.

Code Availability Not applicable.

Declarations

Ethical Approval Not required since this article is a review.

Consent to Participate Not applicable since this article is a review.

Consent for Publication Not applicable since no identifying information is included in this article.

Conflict of Interest Jacob J. Sosnoff is principal owner of Sosnoff Technologies LLC.

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