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5 **Free-living monitoring of Parkinson's disease: lessons from the field**

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33 **Abstract**

34 Wearable technology comprises miniaturized sensors (e.g. accelerometers) worn on the body
35 and/or paired with mobile devices (e.g. smart phones) allowing continuous patient monitoring in
36 unsupervised, habitual environments (termed free-living). Wearable technologies are revolutionising
37 approaches to healthcare due to their utility, accessibility and affordability. They are positioned to
38 transform Parkinson’s disease (PD) management through provision of individualised, comprehensive,
39 and representative data. This is particularly relevant in PD where symptoms are often triggered by
40 task and free-living environmental challenges that cannot be replicated with sufficient veracity
41 elsewhere. This review concerns use of wearable technology in free-living environments for people
42 with PD. It outlines the potential advantages of wearable technologies and evidence for these to
43 accurately detect and measure clinically relevant features including motor symptoms, falls risk,
44 freezing of gait, gait, functional mobility and physical activity. Technological limitations and
45 challenges are highlighted and advances concerning broader aspects are discussed. Recommendations
46 to overcome key challenges are made. To date there is no fully validated system to monitor clinical
47 features or activities in free living environments. Robust accuracy and validity metrics for some
48 features have been reported, and wearable technology may be used in these cases with a degree of
49 confidence. Utility and acceptability appears reasonable, although testing has largely been informal.
50 Key recommendations include adopting a multi-disciplinary approach for standardising definitions,
51 protocols and outcomes. Robust validation of developed algorithms and sensor-based metrics is
52 required along with testing of utility. These advances are required before widespread clinical adoption
53 of wearable technology can be realised.

54 **Introduction**

55 Wearable technology and connected devices (WTCD) are positioned to become ubiquitous in
56 research and healthcare settings. WTCD comprise electronic technology worn on the body or
57 embedded into mobile phones, watches, bracelets, and clothing, amongst others. The generic appeal
58 of WTCD is obvious. Patient monitoring is free from contextual or environment barriers making
59 assessment at home and in the community over continuous time periods (termed free-living) feasible
60 and ecologically valid ¹. Moreover data are free from the confounds of observer bias and attentional
61 compensation associated with a one off testing session under observation ², while devices are
62 relatively low cost making their use economically as well as practically feasible.

63 The benefits of remote monitoring with WTCD are multi-fold. Clinically, continuous
64 monitoring of symptom severity and therapeutic response provides nuanced assessment. A complete
65 picture of disease burden is available both to the clinician and the patient incorporating a broad range
66 of features from the ‘*micro*’ level of detail (e.g. disease symptoms, medication response and
67 fluctuations, gait characteristics, turning, frequency of falls) through to more ‘*macro*’ levels (e.g.
68 habitual patterns of walking/activity, inactivity and sleep) (Figure 1). Enriched measurement, coupled
69 with ease of use, also has implications for industry, paving the way for identification of early disease
70 with the potential for enhanced diagnostic and progression markers (fundamental for trials of novel
71 therapeutics and disease modifying therapies), harmonisation of outcomes and standardized testing
72 protocols to enhance recruitment and assessment of treatments in clinical trials. For the patient,
73 WTCD offer insight into symptoms, therapeutic efficacy and habitual mobility in the context of
74 everyday life contributing to enhanced self-management that is both bespoke and contextualised.

75 Despite the recent explosion of low cost commercially available devices (for the general
76 population) promoting personal monitoring and feedback, the application of WTCD in healthcare has
77 not yet been established ³. The lure of utility (i.e. ease of use, broad application, and low cost) is
78 strong; however standards for clinical adoption and research application are far higher. While
79 technology and design have advanced, algorithm development and data analysis have not kept pace.
80 Validity and reliability are paramount and inform accurate detection and monitoring of disease and
81 this next step is critical before widespread adoption ⁴. Although there are promising signs, there is still

82 no single system/gold standard being used for remote monitoring^{5,6}. Therein lies both the opportunity
83 and the challenge.

84 This paper considers issues related to free-living monitoring from predominantly single
85 sensor-based devices (e.g. accelerometers and gyroscopes). We examine the ability of WCTD
86 algorithms to accurately detect a range of clinical features and report on criterion and discriminative
87 validity of outcomes derived from WCTD. Utility and feasibility are also considered. Clinical features
88 include monitoring of motor symptoms, medication response, sleep, falls and falls risk, freezing of
89 gait (FOG), gait, functional mobility and physical activity (ambulatory activity and sedentary
90 behaviour). This rapidly expanding field and has been the subject of a number of recent systematic
91 reviews⁷⁻⁹ including Sánchez-Ferro et al. within this issue to which the reader is referred. We have
92 therefore adopted a broader approach and provide a structured overview of the current status of
93 continuous patient monitoring in the home and community in Parkinson's disease (PD) which we
94 define as 'free-living'. We address four key aims: (1) the role and benefits of free-living monitoring;
95 (2) the validity and utility (acceptability and feasibility) of WTCD to monitor a range of key clinical
96 features relevant to PD; (3) critical challenges for adoption of WTCD for free-living assessment; and
97 (4) future developments in this rapidly developing field. Throughout we focus mainly on the
98 application of passive (no interaction from patient) single sensor-based devices and their application
99 in PD but where relevant draw from work in ageing cohorts. Finally, we make recommendations
100 based on this overview to progress free-living monitoring in PD.

101

102 **Does free-living monitoring confer an advantage over clinical assessment in PD?**

103 Due to its heterogeneity and complexity, clinical assessment of PD is challenging. The
104 intrinsic, fluctuating nature of PD and biphasic medication response in advanced disease requires
105 continuous evaluation over prolonged periods to gain an accurate picture of symptoms and their
106 fluctuations. The influence of attention on performance is well recognised especially with symptoms
107 such as FOG, leading to an inaccurate clinical picture^{2,8}. Assessments requiring concentration and
108 recall such as falls diaries are further compromised by cognitive impairment, thus limiting utility.
109 Also, use of clinical scales is restrictive. The Unified Parkinson's Disease Rating Scale, (UPDRS)¹⁰,

110 although highly relevant to PD, is dependent on the patient's status at the time of assessment and
111 limited by subjectivity and clinical expertise. WTCD overcome many of these limitations by
112 objectively quantifying clinically relevant outcomes. Variation in testing is reduced ^{3, 11, 12}. Patients
113 also have much to gain from this approach, with less emphasis during clinical visits on symptom
114 recall and evaluation of therapeutic response. Continuous monitoring also provides greater potential
115 for patient involvement in defining optimal management ¹².

116 Measurement with WTCD is diverse. A single WTCD has the potential to provide the
117 clinician/researcher with a comprehensive picture of their patient within one assessment. For example,
118 Figure 1 shows that placement of a single sensor can quantify features such as volume and pattern of
119 habitual behaviours (e.g. walking, sleeping, sedentary time, Figure 1, A) (defined here as *macro*). The
120 raw signal (Figure 1, B) can then be further broken down to detect very discrete features (e.g. a fall,
121 gait characteristics, turning and freezing, figure 1, C-H) (defined here as *micro*). Taking this approach
122 enables multi-level measurement ¹³.

123 <Figure 1>

125 **Free-living assessment of clinically relevant features in PD: a valid alternative to conventional** 126 **clinical assessment?**

127 Despite the obvious advantages of free-living assessment an important question remains – are
128 the outcome measures derived from WTCD suitable for current clinical use and will patients and
129 professionals use WTCD? Table 1, which form the basis of this section, provides an overview of
130 detection accuracy, validity and utility of some WTCD. Our main inclusion criterion was that WTCD
131 had been applied to free-living monitoring under either totally unsupervised or scripted protocol
132 conditions, with an exception made for studies where tests are conducted in formal settings to
133 optimise validation, such as detection of FOG. We report *criterion validity* from studies that examine
134 the association between WTCD-derived outcomes and other measures such as clinical scales. We also
135 report studies that test *discriminative validity*, which we define as the ability of WTCD-derived
136 outcomes to discern groups or phenotypes. The list is by no means exhaustive but provides a current
137 overview and highlights the vast interest in the area. We do not review static postural control despite

138 its obvious relevance to PD ^{14, 15}, because studies are laboratory and/or clinic based, however, facets of
139 postural control (e.g. dynamic, turning) are considered.

140

141 *Motor symptoms, medication response and sleep.* Continuous monitoring has a lot to offer over
142 snapshot clinical assessments which may not reveal the true extent of symptom burden. Earlier use of
143 WTCD for motor symptom measurement focused on evaluation of a single symptom to detect
144 hypokinesia, dyskinesia, tremor, bradykinesia, and akinesia derived on/off medication status ^{16, 17}.
145 This has evolved to assessment of multiple motor symptoms using either a single ¹⁸⁻²⁰ or multiple
146 sensor systems ^{17, 21-24}. To date preliminary results are promising. Overall, motor symptom
147 measurement using WTCD is accurate and comparable with more established methods with some
148 aspects of validity tested. Criterion validity is established for most motor symptoms (tremor,
149 bradykinesia, dyskinesia) showing moderate to high correlations overall ($R > 0.65$) with standard
150 clinical scales (e.g. UPDRS, Abnormal Involuntary Movement Score (AIMS), Modified Bradykinesia
151 Rating Scale (MBRS), etc.) (see Table 1 for references). Measures of bradykinesia also show high
152 specificity (88%) and sensitivity (95%) when compared to standardised tests (e.g. the Dot Slide test)
153 ¹⁸. Studies that test discriminative validity are not as advanced, apart from the work by Horne et al.
154 which discerns motor symptom fluctuations in early stages of PD ²⁰. Single sensors are sufficiently
155 robust for application, although there are question marks over aspects of utility for some systems
156 which require technical mastery and are demanding on the user (see 'Utility' section). Whilst there
157 have been a number of key developments in this area with motor symptom monitoring assessed at
158 home, the test protocols are still largely controlled and scripted as highlighted in table 1. True passive
159 monitoring without patient input is as yet an area to be developed but remains the area of greatest
160 interest as it will give the most ecologically valid picture of motor symptom burden and therapeutic
161 efficacy. Assessment of sleep also shows promise. WTCD-derived outcomes for sleep discriminate
162 PD from older adults (OA) ^{25, 26} for *macro* outcomes (e.g. number and size of movements) with people
163 with PD also showing increased episodes of nocturia, fewer turns during sleep, and greater arm
164 movements.

165

166 *Falls and falls risk.* Accurate detection of falls and falls risk (ideally before the first ever fall) would
167 greatly inform clinical management and therapeutic development and WTCD has a role to play. Real-
168 world detection of falls however is technically challenging. A plethora of algorithms, devices, and
169 device locations (chest, waist or wrist ²⁷⁻³¹) have been tested to improve the accuracy of falls
170 detection, however, studies are almost completely limited to controlled settings and conducted on
171 young healthy adults. Kangas et al. provides a rare example of using WTCD for falls detection in the
172 real-world where falls were measured in institutionalised OA and verified by an observer ³². Fall
173 detection sensitivity was 80% with a falls alarm rate per hour of 0.025, denoting one false alarm over
174 40 hours of recording. This points to high accuracy, although the testing environment was far
175 removed from ‘free-living’, and generalisability is therefore weak. Application in PD remains an area
176 of unmet need. An alternative approach is to predict falls risk using WTCD which, in contrast to falls
177 detection, is a more advanced field for both older adults and PD. Moreover, addressing a falls
178 prevention approach could be argued to have greater clinical relevance ^{33, 34}. Studies have compared
179 groups with and without falls in PD using free-living monitoring over 3-7 days. Falls risk factors
180 derived from gait during free-living walking bouts ^{33, 34} were superior to laboratory-based gait speed
181 and fall history to discriminate fallers from non-fallers ³⁵⁻³⁸. Discriminative validity has been
182 established for both *macro* and *micro* characteristics of gait and sedentary behaviour (Figure 1, A-B)
183 which are associated with type of PD fallers ³⁹ and fall history (fallers vs. non-fallers) in OA ^{38, 40} and
184 PD ⁴¹, respectively. *Micro* features may offer more than *macro* features ^{36, 37}, and contribute
185 substantially to predicting falls both in fallers and non-fallers ^{37, 38}. Further refinement of algorithm
186 and system development is however required to take the field forward.

187

188 *Freezing of gait.* Gait disturbances such as FOG are notoriously difficult to replicate in a controlled
189 environment because of its spontaneous nature and the non-specific and poorly understood triggers
190 that provoke it ³. Clinical scales such as the UPDRS and NFOG ⁴² are subjective and therefore
191 limited. Despite the obvious need, free-living monitoring of FOG in PD has not been achieved.
192 Detection of FOG episodes has been tested in controlled and structured conditions where FOG is

193 provoked during the ‘off’ condition, using either timed-up-and-go (TUG) ⁴³ or walking tasks. ⁴⁴
194 Studies show high sensitivity (range: 84.3%-86.2%) and moderate to high specificity (range 66.7%-
195 98.74%) for detection of FOG, and moderate agreement with clinical measures ^{43, 44}. These results
196 provide a critical step from which validation can be extended to free-living. An alternative approach is
197 to identify potential predictors of FOG to understand the mechanisms and target therapeutic
198 developments. A recent study comparing freezers vs. non-freezers found frequency-based gait
199 characteristics collected during 3 days of free-living discriminated freezers. Gait characteristics were
200 also moderately correlated with clinical measures of FOG ⁴⁵. Further work is needed before free-
201 living monitoring can be used for FOG detection or indeed for understanding the characteristics of
202 FOG but initial results are promising.

203

204 *Gait.* Measurement of gait per se (*micro* characteristics - Figure 1, E-F) is also of interest to the
205 clinician to evaluate efficacy of clinical management (due to dopa-resistance) as well as for its
206 potential for use of discrete gait characteristics as diagnostic, prognostic and progression markers ⁴⁶⁻⁴⁸.
207 Gait assessment during free-living assessment also captures ongoing environmental and cognitive
208 challenges which impair gait performance. Assessment in this context has greater ecological validity
209 and gives a true picture of the burden of disease ^{3, 7, 49}. Algorithms have been validated to detect
210 discrete gait characteristics in the laboratory and also in proxy validation studies ⁵⁰⁻⁵⁵. Results showed
211 good agreement with trusted gold standard reference (e.g. GaitRite or optical motion capture systems)
212 for the majority of gait characteristics with potential advantages for asymmetry and variability
213 measures. Apart from Del Din et al. ⁴⁹, the few studies that have examined gait in free living
214 conditions, quantify few gait characteristics ⁵⁶⁻⁶¹. Discriminative validity has been tested, and has been
215 shown to discriminate between PD and OA ^{49, 57}, phenotypes of PD ⁶¹ and PD with higher or lower
216 cognitive functions ⁶⁰. Aside from studies exploring falls and FOG risk highlighted previously ⁵⁷ only
217 one study has investigated the effect of environment on gait. Free-living gait characteristics showed
218 better discriminative validity than those collected in the laboratory, especially for medium to long
219 bouts ⁴⁹. Although initial work is promising, future work is required to confidently realise continuous
220 monitoring of gait. There are also some fundamental challenges to the field (outlined below).

221

222 *Measures of functional mobility.* Tests of functional mobility such as turning and Timed up and Go
223 (TUG) ⁶²⁻⁶⁴ measure combined movements that invariably incorporate postural transitions. Detection
224 of movements during functional mobility tasks appears accurate ^{62, 63, 65}, and validity (criterion and
225 discriminative) has been established by a limited number of studies ^{62, 65}. Mean turn velocity, slower
226 walking and turning, shorter steps and lower cadence distinguished PD from controls ^{62, 64} and also
227 showed greater sensitivity to dysfunction than clinical rating scales ^{64, 65}. Of interest, free-living
228 assessment appears to discriminate pathology better than testing in the laboratory ⁵⁴ (Figure 1, G).
229 Measurement of functional mobility tasks can therefore be undertaken with a degree of confidence
230 during a standardised test at home, although further work is required to replicate these findings.

231

232 *Ambulatory activity and sedentary behaviour.* One of the earliest applications of WTCD aimed to
233 quantify physical activity (e.g. ambulatory activity) amid rising concerns of the negative effects of
234 sedentary behaviour on well-being. This is particularly relevant for people with PD because of the
235 beneficial health benefits activity confers, and its role in mitigating secondary deficit. Ambulatory
236 activity provides a picture of the true burden of disease and therapeutic efficacy ⁶⁶. Proxy measures
237 such as activity logs and diaries are unreliable and lack responsiveness compared with continuous
238 WTCD monitoring ⁶⁷. Physical activity such as intensity of movement (energy expenditure), temporal
239 periods (bouts) of ambulatory activity (e.g. bouts of walking) and sedentary behaviours are quantified,
240 from which *macro* outcomes can be derived ^{66, 68-70} (Figure 1, A-B). The field has advanced further
241 with the application of non-linear approaches to data analysis which in some instances are more
242 sensitive than measures of central tendency (Table 1, Figure 2), such as pattern (alpha (α)) rather than
243 volume of sedentary behaviour showing discriminative properties ⁷¹. Ambulatory activity
244 differentiates disease stage ⁶⁶, and progression ^{72, 73} and shows increased sensitivity to intervention ^{68,}
245 ⁷⁴. Rochester et al. ⁶⁸ demonstrated the advantages of WTCD versus clinical measures when
246 examining the impact of deep brain stimulation (DBS) on ambulatory activity. Whilst standard
247 clinical measure for gait speed (4 meter test), levels of activity (Nottingham extended activities of
248 daily living index (NEADL)) and disease progression (Hoehn and Yahr) failed to show the positive

249 effects of DBS on the outcomes, WTCD-based measures demonstrated significantly improved
250 patterns of daily activity. Use of WTCD to measure ambulatory activity and sedentary behaviour is
251 the most advanced of all the fields discussed in this section, and the most widely adopted. Nonetheless
252 there are still questions over its application, driven by lack of common definitions of ambulatory
253 activity, validation procedures and structured protocols in controlled settings for validation of
254 algorithms⁶. These will be considered below.

255

256 *Utility and feasibility of WTCD: how acceptable are they?* Most studies do not intentionally test the
257 feasibility and utility of WTCD but instead draw on secondary data such as informal comments from
258 patients, reporting adverse events, data loss, or attrition in sensor use over the study period.
259 Importantly, there are no overwhelmingly negative reports, suggesting that WTCD are broadly
260 accepted. Although few studies have intentionally tested utility (which we describe as ‘formal testing’
261 in Table 1), some focused efforts have been made. Utility has been tested for wearable systems
262 comprising interactive⁷⁵ or multiple sensors^{17, 22, 23, 76}, using both non-standardised and standardised
263 questionnaires and rating scales²³ (e.g. the post-study usability questionnaire), comfort^{75, 76} (e.g.
264 comfort rating scale (CRS)) and ‘wearability’/exertion⁷⁶ (e.g. Borg CR-10 Scale, Rapid Entire Body
265 Assessment (REBA)). Overall the response has been positive, with WTCD generally well tolerated,
266 comfortable and easy to use. Compliance is high, although in some cases results were influenced by
267 socio-cultural aspects which may have positively biased results²³.

268

269 In summary, to date there is no fully validated WTCD system for continuous monitoring of patient
270 clinical features. Overall, studies are small, there is no consistent reporting of outcome measures,
271 protocols differ, and devices differ along with device placement. Comparison to a gold standard is
272 difficult. Knowledge on patient acceptability is limited. A clear process for validation including
273 replication in external data sets is essential with appropriate reporting according to a standard.
274 However the WTDC community is aware that this is an important and emerging area of research with
275 potential for high clinical uptake, and collaborative efforts are underway to redress these issues (see
276 reviews⁷⁻⁹). Challenges to implementation are due at least in part to broader technological and

277 practical concerns which are common to all WTCD and influence their state of readiness, irrespective
278 of application and use. Until these fundamental issues are redressed, robust use of WTCD will be
279 compromised. The next section highlights some of these broad concerns and discusses approaches to
280 advance the field.

281

282 **Challenges to clinical adoption**

283 We address 3 key areas fundamental to the use of WTCD that apply to all areas of
284 measurement: (i) clear definitions of the clinical feature of interest, (ii) validation of real-world data
285 and WTCD technical challenges, and (iii) consensus on outcomes. We illustrate these using examples
286 from our own experience in gait and activity and that of others (Figure 3). Finally we summarise
287 challenges with recommendations for future work and practical suggestions to inform the interested
288 user (Table 2).

289

290 *Defining the clinical feature.* Although on the face of it this seems simple, there are many examples
291 where unclear definitions have led to inconsistencies in outcomes and confusion when comparing
292 between studies. A good example relates to ambulatory activity, from which *macro* (e.g. walking
293 bouts) and *micro* level gait outcomes are derived that underpin many different clinical and research
294 questions (Figure 1). This stems from a basic definition of what constitutes a walking bout. In some
295 studies only purposeful bouts of walking are considered (with a cut-off threshold > 60 seconds)
296 because regular steady state is more likely to be achieved, thus avoiding potential errors in
297 misclassification from short bouts. However this is problematic because adults perform almost 90% of
298 walking bouts in less than 60s ^{40, 49, 77} resulting in significant data loss and potentially missing the
299 most relevant data (such as change in variability of walking pattern). Another approach is to include
300 all bouts of walking ⁴⁹ which is arguably more relevant in patient populations. However this is not a
301 complete solution because disagreement also exists regarding the number of steps required for a bout,
302 which may vary, ranging from >3 steps to >10 steps. As a consequence comparison across studies is
303 impossible where difference in step counts range from 2,000 to 10,000 steps ^{66, 68, 72, 73}. The situation is
304 further complicated by the use of ‘ghost’ (unknown to the end user and hard-wired into WTCD)

305 thresholds used by the manufacturer to define consecutive bouts of walking that have a major impact
306 on *macro* outcomes ⁷⁸ (e.g. total number and pattern of walking bouts) (Figure 3, (1)). This uneven
307 approach significantly impacts on both *macro* and *micro* outcomes and therefore consensus as to a
308 clear definition of walking is urgently required ^{6, 78}. Attempts are underway to improve definitions
309 which will greatly help (Chastin et al.: ALPHABET: Development of A Physical Behaviour
310 Taxonomy with an international open consensus¹).

311

312 *Algorithm development, validation and technical challenges: Influence of context and protocol.*
313 Establishing a gold standard to test algorithm validity for the range of features highlighted in this
314 review during continuous uncontrolled monitoring in a free-living environment is a major challenge
315 without obvious solutions. Real-life is unpredictable and unstructured. For example, context
316 (environment and task) affects walking speed and direction which has implications for accuracy of
317 algorithms used to detect steps and phases of the gait cycle from which gait characteristics are
318 determined (Figure 3). Studies often adopt a number of different testing protocols and various sensor
319 configurations (type and location (upper or lower body, Table 1) which also impacts the signal
320 waveform influencing the accuracy of the algorithm used to extract micro outcomes and other type of
321 information (features, outcomes). Moreover algorithms are usually validated using healthy controls
322 data and adopted for analysing other groups' data (i.e. PD) without considering that speed (fast or
323 slow), pathology itself and disease stage may impact on the raw signal (Figure 3, (2)) and therefore
324 influence algorithm performance. In addition other technical considerations need to be taken into
325 account. Many commercial devices adopt black box designs with un-validated firmware/software ⁷⁹
326 which account for at least some of the significant disagreements in reported results ^{80, 81}. Other
327 uncertainties due to externally induced motion (e.g. cars, lifts) also impact on accuracy to detect
328 features of interest ⁸¹. Static and dynamic re-calibration of WTCD to account for possible axis
329 misalignment or sensor alterations due to damage (device dropped, contact with water etc.) is also
330 advised ⁸², however rarely undertaken because procedures are complicated and expensive. Further
331 sources of variability are also introduced through changes in external factors such as weather, mood

¹ <https://osf.io/2wuv9/>

332 or medication, influencing analysis of the signal. Collectively these result in errors and decreased
333 confidence in outcomes and conformity to everyday use. Algorithm development will ultimately
334 refine extraction and a joint approach such as use of secondary data sources will aid interpretation, for
335 example data from patients' diaries, testimony from carers, and use of clinical records⁸³. All of these
336 potential sources of error should be considered and some suggestions are provided in Table 2.

337

338 *Determining optimal outcome measures.* Table 1 shows the vast range of outcomes reported.
339 Standardised measurement is urgently needed with a clear rationale for selection of outcomes from
340 which clinimetric testing will allow a refined battery of measures to emerge to encourage
341 harmonisation across studies. Examples of measurement frameworks have been described^{46, 49}
342 including our own *micro* and *macro* level structure used throughout this paper⁴⁷. Others^{37, 38, 45, 57, 61}
343 beside volume outcomes (e.g. total number of walking bouts, etc.) defined as '*quantity*' metrics, use
344 novel frequency-based outcomes to characterise gait (a) symmetry, variability and stability (e.g.
345 harmonic ratio, amplitude of dominant frequency, dynamic stability, etc.) defined broadly as '*quality*'
346 metrics. These novel *quality* measures, although very promising for discriminative validity, may be
347 difficult to interpret in clinical practice.

348

349 <Figure 2>

350 <Figure 3>

351

352 **Free-living monitoring in PD: where to next?**

353 Modern devices incorporate a range of inertial sensors such as accelerometers, gyroscopes,
354 magnetometers with Bluetooth connectivity which constitute cutting edge WTCD. While use is
355 currently limited to controlled settings, improvements in battery technology will improve the accuracy
356 of measurement addressing some of the challenges highlighted earlier. Moreover, novel methods for
357 advanced data processing are being developed to reduce computational load with advanced
358 computational processing carried out remotely via smartphone or in the cloud extending the
359 application of WTCD⁸⁴. Studies have also investigated the use of smart phones (and audio devices)

360 which regularly come with the necessary hardware to quantify symptoms, movement or gait ⁸⁵. These
361 devices capture, analyse and relay information via cellular or other wireless networks and also provide
362 a more comprehensive assessment such as the addition of a microphone for use with speech analysis
363 algorithms in PD diagnosis ^{86, 87} and visual displays to facilitate applications (apps) for the study of
364 cognition ⁸⁸. Rigorous device testing however is needed to ensure confidence in their application.

365 Long term monitoring via a smart phone facilitates network interconnectivity and integration
366 to the Internet of Things (IoT) ⁵, through delayed or real-time uploading of data to cloud computing
367 infrastructures. Data can be relayed to the patient (bio-feedback) via unobtrusive displays, haptic and
368 audible cues. Data is stored and sent to clinicians for tracking disease progression, optimising disease
369 management and providing further, more clinically informed feedback to the patient. Data storage and
370 data access on this scale constitutes ‘big data analytics’. Developments in this field can expand
371 assessment to capture the ‘lived experience’ or ‘lifespace’ of PD, capturing the extent to which people
372 travel and their patterns of movement within the community ⁸⁹. This is exemplified by a recent
373 collaborative project between the Michael .J Fox Foundation and Apple utilising their projects,
374 FoxInsight² and the Apple ResearchKit³ (inc. the Parkinson mPower app⁴ available via iTunes),
375 respectively.

376 Collection of data on the scale and in a free-living context raises new ethical challenges with
377 respect to acquisition, analysis and storage. Current ethical reviews may not be sufficient to identify
378 modern issues ⁹⁰. Technology and terminology has evolved faster than legal and ethical systems and
379 unforeseen issues can emerge ⁹¹. Informed, principled, and collaborative experimentation are therefore
380 necessary to ensure privacy and confidentiality, and compliance with ethical principles.

381

382 **Conclusions and recommendations**

383 There is no doubting the possibilities and potential of real world monitoring and assessment
384 of clinical features for people with PD. It is conceivable to imagine a future where *micro* level data is
385 used to enhance diagnostics, measure efficacy of intervention and monitor disease progression, and

² The Michael J. Fox Foundation for Parkinson's Research, <https://foxinsight.michaeljfox.org/>

³ Apple Inc., <http://www.apple.com/uk/researchkit/>

⁴ <http://parkinsonmpower.org/>

386 predict risk of disease, falls and cognitive decline. *Macro* level data, on the other hand, reflects the
387 global burden of disease and impact of therapy. Both sources of data provide insights into
388 personalised treatment. As this special issue in the journal indicates, this is a rapidly developing field.
389 However, much work remains before widespread clinical adoption is a reality. We highlight key
390 recommendations and some practical solutions to move this field forward (Table 2). These challenges
391 are likely to be met most effectively by adopting a multidisciplinary approach between key
392 stakeholders such as clinicians, patients, engineers, computer scientists, and statisticians.

393

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396

397 **Authors' roles**

398 SDD: Manuscript organisation, writing, review and critique.

399 AG: Manuscript writing, review and critique.

400 CM: Manuscript writing, review and critique.

401 SL: Manuscript writing, review and critique.

402 LR: Manuscript conception, writing, review and critique.

403

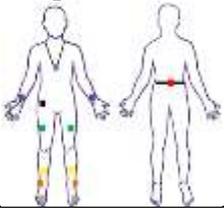
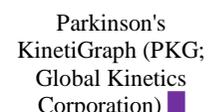
404 **Financial Disclosures of all authors**

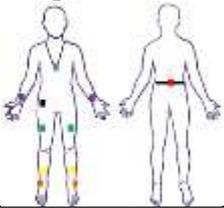
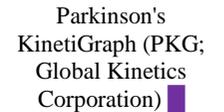
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412 necessarily those of the NHS or NIHR or the Department of Health.

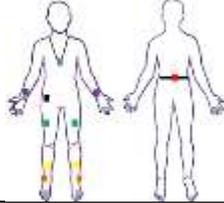
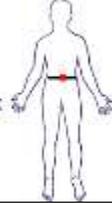
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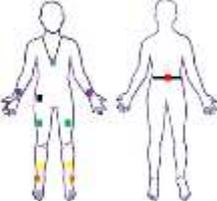
Table 1: Studies examining free-living monitoring of Parkinson's disease (PD) using wearable technology and connected devices (WTCD). Number and position of WTCD used in each study is detailed in column two using a colour code (blue = chest, violet = wrist, black = pocket, green = thigh, yellow = shank, orange = ankle, grey = foot, red = lower back).

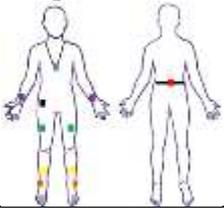
† Clinical feature/ activity detected or measures has been classified using three types of validity: 1) accurate detection of clinical feature/ method of appraisal: the ability of WCTD algorithms to accurately detect a clinical feature/activity which is comparable to detection by another means - in the study cited or previous studies (e.g. self-report, EMG); 2) criterion validity: the association between WTCD-derived outcomes and measures such as clinical scales; and 3) discriminative validity: the ability of WTCD-derived outcomes to discriminate between groups. Formal testing of utility (feasibility/compliance intentionally tested and reported) of WTCD is also reported.

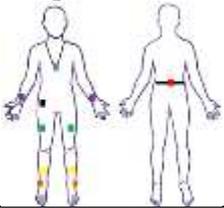
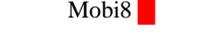
| Study (Year), N, Length of recording | WTCD and placement  | Clinical feature/ Activity | Accurate detection of clinical feature: Method of appraisal† | Measures | Criterion Validity† | Discriminative Validity† | Utility |
|--|---|---|--|--|---|-----------------------------|---|
| <i>Motor symptoms and medication response</i> | | | | | | | |
| Das et al. (2012), 2 PD, 4*21 | Accelerometers  | Dyskinesia, tremor | Yes, against patients' diaries using weakly supervised machine learning technique. | Acceleration derived features (Mean energy, high frequency energy content, correlation, frequency domain entropy) | No | No | No |
| Griffiths et al. (2012), 34 PD/10 OA, 10 ¹⁸ | Parkinson's KinetiGraph (PKG; Global Kinetics Corporation)  | Bradykinesia, dyskinesia | Yes, for bradykinesia against dot slide task measure (specificity 88%, sensitivity 95%) during scripted tests. | Acceleration derived features: Mean Spectral Power within specific bands, peak, amount of time with no movement | Yes, dyskinesia against the AIMS score and both dyskinesia and bradykinesia against UPDRS III and IV | No | No |
| Mera et al. (2012), 10 PD/ 10 OA, 3-6 ¹⁹ | Kinesia™  | Motor tasks, tremor, bradykinesia, motor fluctuations | No | Symptoms severity scale (0-4 points), voluntary movement threshold evaluated with gyroscope derived features (RMS, peak of power spectrum) | Yes, for tremor and bradykinesia. Potential issues of recognition when the 2 symptoms overlap. Yes against videos in the lab for symptom severity scale validated against UPDRS tremor and MBRS speed, amplitude and rhythm scores in previous work ^{75, 92} | No | Yes, formal testing previous work ⁷⁵ |
| Pastorino et al. (2013), 2 PD, 7 | ALA-6g (PERFORM)  | Akinesia, ON/OFF state | Yes, 'proof of concept' validation | Level of akinesia | No | No | Yes, formal testing |

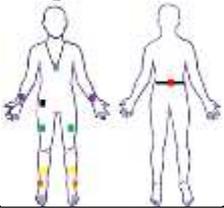
| Study (Year), N, Length of recording | <p>WTCD and placement</p>  | Clinical feature/ Activity | Accurate detection of clinical feature: Method of appraisal† | Measures | Criterion Validity† | Discriminative Validity† | Utility |
|---|---|--|---|---|---|--------------------------|--|
| (but 32 hours analysed) ¹⁷ | | | against patients' diaries | | | | |
| Tzallas et al. (2014), 12 PD, 5 (8 hours per day) ²² | <p>ALA-6g (PERFORM)</p>  | Tremor, LID, Bradykinesia, FOG | Yes, in the lab and during structured test (e.g. for FOG events Opening door/ Straight 10m walking) against video annotations. | Acceleration derived measures (time and frequency domains, RMS, range, entropy, energy) | Yes, machine learning and leave one out validation technique validated in the lab and applied in free-living conditions and compared against patients' diaries. Use of videos in the lab for assessing symptoms severity using UPDRS. | No | Yes, formal testing |
| Ferreira et al. (2015), 11 PD, 12 weeks ²³ | <p>SENSE-PARK System</p>  | Gait, hypokinesia, dyskinesia, tremor, sleep | No/NA (feasibility study and usability) | NA | NA | No | Yes, formal testing |
| Hammerla et al. (2015), 34 PD, 7 ²⁴ | <p>Axivity AX3</p>  | Sleeping, ON/OFF state, dyskinesia | Yes, in the lab (against video recordings) using machine learning and leave one out validation technique, in free-living conditions results are compared against patients' diaries. Model pre-trained in free-living conditions did not give good results (laboratory data is a poor model for naturalistic behaviours) | Acceleration derived measures (magnitude, jerk, power spectral density, etc.) | No | No | Yes, formal testing but in subsequent work ⁹³ |
| Horne et al. (2015), 64 PD/38 OA, 10 ²⁰ | <p>Parkinson's KinetiGraph (PKG; Global Kinetics Corporation)</p>  | Bradykinesia, dyskinesia, fluctuations | Yes, against measures of bradykinesia and dyskinesia (previous work see Griffiths 2012) | Fluctuation Score based on Interquartile Range of bradykinesia and dyskinesia scores. | Yes, against clinical scores derived measure | Yes | No |

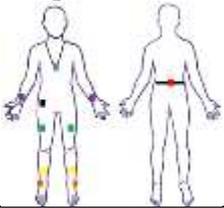
| Study (Year), N, Length of recording | WTCD and placement | | Clinical feature/ Activity | Accurate detection of clinical feature: Method of appraisal† | Measures | Criterion Validity† | Discriminative Validity† | Utility |
|---|---|---|----------------------------------|---|--|---|-----------------------------|--|
| |  |  | | | | | | |
| <i>Sleep</i> | | | | | | | | |
| Prudon et al. (2013), 106 PD/99 OA, 3 nights ⁹⁴ |  | Acti-watch, Camntech | Leg movements during sleep | Yes, in patients with periodic leg movement (against electromyography), previous work | Periodic leg movements index | Yes, against disease severity | No | No |
| Louter et al. (2015), 11 PD, 2 nights ²⁵ |  | Dynaport McRoberts | Turning during sleep | Yes, against polysomnography in adults with obstructive sleep apnoea syndrome, previous work ⁹⁵ | Acceleration derived measures (e.g. mean) and axial movement measures (frequency, size, duration, speed) | Yes, against Acti-watch but in young healthy adults previous work ⁹⁵ | Yes | Yes, no formal testing, previous work |
| Sringean et al. (2015), 19 PD, 1 night ²⁶ |  | NIGHT-Recorder system | Turning, Standing | No, video and sleep diaries collected but validity not formally tested. | Acceleration and gyroscope derived measures (duration of sleep, axial movements, velocity, etc.) | Yes, against clinical scores (UPDRS axial score, item #28, etc.) | Yes | Yes, no formal testing, no adverse events reported |
| <i>Falls and Falls Risk</i> | | | | | | | | |
| Weiss et al. (2013), 71 OA, 3 ³⁵ |  | Dynaport McRoberts | Walking (at least 60s) | No | Number of walking bouts, walking duration, total number of steps, median number of steps per bout, bout duration, cadence, step and stride regularity, frequency domain measures (harmonic ratio, amplitude, slope and width of dominant frequency), step duration, step symmetry, acceleration range, etc. | Yes, against clinical scores of fall risk and laboratory based measures | Yes | No |
| Weiss et al. (2014), 107 PD, 3 ³⁶ |  | Dynaport McRoberts | Walking (at least 60s) | No | Number of walking bouts, % of activity duration, total number of steps, median number of steps per bout, bout duration, cadence, stride regularity, frequency domain measures (harmonic ratio, | Yes, against clinical scores of fall risk | Yes | Yes, no formal testing, data loss reported. |

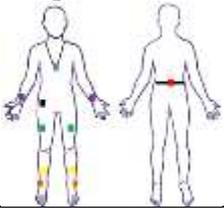
| Study (Year), N, Length of recording | <p>WTCD and placement</p>  | Clinical feature/ Activity | Accurate detection of clinical feature: Method of appraisal† | Measures | Criterion Validity† | Discriminative Validity† | Utility |
|---|---|---|---|--|--|-----------------------------|---------|
| Brodie et al. (2015), 18 EF, 58 (average) ⁴⁰ | Senior Mobility Monitor (SMM, Philips) --■-- | Walking (at least 3 or 8 steps) | No | amplitude and width of dominant frequency), etc. Steps per day, walking bouts per day, steps per bout, cadence, distribution of bout length | No | Yes | No |
| Hiorth et al. (2015), 48 PD, ⁷⁴¹ | activPAL ■ | Sedentary behaviour/ standing/ walking | Yes, but not formal in PD. Previous work in OA against other accelerometer ⁹⁶ and video recordings in people with rheumatoid arthritis during simulation of ADL in the laboratory ⁹⁷ | Volume (e.g. total number of sedentary/standing/walking bouts), pattern (α), variability of sedentary bouts and number of strides per walking bout. | Yes, against clinical scores | Yes | No |
| Mactier et al. (2015), 111 PD, ⁷³⁹ | activPAL ■ | Walking | Yes, but not formal in PD. Previous work in OA against other accelerometer ⁹⁶ and video recordings in people with rheumatoid arthritis during simulation of ADL in the laboratory ⁹⁷ | Volume (e.g. total number of walking bouts), pattern (α), variability of bouts, accumulation of stepping bouts | No | Yes | No |
| Rispen et al. (2015), 113 OA, 14 ³⁸ | Dynaport McRoberts ■ | Walking (at least 10s) | Yes, previous work in OA ⁹⁸ for walking volume parameters against videos, no for gait characteristics. | Acceleration based outcomes: gait speed, speed variability, stride time, stride regularity, stride time variability, stride frequency, frequency domain measures (harmonic ratio, amplitude, slope and width of dominant frequency), etc. | Yes, measures against self- reported fall history | No | No |
| van Schooten et al. (2015), 169 OA, 8 ³⁷ | Dynaport McRoberts ■ | Walking (at least 10s), sitting, lying, and standing | Yes, previous work in OA ⁹⁸ for walking volume parameters against videos, no for | Total duration of walking, sitting, standing, and lying per day, number of | Yes, against falls history | Yes | No |

| Study (Year), N, Length of recording | WTCD and placement  | Clinical feature/ Activity | Accurate detection of clinical feature: Method of appraisal† | Measures | Criterion Validity† | Discriminative Validity† | Utility |
|---|---|----------------------------------|---|---|--|-----------------------------|------------------------------|
| | | | gait characteristics. | strides, number of walking bouts, duration of bouts, number of transitions. Gait characteristics: gait speed, stride frequency, stride length frequency domain measures (harmonic ratio, power at dominant frequency), etc. | | | |
| Kangas et al. (2015), 16 OA, 5-155 ³² | CareTech Ab  | Falls‡ | Yes, fall event against care personnel's reports and in previous work in OA during simulation of fall events in controlled conditions ⁹⁹ in OA | Fall event with alarm generation | No | No | Yes, based on alarm accuracy |
| <i>Freezing of Gait (FOG)</i> | | | | | | | |
| Moore et al. (2013), 25 PD, NA ⁴³ | Xsens MTx  | Turning/ walking (TUG)‡ | Yes, in the laboratory for FOG event against video recordings | FOG event through acceleration derived frequency measures (power spectrum, etc.). | No | No | No |
| Tripoliti et al. (2013), 11 PD/5 OA, NA ⁴⁴ | Body Sensor AGYRO, AGYRO links, ANCO S.A.  | Walking, FOG detection‡ | Yes, against video recordings and visual inspection during structured test (Opening door/ Straight 10m walking) using different classification algorithms and cross-validations | FOG detection through entropy of WTCD signal | No | No | No |
| Weiss et al. (2015), 72 PD, 3 ⁴⁵ | Dynaport McRoberts  | Walking (at least 60s) | No | Number of walking bouts, % of activity duration, total number of steps, median number of steps per bout, bout duration, cadence, stride regularity, frequency domain | Yes, against clinical scores (FOG questionnaire) | Yes | No |

| Study (Year), N, Length of recording | <p>WTCD and placement</p>  | Clinical feature/ Activity | Accurate detection of clinical feature: Method of appraisal† | Measures | Criterion Validity† | Discriminative Validity† | Utility |
|--|---|--|--|---|------------------------------|---|---|
| | | | | measures (harmonic ratio, width of dominant frequency), etc. | | | |
| <i>Gait</i> | | | | | | | |
| Cancela et al. (2011), 10 PD, 1 (not clear) ⁵⁸ | <p>ALA-6g (PERFORM)</p>  | Walking (on vs off medication) | Yes, only for step frequency during 10m scripted protocol against visual examination | Step frequency, stride length and speed, entropy, arm swing | No | Yes, only for entropy in previous work ¹⁰⁰ | No |
| Weiss et al. (2011), 22 PD/17 OA (1PD/1CL at home), ³⁵⁷ | <p>Mobi8</p>  | Walking (during scripted test in the lab and during simulation of ADL and free- living) | No | Acceleration derived measures (time and frequency domains): stride time, stride time variability, amplitude, width, slope of dominant frequency, etc. | Yes, against clinical scores | Yes | No |
| Cancela et al. (2014), 11 PD, 5-7 (8 hours per day) ⁵⁹ | <p>ALA-6g (PERFORM)</p>  | Walking | Yes, only for step frequency, previous work (see Cancela 2011) | Step frequency, step velocity, stride length, entropy | No | Yes, only for entropy in previous work ¹⁰⁰ | Yes, formal testing and also assessed in separate study ⁷⁶ |
| Herman et al. (2014), 110 PD, ³⁶¹ | <p>Dynaport McRoberts</p>  | Walking (at least 60s) | No | Total number of activity bouts, total % of activity duration, total number of steps, mean activity bout duration, median number of steps per bout, cadence, stride regularity, amplitude of dominant frequency, width of dominant frequency, stride regularity, harmonic ratio, Phase Coordination Index. | Yes, previous work | Yes, previous work | No. |
| Weiss et al. (2015), 107 PD, ³⁶⁰ | <p>Dynaport McRoberts</p>  | Walking (at least 60s) | No | Total % of activity duration, total number of steps, cadence, amplitude of dominant frequency, stride regularity, harmonic ratio, | Yes, previous work | Yes, previous work | Yes, no formal testing, data loss reported |

| Study (Year), N, Length of recording | WTCD and placement  | Clinical feature/ Activity | Accurate detection of clinical feature: Method of appraisal† | Measures | Criterion Validity† | Discriminative Validity† | Utility |
|--|--|---|--|---|---|-----------------------------|---|
| <i>Phase Coordination Index.</i> | | | | | | | |
| Del Din et al. (2016), 47 PD/50 OA, 7 ⁴⁹ | Activiy AX3  | Walking (at least 3 steps) | No | 14 gait characteristics: mean step time, stance time, swing time, step length, step velocity, step time variability, stance time variability, swing time variability, step length variability, step velocity variability, step time asymmetry, stance time asymmetry, swing time asymmetry, step length asymmetry. | Yes, gait characteristics validated against laboratory reference (previous work ⁵³) | Yes | No |
| <i>Timed-up-and-go (TUG)</i> | | | | | | | |
| Zampieri et al. (2011), 6 PD/8 OA, 1 ⁶² | Physilog  | Walking/turni ng/postural transitions † | Yes, in previous work ¹⁰¹ | Cadence, stride velocity, stride length, peak arm velocity, turning velocity | No | Yes | No |
| Smith et al. (2016), 12 OA, 5 ⁶³ | SHIMMER  | Walking/turni ng † | No | Time to complete test, cadence, gait characteristics (step time, stride time, stride length, stride velocity, etc.), turning magnitude, etc. | No | No | No |
| <i>Turning</i> | | | | | | | |
| El-Gohary et al. (2013), 12 PD/18 OA, 7* ⁶⁵ | Opal(ADPM) --  -- in the lab / Opal(ADPM) --  --  at home | Turning/ walking (at least 10s) | Yes, in the lab against motion analysis system and video recordings | Number of turns, peak velocity, mean velocity, duration of turn | No | Yes | No |
| Mancini et al. (2015), 13 PD/8 OA, 7* ⁶⁴ | Opal(ADPM) --  --   | Turning/ walking (at least 10s) | Yes, in the lab (previous work, see El-Gohary 2013) | Number of turns/hour, turn angle, turn duration, number of steps/turn, turn mean velocity and coefficient of variation of these measures. | Yes | Yes | Yes, no formal testing, report of 'ease' of use. |
| <i>Ambulatory activity and sedentary behaviour</i> | | | | | | | |
| Chastin et al. (2010), 17 PD/17 OA, 7 ⁷¹ | activPAL  | Sedentary behaviour | Yes, but not formal in PD. Previous work in OA against other | Volume of sedentary bouts, pattern (α), pattern of accumulation of bouts (GINI) | No | Yes | No |

| Study (Year), N, Length of recording | <p>WTCD and placement</p>  | Clinical feature/ Activity | Accurate detection of clinical feature: Method of appraisal† | Measures | Criterion Validity† | Discriminative Validity† | Utility |
|---|---|--|---|---|---------------------|-----------------------------|---|
| | | | accelerometer ⁹⁶ and video recordings in people with rheumatoid arthritis during simulation of ADL in the laboratory ⁹⁷ | index) | | | |
| Dontje et al. (2013), 467 PD, 14 ⁷⁰ | TracmorD, Philips/ --■-- or --■-- or ■ | Physical Activity/Sedentary behaviour | Yes, against doubly labeled water technique (correlation) in adults but not in PD ¹⁰² | Energy expenditure, time spent in activities, distribution of activities, etc. | Yes | No | No |
| Benka Wallen et al. (2015), 95 PD, 7 ¹⁰³ | ActiGraph GT3X+ -- ■-- | Physical Activity/Sedentary behaviour/Steps (60s epochs) | Yes, in young adults under controlled conditions by visual observation but not in PD ¹⁰⁴ | Volume (magnitude vector of acceleration) and time spent in physical activities, steps per day, etc. | No | No | No |
| Lim et al. (2010), 153 PD, 1 ⁷⁴ | Vitaport3, TEMEC Instruments BV ■■■■ | Sitting, standing, walking | Yes in PD against video (under controlled conditions), previous work ¹⁰⁵ | % of time spent on dynamic, static, sitting, standing or walking activities, number of walking bouts > 5s and > 10s | No | No | No |
| Cavanaugh et al. (2012), 33 PD, 7 ⁷² | StepWatch 3 Step Activity Monitor (SAM) ■ | Walking (average every 60s) | Yes, for stride count in PD against instrumented walkway in the lab, previous work ¹⁰⁶ | Total number of steps, maximum output for steps, number of minutes with > 100 steps, number and duration of walking bouts, peak activity index, % of day spent inactive | No | No | Yes, not formal testing, reasons for data loss and attrition in sensor acceptability after 1 year with decrease in participant use reported |
| Rochester et al. (2012), 17 PD, 7 ⁶⁸ | activPAL ■ | Walking | Yes, but not formal in PD. Previous work in OA against other accelerometer ⁹⁶ and video recordings in | Volume of walking bouts, pattern of accumulation of bouts (GINI index) and diversity of bouts, distribution and variability of bouts (S ₂) | Yes | No | No |

| Study (Year), N, Length of recording | WTCD and placement  | Clinical feature/ Activity | Accurate detection of clinical feature: Method of appraisal† | Measures | Criterion Validity† | Discriminative Validity† | Utility |
|--|---|-----------------------------|---|---|---------------------|--------------------------|--|
| Lord et al. (2013), 89 PD/97 OA, 7 ⁶⁶ | activPAL  | Walking | people with rheumatoid arthritis during simulation of ADL in the laboratory ⁹⁷ Yes, but not formal in PD. Previous work in OA against other accelerometer ⁹⁶ and video recordings in people with rheumatoid arthritis during simulation of ADL in the laboratory ⁹⁷ | Volume of walking bouts, pattern (α), time spent walking in short-medium or long bouts, frequency and variability of bouts (S ₂) | Yes | Yes | No |
| Cavanaugh et al. (2015), 17 PD, 7 ⁷³ | StepWatch 3 Step Activity Monitor (SAM)  | Walking (average every 60s) | Yes, for stride count in PD against instrumented walkway in the lab, previous work (see Cavanaugh 2012) | Mean daily steps, maximum output for steps, Moderate intensity minutes (number of minutes with > 100 steps) | Yes | No | Yes, not formal testing, reasons for data loss and attrition in sensor acceptability after 2 years with decrease in participant use reported |

ADL = Activities of Daily Living; Alpha = α ; Lab = Laboratory; Length of recording = number of weeks/days/minutes of recording; MBRS = Modified Bradykinesia Rating Scale; min = minutes; N = number of participants; OA = Older Adults; PD = Parkinson's disease; RMS = Root Mean Square; UPDRS = Unified Parkinson's Disease Rating Scale; % = Percentage; *Night excluded; † = scripted protocol/supervised conditions used.

Table 2: Practical solutions and broad recommendations for WTCD-related research challenges.

| Recommendation | Practical solutions |
|---|--|
| Adopt standardised definition of activity/clinical feature | <ul style="list-style-type: none"> Justify definition of activity/clinical feature with respect to earlier work & clinical expertise. Adopt interdisciplinary collaboration for optimal process, choice of equipment, protocol, data processing and outcomes adhering to research question(s). |
| Select equipment depending on research/clinical question; evaluate trade-off between information needed & equipment available. | <ul style="list-style-type: none"> Consider optimal technical specifications (e.g. sampling frequency, type of data collected; battery life) for outcome measures. Use WTCD with established utility, acceptability and cost-effectiveness, otherwise plan to include tests of utility and acceptability as part of the study. Ensure transparency of all aspects of technology used (specifications, data collection, data pre-processing). |
| Use standardised protocols & validation procedures for algorithms for comparability & reproducibility across studies (e.g. accurate detection of activity/clinical feature, criterion & discriminative validity). | <ul style="list-style-type: none"> Justify use of standardised protocol & methods to define activities/clinical features. Use algorithms previously validated for the current application or provide validation results for novel algorithms. Use appropriate gold standards (e.g. video recording) to validate outcomes/metrics in free-living conditions, not limiting validation to scripted protocols or controlled conditions. Account for influence of context and disease severity on algorithm performance. If proprietary software is used ensure transparency of manufacturer algorithms or report published validated algorithm. |
| Achieve consensus for summary outcomes for comparability across studies. | <ul style="list-style-type: none"> Use WTCD-based outcomes validated in free-living; or provide validation results in the current study using semi-structured activities. Describe (if any) dependence of chosen summary outcomes & on chosen data processing/algorithm. |

Figures

Figure 1:

Use of wearable technology and connected devices (WTCD) (adapted with permission from previous work)⁴⁷ A) *macro* level quantification of activities over an extended period of time (volume, patterns and variability); (B) bouts of activities (e.g. lying (sleeping), walking, sitting); (C-H) *micro* level quantification from specific events: C) and D) postural transitions, E) shuffling, F) gait, G) turning, H) freezing of gait (FOG) and fall.

Figure 2:

Examples of linear and non-linear approaches to activity data analysis: volume and pattern metrics for two subjects (Subject 1 and 2) (published with permission)⁶⁸.

A1 and A2 - Patterns of activity indicating bouts of sedentary, standing and walking at different stepping rates (cadences).

B1 and B2 - Volume Metrics: total walking time for the two subjects is equal but made up of walking bouts at different cadences.

C - Pattern Metrics: (i) and (ii) distribution of walking bouts for these two subjects with equal mean (M) and different dispersion (S²). C (iii) Accumulation pattern of walking time for subject 1 and 2; subject 2 tends to accumulate walking time with predominantly longer periods.

Figure 3:

Challenges/limitations of free-living measurement using examples from gait in free-living collected with a single accelerometer-based WTCD. Data (unpublished) from the Incidence of Cognitive Impairment in Cohorts with Longitudinal Evaluation-GAIT (ICICLE-GAIT) study¹⁰⁷.

Panel (1) – Definition of feature of interest (e.g. walking):

A) Impact of “selected” definition of walking on data processing: different threshold of walking bout length and (ghost) maximum resting period (MRP) between consecutive walking bouts can be utilised.

Examples: (i): use of walking bout threshold of 60s and no MRP (MRP = 0s) (only bouts longer than 60 s will be considered); (ii): use of walking bout threshold of 3 steps and no MRP (MRP = 0s); (iii) use of walking bout threshold of 3 steps and MRP = 5s.

B) Impact of choice in A) on *macro* outcomes (e.g. number of bouts considered, total number of steps reported for people with Parkinson’s disease (PD) and controls (CL)). For example using definition (i) only a small percentage of all the walking bouts will be considered (bouts > 60s only) and therefore fewer steps will be reported if compared to results of using definition (ii).

C) Impact of choice in A) on *micro* gait characteristics (e.g. reported step velocity may vary across studies due to choice of definition ((i), (ii) or (iii)).

Panel (2) – Influence of free-living protocol on data:

Walking speed changes with respect to the environment, task, and disease severity which influences the accelerometer raw signal (D) impacting on algorithm performance and evaluation of outcomes (E).

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