Gait & Posture 109 (2024) 89–94

Contents lists available at ScienceDirect

Gait & Posture

journal homepage: www.elsevier.com/locate/gaitpost

Validation of ActiGraph and Fitbit in the assessment of energy expenditure in Huntington's disease

Lucía Simón-Vicente [a,b,*], Alejandro Rodríguez-Fernández [c], Jéssica Rivadeneyra-Posadas [a,b], María Soto-Célix [d,g], Javier Raya-González [f], Daniel Castillo-Alvira [e], Sara Calvo [b], Natividad Mariscal [b], Álvaro García-Bustillo [a,b], Laura Aguado [b], Esther Cubo [a,b]

[a] University of Burgos, Spain
[b] Hospital Universitario de Burgos, Spain,
[c] VALFIS Research Group, Institute of Biomedicine (IBIOMED), Faculty of Sciences of Physical Activity and Sports. University of Leon, León, Spain
[d] Faculty of Health Sciences, Universidad Isabel I, Burgos, Spain,
[e] Universidad de Valladolid, Spain
[f] Faculty of Sport Sciences, University of Extremadura, Cáceres, Spain
[g] Endocrinología y Nutrición. Servicio Medicina Interna. Hospital Reina Sofía. Área de Salud de Tudela, Servicio Navarro de Salud – Osasunbidea

ARTICLE INFO

Keywords:
Health promotion
Physical activity
Activity monitor
Rehabilitation
Exercise
Validation

ABSTRACT

Background: Consumer and research activity monitors have become popular because of their ability to quantify energy expenditure (EE) in free-living conditions. However, the accuracy of activity trackers in determining EE in people with Huntington's Disease (HD) is unknown.
Research question:
Can the ActiGraph wGT3X-B or the Fitbit Charge 4 accurately measure energy expenditure during physical activity, in people with HD compared to Indirect Calorimetry (IC) (Medisoft Ergo Card)?
Methods: We conducted a cross-sectional, observational study with fourteen participants with mild-moderate HD (mean age 55.7 ± 11.4 years). All participants wore an ActiGraph and Fitbit during an incremental test, running on a treadmill at 3.2 km/h and 5.2 km/h for three minutes at each speed. We analysed and compared the accuracy of EE estimates obtained by Fitbit and ActiGraph against the EE estimates obtained by a metabolic cart, using with Intra-class correlation (ICC), Bland-Altman analysis and correlation tests.
Results: A significant correlation and a moderate reliability was found between ActiGraph and IC for the incremental test (r = 0.667)(ICC=0.633). There was a significant correlation between Fitbit and IC during the incremental test (r = 0.701), but the reliability was poor at all tested speeds in the treadmill walk. Fitbit significantly overestimated EE, and ActiGraph underestimated EE compared to IC, but ActiGraph estimates were more accurate than Fitbit in all tests.
Significance: Compared to IC, Fitbit Charge 4 and ActiGraph wGT3X-BT have reduced accuracy in estimating EE at slower walking speeds. These findings highlight the need for population-specific algorithms and validation of activity trackers.

1. Introduction

Huntington's Disease (HD) is an inherited autosomal dominant neurodegenerative disorder caused by an expanded triplet (CAG) repeat in *HTT* gene on chromosome 4p [1]. The disease has an estimated prevalence of 3–7/100.000 people and it is characterized by movement disorders, cognitive alterations, and psychiatric symptoms [1,2]. HD patients tend to be frail, highly dependent on others, prone to losing weight, and physically inactive. Inactivity can have negative health consequences such as cardiovascular complications and sepsis [3].

Physical activity (PA) is one of the various lifestyle factors which seems to modify neurodegenerative disease progression [4]. Regular participation in PA is associated with a decreased risk of premature mortality and has positive effects on maintaining function and independence as well as improving quality of life. Furthermore, participation in regular exercise has potential to result in improved strength, exercise

* Correspondence to: Universidad de Burgos, Pº Comendadores, s/n., 09001 Burgos, Spain.
E-mail address: lsvicente@ubu.es (L. Simón-Vicente).

https://doi.org/10.1016/j.gaitpost.2024.01.028
Received 6 October 2022; Received in revised form 20 November 2023; Accepted 22 January 2024
Available online 28 January 2024

tolerance, cardiovascular fitness, mood and mobility [5,6].

Several studies suggest that PA may be beneficial for individuals with HD in terms of motor function, gait speed, and balance [7]. However, in order for training to have a significant impact on the management of HD, it is important to exercise at the right volume and intensity. For this reason, it is crucial to have accurate devices to measure these metrics in research and clinical practice, being particularly interesting to multidisciplinary health teams [8].

Estimates of daily energy expenditure (EE) are an important component in studies of PA. Indirect Calorimetry (IC) is a non-invasive technique that has been used as a gold standard for assessing intensity and EE of PA by measuring oxygen consumption (O_2) and carbon dioxide production (CO_2) (pulmonary gas exchanges). Although it is the best tool to measure and monitor EE, it is a costly and complexity method that cannot be used in free-living environments [9,10].

With advances in technology, commercial activity trackers (also referred to as accelerometers) such as Garmin, Fitbit devices or Actigraph are increasingly used in PA research and allow an estimate of EE. Recent studies have compared PA measurements taken by low-cost and easy-to-interpret devices with measurements taken by high-cost devices, with some research focused on healthy populations and others focused on populations with disease [10]. For example, the Actigraph has been used in large-scale epidemiological studies [9] as well as a review article that reported an exponential increase in the use of a popular commercial activity monitor (Fitbit) in research [12]. These devices that are typically worn on the wrist or waist, can be summarized in "counts per minute" or transformed using different algorithms to estimate EE of the task and Metabolic equivalents (METs), where 1 MET is how much energy a person uses up while at rest [13]. Although most of the monitors currently available have been validated in different populations, the accuracy of low-cost devices has not been evaluated for participants with HD [9]. Because people with HD have difficulties with gait and walking performance due to hyperkinetic and hypokinetic movements, it is especially important to evaluate the validity of monitors in order to avoid inaccurate conclusions [7].

To begin to fill this gap in information about the use of accelerometers in HD, this study aimed to determine the accuracy of two accelerometers (research-focused device and low-cost device) in estimating EE compared to IC (the gold standard) in participants with HD.

2. Materials and methods

2.1. Design

A cross-sectional, observational study was conducted at the University Isabel I and Burgos University Hospital, Spain. The study was conducted in two visits. In the first one, we collected clinical information, and in the second visit, within three months, we collected total EE data.

2.2. Participants

A convenience sample of symptomatic, ambulatory people diagnosed with HD with a confirmed genetic mutation of $>$ 36 CAG repeats in the *HTT* gene was recruited. Considering the low prevalence of HD and sample sizes included in previous validation studies [14], 14 HD participants were included. Symptomatic HD participants were defined with a score greater than 4 on the motor subdomain of the Unified Huntingtońs Disease Rating Scale (UHDRS) [15], and a diagnostic confidence level (DCL) of 4, able to walk with minimal support.

People diagnosed with diabetes mellitus, thyroid disturbances, active cancer, neurodegenerative conditions, cardiac, pulmonary, or skeletal-muscular diseases were excluded. People who were pregnant or breastfeeding, or taking medication that could affect metabolism/endocrine function were also excluded.

This study was conducted in accordance with Good Clinical Practice standards involving humans and was approved by the Institutional Review Board (University Isabel I and Burgos University Hospital, Certificate number: CEIM-2429, January 26th, 2021). All participants provided informed consent by signing the consent form prior to participating.

2.3. Test protocol

Participants were instructed to avoid vigorous exercise on the day before testing and refrain from alcohol, nicotine, and caffeine four hours before the study visit. The determination of total EE was performed by fasting for at least 5 h.

In the second session, all participants received adequate time to familiarize themselves with the treadmill prior to the test. Participants were accustomed to walking at different speeds without using the handrails while breathing through the facemask. They were advised to stop at any time by giving an agreed signal or pressing the stop button. EE related to PA was evaluated with a treadmill walk (Cosmos Pulsar 4.0, Cosmos Sports & Medical, Nussdorf-Traunstein, Germany) with a constant slope (1%), under three different speed conditions: i) walking at 3.2 km/h for three minutes, ii) walking at 5.2 km/h for three minutes and iii) walking speed started at 1.5 km/h and was increased by 0.5 km/h every minute until the participant expressed, they were unable to continue. The participant used a harness throughout the test (risk protection) and were encouraged to only use the sidebars if they needed to.

Walking at a constant intensity of 3.2 km/h with a constant gradient of 1%, served as a measure of the activity of daily living – walking; at a constant intensity of 5.2 km/h with a constant gradient of 1% as a measure of moderate activity; and the incremental test as a measure of vigorous activity [16]. During the test protocol, participants breathed through the mask equipped with inspiratory valves that transmitted the O_2 data to a computer for analysis [17]. Gas exchange was continuously monitored to analyse O_2 and CO_2 concentrations by the use of a breath-by-breath system (Ergo Card®, Medisoft, Sorinnes, Belgium). Prior to each test, the analyser was calibrated by means of a syringe (Hans Rudolph®. Model 3800. Kansas. USA) and gas cylinder with gas mixture (G5512 5.04% CO_2 and 11.87% O_2. Airliquide), coupled to a pressure reducer (Gloor®. Switzerland). The data were analysed by specific software (Medisoft®, Sorinnes, Belgium).

2.4. Functional assessments

A certified movement disorder neurologist evaluated all HD participants at baseline using a standardized HD assessment tool, the UHDRS, including the motor subscale (UHDRS-TM) with high scores denoting greater impairment [15]. Disease severity was assessed using the Total Functional Capacity (TFC) [18], with higher scores indicating more intact functioning. The severity of psychiatric symptoms was assessed using the Problem Behaviors Assessment (PBA), with higher scores indicating greater severity [19]. Cognition was screened using the Mini-Mental State Examination (MMSE) [20].

2.5. Activity monitors

The ActiGraph accelerometer (wGT3X-BT), the most commonly used accelerometer for assessing PA in research under free-living conditions, was used for PA assessment [10]. It was a small (4.6 cm $\times$ 3.3 cm$\times$1.5 cm) and lightweight (19 g) device that used a triaxial accelerometer to measure accelerations in the range of 8 G G's with a band-limited frequency of 30–100 Hertz. Ten minutes before starting the protocol, the device was attached to a nylon belt and positioned on the right hip following the manufacturer's instructions. Raw accelerometer data were downloaded using Actilife 6 software and then transformed into 10-second epochs files. Freedson and colleagues [21] developed an equation to convert counts per minute into METS, the standard unit for measured activity intensity. This equation allowed for meaningful interpretation of ActiGraph data and the classification of activity intensities into light,

moderate or vigorous. All data were transformed using the following equation: "activity intensity (METS) = 1.439008 + (0.000795 x counts·min^{1})".

The Fitbit Charge 4, a wrist-worn activity monitor (3.58 ×2.27 ×1.25 cm and weighs 20 g) that measures distance, active minutes, step counts, and calories, was also used. Ten minutes before starting the protocol, the device was positioned on the dominant hand's wrist [12]. This activity monitor calculates METs through a ratio (rate of energy expended during an activity: rate of energy expended during rest), considering that during rest or sitting quietly people expend 1 MET [22]. Raw data were exported to CSV and then converted into an Excel file for data interpretation.

2.6. Statistical analysis

Similar to previous studies [10], EE estimation was compared to IC. Descriptive statistics for participants and main outcomes are presented as the mean and standard deviation (SD) for continuous variables, the median, and the 25th-75th percentiles for non-normally distributed or ordinal data. The normality of the variables was evaluated using the Shapiro Wilk test. We calculated the frequency distribution and percentages to describe categorical variables.

The accuracy of METs obtained from Fitbit Charge 4 and the ActiGraph wGT3X-BT compared to IC (gold standard) was calculated with Intra-class correlation (ICC) using two-way mixed models with absolute agreement and correlation assessment with Pearson and Spearman's test. ICCs were analysed separately for both activity monitors measuring EE. ICC values can range from 0 (measurements are not in agreement) to 1(measurements are reliable). These values may be interpreted as excellent reliability if ICC > 0.90, ICC between 0.75 and 0.90 indicates good reliability, values between 0.5 and 0.75 indicate moderate reliability and ICC < 0.5 is interpreted as poor reliability [23]. Bland-Altman statistics were performed to determine the limits of agreement (LoA) for each device compared with the criterion measure. Data were analysed using SPSS version 28 for Windows (SPSS Inc., Chicago, IL, USA) and Microsoft Excel. The level of significance was set at $p < 0.05$. Scatterplot were used to evaluate the linearity of the association between IC with ActiGraph wGT3X-BT and Fitbit Charge 4.

3. Results

A total of 14 HD participants (7 women) with a mean age of 55.7 ± 11.47 years were included in this study. Clinical and Anthropometric data are provided in Table 1. Compared to IC, ActiGraph wGT3X-BT provided lower mean measures of EE at the speed of 3.2 km/h and higher mean measures at the speed of 5.2 km/h as well as during the incremental test. Compared to IC, Fitbit Charge 4 provided higher mean measures of EE in all tests (Table 2). During the incremental test, ActiGraph wGT3X-BT, could not provide values when the speed was very low.

Across the devices, we found a moderate agreement between ActiGraph wGT3X-BT and IC during the incremental test (ICC=0.633) and a poor agreement in the overall treadmill walk in relation to Fitbit Charge 4 and IC (Table 3). The criterion of IC derived activity EE yielded the strongest correlations with activity EE estimates from ActiGraph wGT3X-BT ($p = 0.667$, $p \leq 0.001$) and with Fitbit Charge 4 during incremental test ($p = 0.701$, $p \leq 0.001$).

Bland-Altman plots (Fig. 1) reflect the difference between ActiGraph wGT3X-BT EE with IC, and Fitbit Charge 4 EE estimates with IC. Compared to IC, at the speed of 3.2 km/h (light intensity), ActiGraph wGT3X-BT provided the narrowest 95% LoA. In relation to Fitbit Charge 4, the narrowest 95% LoA were at a speed of 3.2 km/h. In addition, the plots indicated a lower systematic bias for IC and ActiGraph wGT3X-BT at 5.2 km/h, followed by the incremental test. In this regard, Fitbit Charge 4 overestimated EE at a speed of 3.2, 5.2 km/h, and during incremental test compared to IC.

Regarding the percentage of error, ActiGraph wGT3X-BT was more accurate than Fitbit Charge 4 in all tests (3.2 km/h, 5.2 km/h, and incremental). ActiGraph showed the lowest error percentage at 3.2 km/h and Fitbit at 5.2 km/h (Table 3).

Table 1
Descriptive characteristics of the participants.

Variable	n = 14
Height (cm), mean ± SD	161.1 ± 6
Weight (kg), mean ± SD	64.2 ± 11.6
BMI (kg/m^2), mean ± SD	24.8 ± 5.1
TMS, mean ± SD	29.3 ± 13.6
TFC, median (range)	10 (8-13)
PBA, median (range)	1 (0-9.25)
MMSE, mean ± SD	27.2 ± 2.7

BMI, Body mass index; TMS, Total Motor Score; TFC, Total Function Capacity; PBA, Problems Behaviors Assessment; MMSE, Mini-Mental State.

Table 2
Instrument variability.

	Test	Mean ± SD	SEM
Indirect Calorimetry	3.2 km/h	2.61 ± 0.31	0.086
	5.2 km/h	3.35 ± 0.47	0.135
	Incremental	2.96 ± 0.96	0.081
ActiGraph wGT3X-BT	3.2 km/h	1.68 ± 0.74	0.212
	5.2 km/h	3.45 ± 1.14	0.345
	Incremental	2.69 ± 1.8	0.161
Fitbit Charge 4	3.2 km/h	5.75 ± 1.47	0.425
	5.2 km/h	6.17 ± 1.6	0.480
	Incremental	5.36 ± 2.28	0.204

SEM: Standard error of the mean

4. Discussion

To our knowledge, this is the first study that analyses the accuracy of two accelerometers to quantify EE at different exercise intensities under controlled conditions for HD participants.

We found that both devices in all speeds have poor agreement with IC, the gold standard for EE measurements, except during the incremental test, for which the Actigraph wGT3X-BT indicated moderate reliability. During the incremental test, there was a moderate correlation of both devices with IC, but as exercise intensity increased, the Fitbit Charge 4 overestimated EE compared to IC and the ActiGraph wGT3X-BT.

Previous studies have examined the accuracy of various commercial activity accelerometers during different activities on the treadmill in healthy adults [10,12,24]. Vanhelst et al. [25] found a high correlation ($r = 0.89$) between accelerometry and oxygen consumption, with a mean difference very close of 0 (1.1 ± 1.3), with the LoA ranging from − 2.9 to 2.9, suggesting that is a valid measure of PA at varying levels of intensity.

By contrast, Brazeau et al. [26] evaluated the accuracy of SenseWear Armband and Actical compared to IC. These authors found a significant correlation between both activity monitors with IC ($r = 0.804$; $r = 0.807$; $p < 0.05$, respectively), with good and excellent reliabilities (ICC of 0.892 and 0.906, respectively), but these devices were not accurate for EE estimations during specific exercise and rest. Similarly, Anastasopoulou et al. [27] found a moderate correlation between ActiGraph GT3X (r = 0.53; r = 0.70; $p < 0.05$) and IC (for both walking and fast walking activity), but the devices did not show agreement (ICC=0.23; ICC=0.35). Kossi et al. [28] compared the EE estimations by ActiGraph GT3X+ with a gold standard measurement and also found that the agreement between both were poor (ICC=0.32; ICC=0.21). Furthermore, the device does not provide accurate EE estimates across a range of placement locations during moderate and high-intensity PA.

Table 3
Comparison of EE of ActiGraph and Fitbit with Indirect Calorimetry (criterion).

Activity Monitor	Test	n	Mean difference[1]	Lower LoA[2]	Upper LoA[2]	Absolute percentage error	ICC	95% CI		Correlation coefficient
								Lower	Upper	
ActiGraph wGT3X-BT	3.2 km/h	14	0.924	-0.803	2.651	132	-0.055	-0.253	0.308	-0.160 (0.601)[3]
	5.2 km/h	14	-0.097	-2.482	2.287	142	0.131	-0.520	0.65	0.159 (0.622)[4]
	Incremental	125	0.169	-2.383	2.723	165	0.633	0.515	0.728	0.667 * * (<0.001)[4]
Fitbit Charge 4	3.2 km/h	14	-3.169	-6.304	-0.033	243	-0.009	-0.084	0.177	0.579 (0.170)[4]
	5.2 km/h	14	-2.9	-6.121	0.321	197	0.020	-0.088	0.272	0.523 (0.081)[4]
	Incremental	122	-2.59	-6.143	0.962	260	0.188	-0.080	0.435	0.701 * * (<0.001)[4]

Mean difference= difference between the gold standard and the activity monitors for each speed [1]
95% LoA= Limits of agreement [2]
ICC= Intra-class correlation
CI= Confidence interval
Pearson's test [3]
Spearman's test [4]

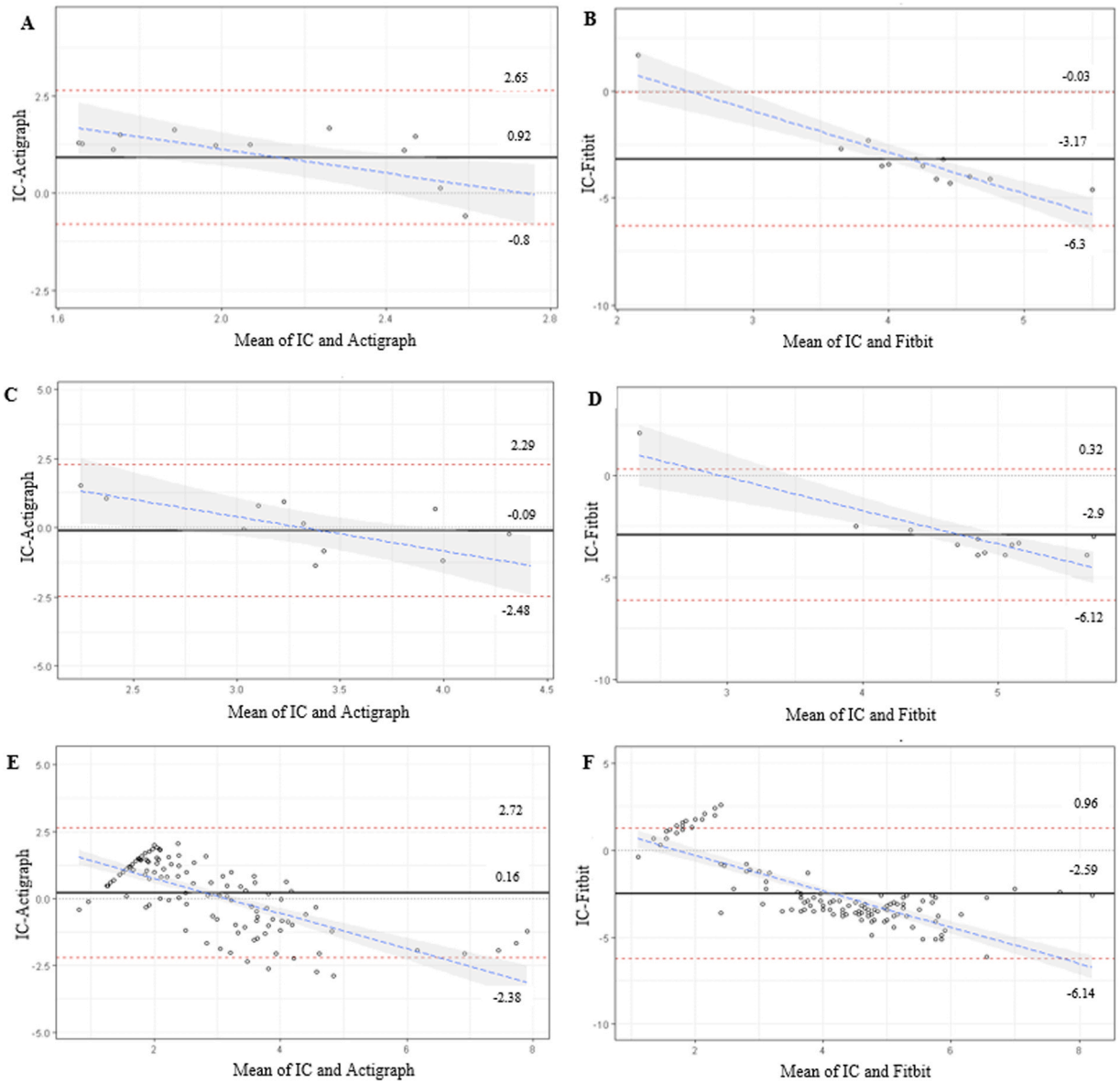

Fig. 1. - Bland-Altman plot visualizing agreement of energy expenditure (MET) **(A)** Actigraph v's IC at 3.2 km; **(B)** Fitbit v's IC at 3.2 km/h; **(C)** Actigraph v's IC at 5.2 km; **(D)** Fitbit v's IC at 5.2 km/h; **(E)** Actigraph v's IC during Incremental test; **(F)** Fitbit v's IC during Incremental test.

In diseased populations, including participants with Multiple Sclerosis, ActiGraph estimates of EE compared to IC have shown good agreements (ICC= 0.859). However, in Bland Altman plots, the differences per treadmill speed between both measurements were generally within 2 SD, with up to 30.3% discrepancy on slow-walking speeds. The disagreement between both devices could be explained by the difference in output under slow-walking conditions [29]. Likewise, Abel et al. [30], found that ActiGraph was not accurate for low-intensity movements. These results agree with our results, with poor sensitivity for EE of the Actigraph at low speeds during the incremental test. The lack of agreement could be because the device may not be sensitive by clinical characteristics of the participants, the disease itself, or that the logarithms used are not validated for people with chorea.

In other populations, Sean et al. [31] evaluated the validity of ActiGraph in people with acquired brain injury and they found positive, moderate correlations (range 0.58 – 0.70, $p < 0.05$). However, Bland–Altman plot spanned 5.1 METs and, when compared with measured MET levels, METs ranged from 1.6 METs overprediction to 4.3 METs underprediction, so the absolute agreement between measured and predicted METs was not strong, limiting the validity of the Actigraph. Again, the discrepancy between devices may be because people with acquired brain injury who participated in the study had related gait pattern impairments affecting the conditions and performance of the study substantively. Mandigout et al. [32] also compared the EE evaluated by IC, this time in subacute post-stroke patients. During a scenario consisting of everyday activities, they estimated the EE using several sensors and concluded a low correlation ($r = 0.04$) and a very poor agreement for all sensors.

Overall, our results agree with previous research with healthy adults. In these studies, reported Fitbit Charge 4 overestimated EE with a negative bias when activities were performed on the treadmill (−19.3% [SD 28.9]) [33], and a trend to overestimate EE compared with IC with a difference for estimates of total EE of − 29.6% [34]. Our findings agree with a previous study carried out by Sjöberg [35] that concluded that Fitbit systematically overestimated EE in participants with chronic pain (ICC= –0.03). Likewise, in agreement with our results, Herkert et al. [36] demonstrated low accuracy of Fitbit (ICC=0.10) in estimating EE in people with coronary artery disease. A possible explanation for these results might be due to Fitbit algorithm employs an equation for estimating resting metabolic rate that is still not debugged [37]. On the other hand, in people with Chronic Obstructive Pulmonary Disease, ActiGraph seems to measure standardized and common physical activities accurately, and it is recommended for assessing activities of patients in terms of intensity and/or amount. However, ActiGraph seems to be still imperfect for measuring EE in this population [38].

Differences between ActiGraph and Fitbit estimates may be due to the location of the device. Hip-worn monitors, which are close to the center of mass, estimates MET values and total EE better than wrist-worn devices [11]. A review performed to evaluate the influence of body placement to the accuracy of EE estimation concluded that wrist-worn monitors generally lead to overestimating EE [39]. This could be why Fitbit Charge 4, located on the wrist, estimated METs values worse than ActiGraph wGT3X-BT, located on the hip. In addition, other confusing factors including HD motor abnormalities such as chorea, involuntary jerking or writhing movements, may affect and cause differences in the estimation of the EE [40].

5. Limitations

A potential limitation of this study is that the accuracy of the ActiGraph wGT3X-BT and Fitbit Charge 4 was examined only during walking and jogging exercise intensities (i.e., light, moderate, and vigorous intensity) in a laboratory under controlled conditions. However, it is unclear whether similar findings would be observed under different environmental conditions.

Because this was a laboratory-based study, participants only had to wear the wearables for approximately 1 h 30 min. This study cannot determine whether people with HD would be willing to wear the devices for longer periods. In addition, we cannot extrapolate the results to a community-dwelling individuals with HD in free-living conditions. However, despite these limitations, we believe that our study has several strengths, including being the first study providing evidence about the accuracy of two common accelerometers in detecting EE in people with HD in different body positions.

6. Conclusion

There is a growing interest in using activity monitor devices to promote healthy lifestyles and physical exercise. Compared to IC, our results suggest that Fitbit Charge 4 and ActiGraph wGT3X-BT have reduced accuracy in estimating EE at slower walking speeds. The location of the device is another parameter to consider since hip-worn monitors estimate total EE better than wrist-worn devices. These findings highlight the need for population-specific algorithms and validation of activity trackers.

Despite the finding that the Fitbit device overestimated METS, it could still be a beneficial tool for clinical applications in people with HD given the ease of use, the relatively low cost, and its ability to give immediate feedback. Furthermore, when people with HD monitor their PA behaviours, this can increase their motivation and promote the adoption or maintenance of healthy PA habits. Over time, these behaviours could have a significant positive impact on peoples´ daily lives by increasing their levels of autonomy and independence as well as potentially delaying their age of institutionalization.

CRediT authorship contribution statement

Mariscal Natividad: Methodology, Visualization, Writing – review & editing. **García-Bustillo Alvaro:** Supervision, Writing – review & editing. **Aguado Laura:** Investigation, Project administration, Validation, Writing – review & editing. **Cubo Esther:** Conceptualization, Data curation, Formal analysis, Funding acquisition, Validation, Writing – original draft, Writing – review & editing. **SIMÓN LUCÍA:** Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Software, Validation, Writing – original draft, Writing – review & editing. **Castillo-Alvira Daniel:** Data curation, Formal analysis, Investigation, Software, Supervision, Writing – original draft, Writing – review & editing. **Calvo Sara:** Data curation, Formal analysis, Validation. **Rodríguez-Fernández Alejandro:** Conceptualization, Investigation, Methodology, Project administration, Software, Writing – original draft, Writing – review & editing. **Rivadeneyra-Posadas Jessica:** Data curation, Supervision, Writing – review & editing. **Soto-Célix María:** Conceptualization, Funding acquisition, Investigation, Writing – review & editing. **Raya-González Javier:** Investigation, Methodology, Software, Validation.

Declaration of Competing Interest

The authors have no conflict of interest to declare.

Acknowledgments

The research leading to these results has received funding from “la Caixa” Foundation and Caja de Burgos Foundation, under agreement LCF/PR/PR18/51130008".

We would like to thank the patients, the caregivers, all the people who have collaborated in this project and the Fundación la Caixa and Fundación Caja de Burgos. We also thank the Domino-HD Consortium for their support (Multi-Domain Lifestyle Targets for Improving PrognOsis in Huntington’s Disease. DOMINO-HD. Horizon 2020), and especially to Dr. Bernhard Landermeyer.

Javier Raya-González was supported by a Ramón y Cajal

postdoctoral fellowship (RYC2021-031072-I) 2 given by the Spanish Ministry of Science and Innovation, the State Research Agency (AEI), and the European Union (NextGenerationEU/PRTR).

References

[1] N. Quinn, A. Schrag, Huntington's disease and other choreas, J. Neurol. 245 (11) (1998) 709–716.

[2] C. Cepeda, X.P. Tong, Huntington's disease: from basic science to therapeutics, CNS Neurosci. Ther. 24 (4) (2018) 247–249.

[3] A.C. Ogilvie, P.C. Nopoulos, J.L. Schultz, Quantifying the onset of unintended weight loss in Huntington's disease: a retrospective analysis of enroll-HD, J. Huntington's Dis. 10 (4) (2021) 485–492, https://doi.org/10.3233/JHD-210488.

[4] S.M. Mueller, J.A. Petersen, H.H. Jung, Exercise in Huntington's disease: current state and clinical significance, Tremor Other Hyperkinetic Mov. (2019).

[5] K.S. Bhalsing, M.M. Abbas, L.C.S. Tan, Role of physical activity in Parkinson's disease, Ann. Indian Acad. Neurol. 21 (2018) 242–249.

[6] K. Do, B.T. Laing, T. Landry, W. Bunner, N. Mersaud, T. Matsubara, et al., The effects of exercise on hypothalamic neurodegeneration of Alzheimer' s disease mouse model, PLoS One 17 (1) (2018).

[7] L. Quinn, M. Busse, J. Carrier, N. Fritz, J. Harden, L. Hartel, D. Kegelmeyer, A. Kloos, A. Rao, Physical therapy and exercise interventions in Huntington's disease: a mixed methods systematic review protocol, JBI Database Syst. Rev. Implement. Rep. 15 (7) (2017) 1783–1799, https://doi.org/10.11124/JBISRIR-2016-003274.

[8] D.E.R. Warburton, S.S.D. Bredin, Health benefits of physical activity: a systematic review of current systematic reviews, Curr. Opin. Cardiol. [Internet] 32 (5) (2017). Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/28708630/⟩.

[9] R.P. Troiano, J.J. McClain, R.J. Brychta, K.Y. Chen, Evolution of accelerometer methods for physical activity research, Br. J. Sports Med [Internet] 48 (13) (2014) 1019–1023. Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/24782483/⟩.

[10] P. Topalidis, C. Florea, E.S. Eigl, A. Kurapov, C.A.B. Leon, M. Schabus, Evaluation of a low-cost commercial actigraph and its potential use in detecting cultural variations in physical activity and sleep, Sensors 21 (11) (2021 1). Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/34072347/⟩.

[11] C.E. Morris, P.A. Wessel, R.A. Tinius, M.A. Schafer, J.M. Maples, Validity of activity trackers in estimating energy expenditure during high-intensity functional training (Available from:), Res Q Exerc Sport 90 (3) (2019), https://doi.org/10.1080/02701367.2019.1603989].

[12] S.P. Wright, T.S. Hall Brown, S.R. Collier, K. Sandberg, How consumer physical activity monitors could transform human physiology research, Am. J. Physiol. -Regul., Integr. Comp. Physiol. 312 (3) (2017) R358–R367, https://doi.org/10.1152/ajpregu.00349.2016).

[13] J. Siddique, D. Aaby, S.E. Montag, S. Sidney, B. Sternfeld, W.A. Welch, et al., Individualized relative-intensity physical activity accelerometer cut points, Med Sci. Sports Exerc 52 (2) (2020 1).

[14] R.M. Lamont, H.L. Daniel, C.L. Payne, S.G. Brauer, Accuracy of wearable physical activity trackers in people with Parkinson's disease, Gait Posture 63 (2018 1). Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/29729611/⟩.

[15] K. Kieburtz, Unified Huntington's disease rating scale: reliability and consistency, Huntingt. Study Group. Mov. Disord. [Internet] 11 (2) (1996) 136–142. Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/8684382/⟩.

[16] H. Nero, M. Benka Wallén, E. Franzén, A. Ståhle, M. Hagströmer, Accelerometer cut points for physical activity assessment of older adults with Parkinson's disease, PLoS One 10 (9) (2015) e0135899, https://doi.org/10.1371/journal.pone.0135899.

[17] M. Delsoglio, N. Achamrah, M.M. Berger, C. Pichard, Indirect calorimetry in clinical practice, J. Clin. Med [Internet] 8 (9) (2019 1). Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/31491883/⟩.

[18] I. Shoulson, Huntington disease: functional capacities in patients treated with neuroleptic and antidepressant drugs, Neurol. [Internet]ogy 31 (10) (1981) 1333–1335. Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/6125919/⟩.

[19] E.M. Kingma, E. van Duijn, R. Timman, R.C. van der Mast, R.A.C. Roos, Behavioural problems in Huntington's disease using the Problem Behaviours Assessment, Gen. Hosp. Psychiatry 30 (2) (2008) 155–161. Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/18291297/⟩.

[20] M.F. Folstein, S.E. Folstein, P.R. McHugh, "Mini-mental state". A practical method for grading the cognitive state of patients for the clinician, J. Psychiatr. Res. 12 (3) (1975) 189–198 (Available from), ⟨https://pubmed.ncbi.nlm.nih.gov/1202204/⟩.

[21] P.S. Freedson, E. Melanson, J. Sirard, Calibration of the computer science and applications, Inc. accelerometer, Med Sci. Sports Exerc [Internet] 30 (5) (1998) 777–781. Available from: ⟨https://europepmc.org/article/med/9588623⟩.

[22] M. Jetté, K. Sidney, G. Blümchen, Metabolic equivalents (METS) in exercise testing, exercise prescription, and evaluation of functional capacity, Clin. Cardiol. 13 (8) (1990) 555–565. Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/2204507/⟩.

[23] T.K. Koo, M.Y. Li, A guideline of selecting and reporting intraclass correlation coefficients for reliability research, J. Chiropr. Med [Internet] 15 (2) (2016) 155–163. Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/27330520/⟩.

[24] J.E. Barkley, E. Glickman, C. Fennell, M. Kobak, M. Frank, G. Farnell, The validity of the commercially-available, low-cost, wrist-worn Movband accelerometer during treadmill exercise and free-living physical activity, J. Sports Sci. 37 (7) (2019 3) 735–740. Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/30238836/⟩.

[25] J. Vanhelst, R. Hurdiel, J. Mikulovic, G. Bui-Xuân, P. Fardy, D. Theunynck, et al., Validation of the Vivago Wrist-Worn accelerometer in the assessment of physical activity, BMC Public Health 12 (1) (2012). Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/22913286/⟩.

[26] A.S. Brazeau, N. Beaudoin, V. Bélisle, V. Messier, A.D. Karelis, R. Rabasa-Lhoret, Validation and reliability of two activity monitors for energy expenditure assessment, J. Sci. Med Sport 19 (1) (2016) 46–50. Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/25466490/⟩.

[27] P. Anastasopoulou, M. Tubic, S. Schmidt, R. Neumann, A. Woll, et al., Validation and comparison of two methods to assess human energy expenditure during free-living activities, PLoS One 9 (2) (2014) e90606, https://doi.org/10.1371/journal.pone.0090606.

[28] Oyéné Kossi, Justine Lacroix, B.éatrice Ferry, Charles S.èbiyo Batcho, Anne Julien-Vergonjanne, et al., Reliability of ActiGraph GT3X+ placement location in the estimation of energy expenditure during moderate and high-intensity physical activities in young and older adults, J. Sports Sci. (2021) 1–8.

[29] B.M. Sandroff, R.W. Motl, Comparison of ActiGraph activity monitors in persons with multiple sclerosis and controls, Disabil. Rehabil. 35 (9) (2013) 725–731.

[30] M.G. Abel, J.C. Hannon, K. Sell, T. Lillie, G. Conlin, D. Anderson, Validation of the Kenz Lifecorder EX and ActiGraph GT1M accelerometers for walking and running in adults, Appl. Physiol. Nutr. Metab. 33 (6) (2008) 1155–1164. Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/19088773/⟩.

[31] S.M. Tweedy, S.G. Trost, Validity of accelerometry for measurement of activity in people with brain injury, Med Sci. Sports Exerc [Internet] 37 (9) (2005) 1474–1480. Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/16177597/⟩.

[32] S. Mandigout, J. Lacroix, B. Ferry, N. Vuillerme, M. Compagnat, J.C. Daviet, Can energy expenditure be accurately assessed using accelerometry-based wearable motion detectors for physical activity monitoring in post-stroke patients in the subacute phase? Eur. J. Prev. Cardiol. 24 (18) (2017) 2009–2016, https://doi.org/10.1177/2047487317738593. Epub 2017 Oct 25. PMID: 29067851.

[33] R. Kondama Reddy, R. Pooni, D.P. Zaharieva, B. Senf, J. El Youssef, E. Dassau, et al., Accuracy of wrist-worn activity monitors during common daily physical activities and types of structured exercise: evaluation study, JMIR mHealth uHealth 6 (12) (2018). Available from: /pmc/articles/PMC6305876/.

[34] Y. Bai, P. Hibbing, C. Mantis, G.J. Welk, Comparative evaluation of heart rate-based monitors: apple Watch vs Fitbit Charge HR, J. Sports Sci. 36 (15) (2018) 1734–1741, https://doi.org/10.1080/02640414.2017.1412235. Epub 2017 Dec 6. PMID: 29210326.

[35] V. Sjoberg, J. Westergren, A. Monnier, R. Lo Martire, M. Hagstromer, B.O. Ang, et al., Wrist-worn activity trackers in laboratory and free-living settings for patients with chronic pain: criterion validity study, JMIR mHealth uHealth 9 (1) (2021 1) [cited 2022 May 13];.

[36] C. Herkert, J.J. Kraal, E.M.A. Van Loon, M. Van Hooff, H.M.C. Kemps, Usefulness of modern activity trackers for monitoring exercise behavior in chronic cardiac patients: validation study, JMIR mHealth uHealth 7 (12) (2019) [cited 2022 Jul 12];.

[37] Gerrior S., Juan W.Y., Basiotis P. An Easy Approach to Calculating Estimated Energy Requirements. Prev Chronic Dis [Internet]. 2006 [cited 2022 Jul 12];3(4). Available from: /pmc/articles/PMC1784117/.

[38] H. Van Remoortel, Y. Raste, Z. Louvaris, S. Giavedoni, C. Burtin, D. Langer, et al., Validity of six activity monitors in chronic obstructive pulmonary disease: a comparison with indirect calorimetry, PLoS One 7 (6) (2012).

[39] L.M. Feehan, J. Geldman, E.C. Sayre, C. Park, A.M. Ezzat, J. Young Yoo, et al., Accuracy of fitbit devices: systematic review and narrative syntheses of quantitative data, JMIR mHealth uHealth 6 (8) (2018). Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/30093371/⟩.

[40] P. McColgan, S.J. Tabrizi, Huntington's disease: a clinical review, Eur. J. Neurol. 25 (1) (2018) 24–34. Available from: ⟨https://pubmed.ncbi.nlm.nih.gov/28817209/⟩.