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► **To cite this version:**

Pierre Jéhannin, Alexis Le Faucheur, Ségolène Chaudru, Aline Taoum, Guillaume Mahé, et al.. Agreement Between StepWatch3 and ActiGraph wGT3X+ for Measuring Step-Based Metrics in People With Peripheral Artery Disease. *Journal of Aging and Physical Activity*, 2022, 30 (2), pp.225-236. 10.1123/japa.2020-0499 . hal-03512836

**HAL Id: hal-03512836**

**<https://uco.hal.science/hal-03512836>**

Submitted on 25 May 2022

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1 **Agreement between StepWatch3 and ActiGraph wGT3X+ for**  
2 **measuring step-based metrics in people with peripheral artery disease**

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1 **ABSTRACT**

2 We investigated the agreement between StepWatch3™ (SW3) and ActiGraph™ wGT3X+  
3 monitors for measuring step-based metrics in peripheral artery disease (PAD) patients and  
4 older adults. In 23 PAD and 38 older participants, we compared metrics obtained during an  
5 outdoor (400-m track) walking session (OWS) (step count) and a 7-day free-living period (step  
6 count and 60/30/5/1-min maximal or peak step accumulation) using the SW3 (ankle) and the  
7 wGT3X+ (hip) with the low frequency extension filter enabled (wGT3X+/LFE) or not  
8 (wGT3X+/N). During OWS, agreement was high, particularly for wGT3X+/LFE: correlations  
9  $\geq 0.98$ ; median absolute percentage errors (MAPEs)  $< 1\%$ ; significant equivalence using a  
10  $\pm 15\%$ -equivalence zone (EZ) or narrower. In free-living, no wGT3X+ method was equivalent  
11 to SW3 for step count. wGT3X+/LFE was equivalent to SW3 regarding all step accumulation  
12 metrics using a  $\pm 20\%$ -EZ or narrower, with MAPEs  $< 11\%$ . The wGT3X+/LFE method is the  
13 best option for comparisons with SW3 in PAD and older adults.

14 **Key-words.** Physical activity, accelerometers, pedometers, step rate, intermittent claudication

## 1 INTRODUCTION

2 Lower extremity peripheral artery disease (PAD) represents an important public health  
3 problem that is associated with increasing disability and mortality and that affects by now more  
4 than 236 million people worldwide (Song et al., 2019). During the past twenty years, several  
5 studies conducted in people with PAD have used monitor-based physical activity measurement  
6 methods to investigate their usual physical or walking behavior and their relationships with  
7 clinical and functional outcomes, or to quantify the training load during home-based walking  
8 programs (de Müllenheim, Chaudru, Mahé, Prioux, & Le Faucheur, 2016). The StepWatch3™  
9 (SW3) accelerometer-based pedometer (Orthocare Innovations™ / Modus Health™, LLC,  
10 Edmonds, WA) and the ActiGraph™ accelerometers of the GT3X generation (i.e. GT3X,  
11 GT3X+, wGT3X+; ActiGraph™, LLC, Pensacola, FL) are research-grade monitors that have  
12 been commonly used to count steps in healthy (Bassett, Toth, LaMunion, & Crouter, 2017) and  
13 PAD populations (de Müllenheim et al., 2016; Murrow et al., 2019; Parsons et al., 2016; Tew  
14 et al., 2015). These monitors are of particular interest in the field of physical activity  
15 measurement for health purpose since they have received US Food and Drug Administration  
16 clearance as a Class II medical device, and thus appear to be good candidates to be integrated  
17 into the standard-of-care for management of certain diseases (Bassett et al., 2017). Moreover,  
18 the SW3 is the most accurate pedometer for counting steps during walking (Bassett et al.,  
19 2017), and the monitors of the GT3X generation are currently used in several large-scale  
20 studies to prospectively investigate various relationships between physical activity and health  
21 (Bassett et al., 2017).

22 Because of the increasing number of studies using either the SW3 or the GT3X  
23 generation monitors in PAD, it is important to know how well these monitors provide  
24 comparable step-based metrics in this population to allow researchers to make meaningful  
25 comparisons between studies and to allow clinicians to better compare their own data that

1 would have been obtained with a given monitor (e.g., an SW3) with future clinical trials or  
2 normative data that would have be obtained using another monitor (e.g., an ActiGraph GT3X  
3 generation monitor). Most of the validity studies that have provided results allowing the  
4 comparisons between the SW3 and the GT3X generation monitors have been conducted using  
5 a treadmill or overground walking, in young adults (Feito, Bassett, & Thompson, 2012; Feito,  
6 Garner, & Bassett, 2015; Hickey, John, Sasaki, Mavilia, & Freedson, 2016), overweight and  
7 obese individuals (Feito et al., 2012), older adults with diverse disorders (Hergenroeder et al.,  
8 2018; Treacy et al., 2017; Webber & St John, 2016), people with Rett syndrome (Downs et al.,  
9 2015), and people with multiple sclerosis (Sandroff et al., 2014). Some studies have also  
10 conducted measurements during various physical activities (Hickey et al., 2016) and daily  
11 living (Feito et al., 2012; Feito et al., 2015; Webber & St John, 2016).

12         Results from the validity studies that have been conducted in healthy adults and people  
13 with various chronic disease conditions may not be directly applicable to people with PAD,  
14 because this population present gait modifications when lower-limb pain appears during  
15 walking due to arterial insufficiency, such as lower walking speed, shorter stride length, and  
16 asymmetric gait to favor the asymptomatic limb during stance phases (Gardner, Montgomery,  
17 Ritti-Dias, & Forrester, 2010). Because no study has compared the SW3 and GT3X generation  
18 monitors for counting steps in people with PAD, additional work is required to fill this gap.  
19 Moreover, the comparisons of these monitors in previous studies were performed by essentially  
20 considering total step counts. However, other step-based metrics that may present an interest  
21 in studying relationships between physical activity and health (Tudor-Locke et al., 2017)  
22 deserve comparisons across different monitors.

23         The main objective of this study was to investigate the agreement between the SW3 and  
24 the GT3X generation monitors (here a wGT3X+) for measuring relevant step-based metrics in  
25 people with PAD in two contexts of interest: an outdoor walking session as it could be

1 performed during a home-based walking program in PAD (Gardner, Parker, Montgomery,  
2 Scott, & Blevins, 2011; McDermott et al., 2013) and during which one would want to know  
3 the volume of physical activity performed; and a 7-day free-living period as usually performed  
4 to determine the daily walking pattern in PAD research (de Müllenheim et al., 2016).  
5 Secondary objectives included the followings: (i) explore the influence of PAD on the  
6 agreement between the monitors by conducting the same measurements and analyses in a  
7 healthy population of the same age as in PAD; (ii) explore the effect of pain occurrence on the  
8 agreement between the monitors in PAD during the outdoor level walking session; (iii)  
9 determine, where appropriate, correction models to make the step-based metrics from the SW3  
10 and the wGT3X+ more comparable.

## 1 **METHODS**

### 2 *Study design*

3       To conduct the present study, we used data collected in two populations from two  
4 research projects: people with PAD from the “[Blinded for review]” project (NCT[Blinded for  
5 review]) and healthy older adults from the “[Blinded for review]” project (NCT[Blinded for  
6 review]). Both projects were approved by the local ethics committee of [Blinded for review].  
7 All the PAD and healthy older participants gave their written informed consent to participate.  
8 The PAD participants were recruited during their medical appointment at our Vascular  
9 Medicine Unit ([Blinded for review]), whereas healthy older adults were recruited from seniors’  
10 physical activity associations. PAD participants had to be  $\geq 18$  years old, have an ankle-brachial  
11 index (ABI)  $\leq 0.90$  (or if resting ABI  $> 0.90$  and  $< 1.00$ , a decrease in recovery ankle systolic  
12 pressure or in recovery ABI from treadmill exercise higher than 30 mmHg or 20%,  
13 respectively), have a maximal walking distance on the treadmill (modified Strandness test: 3.2  
14 km/h, 10% grade)  $< 500$  m (as assessed during the medical appointment), and complain of  
15 exertional lower-limb pain that sometimes can begin at rest, causes the participant to stop  
16 walking, and relieves or lessens within 10 minutes of rest (confirmed during treadmill testing).  
17 A full description of the inclusion criteria for the PAD participants is provided elsewhere  
18 (Chaudru et al., 2019). The healthy older adults had to be  $\geq 50$  years old, have an ABI  $\geq 1.00$   
19 and  $\leq 1.40$ , have no pain in the lower limbs during walking, and have no functional limitation  
20 during treadmill walking (15 min at 3.2 km/h and 10% grade).

21       During the “[Blinded for review]” and “[Blinded for review]” protocols, the PAD and  
22 healthy older participants completed an outdoor walking session and a 7-day free-living period  
23 while wearing the SW3 monitor (initially released by Orthocare Innovations™ [LLC,  
24 Edmonds, WA], now by Modus Health™ [LLC, Edmonds, WA]), and an ActiGraph™  
25 wGT3X+ monitor.

1

2 *The outdoor walking session*

3           The PAD participants completed an outdoor walking session that consisted of walking  
4 on a 400 meters flat athletic track during a 40 – 60 min period (walks and rests included)  
5 depending on the capabilities of the participants, while respecting the following instructions:  
6 (i) walking at their usual pace; (ii) walking up to maximal claudication pain forces to stop  
7 walking; (iii) recovering as usually done during daily life (Le Faucheur et al., 2008). During  
8 the session, the PAD participants were equipped with the SW3 and the wGT3X+ monitors.  
9 They also wore a DG100 GPS receiver (GlobalSat, Taipei, Taiwan) to obtain speed information.  
10 During the session, patients were asked to use a watch to push a specific marker button to  
11 record pain manifestations in the lower limbs while walking. Pain-free walking time was the  
12 time measured by the investigators using a stopwatch between the start of a walking bout and  
13 the time when the patient pushed the button of the watch to indicate the occurrence of pain  
14 during walking (Chaudru et al., 2019). Maximal walking time was the duration of a maximal  
15 walking bout detected using the GPS speed signals along with a validated data processing  
16 methodology as previously performed (Le Faucheur et al., 2008). The actual duration of the  
17 session was recorded by the investigators using a chronometer.

18           The healthy older participants completed an outdoor walking session that was divided  
19 into a first part at spontaneous walking speed and a second part at 4 km/h, with both parts  
20 performed on the same 400 meters flat athletic track as for the PAD participants. Each part  
21 consisted of a first walking period of 6 minutes followed by various randomized walking  
22 periods (i.e. 30 s, 1 min, 1.5 min, 2 min) separated by recovery periods. Using such a procedure,  
23 we aimed at: (i) having a walking session that would include different walking durations as in  
24 PAD participants, since healthy older participants are not limited; (ii) and having a walking  
25 speed close to that of the PAD participants (Gernigon et al., 2014). During the session, the

1 healthy older participants were equipped with the SW3 and the wGT3X+ monitors, and with a  
2 Qstarz BT-Q1000XT GPS receiver (Qstarz International Co., Ltd., Taipei, Taiwan) for  
3 measuring walking speed.

4

#### 5 *The 7-day free-living period*

6 Each day of the 7-day free-living period, both the PAD and healthy older participants  
7 were asked to put on the monitors when they woke up and to remove them just before going to  
8 bed or during water-related activities (e.g., taking a shower). A booklet was given to the  
9 participants to provide any comment about the use of the monitors and to indicate when the  
10 monitors were removed during the day where appropriate. All the participants were equipped  
11 with the monitors at the end of the first visit of their respective protocol and they brought them  
12 back at the subsequent visit of the protocol that was scheduled at least seven full days after the  
13 first visit. Thus, for all participants, the 7-day free-living measurement was completed before  
14 the outdoor walking session.

15

#### 16 *The wearable monitors*

17 *SW3*. The SW3 used in the present study is a small ( $7.5 \times 5.0 \times 2.0$  cm) and light (38 g)  
18 accelerometer-based pedometer. For all the participants, this monitor was worn at the right  
19 ankle, except for one PAD participant who wore it at the left ankle due to preexisting skin  
20 irritation. The SW3 was set to record strides (i.e., ipsilateral steps) using 10-s epochs. The  
21 initialization of the SW3 was performed using the preprogrammed “quick start” settings of  
22 StepWatch software. The “Walking speed” and “Leg motion” settings were set based on the  
23 characteristics of the participants as recommended by the manufacturer.

24 *wGT3X+*. The wGT3X+ used in the present study is a small ( $4.6 \times 3.3 \times 1.5$  cm) and  
25 light (19 g) tri-axial accelerometer. In all the participants, this monitor was worn at the right

1 hip, except for one PAD participant who wore it at the left hip so that it was placed on the same  
2 side as the SW3. The wGT3X+ was secured in a nylon pouch linked to a nylon belt and was  
3 set to record raw acceleration at a 30-Hz sampling rate (firmware version: 2.2.1 to 2.5.0). The  
4 initialization of the wGT3X+ was performed using Actilife 6 software. Following the  
5 measurement period, the wGT3X+ data were accumulated into 10-s epochs using Actilife 6  
6 software with either the low frequency extension filter (wGT3X+/LFE) or the normal filter  
7 (wGT3X+/N) enabled.

8 *GPS receivers.* The DG100 GPS receiver ( $8.0 \times 5.5 \times 1.8$  cm, weight ~60 g for the unit;  
9 Abraham et al. (2012), Noury-Desvaux et al. (2011)) and the Qstarz BT-Q1000XT GPS  
10 receiver ( $7.2 \times 4.7 \times 2$  cm, weight ~65 g for the unit) were used to measure walking speed in  
11 the PAD and healthy older participants, respectively. The Qstarz BT-Q1000XT was used in  
12 the healthy older participants in place of the DG100 because the DG100 was no longer  
13 marketed. Both these GPS receivers have close accuracy for detecting walking and stopping  
14 bouts and estimating walking speed in environments with low level of obstruction (Taoum et  
15 al., 2021). The GPS receivers were set at a 1-Hz recording rate using a personal computer and  
16 the corresponding manufacturer's software (DG100: Data Logger Utility, version 1.1; Qstarz  
17 BT-Q1000XT: Q-Travel, version 1.53.000).

18 For both the outdoor walking session and the 7-day free-living period, all devices were  
19 systematically initialized using the Coordinated Universal Time to ensure the synchronization  
20 of the device recordings.

21

## 22 *Data analysis*

23 The timestamped SW3 strides, the wGT3X+/LFE and wGT3X+/N activity counts and  
24 steps, and the DG100 or Qstarz speed, were exported to spreadsheets for further analysis in R  
25 software (versions 3.5.3/3.6.0). For all step-related analyses, we aligned and synchronized the

1 three activity monitor data files (SW3, wGT3X+/LFE, wGT3X+/N) based on the timestamp of  
2 the files, and we obtained the SW3 steps by doubling the number of the SW3 strides.

3 *The outdoor walking session.* We calculated the total number of steps recorded from  
4 the activity monitor (SW3, wGT3X+/LFE, wGT3X+/N) over the entire walking session.  
5 Moreover, to investigate the effect of lower-limb pain symptoms occurrence on the agreement  
6 between the monitors in the PAD participants, we calculated from the activity monitor data  
7 files the total step count corresponding to walking without pain and to walking with pain during  
8 the first maximal walking bout of the session. Only the first walking bout was considered to  
9 attempt to capture the potential effect of pain on the agreement between the monitors while  
10 minimizing the potential additional effect of fatigue that could have been introduced  
11 throughout the repetition of the maximal walking bouts. To better interpret the potential  
12 differences in the step counts obtained from the different methods, we determined the mean  
13 walking speed adopted over the walking session as well as the mean walking speed related to  
14 walking without pain and to walking with pain during the first maximal walking bout of the  
15 session for the PAD participants. Speed data from the GPS devices were processed according  
16 to the method proposed by Le Faucheur et al. (2007) implemented in R software.

17 *The 7-day free-living period.* We analyzed the first seven full days of measurement.  
18 The 10-s epochs of the merged data files were collapsed into 1-min epochs and marked for  
19 wear and non-wear-time using the wGT3X+/LFE vector magnitude (VM) counts and the Choi  
20 et al. algorithm (Choi, Ward, Schnelle, & Buchowski, 2012) with the “PhysicalActivity” R  
21 package (version 0.2-2, 2018). Thereafter, a graphical inspection of the data related to each day  
22 was implemented to check that: (i) wear-time periods corresponded to waking-time periods  
23 only (and not to in-bed night-time periods, which could be the case when the participant forgot  
24 to remove the wGT3X+, and also possibly the SW3, before going to bed at night); (ii) each  
25 participant wore the SW3 in addition to the wGT3X+ at the beginning of her/his first out-of-

1 bed waking-time period of the day. All the epochs that were initially related to wGT3X+ wear-  
2 time were reconsidered as non-wear-time when they corresponded to in-bed night-time periods  
3 or when it was determined that both monitors were not simultaneously worn at the beginning  
4 of the day. This procedure aimed to remove “artificial” extra wGT3X+ steps compared to the  
5 SW3 and thus obtain more accurate comparisons of the SW3 and wGT3X+ step-based metrics.  
6 The details of the graphical inspection procedure are provided and illustrated in the  
7 supplemental materials (eText and eFigure). Finally, the 1-min epochs with visually abnormal  
8 step counts were removed (a 1-min epoch with 542 SW3 steps from a PAD participant dataset  
9 and another 1-min epoch with 290 SW3 steps from another PAD participant dataset were  
10 removed).

11 We considered a day as valid if there was both a wGT3X+/LFE wear time  $\geq 600$  min  
12 (Migueles et al., 2017) and an SW3 step count  $\geq 1500$  (Tudor-Locke, Barreira, & Schuna,  
13 2015). Then, using the valid days and the wear time epochs, we calculated the daily means for  
14 the following step-based metrics from each method: the steps per day, the maximum step  
15 accumulation over a sliding window of 60, 30, and 5 continuous minutes, and the peak step  
16 accumulation over the top 60, 30, and 1 minute(s) of the day that could be continuous or  
17 discontinuous. These metrics have been chosen as they have been regularly used in PAD  
18 studies (de Müllenheim et al., 2016) or they might present an interest in epidemiologic studies  
19 (Tudor-Locke et al., 2017).

20

## 21 *Statistical analysis*

22 *Descriptive statistics.* Statistical analyses were conducted using R software. The  
23 quantitative variables are shown as means  $\pm$  standard deviations (SD) when normally  
24 distributed (as inferred from Shapiro-Wilk tests) and as medians (25<sup>th</sup> – 75<sup>th</sup> percentiles)

1 otherwise. For consistency purposes with specific inferential analyses, some variables that  
2 were skewed are shown as geometric means  $\times/\div$  factors for SD.

3 *Agreement between the monitors.* First, we conducted a correlation analysis. When the  
4 hypothesis of bivariate normality (tested using the Royston's method implemented in the  
5 "MVN" package (Korkmaz, Goksuluk, & Zararsiz, 2014)) concerning the SW3 and the  
6 wGT3X+ data (or the log-transformed data when necessary) was not rejected ( $P>0.05$ ), we  
7 used the Pearson coefficient ( $R$ ) and its corresponding 95% confidence interval (CI). When the  
8 bivariate normality hypothesis was rejected even when using the log-transformed data, the  
9 Spearman rho coefficient with its 95% jackknife empirical likelihood CI was computed using  
10 the "spearmanCI" package (version 1.0, 2018). Correlation coefficients with 95% CIs that did  
11 not include zero were considered as statistically significant.

12 Second, we calculated the median percent error (MPE) and the median absolute percent  
13 error (MAPE), with error computed as wGT3X+ minus SW3, as previously described (DeShaw  
14 et al., 2018). MPE and MAPE are shown along with their respective 95% bias-corrected and  
15 accelerated bootstrap (BCa) CIs (obtained with 999 bootstrap replicates) that were calculated  
16 using the "rcompanion" package (version 2.3.25, 2020) (Mangiafico, 2016). MPE and MAPE  
17 with CIs that did not include zero were considered statistically significant.

18 Third, we conducted 95% equivalence testing (Dixon et al., 2018). In the present study,  
19 the wGT3X+ was considered as significantly equivalent to the SW3 when the 90% CI for the  
20 wGT3X+ means fell into a given equivalence zone defined for the SW3 ( $\pm 10\%$ ,  $\pm 15\%$ , or  
21  $\pm 20\%$  of the SW3 mean score). While the  $\pm 10\%$  equivalence zone has been classically used,  
22 the  $\pm 15\%$  and  $\pm 20\%$  equivalence zones have been considered as "viable targets" for the  
23 measurement of physical activity (35). The 90% CIs for the wGT3X+ means were calculated  
24 from a mixed model with an unstructured covariance matrix (Baguley, 2012). The model used

1 the considered step-based metric as the response variable, the wGT3X+ method  
2 (wGT3X+/LFE; wGT3X+/N) as a fixed predictor, and the participant as a random predictor.

3 *Effect of lower-limb pain occurrence on the agreement between the monitors during*  
4 *outdoor walking in PAD.* We studied the effect of walking pain on the agreement between the  
5 SW3 and the wGT3X+ for step counting in PAD using the data related to the first walking bout  
6 of the outdoor walking session. For the wGT3X+/LFE and wGT3X+/N methods, we  
7 calculated, for each participant, the difference of absolute percent error (APE) between walking  
8 with pain and walking without pain. Then, for a given wGT3X+ method, we computed the  
9 95% BCa CI for the median of the APE differences. The percent errors related to walking  
10 without pain and with pain were also calculated to show the direction of the error  
11 (underestimation or overestimation) when walking without pain and with pain. We also  
12 calculated the 95% normal CI for the mean change in speed after pain occurrence, considering  
13 that the change would be substantial if the CI would fall outside the range of  $\pm 0.2$  km/h (that  
14 is, two times the typical error related to the estimation of walking speed using the DG100  
15 (Noury-Desvaux et al., 2011)).

16 *Correction models.* We developed correction models for the wGT3X+ as compared  
17 with the SW3 regarding the step-based metrics for which there was a clear need for correction,  
18 that is for which there was no significant equivalence for both wGT3X+ methods, even when  
19 using the widest equivalence zone tested (i.e.,  $\pm 20\%$  of the SW3 mean score). Linear regression  
20 models were constructed to make predictions of the considered SW3 metric from either the  
21 wGT3X+/LFE or the wGT3X+/N method, in the PAD and the healthy older participants  
22 separately. Each model and the corresponding  $R^2$  coefficient and root-mean-squared error  
23 (RMSE) were computed using a leave-one-out procedure implemented using the “caret”  
24 package (version 6.0-85, 2020) (Kuhn, 2008).

## 1 RESULTS

2 Twenty-three PAD participants (3 women / 20 men; age:  $60 \pm 10$  y, height:  $1.69 \pm 0.08$   
3 m, weight:  $79.0 \pm 16.2$  kg, body mass index:  $27.36 \pm 4.71$  kg·m<sup>-2</sup>, ABI: 0.61 (0.53 – 0.74)),  
4 and 38 healthy older participants (14 women / 24 men; age:  $64 \pm 6$  y, height:  $1.69 \pm 0.10$  m,  
5 weight:  $68.7 \pm 12.0$  kg, body mass index:  $23.89 \pm 3.01$  kg·m<sup>-2</sup>, ABI: 1.19 (1.00 – 1.38)), were  
6 studied. All PAD participants were limited during the treadmill test due to leg pain.

7 The results regarding the agreement between the monitors for step counting during the  
8 outdoor walking session are shown in Table 1 and Figure 1. The median (25th – 75th  
9 percentiles) duration of the session was of 52.5 (48.6 – 55.4) minutes. One PAD participant  
10 and three healthy older participants had incomplete step data due to lack of monitors  
11 availability. Moreover, the walking speed was missing for one healthy older participant due to  
12 an error when downloading the data from the GPS receiver. In the PAD participants, the  
13 wGT3X+/LFE and wGT3X+/N methods were both significantly and nearly perfectly  
14 correlated to the SW3 ( $R \geq 0.99$ ). However, as shown in Table 1, the wGT3X+/N method  
15 significantly underestimated the SW3 with an MPE of ~-5%, while the wGT3X+/LFE method  
16 reached an MPE and a MAPE inferior to 1%. Figure 1 shows that the wGT3X+/LFE and  
17 wGT3X+/N methods were significantly equivalent to the SW3 when considering equivalence  
18 zones of respectively  $\pm 15\%$  and  $\pm 20\%$  of the SW3 mean score. In the healthy older participants,  
19 for whom the session walking speed ( $4.9$  [4.7 – 5.1] km/h) was slightly higher than in the PAD  
20 participants ( $4.2 \pm 0.4$  km/h), the wGT3X+ methods were also significantly and highly  
21 correlated to the SW3 ( $\rho \geq 0.97$ ). The wGT3X+/N method significantly underestimated the  
22 SW3 with an MPE of only -1.4%, and the wGT3X+/LFE method, as for the PAD participants,  
23 reached an MPE and a MAPE inferior to 1% (Table 1). Both the wGT3X+ methods were  
24 significantly equivalent to the SW3 when considering the equivalence zone of  $\pm 10\%$ .

1           Figure 2 shows the results regarding the effect of pain on the agreement between the  
2 monitors for step counting during the first walking bout of the outdoor walking session in the  
3 PAD participants. The results are related to 17 participants who indicated the occurrence of  
4 pain during the walking bout. For both the wGT3X+/LFE and the wGT3X+/N methods, the  
5 median of the APE differences between walking with pain and without pain was not  
6 significantly different from zero, suggesting no effect of pain on the agreement between the  
7 monitors for each of the wGT3X+ methods. However, we could observe that a few PAD  
8 participants had an APE that markedly increased when walking with pain in comparison with  
9 walking without pain with the wGT3X+/N method (Figure 2, panel B). Figure 2 (panel D) also  
10 shows that the change in walking speed was not substantial.

11           The results regarding the agreement between the monitors for step counting during daily  
12 living are shown in Table 2 and Figure 3. Twenty-one PAD participants had complete data  
13 after data analysis using graphical inspection. In the PAD participants, the wGT3X+ methods  
14 yielded significant and high correlations with the SW3 ( $R$  and  $\rho \geq 0.90$ ) for all the step-based  
15 metrics. However, the wGT3X+/LFE method significantly overestimated the SW3 daily step  
16 count by more than 20%, while it reached a MAPE  $< 11\%$  for all the other step-based metrics,  
17 with a lower error for the metrics reflecting a higher intensity of walking. The wGT3X+/N  
18 method significantly underestimated the SW3 daily step count by 45%, and significantly  
19 underestimated all the SW3 step-based metrics by at least 15% except for the peak 1-min step  
20 accumulation with an underestimation by less than 10%. Both the wGT3X+ methods were not  
21 significantly equivalent to the SW3 for the daily step count, but the wGT3X+/LFE method was  
22 significantly equivalent to the SW3 for all the other step-based metrics when considering an  
23 equivalence zone of  $\pm 20\%$ , and for the maximum 5-min step accumulation and the peak  
24 60/30/1-min step accumulation when considering an equivalence zone of  $\pm 10\%$  (Figure 3). The  
25 wGT3X+/N method was significantly equivalent to the SW3 only for the peak 1-min step

1 accumulation (using an equivalence zone of  $\pm 15\%$ ). In the healthy older participants, the results  
2 were similar to those obtained in the PAD participants with the following noticeable  
3 exceptions: correlations between the wGT3X+ methods and the SW3 were  $< 0.80$  for the peak  
4 1-min step accumulation; the error for the wGT3X+/N method consistently seemed lower than  
5 in the PAD participants with a MAPE  $< 15\%$  for all the step-based metrics except the daily step  
6 count; the wGT3X+/N method was significantly equivalent to the SW3 for all the step-based  
7 metrics (when considering an equivalence zone of  $\pm 20\%$ ) except for the daily step count and  
8 for the maximum 60-min step accumulation.

9         Basing on the large disagreement between the monitors regarding daily step count, we  
10 constructed linear models to correct the wGT3X+/LFE or wGT3X+/N daily step count as  
11 compared with the SW3 daily step count (Table 3). While the wGT3X+/LFE and wGT3X+/N  
12 models reached quite similar accuracies in both the PAD and the healthy older participants, the  
13 wGT3X+/N model was the most accurate in the PAD participants, while this was the  
14 wGT3X+/LFE model that performed better in the healthy older participants.

## 1 DISCUSSION

2           The present study adds several new results to the current literature for comparing step-  
3 based metrics from the SW3 and the GT3X generation monitors (Downs et al., 2015; Feito et  
4 al., 2012; Feito et al., 2015; Hergenroeder et al., 2018; Hickey et al., 2016; Sandroff et al.,  
5 2014; Treacy et al., 2017; Webber & St John, 2016). Indeed, these results are unique in the  
6 PAD population, as well as in the general population regarding the comparisons of these  
7 monitors for several step-based metrics that may be of interest from clinical and  
8 epidemiological perspectives. Moreover, a particularity of the present study is that we provide  
9 results in two contexts where monitors are likely to be of interest for practitioners and  
10 researchers: an outdoor walking session where monitors can be used to quantify the training  
11 load; and a free-living period where monitors can be used to characterize the usual walking  
12 behavior.

13           Our results suggest that the GT3X generation monitors, when worn at the hip, provide  
14 step counts that can be easily compared to those of the SW3 in the context of an outdoor level  
15 walking session, regardless of the method used (i.e., enabling the LFE filter or not), in both the  
16 PAD and the healthy older populations represented in the present study. Thus, the presence of  
17 PAD did not seem to have a marked influence on the agreement between the monitors during  
18 the outdoor walking session as compared with the healthy older adults, although percent errors  
19 seemed slightly higher in the PAD participants when using the normal filter. This high level of  
20 agreement between the monitors, in particular in terms of percent errors, can be explained by  
21 the participants mean walking speeds that fell into the range of walking speeds (speeds  $\geq 4$  km/h  
22 or 67 m/min) for which the GT3X generation monitors can provide step count estimates that  
23 are close to those of the SW3 (Feito et al., 2015). However, these results should be used with  
24 caution because our PAD participants walked faster than that previously reported by Gernigon  
25 et al. (Gernigon et al., 2014) in a quite large sample of people with PAD ( $N = 203$ ; median: 3.6

1 km/h). Moreover, our healthy older participants were likely to have a higher physical condition  
2 than in the normal population of the same age. These considerations are important because  
3 walking slower than 4 km/h is likely to be associated with the range of the combinations of  
4 acceleration frequency and amplitude thresholds for which Actilife software does not count  
5 steps, at least when the ActiGraph™ LFE filter is not enabled (John, Morton, Arguello, Lyden,  
6 & Bassett, 2018). When conducting measurements with the GT3X generation monitors during  
7 an outdoor walking session, enabling the LFE filter could be the best choice to get step counts  
8 that are comparable to those of the SW3. Indeed, the LFE filter allows to get closer estimates  
9 to those of the SW3 at walking speeds that are  $\geq 4$  km/h (Feito et al., 2015), and it allows to get  
10 step counts that are likely to remain close to those of the SW3 at slow walking speeds contrary  
11 to the normal filter (Feito et al., 2015).

12       When considering the daily living context, the level of the agreement between the  
13 monitors varied according to the investigated step-based metric and the use of the LFE filter or  
14 not along with the wGT3X+. No wGT3X+ method was significantly equivalent to the SW3 for  
15 measuring daily step count in the present study. This is consistent with the results from the  
16 study by Feito et al. (2015) who found a large positive MPE for the GT3X/LFE method (+36%)  
17 and a large negative MPE for the GT3X/N method (-25%) in young adults. As previously  
18 discussed (Toth et al., 2018), the LFE filter likely allows the capture of artifact movements  
19 during the day due to the extension of the range of the movement frequencies that the monitor  
20 can detect. On the opposite, the use of the normal filter does not allow to correctly capture all  
21 the daily living steps, likely because a large part of these steps may be performed at frequencies  
22 and at walking speeds that are too low (when walking at home for example) for the sensitivity  
23 of the normal filter. Although the GT3X monitors have been shown to be less accurate in step  
24 count estimation than the SW3, the latter has also been reported to show a lower accuracy  
25 during some daily-life activities such as cycling or running (Hickey et al., 2016; Karabulut,

1 Crouter, & Bassett, 2005). This could also contribute to the weaker between-monitor  
2 agreement during the free-living period in comparison with the outdoor walking session.  
3 Interestingly, a better agreement between the monitors was obtained for daily living regarding  
4 the step-based metrics related to the maximum and the peak step accumulation metrics in both  
5 our PAD and healthy older participants, particularly when using the LFE filter. Thus, while the  
6 daily step counts from GT3X generation monitors should be corrected to be compared with  
7 those of the SW3, it seems that no important correction is needed for the step accumulation-  
8 based metrics if the LFE filter is enabled, particularly regarding the maximum 5-min step  
9 accumulation and the peak (1 to 60-min) step accumulation metrics. The better agreement  
10 related to these last metrics (compared with the daily step count) and obtained when using the  
11 LFE filter enabled, could be explained by the fact that the steps taken in these cases reflect the  
12 best physical performances of the day in terms of step accumulation, which could be more  
13 likely related to actual walking periods, thus limiting the counting of artifact extra step counts  
14 in the calculation of the metric. When using the normal filter, the observed better agreement  
15 could be explained by the fact that the steps performed in these situations were likely to be  
16 related to the top part of the spectrum of the walking speeds adopted by the participant over  
17 the day, these speeds falling into the range of speeds for which the normal filter allows an  
18 accurate capture of steps.

19         The occurrence of pain during the outdoor walking sessions in the PAD participants did  
20 not modify the agreement between the monitors for step counting. This result could be related  
21 to a decrease in mean walking speed that was not substantial, leading to a mean walking speed  
22 of 4.0 km/h after pain occurrence. Thus, speed remained sufficiently high to not alter the ability  
23 of the wGT3X+ to capture steps, in particular when using the normal filter. However, two PAD  
24 participants had a marked increase in APE after pain occurrence (Figure 2) when using the  
25 normal filter, which could not be fully explained by a decrease in speed because other

1 participants with similar walking speeds and a similar decrease in walking speed after pain  
2 occurrence did not show such increases in APE. This suggests the potential influence of other  
3 gait-related mechanisms, such as a reduction in cadence or asymmetric swing and stance phases  
4 related to the painful limb (Gardner, Montgomery, et al., 2010), that could affect the capability  
5 of the GT3X generation monitors to detect steps, at least when using the normal filter, while  
6 the accuracy of the SW3 is more likely to remain high in patients with gait impairment  
7 (Sandroff et al., 2014; Webber & St John, 2016). Further studies are required to state the  
8 potential effects of such gait impairments on pedometer step counts accuracy.

9

10         The present study has confirmed the particular need to correct the GT3X generation  
11 monitor daily step count when we want to compare it with that of the SW3. We constructed  
12 separate models for the PAD and the healthy older participants. This was justified as the models  
13 we obtained showed different intercepts and slopes, meaning different correction needs  
14 depending on the population tested and the data filter used (LFE or normal). Our results suggest  
15 that if the daily step count is the only metric of interest in PAD, using the normal filter along  
16 with a GT3X generation monitor, and then correcting the daily step count with the proposed  
17 equation, would reach a better agreement with the SW3 daily step count as compared with the  
18 use of the LFE filter and the corresponding equation. However, if a GT3X generation monitor  
19 would be used with the intention to study other step-based metrics and to conduct comparisons  
20 with the SW3 in PAD, it would be more valuable to enable the LFE filter since there is better  
21 equivalence with the SW3 for various metrics when using this method as compared with the  
22 use of the normal filter. In the healthy older participants, using the LFE filter seems to be the  
23 best option to get step-based metrics comparable to those of the SW3 since the performance of  
24 the correction model for daily step count was slightly higher when using the LFE filter and the

1 agreement with the SW3 was better for all the other step-based metrics when using the LFE  
2 filter.

3         The main limit of the present study is that it was exploratory and based on convenience  
4 samples. Thus, several of our results should be confirmed with confirmatory studies with  
5 adequate statistical power. Other limits regarding secondary objectives could also be evoked.  
6 First, the overground walking session protocols implemented with the PAD and the healthy  
7 older participants were not the same, thus the comparisons between the results obtained for the  
8 PAD and the healthy older participants during the overground walking session protocol should  
9 be used with caution. Second, we were not able to distinguish the effect of speed from the  
10 potential effects of gait abnormalities and pain on the agreement between the monitors in the  
11 PAD participants. Future studies could investigate the independent and combined effects of  
12 walking speed, gait features, and pain on the agreement between various monitors in PAD,  
13 particularly using a range of low walking speeds, to provide information about the  
14 comparability of different monitors in PAD patients with various walking impairments levels.  
15 Third, the sex distributions in both the PAD and the healthy older participants were very  
16 unequal in terms of sex distribution, with substantially more men within each group and overall  
17 (13% of women in the PAD participants and 37% of women in the healthy older adults). It  
18 could be questioned whether this may affect the external validity of our results since it has been  
19 shown that women have gait features (e.g., walking speed) that are different from men  
20 (Frimenko, Goodyear, & Bruening, 2015; Gardner, Parker, et al., 2010), which could  
21 potentially affect monitor accuracy for counting steps. However, to our knowledge, no gender  
22 effect on monitor accuracy during walking has been reported (Leicht & Crowther, 2007, 2009;  
23 Shepherd, Toloza, McClung, & Schmalzried, 1999). Fourth, although we developed an  
24 approach to ensure a simultaneous wearing of both devices, we acknowledge that without an  
25 available validated algorithm to detect wear and non-wear periods from the SW3, it cannot

1 totally be ruled out that short periods of non-wear with the SW3 were missed. We are not aware  
2 of studies that proposed a more robust methodology when using the SW3 and the GT3X/+  
3 concurrently (Feito et al., 2012; Feito et al., 2015). Fifth, our correction models to predict SW3  
4 daily step count from wGT3X+ step count were developed using samples that could be  
5 considered as too small to provide accurate predictions across the spectrum of the predicted  
6 values, particularly from the perspective of some guidelines that have been proposed for  
7 developing a clinical prediction model (Riley et al., 2020). However, our analysis was  
8 exploratory only, and the statistics we have provided, in particular  $R^2$  coefficients, could be  
9 valuable information for planning sample size in view of building an accurate prediction model  
10 (Riley et al., 2020). Moreover, some authors (Wanner, Martin, Meier, Probst-Hensch, &  
11 Kriemler, 2013) have shown that building a correction model using a relatively small sample  
12 ( $N=33$ ) can be valuable for substantially reducing mean between-method difference for step  
13 counting at the group level. Importantly, the ability of our models to reduce mean difference  
14 between the SW3 and the wGT3X+ monitors for step counting should be tested in additional  
15 studies.

16

## 17 **CONCLUSION**

18 The SW3 and the wGT3X+ monitors provided comparable step counts during an  
19 outdoor walking session in our samples of PAD and healthy older participants. However, the  
20 monitors did not provide comparable daily step counts during a 7-day free-living measurement  
21 in both populations. Interestingly, when considering daily step accumulation metrics, the  
22 monitors became more comparable, with better equivalence for the metrics representing a  
23 higher walking intensity.

1           When using a GT3X generation monitor to describe daily physical behavior using  
2 various step-based metrics to get results comparable to those of the SW3, enabling the LFE  
3 filter is likely to be the best option to choose, both in PAD and in healthy older populations.

4

5 **CONFLICT OF INTEREST**

6           The authors declare no conflict of interest.

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- 15

## 16 TABLES

17 **Table 1.** Agreement between the SW3 and wGT3X+ step counts related to the outdoor walking session

	People with PAD ( <i>N</i> = 22)			Older adults ( <i>N</i> = 35)		
	Session walking speed (km/h) : 4.2 ± 0.4			Session walking speed (km/h) : 4.9 (4.7 – 5.1) <sup>a</sup>		
	SW3	wGT3X+/LFE	wGT3X+/N	SW3	wGT3X+/LFE	wGT3X+/N
Mean ± SD (or ×/÷ factor)	3879 ± 1373	3879 ± 1370	3694 ± 1393	2455 ×/÷ 1.1	2480 ×/÷ 1.1	2406 ×/÷ 1.1
Corr. coeff. [95% CI]		1.00 [1.00; 1.00]	0.99 [0.98; 1.00]		<i>0.98 [0.94; 1.00]</i>	<i>0.97 [0.94; 1.00]</i>
MPE [95% CI], %		-0.1 [-0.3; 0.4]	-5.2 [-7.3; -2.8]		0.8 [0.2; 1.2]	-1.4 [-1.6; -1.2]
MAPE [95% CI], %		0.5 [0.2; 0.8]	5.2 [2.8; 7.0]		0.8 [0.3; 1.2]	1.4 [1.1; 1.6]

*Note.* Descriptive statistics are means ± SD, medians (25<sup>th</sup> – 75<sup>th</sup> percentiles), or geometric means ×/÷ factors for SD. *N* = Number of the participants available for the analysis; Corr. coeff. = correlation coefficient (values in italics are Spearman rho coefficients; otherwise, values are Pearson r coefficients); MPE = median percent error; MAPE = median absolute percent error; 95% CI = 95 % confidence interval.

<sup>a</sup>Based on 34 participants because data were lost for one participant.

18

19 **Table 2.** Agreement between the SW3 and wGT3X+ step-based metrics related to the 7-day free-living period

	People with PAD ( <i>N</i> = 21)			Older adults ( <i>N</i> = 32)		
	Number of valid days : 7 (6 – 7)			Number of valid days : 7 (6 – 7)		
	Mean daily wear time (min) : 764 (725 – 840)			Mean daily wear time (min) : 856 ± 57		
	SW3	wGT3X+/LFE	wGT3X+/N	SW3	wGT3X+/LFE	wGT3X+/N
<b>Step count</b>						
Mean ± SD (or ×/÷ factor)	9194 ×/÷ 1.5	11394 ×/÷ 1.4	5072 ×/÷ 1.6	15958 ×/÷ 1.4	19531 ×/÷ 1.3	10754 ×/÷ 1.5
Corr. coeff. [95% CI]		0.92 [0.80; 0.97] <sup>a</sup>	0.94 [0.85; 0.97] <sup>a</sup>		0.96 [0.93; 1.00]	0.92 [0.84; 1.00]
MPE [95% CI], %		20.5 [11.8; 27.5]	-44.9 [-51.1; -41.1]		21.9 [16.3; 25.3]	-31.6 [-36.5; -28.6]
MAPE [95% CI], %		20.5 [11.8; 27.5]	44.9 [39.2; 49.1]		21.9 [16.3; 25.3]	31.6 [28.6; 35.8]
<b>Max 60-min steps accumulation (steps/min)</b>						
Mean ± SD (or ×/÷ factor)	35.6 ± 10.5	38.9 ± 8.4	23.9 ± 8.9	67.1 ×/÷ 1.3	71.0 ×/÷ 1.3	57.2 ×/÷ 1.4
Corr. coeff. [95% CI]		0.91 [0.79; 0.96] <sup>a</sup>	0.96 [0.89; 0.98]		0.96 [0.91; 0.98] <sup>a</sup>	0.95 [0.90; 0.98] <sup>a</sup>
MPE [95% CI], %		8.6 [2.3; 12.1]	-31.6 [-40.1; -29.3]		3.1 [1.4; 8.3]	-13.2 [-17.7; -10.0]
MAPE [95% CI], %		10.9 [4.1; 13.3]	31.6 [26.9; 35.7]		4.0 [1.9; 8.3]	14.5 [10.1; 17.7]
<b>Max 30-min steps accumulation (steps/min)</b>						

Mean $\pm$ SD (or $\times/\div$ factor)	46.1 $\pm$ 12.9	48.0 $\pm$ 10.4	32.9 $\pm$ 12.2	84.1 $\times/\div$ 1.2	86.3 $\times/\div$ 1.2	75 $\times/\div$ 1.4
Corr. coeff. [95% CI]		0.96 [0.90; 0.98]	0.96 [0.90; 0.98]		0.96 [0.92; 0.98] <sup>a</sup>	0.94 [0.88; 0.97] <sup>a</sup>
MPE [95% CI], %		4.7 [-1.3; 7.1]	-29.3 [-38.1; -22.9]		1.3 [-0.2; 2.3]	-10.0 [-11.8; -7.9]
MAPE [95% CI], %		5.2 [2.6; 8.9]	29.3 [22.6; 34.5]		1.7 [0.8; 2.4]	10.2 [8.6; 11.8]
<b>Max 5-min steps accumulation (steps/min)</b>						
Mean $\pm$ SD (or $\times/\div$ factor)	81.9 $\pm$ 15.2	80.7 $\pm$ 15.3	69.0 $\pm$ 19.1	108.5 $\pm$ 12.9	109.7 $\pm$ 15.6	103.8 $\pm$ 19.6
Corr. coeff. [95% CI]		0.99 [0.98; 1.00]	0.97 [0.91; 0.99]		0.90 [0.81; 0.95]	0.91 [0.81; 0.95]
MPE [95% CI], %		-0.9 [-1.8; -0.7]	-14.7 [-21.8; -10.4]		-0.2 [-0.6; 0.1]	-4.1 [-9.1; -2.6]
MAPE [95% CI], %		1.4 [0.9; 1.6]	14.7 [10.3; 18.6]		1.2 [0.3; 2.2]	5.0 [3.3; 9.5]
<b>Peak 60-min steps accumulation (steps/min)</b>						
Mean $\pm$ SD (or $\times/\div$ factor)	66.8 $\pm$ 11.4	64.9 $\pm$ 10.5	47.0 $\pm$ 13.5	94.9 $\times/\div$ 1.2	95.0 $\times/\div$ 1.2	82.8 $\times/\div$ 1.3
Corr. coeff. [95% CI]		0.95 [0.88; 0.98]	0.93 [0.83; 0.97]		0.94 [0.88; 0.97] <sup>a</sup>	0.93 [0.86; 0.97]
MPE [95% CI], %		-1.5 [-4.8; -0.6]	-28.2 [-36.2; -25.7]		-0.1 [-1.2; 0.2]	-11.1 [-16.0; -7.6]
MAPE [95% CI], %		3.9 [0.8; 4.8]	28.2 [24.3; 33.3]		1.2 [0.6; 1.9]	11.5 [7.6; 16.9]
<b>Peak 30-min steps accumulation (steps/min)</b>						
Mean $\pm$ SD (or $\times/\div$ factor)	79.7 $\pm$ 12.1	77.2 $\pm$ 11.8	61.7 $\pm$ 15.9	105.0 $\times/\div$ 1.1	105.2 $\times/\div$ 1.1	96.6 $\times/\div$ 1.2

Corr. coeff. [95% CI]		0.97 [0.91; 0.99]	0.93 [0.84; 0.97]		0.91 [0.82; 0.96] <sup>a</sup>	0.89 [0.79; 0.95]
MPE [95% CI], %		-2.2 [-3.5; -1.7]	-19.1 [-27.5; -17.4]		-0.2 [-0.8; 0.0]	-6.6 [-9.5; -3.7]
MAPE [95% CI], %		2.9 [1.4; 3.4]	19.1 [16.7; 26.7]		0.6 [0.4; 1.5]	7.8 [4.2; 10.4]
<b>Peak 1-min steps accumulation (steps/min)</b>						
Mean ± SD (or ×/÷ factor)	104.5 ± 9.5	103.1 ± 11.1	96.2 ± 14.8	119.3 ×/÷ 1.1	120.8 ×/÷ 1.1	116.7 ×/÷ 1.1
Corr. coeff. [95% CI]		0.99 [0.98; 1.00]	0.96 [0.90; 0.98]		<i>0.76 [0.44; 0.95]</i>	<i>0.75 [0.42; 0.95]</i>
MPE [95% CI], %		-1.1 [-2.1; -0.5]	-7.4 [-11.0; -4.4]		0.2 [-0.8; 1.9]	-2.2 [-3.7; -0.6]
MAPE [95% CI], %		1.3 [0.6; 1.4]	7.4 [3.1; 8.7]		1.9 [1.0; 2.6]	3.1 [1.8; 6.6]
<p><i>Note.</i> Descriptive statistics are means ± SD, medians (25<sup>th</sup> – 75<sup>th</sup> percentiles), or geometric means ×/÷ factor for SD. <i>N</i> = Number of the participants available for the analysis; 95% CI = 95 % confidence interval; Corr. coeff. = correlation coefficient (values in italics are Spearman rho coefficients; otherwise, values are Pearson r coefficients); MPE = median percent error; MAPE = median absolute percent error.</p> <p><sup>a</sup>Calculated after log transformation of the variables.</p>						

20

21 **Table 3.** Linear models for predicting SW3 daily step count from wGT3X+ daily step count

Method	Model for predicting SW3 steps/day	$R^2$	RMSE
<b>People with PAD</b>			
wGT3X+/LFE	$-30.30477 + 0.82201 \times \text{steps/day}$	0.85	1663
wGT3X+/N	$1704.7047 + 1.4690 \times \text{steps/day}$	0.89	1392
<b>Older adults</b>			
wGT3X+/LFE	$-1897 + 0.9193 \times \text{steps/day}$	0.95	1298
wGT3X+/N	$4903 + 1.013 \times \text{steps/day}$	0.93	1574

*Note.* Steps/day is the mean of the daily step count calculated using the valid days.  $R^2$  coefficient and root-mean-squared error (RMSE) were computed using the leave-one-out method.

22

## 23 FIGURES CAPTIONS

### 24 **Figure 1. Step counts from the SW3 and wGT3X+ monitors related to the outdoor** 25 **walking session**

26 On the scatter plots, the solid line shows the identity, and the dashed lines show the regressions  
27 of the wGT3X+/LFE and wGT3X+/N data on the SW3 data respectively. On the equivalence  
28 plots, the thick, thin, and very thin black lines show the  $\pm 10\%$ ,  $\pm 15\%$ ,  $\pm 20\%$  SW3 equivalence  
29 zones, respectively; LFE = lower frequency extension filter; N = normal filter; EZs =  
30 equivalence zones; 90% CI = 90% confidence interval.

31

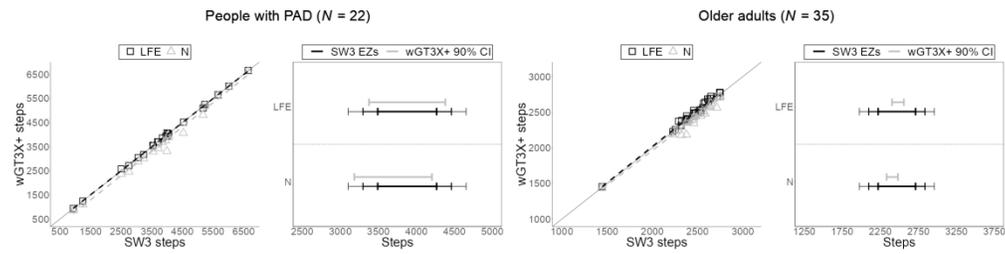
### 32 **Figure 2. Effect of pain occurrence on the agreement between the SW3 and wGT3X+** 33 **monitors and on walking speed**

34 Panel A shows, for each wGT3X+ method, the individual percent errors (PE) for walking  
35 without pain and for walking with pain. Panel B shows, for each wGT3X+ method, the  
36 individual differences of absolute percent error (APE) between walking with pain and walking  
37 without pain (Change in APE = APE[with pain] minus APE[without pain]), along with the  
38 corresponding medians (grey bars) and 95% confidence intervals (black error bars). Panel C  
39 shows the individual walking speeds when walking without pain and walking with pain. Panel  
40 D shows the differences in walking speed (Change in speed = speed[with pain] minus  
41 speed[without pain]), with the mean difference and its corresponding 95% confidence interval.  
42 The grey zone depicts non-substantial change in speed. The results are related to 17 participants  
43 who indicated the occurrence of pain during the first walking bout.

44

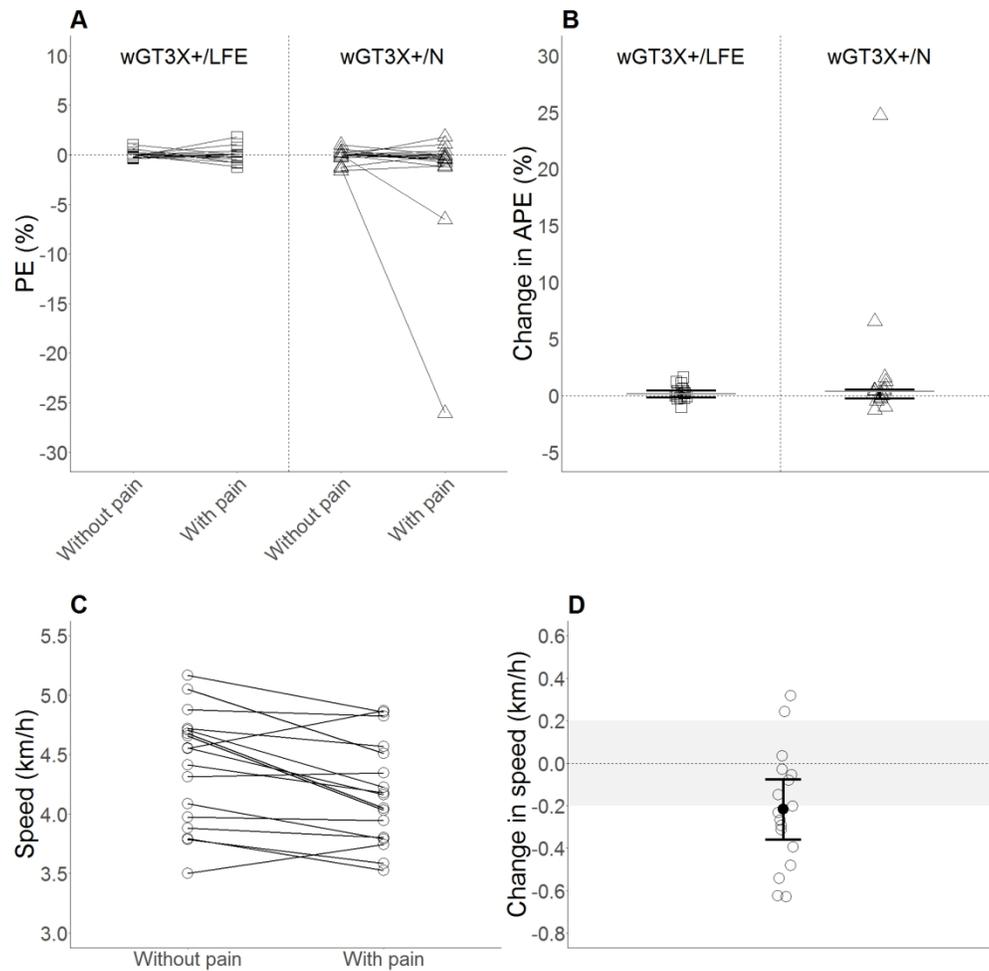
### 45 **Figure 3. Step-based metrics from the SW3 and wGT3X+ monitors for the 7-day free-** 46 **living period**

47 On the scatter plots, the solid line shows the identity, and the dashed lines show the regressions  
48 of the wGT3X+/LFE and wGT3X+/N data on the SW3 data respectively. On the equivalence  
49 plots, the thick, thin, and very thin black lines show the  $\pm 10\%$ ,  $\pm 15\%$ ,  $\pm 20\%$  SW3 equivalence  
50 zones, respectively; LFE = lower frequency extension filter; N = normal filter; EZs =  
51 equivalence zones; 90% CI = 90% confidence interval.



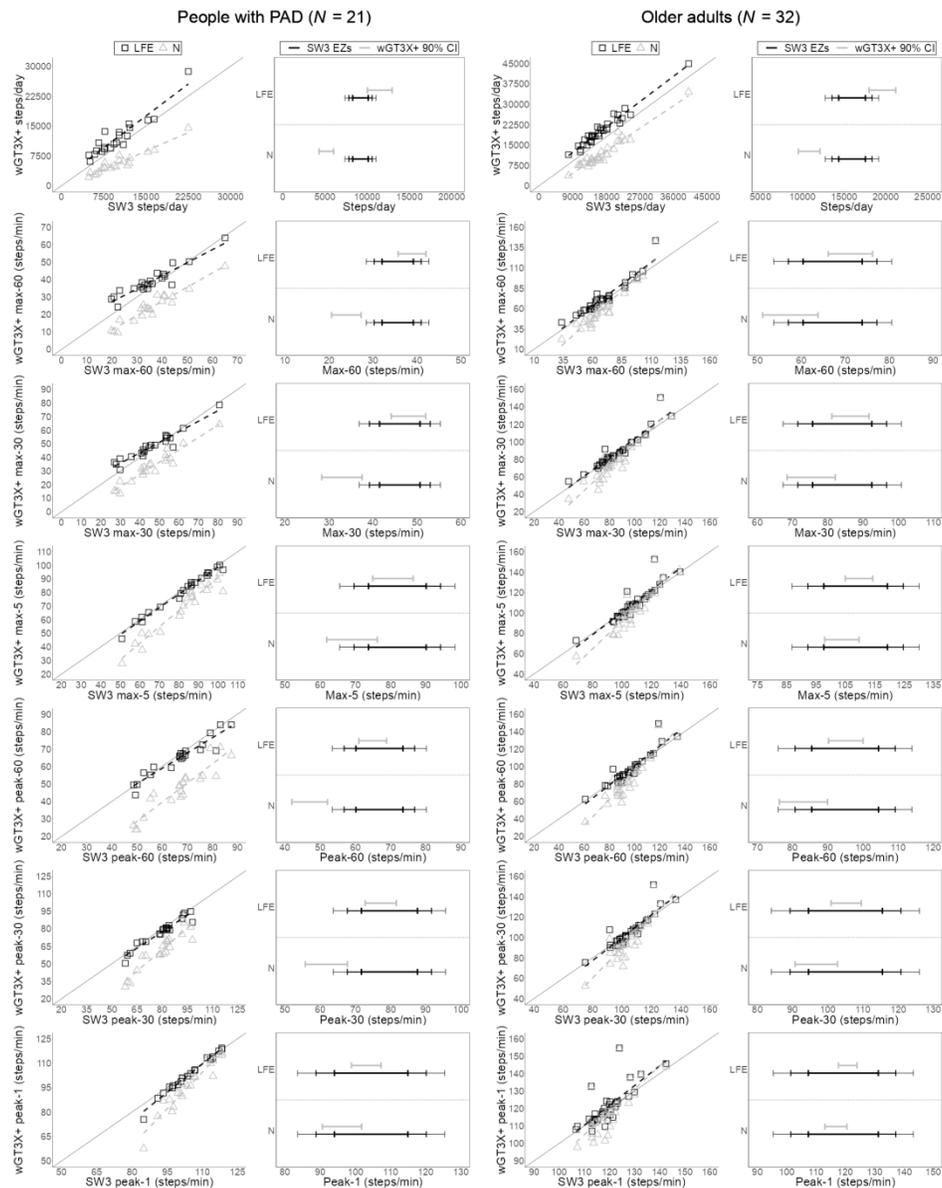
On the scatter plots, the solid line shows the identity, and the dashed lines show the regressions of the wGT3X+/LFE and wGT3X+/N data on the SW3 data respectively. On the equivalence plots, the thick, thin, and very thin black lines show the  $\pm 10\%$ ,  $\pm 15\%$ ,  $\pm 20\%$  SW3 equivalence zones, respectively; LFE = lower frequency extension filter; N = normal filter; EZs = equivalence zones; 90% CI = 90% confidence interval.

179x49mm (300 x 300 DPI)



Panel A shows, for each wGT3X+ method, the individual percent errors (PE) for walking without pain and for walking with pain. Panel B shows, for each wGT3X+ method, the individual differences of absolute percent error (APE) between walking with pain and walking without pain (Change in APE = APE[with pain] minus APE[without pain]), along with the corresponding medians (grey bars) and 95% confidence intervals (black error bars). Panel C shows the individual walking speeds when walking without pain and walking with pain. Panel D shows the differences in walking speed (Change in speed = speed[with pain] minus speed[without pain]), with the mean difference and its corresponding 95% confidence interval. The grey zone depicts non-substantial change in speed. The results are related to 17 participants who indicated the occurrence of pain during the first walking bout

705x705mm (72 x 72 DPI)



On the scatter plots, the solid line shows the identity, and the dashed lines show the regressions of the wGT3X+/LFE and wGT3X+/N data on the SW3 data respectively. On the equivalence plots, the thick, thin, and very thin black lines show the  $\pm 10\%$ ,  $\pm 15\%$ ,  $\pm 20\%$  SW3 equivalence zones, respectively; LFE = lower frequency extension filter; N = normal filter; EZs = equivalence zones; 90% CI = 90% confidence interval.

179x229mm (250 x 250 DPI)

## Supplemental material

**eText. Procedure to remove the initial wGT3X+ wear time periods where the comparison of the monitors was not appropriate**

**eFigure. Visualizations of the cases where the “wear” in-bed night-time epochs (panels A, B, and C) or the waking-time epochs (panel D) were reconsidered as “nonwear” after graphical inspection**

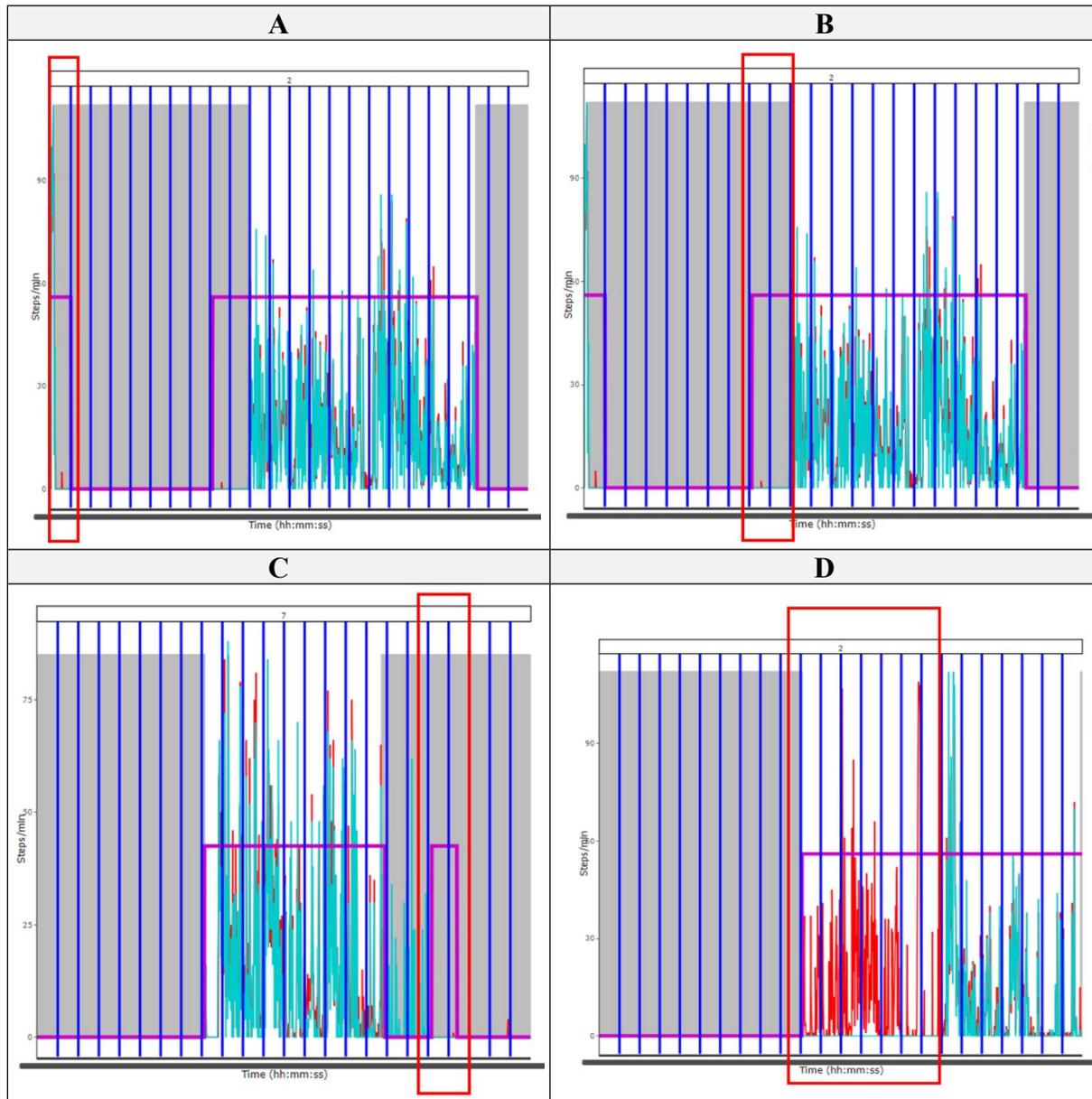
### **eText. Procedure to remove the initial wGT3X+ wear time periods where the comparison of the monitors was not appropriate**

Before conducting the graphical inspection, in-bed time was determined using the “PhysActBedRest” R package (version 1.0, 2016) provided by Tracy et al. (Tracy, Acra, Chen, & Buchowski, 2018). In-bed time was marked into the merged data file using the Tracy et al. (Tracy et al., 2018) algorithm, the wGT3X+/LFE vector magnitude (VM) counts, and the optimal cut-points ( $CP_0 = 50$ ;  $CP_1 = 210$ ;  $CP_2 = 350$ ) provided by Belletiere et al. (Belletiere et al., 2019). The beginning of the in-bed night-time period was considered as the beginning of the in-bed time period visible at the end of the 24-h day (or as the beginning of the first in-bed time period of the following day if any) that appeared after the last out-of-bed time period of the day. Graphical inspection was conducted in R by plotting both the SW and wGT3X+/LFE steps, wGT3X+/LFE wear time, and in-bed time, against time (see eFigure below), and by using the “plotly” package. In the following three cases, all the concerned “wear” in-bed night-time epochs were reconsidered as “nonwear”: (i) when an initial wear time period began in an out-of-bed time period and was prolonged into an in-bed night time period for  $\geq 30$  min (eFigure, panel A); (ii) when an initial wear time period began during an in-bed nighttime period more than 30 min before to be prolonged into the next out-of-bed time period (eFigure, panel B); (iii) when an initial wear time period both began and ended during an in-bed night-time period (eFigure, panel C). In addition, if the first out-of-bed time period of the day included more than 30 min of wGT3X+/LFE wear time without SW steps, the corresponding epochs were reconsidered as “nonwear” (eFigure, panel D).

### **References**

- Belletiere, J., Zhang, Y., Berardi, V., Full, K. M., Kerr, J., LaMonte, M. J., . . . Di, C. (2019). Parameterizing and validating existing algorithms for identifying out-of-bed time using hip-worn accelerometer data from older women. *Physiol Meas*, *40*(7), 075008.
- Tracy, J. D., Acra, S., Chen, K. Y., & Buchowski, M. S. (2018). Identifying bedrest using 24-h waist or wrist accelerometry in adults. *PLoS One*, *13*(3), e0194461.

**eFigure. Visualizations of the cases where the “wear” in-bed night-time epochs (panels A, B, and C) or the waking-time epochs (panel D) were reconsidered as “nonwear” after graphical inspection**



*Note.* The cyan lines, red lines, and purple lines, show the SW3 steps, the wGT3X+/LFE steps, and the wGT3X+/LFE wear time, respectively. The grey background shows the in-bed time. The vertical blue lines show each hour of the day. Red rectangles highlight the wear time periods to be removed. A: An initial wear time period began in an out-of-bed time period and was prolonged into an in-bed night time period for  $\geq 30$  min; B: An initial wear time period began during an in-bed nighttime period more than 30 min before to be prolonged into the following out-of-bed time period; C: An initial wear time period both began and ended during an in-bed night-time period; D: The first out-of-bed time period of the day with wear time included more than 30 min of wGT3X+/LFE steps without SW3 steps.