Differences Among Physical Activity Actigraphy Algorithms in Three Chronic Illness Populations

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Abstract

Objectives: In three chronic illness populations and in a combined sample, we assessed differences in two algorithms to determine wear time (WT%) and four algorithms to determine: Kilocalories, light physical activity (PA), moderate-to-vigorous PA (MVPA), and metabolic equivalents (METs).

Methods: Data were collected in 29 people living with HIV (PLHIV), 27 participants recovering from a cardiac event, and 15 participants with hypertension. Participants wore the ActiGraph™ wGT3X-BT for ≥ 3 days on their hip. Analysis of variance was used to assess differences among algorithms.

Results: No differences were found between the two algorithms to assess WT% or among the four algorithms to assess kilocalories in each of the chronic illness populations or in the combined sample. Significant differences were found among the four algorithms for light PA (p<.001) and METs (p<.001) in each chronic illness population and in the combined sample. MVPA was significantly different among the four algorithms in the PLHIV (p=.007) and in the combined sample (p<.001), but not in the cardiac (p=.064) or hypertension samples (p=.200).

Discussion: Our findings indicate that the choice of algorithm does make a difference in PA determination. Differences in algorithms should be considered when comparing PA across different chronic illness populations.

Keywords: Actigraphy Algorithms, Cut Points, Chronic Illness Populations, Metabolic Equivalents, Physical Activity

Differences Among Physical Activity

Actigraphy Algorithms in Three Chronic Illness Populations

Chronic illnesses are the leading causes of death and disability in the United States, and each year individuals with a chronic illness consume $3.5 trillion in health care costs.[1] Lifestyle modification alone can reduce the risk of developing a chronic illness. Physical inactivity is the fourth leading cause of death in the United States and is one of the most important factors in preventing and treating chronic illness.[1, 2] Adults living with a chronic illness should participate in $\geq$ 150 minutes per week of moderate-to-vigorous physical activity (MVPA).[3, 4] Still, only 25% of adults meet the minimal requirement of physical activity (PA) needed to maintain a healthy lifestyle.[1, 5, 6] Replacing sedentary time with light or higher PA levels improves health outcomes.[7]

Actigraphy is often used in a free-living environment, but it can also be used in other settings such as laboratory validation studies.[8] In 2009-2010, ActiGraph[9] released the triaxial actigraphy device and it currently is a commonly used objective measures of PA in research.[10] The ActiGraph has the capability of measuring frequency, intensity, and duration of movement at a specified sampling rate and recording duration in a free-living environment.[11] There are a variety of predictive cut-point algorithms that can be applied to the data for PA interpretation. When processing actigraphy data, it is critical that researchers select device metrics and algorithm settings with consideration of the population age and health status. It is also important to select a PA interpretation algorithm for the specific PA type (e.g. structured versus free-living) and duration of interest. With the rapid increase in the number of actigraphy algorithms and the number of chronic illness populations, more knowledge is needed about the use of different actigraphy algorithms in PA measurement in chronic illness populations.

There are several data collection, processing, and statistical metrics to consider when using actigraphy for PA measurement.[12] Current validation studies are centered on cut-points that correspond to PA intensity levels (e.g. light or moderate). While many sets of cut-points have historically been derived from the vertical x-axis (uniaxial) data, more recent cut-points have also been derived from the triaxial (vector magnitude) data such as the Freedson Adult VM[13] cut-points utilized in this analysis. Uniaxial and triaxial accelerometry are comparable when assessing routine activity but not for sport-specific movement patterns.[14] Most of the current cut-point scoring algorithms and kilocalorie equations in the ActiGraph[9] GT3X have been validated in a well-controlled, moderate PA intensity lifestyle setting with a younger, healthy adult population, creating a challenge in analysis of data from an older adult population.[11, 15-17] While there are several validated PA actigraphy algorithms for cut-points, the estimations are predictive and may not accurately reflect the population, age, and health condition of interest. Current evidence suggests that there is a lack of validated predictive actigraphy algorithms for use in adults with a chronic illness.

The purpose of this study was to assess differences among actigraphy algorithms to measure wear time % (WT%) and PA in three chronic illness populations and in a combined sample of the three chronic illness populations. The ActiGraph[9] wGT3X-BT was used to measure PA. The three chronic illness populations assessed were people living with HIV (PLHIV), individuals recovering from a cardiac event, and individuals with uncontrolled hypertension (HTN). In each of these populations and in a combined sample of the three populations, we assessed differences in: Two algorithms to determine WT% and four algorithms to determine PA indicators: Kilocalories, light PA, MVPA and metabolic equivalents (METs).

Methods

Study Design

This study was a secondary analysis of data collected in three pilot studies associated with a National Institutes of Health-funded Center of Excellence for Self-Management Research (SMART Center) at Case Western Reserve University.[18] The mission of this center is to develop, implement, and disseminate research on the effectiveness of self-management interventions in chronic illness populations. The three pilot studies received ethical approval from the Institutional Review Board at University Hospitals of Cleveland (Study20181112). Written consent was obtained for anonymized information to be published. Each of the pilot studies used a two-group design to test a self-management intervention on a number of outcomes and used common measures.[18] Baseline data from 2015-2019 were used for the analyses reported herein.

Study Sample and Study Procedures

Seventy-one individuals with a chronic illness were included: 29 PLHIV, 27 individuals recovering from a cardiac event and 15 individuals with uncontrolled HTN. Individuals were enrolled from clinic registries and by flyers. Interested individuals were screened by telephone and medical record review. Inclusion criteria for the PLHIV sample were $\geq$18 years of age, HIV+, receiving antiretroviral therapy, at high risk for cardiovascular disease based on the Framingham risk score, on a stable dose of statins, and had a recent viral load <400 copies/mL. Exclusion criteria for the PLHIV sample were those who: Were not able to safely engage in planned exercise, had $\geq$150 minutes of MVPA or 75 minutes of vigorous exercise per week, had uncontrolled diabetes, or were enrolled in a formal exercise, diet, or weight loss program.[19] Inclusion criteria for the cardiac sample were individuals who were $\geq$40 years of age, experienced a first cardiac event (myocardial infarction or revascularization), and had a planned

12 weeks of cardiac rehabilitation. Exclusion criteria the cardiac sample were those who had experienced cardiac arrest. Inclusion criteria for the HTN sample were African American adults who were ≥25 years, had HTN based on a blood pressure >140/80mmHg, on at least one anti-hypertensive medication, and owned a smartphone. Exclusion criteria for the HTN sample were those actively participating in psychological training. Excluded individuals across all studies were pregnant, could not speak English, or had a medical history that was contraindicated for functional magnetic resonance imaging, which was part of the parent study protocol.[18]

Study Measures

Sample characteristics including age, gender, race/ethnicity, education, marital status, and employment were collected by self-report and chart review at enrollment to each study. Body mass index (BMI) was measured using a standard laboratory protocol.

Physical Activity

PA was measured using the triaxial ActiGraph[9] wGT3X-BT in all studies. Participants were asked to wear the device for 7 to 8 days on their non-dominant hip during waking hours only. In this secondary analysis of which the purpose was to compare algorithms across three pilot studies, the minimum wear time that was selected was available across all studies. Therefore, we used a minimum wear time of ≥ 3 days and ≥ 360 minutes per day which is shorter than the wear time recommended for some actigraphy studies. Participants returned the device by mail. Data were analyzed using ActiLife v6.13.3 at 60-second epochs with a normal activity filter and sampling frequency of 30 Hz. MET categories of light PA for the Freedson Adult[20, 21] algorithm was < 3 and for the Hendelman Adult[22] algorithm was 1-2.99; moderate was 3-5.99 and hard was 6-8.99.

Table 1 shows the actigraphy algorithms assessed. The details of each algorithm parameter are presented in the Appendix. As shown in Table 1, the two WT% algorithms resulted in a matrix of four algorithms. Data were filtered by WT and then analyzed by four different algorithms used to measure kilocalories, METs, and cut-points (light PA and MVPA). WT% is the amount of time the device is on compared to the amount of time the device is not on the subject. WT% is the mean percentage of each valid day that was wear time. It is important to accurately measure WT% since this parameter is used in the calculation of other PA indicators (e.g., MVPA, METs, etc.). The four algorithms were selected because they are commonly used to measure PA in adult populations. For interpretation of WT%, Troiano[23] was used in algorithms 1 and 3 and Choi[24] was used in algorithms 2 and 4. Algorithm 1 consisted of Freedson VM3 Combination,[13, 20] Freedson Adult,[20, 21] and Freedson Adult VM3[13]; Algorithm 2 consisted of Freedson VM3 Combination,[13, 20] Freedson Adult,[20, 21] and Freedson Adult VM3[13]; Algorithm 3 consisted of Freedson Combination,[20, 21] Hendelman Adult,[22] and Freedson Adult[21]; Algorithm 4 consisted of Freedson Combination,[20, 21] Hendelman Adult,[22] and Freedson Adult.[21]

[Insert Table 1]

Table 1

Comparison of Algorithm Features

Algorithm	WT %	Kilocalories	METs	Cut-Points (Light PA & MVPA)
1	Troiano[23]	Freedson VM3 Combination[13, 20]	Freedson Adult[20, 21]	Freedson Adult VM3[13]
2	Choi[24]	Freedson VM3 Combination[13, 20]	Freedson Adult[20, 21]	Freedson Adult VM3[13]
3	Troiano[23]	Freedson Combination[20, 21]	Hendelman Adult[22]	Freedson Adult[21]
4	Choi[24]	Freedson Combination[20, 21]	Hendelman Adult[22]	Freedson Adult[21]

Note. METs = metabolic equivalents; MVPA = moderate-to-vigorous physical activity; PA = physical activity; WT % = wear time.

Statistical Analysis

Descriptive statistics were used to describe the sample. A one-way analysis of variance (ANOVA) was used to test differences among the algorithms. An *F*-test statistic was computed for each comparison, followed by the Tukey's post-hoc tests to further determine where the specific differences occurred. A *p*-value <.05 was used to determine statistical significance. All statistical analyses were conducted using IBM SPSS version 27.[25]

Results

Characteristics of the Sample

Table 2 displays the sample characteristics. Participants were primarily middle-aged adults, African American, male, with a high school education or more, and obese. Participants in the cardiac event sample were older, predominately male, white, and married compared to participants in the PLHIV and HTN samples. The PLHIV sample had significantly less education and greater unemployment, despite their younger age, than participants in the cardiac event and HTN samples. Some participants wore the device longer than requested. Although the mean number of valid days of wear time across all groups was 7.10, there was a wide range of 3 to 14 days because some participants wore the device longer than what was required. The final analysis included individuals who wore the device for $\geq$ 3 days and $\geq$ 360 minutes per day.

[Insert Table 2]

Table 2

Sample Characteristics

Variable	PLHIV (*N*=29)	Cardiac (*N*=27)	HTN (*N*=15)	Combined (*N*=71)	*F* Test[a]	*p*-value[a]
Age (Yrs)	53.00±8.05	63.48±7.69	57.07±17.05	57.85±11.32	*F*=7.09	***p*=.002**
BMI (kg/m^2)	30.44±9.13	30.27±7.84	36.24 ± 9.25	31.62±8.91	*F*=2.69	*p*=.075
Actigraphy Total Days	6.76±1.75	7.96±1.79	6.20±1.52	7.10±1.84	*F*=6.04	***p*=.004**
Gender						
Male	17 (59%)	23 (85%)	3 (20%)	43 (61%)	*F*=9.48	***p*=.000**

Female	11 (38%)	4 (15%)	12 (80%)	27 (38%)		
Transgender	1 (3%)	0 (0%)	0 (0%)	1 (1%)		
Race/Ethnicity %						
African American	28 (97%)	6 (22%)	15 (100%)	49 (70%)		
Asian/Pacific Islander	0 (0%)	1 (4%)	0 (0%)	1 (1%)	*F*=50.85	***p*=.000**
Native American Indian	0 (0%)	1 (4%)	0 (0%)	1 (1%)		
White/Angelo (Non-Hispanic)	1 (3%)	19 (70%)	0 (0%)	20 (28%)		
Education %						
Did not finish HS	9 (31%)	1 (4%)	0 (0%)	10 (14%)		
HS Diploma/GED	7 (24%)	2 (7%)	0 (0%)	9 (13%)	*F*=21.64	***p*=.000**
College/Technical Degree	12 (41%)	9 (33%)	7 (47%)	28 (39%)		
4-Year Degree or Higher	1 (3%)	15 (56%)	8 (53%)	24 (34%)		
Not Married %	28 (97%)	10 (37%)	11 (73%)	49 (69%)	*F*=16.63	***p*=.000**
Employed %	2 (7%)	16 (59%)	8 (53%)	26 (37%)	*F*=11.71	***p*=.000**

Note. Data are presented as mean ± standard deviation and number (%). Bolded text indicates a *p*-value < .05. BMI = body mass index; GED = general education degree; HS = high school; kg = kilograms; m^2 = meters squared; yrs = years; PLHIV = people living with HIV; HTN = hypertension.

[a] = differences across the three populations: PLHIV, cardiac, and HTN.

Comparison of Wear Time % Algorithms

Table 3 shows the results of the ANOVA tests of differences between the two WT% algorithms. The Choi[24] wear time algorithm indicated a higher WT% compared to the Troiano[23] algorithm in each chronic illness sample and in the combined chronic illness sample, but this difference was not statistically significant. [Insert Table 3]

Table 3

ANOVA Results for Wear Time % Algorithm Comparisons

Algorithm	PLHIV (*N*=29)		Cardiac (*N*=27)		HTN (*N*=15)		Combined[a] (*N*=71)	
	M±*SD*	*F* Test *p*-value	*M*±*SD*	*F* Test *p*-value	*M*±*SD*	*F* Test *p*-value	*M*±*SD*	*F* Test *p*-value
Troiano[23]	36.76±14.75	*F*=0.18	61.79±18.07	*F*=1.73	48.49±13.56	*F*=0.41	48.75±19.24	*F*=1.34
Choi[24]	38.38±14.54	*p*=.674	68.59±19.90	*p*=.195	51.79±14.74	*p*=.529	52.70±21.39	*p*=.250

Note. Data are presented as mean ± standard deviation. ANOVA = analysis of variance; PLHIV = people living with HIV; HTN = hypertension. [a]Aggregate means and standard deviations of all data was used for the combined analysis.

Comparison of Kilocalories Expended

Table 4 shows the results of the ANOVA tests of differences in kilocalories expended among the four algorithms. Algorithm 1 had the highest and Algorithm 4 had the lowest number of kilocalories for each chronic illness sample and in the combined sample, although these differences were not statistically significant. [Insert Table 4]

Table 4

ANOVA Results for Physical Activity Actigraphy Algorithm Comparisons

PA Indicators	Algor-ithm	PLHIV ($N = 29$)		Cardiac ($N = 27$)		HTN ($N = 15$)		Combined Sample[e] ($N = 71$)	
		$M \pm SD$	F Test p-value	$M \pm SD$	F Test p-value	$M \pm SD$	F Test p-value	$M \pm SD$	F Test p-value
Daily Kcals	1[a]	508.87±246.15		380.30±223.36		346.00±256.31		425.57±246.83	
	2[b]	500.75±248.68	F=1.19	361.57±184.05	F=0.36	332.98±238.80	F=0.17	412.38±233.04	F=1.50
	3[c]	426.57±218.72	p=.316	345.37±190.88	p=.783	305.22±216.60	p=.917	370.06±210.98	p=.216
	4[d]	419.55±219.30		328.90±160.22		293.50±199.64		358.45±198.82	
Daily Light PA Minutes	1[a]	660.41±110.43		942.90±176.32		813.21±161.30		800.12±193.95	
	2[b]	674.18±121.76	F=21.81	1009.65±203.68	^{w}F=243.88	845.99±171.41	^{w}F= 111.15	838.05±222.96	^{w}F=305.57
	3[c]	340.60±468.59	**p=.000**	232.43±66.88	**p=.000**	211.90±77.62	**p=.000**	272.28±306.63	**p=.000**
	4[d]	251.32±71.54		224.36±64.96		205.56±71.64		231.40±70.48	
Daily MVPA Minutes	1[a]	44.48±28.65		24.31±19.03		15.95±15.75		30.78±25.56	
	2[b]	43.41±28.41	F=4.27	23.05±16.13	F=2.50	15.43±15.52	^{w}F=1.65	29.76±24.62	^{w}F=6.60
	3[c]	26.49±25.02	**p=.007**	16.23±12.46	p=.064	8.51±8.37	p=.200	18.79±19.28	**p=.000**
	4[d]	25.85±24.76		15.46±11.02		8.21±8.24		18.18±18.77	
Daily METs	1[a]	1.17±0.14		1.09±0.07		1.06±0.06		1.12±0.11	
	2[b]	1.17±0.14	^{w}F=107.03	1.08±0.06	^{w}F=95.28	1.06±0.06	^{w}F=47.42	1.11±0.11	^{w}F=163.61
	3[c]	1.90±0.27	**p=.000**	1.55±0.18	**p=.000**	1.57±0.22	**p=.000**	1.70±0.28	**p=.000**
	4[d]	1.87±0.27		1.51±0.18		1.54±0.22		1.67±0.28	

Note. Data are presented as mean ± standard deviation. [e]Aggregate means and standard deviations of all data was used for the combined analysis. Bolded text indicates a p-value < .05. ANOVA = analysis of variance; METs = metabolic equivalents; MVPA = moderate-to-vigorous physical activity; PA = physical activity; PLHIV = people living with HIV; HTN = hypertension; kcals = kilocalories. ^{w}F = Welch F statistic. [a]Algorithm 1: Troiano[23] for WT%, Freedson VM3 Combination[13, 20] for kcals, Freedson Adult[20, 21] for METs, and Freedson Adult VM3[13] for cut-points (light PA, MVPA). [b]Algorithm 2: Choi[24] for WT%, Freedson VM3 Combination[13, 20] for kcals, Freedson Adult[20, 21] for METs, and Freedson Adult VM3[13] for cut-points. [c]Algorithm 3: Troiano[23] for WT%, Freedson Combination[20, 21] for kilocalories, Hendelman Adult[22] for METs, and Freedson Adult[21] for cut-points. [d]Algorithm 4: Choi[24] for WT%, Freedson Combination[20, 21] for kilocalories, Hendelman Adult[22] for METs, and Freedson Adult[21] for cut-points.

Comparison of Light Physical Activity

Table 4 displays the results of the ANOVA test of differences in light PA among the four algorithms. Algorithms 2 had the highest and Algorithm 4 had the lowest number of light PA minutes for each chronic illness sample and in the combined sample. Significant differences in light PA in each chronic illness population and in the combined sample were found. A Tukey post-hoc test indicated significant differences in the light PA for each chronic illness population and in the combined sample between algorithms 1 and 3, 1 and 4, 2 and 3, and 2 and 4. The mean difference of light PA in the combined chronic illness sample was 527.84 between algorithms 1 and 3, 565.77 between algorithms 2 and 3, and 606.65 between algorithms 2 and 4. Similar differences were also found in the PLHIV, cardiac, and HTN groups (See Table 4).

Comparison of Moderate-to-Vigorous Physical Activity

Table 4 displays the results of the ANOVA test of differences in MVPA among the four algorithms. Algorithm 1 had the highest and Algorithm 4 had the lowest number of MVPA minutes for each chronic illness sample and in the combined sample. Significant differences were found in MVPA in the PLHIV sample and in the combined sample; these differences were not found in the cardiac or HTN samples. In the PLHIV sample, a Tukey post-hoc test indicated significant differences in MVPA between algorithms 1 and 4. In the combined sample, the Tukey post-hoc test indicated significant differences in MVPA between algorithms 1 and 3, 1 and 4, 2 and 3, and 2 and 4. The mean difference of MVPA in the combined chronic illness and PLHIV samples were 11.99 and 17.99 between algorithms 1 and 3, 12.6 and 18.63 between algorithms 1 and 4, 10.97 and 16.92 between algorithms 2 and 3, and 11.58 and 17.56 between algorithms 2 and 4.

Comparison of Metabolic Equivalents

Table 4 also shows the results of the ANOVA test of differences in METs among the four algorithms. Algorithm 3 had the highest number of METs and Algorithms 1 and 2 had the lowest number of METs, which would be light intensity, for each chronic illness sample and in the combined sample. Statistically significant differences in METs among the four algorithms were found for each chronic illness sample and in the combined sample. The Tukey post-hoc results indicated significant differences in METs between algorithms 1 and 3, 1 and 4, 2 and 3, and 2 and 4. The mean difference of METs in the combined chronic illness sample was -0.58 between algorithms 1 and 3, -0.55 between algorithms 1 and 4, -0.59 between algorithms 2 and 3, and -0.56 between algorithms 2 and 4. Similar differences were also found in the PLHIV, cardiac, and HTN groups (See Table 4).

Discussion

In each chronic illness sample and in a combined chronic illness sample, the purpose of the study was to assess differences in: Two actigraphy algorithms to determine WT% and four actigraphy algorithms to determine kilocalories, light PA, MVPA, and METs. Our findings show that the two wear time algorithms did not differ in their WT% calculations in each of the different chronic illness samples and in the combined sample. We found no significant differences in measurement of kilocalories expended among the four algorithms in each chronic illness sample and in the combined sample. Significant differences in light PA and METs were found among the four algorithms in each chronic illness sample and in the combined sample. Our findings showed significant differences in amount of MVPA among the four algorithms in the PLHIV sample and in the combined sample, but these differences were not found in the cardiac or HTN samples.

While our results indicated no differences in the calculation of kilocalories across the four algorithms, the literature addressing actigraphy measurement cautions that accurate characterization of kilocalories is a challenge.[26, 27] For example, Rothney, Brychta [26] found that variability in kilocalories was attributed to variations in PA types (e.g. biking). We are aware that in our study, the PLHIV and HTN samples comprised individuals who not were enrolled in a structured exercise program; whereas, the cardiac sample comprised individuals who were actively enrolled in a 12-week structured exercise program. However, we did not consider the type of PA in this study. If chronic illness samples are combined, future studies should consider PA type differences (structured versus free-living) in each chronic illness sample and select the appropriate algorithm. Also, the validation of actigraphy algorithms in chronic illness populations, compared to a healthy control group, is needed for correct interpretation of PA outcomes among and across chronic illness populations. In light of these findings, we recommended that the interpretation of kilocalories in actigraphy algorithms should consider that PA type differences could impact the study findings when combining chronic illness samples.

The significant differences identified among the four actigraphy algorithms indicate that algorithm choice can influence the interpretation of METs but not the classification of PA intensity. We used MET categories to classify each chronic illness sample and the combined sample into different intensity categories: light < 3, moderate = 3-5.99, and hard > 6. Although our results show significant differences in METs among each chronic illness sample and the combined chronic illness sample, there were no clinically meaningful differences in MET categories. For example, METs in each chronic illness sample and in the combined chronic illness sample were categorized as light intensity and the findings were consistent among the

four algorithms. MET categories should still be interpreted with caution among chronic illness populations with light (e.g., walking) PA intensity levels.

The differences that we found among the four actigraphy algorithms for interpretation of MVPA and light PA in different chronic illness populations are the first to appear in the literature. In the combined chronic illness sample we found a clinically meaningful difference for light PA and MVPA. Previous research reflects that algorithm validation studies have been predominately conducted in healthy adult populations.[13] Minimal research has been conducted examining the difference among actigraphy cut-point algorithms in chronic illness populations.[11, 15] Our findings for light PA could be influenced by differences in cut-point start values of 0 for the Freedson Adult VM3 and 100 for the Freedson Adult algorithms. The differences we found for the interpretation of MVPA and light PA might also be due to difference in the individual characteristics of each chronic illness sample. Another factor to consider is that the PLHIV sample had nearly double the amount of MVPA minutes compared to the cardiac and HTN samples. This difference could be heavily influenced by the length and intensity of bouts of PA, age of the PLHIV sample, which was almost 4-10 years younger than the cardiac and HTN samples. Therefore, our findings, with a small sample, might begin to shed light on the use of different actigraphy algorithms in different chronic illness populations. Future research should address specific characteristics such as different diagnoses or health status, age, and BMI.

Interpretation of our results should take into account some limitations of the study. More research is needed to determine if these results would be similar among actigraphy algorithms for PA interpretation in larger and more diverse chronic illness samples. Another limitation of this study is that we examined two wear time and four PA actigraphy algorithms; therefore, it is possible that if we assessed different algorithms our results could be different. Interpretation of

the study results should also take into consideration that we used an actigraphy minimum wear time of ≥ 3 days and ≥ 360 minutes per day which is shorter than the wear time recommended for some actigraphy studies. Although we selected PA indicators commonly used in research studies, we did not examine all actigraphy PA indicators (i.e., steps or total activity counts), thus our findings are limited to a few of the possible indicators. Last, future studies can examine if actigraphy algorithm differences in steps and MVPA differ among different chronic illness populations. Although this study highlights that selecting a different algorithm may produce different results, this study does not provide information on which algorithm is most accurate. Thus, there is a need for validation studies in specific populations. Therefore, our results indicate that future studies should comprehensively examine differences in actigraphy PA algorithms in larger and more diverse chronic illness samples.

Our findings suggest that researchers carefully select an actigraphy algorithm based on a combination of factors. Familiarity with a particular algorithm or random selection should not be the basis for algorithm selection. Our findings indicate that the population being studied does make a difference and that actigraphy algorithm selection may be a complex decision to make when a study includes several chronic illness populations. The researcher should also consider differences in the type of PA being assessed. For example, free-living PA might impact the results differently compared to a structured exercise program. The researcher should consider uniaxial and triaxial accelerometry differences in PA movement patterns.[14] Another factor to consider in algorithm selection is how the individual characteristics of a specific chronic illness population may influence PA calculations. Although it is tempting to researchers to always use the algorithm that is most commonly used in their field of study or population of interest, our findings indicate that selection of an algorithm is a complex decision and should be based on

several factors. We suggest that several algorithms might be used to assess different PA indicators for comparison of outcomes in one study, thus adding to our collective understanding of appropriate use of algorithms for measurement of PA within and across different populations. Moreover, the researcher should carefully evaluate if one algorithm is appropriate for the combined findings compared to a specific actigraphy algorithm for each population.

Our findings support that the choice of actigraphy algorithm does make a difference in the measurement of light PA, MVPA, and METs and may not make a difference in the measurement of WT% and kilocalories. Considering these findings, we suggest that systematic review of the actigraphy algorithms available, including newly developed and validated ones, and careful selection of the appropriate actigraphy algorithm be based on a combination of factors including differences among: Algorithms for MET intensity classification, activity types (structured versus free-living), and individual sample characteristics (diagnoses or health status, age, and BMI). More validation studies using head-to-head comparisons of actigraphy algorithms are needed among different chronic illness population.

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