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Determinants of Variance in the Habitual Physical Activity of Overweight Adults

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***Background*:** The number of days of data and number of subjects necessary to estimate total physical activity (TPA) and moderate-to-vigorous physical activity (MVPA) requires an understanding of within- and between-subject variances, and the influence of sex, body composition, and age. ***Methods*:** Seventy-one adults wore accelerometers for 7-day intervals over 6 consecutive months. ***Results*:** Body fat and sex influenced TPA and MVPA. The sources of subject-related variation for TPA and MVPA were within-subject (48.4% and 54.3%), between-subject (34.3% and 31.8%), and calendar effects (17.3% and 13.9%). Based on within-subject variances, the error associated with estimating TPA and MVPA by collecting 1 to 7 days of data ranged from 28.2% to 13.3% for TPA and 62.0% to 28.6% for MVPA. Based on between-subject variances, detecting a 10% difference between 2 groups at a power of 90% requires approximately 200 and 725 subjects per group for TPA and MVPA, respectively. ***Conclusions*:** Estimates of MVPA are more variable than TPA in overweight adults, therefore more days of data are required to estimate MVPA and larger sample sizes to detect treatment differences for MVPA. Log-transforming data reduces the need for additional days of data collection, thereby improving chances of detecting treatment effects.

***Keywords*:** activity monitor, sample size, accelerometry

Given the important benefits of both habitual total physical activity (TPA) and moderate-to-vigorous physical activity (MVPA),[1,2] the ability to plan well-designed studies that assess TPA or MVPA with an acceptable degree of confidence depends on measuring a sufficient number of subjects and sampling an adequate number of days.[3] The same issues apply to studies designed to detect differences in TPA and MVPA between 2 or more groups. There are a number of techniques for monitoring TPA and MVPA, but increasing importance has been placed on the use of accelerometers.[4] Different studies using accelerometers have adopted a variety of strategies for collecting and analyzing the resulting count data, and conclusions regarding sampling strategies differ, detailed below.

Estimates of TPA and MVPA are influenced by within-subject variability (which determines the number of days of data required per subject) and between-subject variability (which determines the number of study subjects required). Within-subject variance for TPA has been estimated to explain 29% to 60%[5–7] and 34% to 38% of the total variance for different intensities of physical activity,[5] while the between-subject variance for TPA has been estimated to explain 53% to 62%[5,6] and 53% to 57% of the total variance for different intensities of physical activity.[5] Other important contributors to variance are day-of-week, weekend vs. weekday, month, and/or season.[5,7–9] An array of demographic factors may also influence the variability in TPA and MVPA, such as sex, body composition, and age.[5,7]

Different studies have taken various approaches to determine the adequate number of days of data collection to assess TPA and MVPA, ranging from 7 days of data collection,[6,9] 14 days of data collection spread out over the course of a year,[7] and 21 continuous days of data collection.[5] In these studies, the criterion for determining an adequate number of days of data collection used the Spearman-Brown Prophecy formula,[7,9] generalizability theory,[6] and intraclass correlation coefficients (ICC).[5] Overall, the most current recommendations for sampling an adequate number of days of data in adults is 3 to 5, based on the criterion of an ICC of at least 0.80.[3]

Although all of the aforementioned studies have advanced the field of physical activity assessment via accelerometry tremendously, limitations of these studies can result in imprecise estimates of within- and between-subject variances. First, although it is recognized that there are daily, monthly, and/or seasonal variations in physical activity, the short data collection periods of these studies (repeated 48-hr observations and 7 to 21 days of continuous monitoring) can bias downward the estimates of within-and between-subject variance. Second, many of these studies had a relatively homogenous subject pool (reducing between-subject variance), did not account for variables such as body fat percentage (increasing between-subject variance), and failed to differentiate between TPA and MVPA (increasing within-subject variance). Lastly, the use of an ICC of 0.8 (or Spearman-Brown Prophesy formula of 0.8) has been questioned.[3,10] These limitations likely produce excessively liberal (too small) estimates of the number of days of data necessary to estimate TPA and MVPA.[10]

The purposes of this study were to monitor the habitual (6 month) TPA and MVPA of a group of overweight adults over a prolonged period of time, then 1) determine different scenarios for the number of days of data necessary for reasonable estimates of TPA and MVPA and 2) generate sample size estimates for detecting biologically realistic differences between groups of subjects for TPA and MVPA.

Methods

Subjects

Female and male volunteers who were overweight or obese and at increased risk of disease (individuals who were mildly

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Table 1 Characteristics of the Study Subjects

	Women*	Men*
n	37	34
Age (yrs)	49.5 (9.7)	53.2 (7.92)
Body mass index ($kg \cdot m^{-2}$)	31.1 (2.5)	30.8 (2.14)
Body fat (%)	41.0 (4.3)	29.4 (5.39)**
Total physical activity ($counts \cdot min^{-1}$)	187.7 (53.6)	197.3 (69.7)
Moderate-to-vigorous physical activity ($min \cdot d^{-1}$)	22.7 (14.1)	30.4 (17.8)**

* Numbers are mean (SD).

** Significant difference between sexes, $P < .05$.

hypercholesterolemic, prediabetic, or prehypertensive were included) were recruited to participate in this study (Table 1). Inclusion criteria included body mass index (BMI) of 28 to 35 $kg \cdot m^{-2}$, body weight less than 137 kg, and 35 to 65 years of age. The study protocol was approved by the MedStar Research Institute Institutional Review Board. Before participation, subjects provided written informed consent and received a medical evaluation by a physician that included measurement of blood pressure, and fasting blood and urine samples for clinical tests (including a profile of hematological and biochemical parameters). A pregnancy test was performed on blood samples from females.

Physical Activity Monitoring

Subjects were instructed to wear the accelerometer (Actigraph Model 7164) twice per month (1 week on and 1 week off) for 6 months (February to July). After confirming proper calibration of the accelerometer using the device provided by the manufacturer, the accelerometer was set to record the data in 1-min epochs of time. Subjects were asked to wear the accelerometer on the right hip, unless they reported being unable to do so. Regardless of the accelerometer placement, it was worn on the same side and location. The accelerometer was worn as a snuggly-fitting belt worn on the waist (according to the manufacturer's instructions), with a manufacturers' "notch" facing upwards. Ninety-five women and men were recruited to participate in the study, with 73 completing the 6-month study. Two subjects were removed from the analysis due to poor adherence (less than 30 days of data; see below).

Since accelerometers are commonly removed periodically during the day (eg, showering, personal care) and/or subjects demonstrate poor adherence, it is rare to find subjects that wear them for 24 hr/day (although subjects were free to do so if they chose). Therefore, our criterion for inclusion was accelerometer data for a minimum of 12 hr/day, where 20 min of consecutive zeros constituted nonwearing times.[11] We have shown previously that the zeros resulting from accelerometer removal, poor adherence, and differences in sleeping hours can have detrimental effect on the estimation of physical activity, therefore we developed a procedure (applied to each subject) to adjust data for sleep hours and short periods of accelerometer removal.[11] Daily data were scanned for the presence of physical activity > 32,000 $counts \cdot min^{-1}$, which indicates monitor malfunction (days where this occurred were removed from the analysis).

Physical activity was categorized as daily averages ($counts \cdot min^{-1} \cdot day^{-1}$) and the amount of MVPA in $min \cdot day^{-1}$. The cut-off for characterizing MVPA (2020 $counts \cdot min^{-1}$) was based on Troiano et al.[2]

Body Weight and Composition

Body composition was measured by dual-energy x-ray absorptiometry (DEXA; QDR 4500, Hologic, Inc, Waltham, MA). Height and weight were measured to the nearest 0.1 cm and 0.1 kg, respectively. Body mass index (BMI) was calculated as weight (kg)/height $(m)^2$.

Statistics

Differences between the demographics of women and men were analyzed with the PROC TTEST procedure in SAS.[12] The analyses of differences in TPA and MVPA by day-of-week, week, and month were made with the SAS PROC MIXED procedure, with the Tukey multiple comparisons *P*-value adjustment for error containment.

To estimate within- and between-subject variances for TPA and MVPA, a 2-part process was used. First, different combinations of fixed effects (day-of-week, calendar week, month, sex, body composition, BMI, and age) were tested to determine whether each explained a significant amount of variance using the SAS PROC MIXED procedure with variance components estimated using maximum likelihood. Next, different combinations of random effects (subject, day-of-week, calendar week, and month) were tested using the SAS PROC MIXED procedure with variance components estimated using restricted maximum likelihood. The final model chosen was the lowest value of Akaike's Information Criterion (AIC) used as the criterion. Analyses were performed using both raw and log-transformed data because our previous work has demonstrated the presence of heteroscedasticity in raw accelerometer data.[11,13] Many comparable studies do not report checking for nonnormality or normalizing the data.[2,5,14–16] Raw data were analyzed so that our results could be directly compared with others that did not transform. However, we found that a log (counts/min + 1) or log (min/d + 1) transformation considerably improved the distributional characteristics of the data such that the positive relationship between the variance and mean for raw data were largely eliminated and that residuals of models had an approximately normal distribution

A variance decomposition was used to estimate the contribution of within- and between-subject variances, and other sources of variance. Variances were estimated using the SAS PROC MIXED procedure using restricted maximum likelihood. We used the between-subject mean (averaged first each subject, then across all subjects) and variance (from the variance decomposition) to estimate the statistical power to detect 10, 15, 20, and 25% differences in TPA and MVPA between 2 different populations, as described by Castelloe[17] (assuming an $\alpha = 0.05$). The mean ± standard deviation (square root of the variance) and Coefficient of Variation (CV) for TPA was 192.3 ± 59.3 (CV= 30.8%) and 5.14 ± 0.33 (CV = 6.4%) $counts \cdot min^{-1}$ for raw and log-transformed data, respectively (Table 3). The mean ± standard deviation (and CV) for MVPA was 26.4 ± 15.6 (CV= 59.0%) and 2.82 ± 0.67 (CV = 23.8%) $min \cdot d^{-1}$ for raw and log-transformed data, respectively.

To determine the effect of different days of sampling on the estimate of habitual (6 months) TPA and MVPA, all subjects with 7 consecutive acceptable days of data were identified (n = 62). Then, a resampling technique based on the SAS PROC SURVEY procedure was used to take 1000 samples of data in 1, 2, 3, 4, 5, 6, and 7 consecutive day intervals. The average TPA and MVPA from these intervals were then compared with habitual (6 months) TPA and MVPA by calculating a percent absolute difference.

Results

Characteristics of Study Subjects

Characteristics of the study subjects are given in Table 1. Overall, a total of 4228 days of data were included in the analysis, an average of 60.1 ± 8.8 days of data per study subject (ranging from 37 to 76 days per subject). The average accelerometer wear time of the subjects was 17.1 ± 2.5 hrs/day, assuming nonwear[2] was detected by intervals of at least 60 min of consecutive zeros with allowance for 1 to 2 min of physical activity between 0 to 100 counts·min^{-1}.

Effect of Daily, Weekly, and Monthly Variability in TPA and MVPA

The effect of day of week can be observed in Table 2; TPA and MVPA were significantly lower on Sunday than the other days of the week (but other days were not significantly different from each other). There were no significant differences for TPA or MVPA due to week or month (data not shown).

Models for TPA and MVPA

The best model (lowest value for AIC) for estimating TPA (raw and log-transformed data) included day-of-week, sex, body fat percentage, and calendar week as fixed effects. The final model for MVPA (raw and log-transformed data) included day-of-week, body fat percentage, and calendar week as fixed effects. Random effects for TPA and MVPA (raw and log-transformed data) were subject, and, all nested within subject, calendar week, day-of-week, and month. A variance decomposition is given in Table 3.

Table 2 Total and Moderate-to-Vigorous Physical Activity as a Function of Day-of-Week

	TPA	MVPA
	Counts·min^{-1}*	Min·d^{-1}*
Sunday	176.8 (3.9)**	21.8 (1.1)**
Monday	195.6 (4.1)	27.3 (1.1)
Tuesday	197.8 (4.2)	29.2 (1.1)
Wednesday	194.7 (4.2)	27.6 (1.2)
Thursday	197.3 (3.8)	28.6 (1.0)
Friday	193.5 (3.8)	26.7 (1.0)
Saturday	199.3 (3.9)	27.0 (1.1)

* Least squares mean (standard error).

** Sunday significantly different from all other days of the week, $P < .05$.

Abbreviations: TPA, total physical activity; MVPA, moderate-to-vigorous physical activity.

Days of Monitoring Required To Estimate TPA and MVPA

Table 4 demonstrates the effect of sampling 1 to 7 sequential days of data to estimate habitual TPA and MVPA over the 6-month measurement period. If only a single day of data are sampled, the differences with habitual TPA and MVPA are 28.2 and 62.0% (5.5 and 26.1% using log transformed data), respectively. Increasing the number of days sampled to 7 reduces the error to 13.3 and 28.6% (5.1 and 10.8% using log transformed data) for TPA and MVPA, respectively.

Power Calculations

Figure 1 depicts sample size and power estimates for detecting differences in TPA and MVPA between 2 different populations given true differences of 10%, 15%, 20%, and 25% and an α of 0.05. A sample size of 175 and 10 subjects per group (raw and log-transformed, respectively) is sufficient to detected a 10% difference in TPA at a power of 90%. However, approximately 625 and 110 subjects per group (raw and log-transformed, respectively) are required for MVPA at a power of 90%.

Discussion

The results of this investigation indicate that several variables affect the estimates of habitual (6 mo) physical activity in adults, which in turn, have implications for determining the number of days of data needed to reasonably estimate TPA and MVPA. Across subjects, day-of-week (Sunday specifically) is a significant consideration, though calendar week and month are not. There are week-to-week differences for individuals (captured as a within-subject random effect); but calendar weeks were not a systematic effect (ie, physical activity doesn't increase for everyone on the 15th week of the year). Our models also included a random within-subject day-of-week, calendar week, and month effects, indicating that subjects did respond to other calendar effects, but not in a consistent way across subjects. Body composition affects the estimates of both TPA and MVPA, while sex is only predictive for TPA. Lastly, these results indicate the importance of checking residuals from modeling TPA and MVPA for heteroscedasticity (eg, using the log [counts/min + 1]

Table 3 Variance Decomposition for the Estimates of Habitual Total and Moderate-to-Vigorous Physical Activity

	Total physical activity				Moderate-to-vigorous physical activity			
	Raw		Log+1		Raw		Log+1	
Source of variance	Variance	%	Variance	%	Variance	%	Variance	%
Between-subject	3514.8	34.3	0.0970	39.8	244.5	31.8	0.4444	37.5
Within-subject	4962.6	48.4	0.1117	45.8	416.8	54.3	0.5591	47.2
Week*	976.3	9.5	0.0162	6.7	53.0	6.9	0.0743	6.3
Day-of-week*	485.9	4.7	0.0117	4.8	36.6	4.8	0.0821	6.9
Month*	322.4	3.1	0.0071	2.9	16.9	2.2	0.0243	2.1
Total	10262.0		0.2438		767.9		1.1843	

* Nested within-subject.

Table 4 Differences[a] Between Sampling 1 to 7 Days of Data When Compared With Habitual Total and Moderate-to-Vigorous Physical Activity

	Total physical activity				Moderate-to-vigorous physical activity			
	Raw		Log +1		Raw		Log +1	
	Counts·min^{-1}	%	Counts·min^{-1}	%	Min·d^{-1}	%	Min·d^{-1}	%
All	192.0 (60.6)		5.14 (0.32)		26.1 (15.6)		2.80 (0.70)	
1	185.2 (92.2)	28.2 (24.1)	5.52 (0.46)	5.53 (4.65)	24.9 (26.3)	62.0 (70.0)	2.77 (1.06)	26.1 (25.4)
2	186.1 (76.7)	20.6 (17.5)	5.13 (0.39)	3.93 (3.31)	25.3 (22.0)	48.8 (56.4)	2.77 (0.90)	19.3 (19.5)
3	186.1 (69.6)	17.7 (13.6)	5.13 (0.36)	3.41 (2.65)	25.3 (20.3)	41.9 (43.8)	2.77 (0.82)	16.1 (13.8)
4	186.2 (63.2)	14.6 (10.7)	5.13 (0.34)	2.79 (2.17)	25.1 (17.2)	30.9 (34.0)	2.80 (0.77)	11.3 (10.3)
5	186.6 (62.5)	13.2 (10.4)	5.13 (0.33)	2.51 (2.10)	25.8 (17.9)	32.1 (42.0)	2.78 (0.74)	11.1 (11.7)
6	186.2 (61.5)	12.8 (10.3)	5.13 (0.32)	2.48 (2.02)	25.3 (17.2)	30.5 (37.4)	2.77 (0.72)	10.7 (11.8)
7	185.1 (60.7)	13.3 (10.4)	5.12 (0.32)	2.59 (2.21)	24.9 (16.3)	28.6 (32.9)	2.77 (0.70)	10.8 (10.9)

[a] Mean (SD).

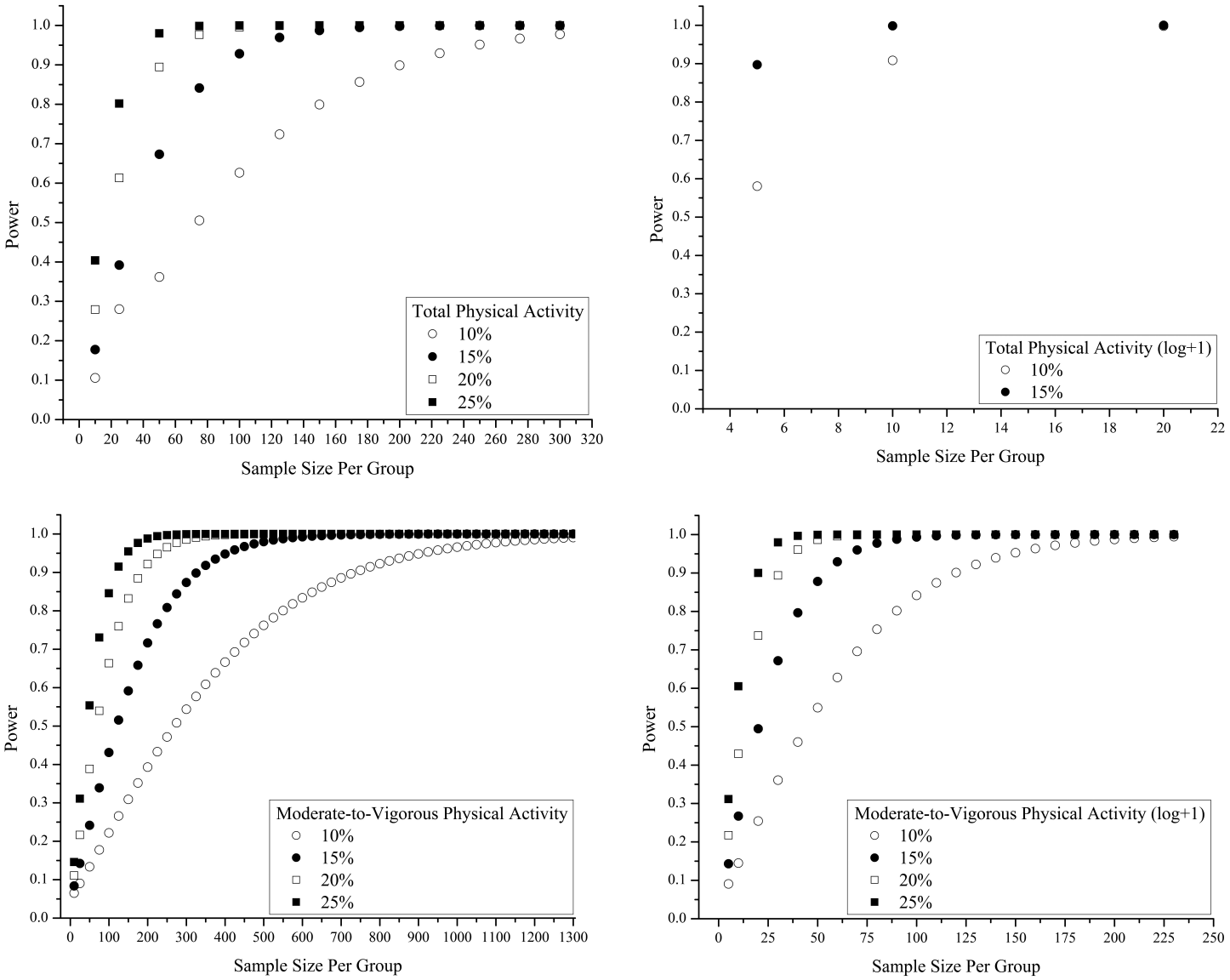

Figure 1 — Sample size and statistical power to detect 10%, 15%, 20%, and 25% differences between 2 groups of subjects ($\alpha = 0.05$) for total and moderate-to-vigorous physical activity (raw data and log+1).

transformation greatly reduced heteroscedasticity), and performing the appropriate transformation if necessary.

A number of studies have demonstrated the influence of daily and monthly variability on the estimate of physical activity. Gretebeck[9] reported lower TPA (kcal·d^{-1}) on Sundays when compared with Wednesday, Thursday, and Friday. Similarly, Matthews[5] found that women spent less time in MVPA on Sunday vs. Saturday. Seasonal variability in TPA has also been reported, where winter TPA may be less than summer and spring/fall,[8] or higher levels of TPA in warmer months vs. colder months.[7] Although the current study demonstrates that day-of-week, weekly, and monthly variability may be important considerations, these effects differ substantially by subject.

The amount of within- and between-subject variance for TPA are not consistent in the literature, and few differentiate between TPA and MVPA. The within-subject variance for TPA in the current study (48.4%, raw data) was comparable to Coleman[6] (46%), but lower than Levin[7] (60%), and higher than Matthews[5] (29% to 37%). The between-subject variance estimate for TPA for the current study (34.3%, raw data) was lower than Coleman[6] (53%) and Matthews[5] (60% to 62%). We replicated the same model for TPA as Matthews,[5] and found the within-and between-subject variances were 58.0 and 37.8%, respectively, with week (nested within subject) explaining 4.2%. Matthews et al[5] is one other study that has reported within- and between-subject variances for MVPA (34% to 38% and 53% to 57%, respectively), which differed from the current study (54.3% and 31.8%, respectively for raw data). These are important differences since they have implications for the estimation of how much data are needed to estimate TPA and MVPA.

There are a number of possible explanations for the lack of agreement among the estimates of within- and between-subject variance for the current study and that of others. First, the data collection periods were different (7 to 21 days of data collection[6,5]). Coleman[6] had a relatively homogenous population of men (18–30 yrs; so one might expect less subject-to-subject variation) and a different device. Matthews[5] nested day-of-week within subject, but didn't include week and month nested within subject as random variables. Based on our results, much but not all of this additional 9% to 13% of the variation from these latter 2 components can be assigned to the within-subject variance. The MVPA cut-off for Matthews[5] (1952 counts/min) was also different from the current study (2020 counts/min).

One important consideration is that the estimates of within-and between-subject variances mentioned above are based on untransformed count data. However, the presence of residual heteroscedasticity suggested the need to log-transform our data. When this was performed, there were large changes in our variance estimates, in particular the within-subject percent variance decreased; this would presumably be true for others as well.

Days of Monitoring Required To Estimate TPA and MVPA

A common measurement period of 7 days is used because that is believed to yield a reliability of 80%.[18] The current study indicates that 7 days of data collection results in a 2.59% and 13.3% (log-transformed and raw data, respectively) average difference with habitual TPA (defined as the 6-month average). The same 7 days of data collection results in an average difference of 10.8% and 28.6% for MVPA (log-transformed and raw data respectively). Another measure of variability, the standard deviation of estimates, produces similar results (Table 4). Therefore, investigators must carefully consider the magnitude of the effects they wish to detect when deciding how much data to collect. Since log-transforming the data greatly improved the estimates for both habitual TPA and MVA, we recommend adopting this or a similar transformation when analyzing accelerometer data.

A common question in the literature is "how many days of data are needed?" to estimate habitual physical activity.[3,10,18] The results of the current study indicate that the number of days of data needed are dependent on the type of habitual physical activity of interest (TPA or MVPA) and postcollection treatment of the data (eg, use of heteroscedasticity reducing or variance stabilizing transformation). The number of study subjects needed to detect differences in habitual physical activity between groups also depends on the type of physical activity of interest and the demographic characteristics of the study subjects. Unfortunately, due to the study design, we cannot estimate how close to habitual TPA and MVPA estimates would become beyond 7 days, though clearly using more days will gradually converge on the 6 mo mean. Using log transformed TPA data, an approximate 95% upper confidence limit for 7 sequential days of data are 2.57% + 2 × 2.21% ≈ 7% error, and fewer days (eg, 4) yield only slightly larger values. This may be sufficiently accurate for some purposes. Unfortunately, for MVPA, even 7 days of data would not be sufficient to accurately estimate habitual physical activity.

For practical applications of these results to epidemiological studies interested in estimating habitual MVPA, we would like to make comparisons with Troiano et al.[2] The subjects from Troiano et al[2] were asked to wear an accelerometer for 7 days, whereby approximately 32% of the 40- to 59-year-olds fulfilled this criteria. Based on the results of the current study, the measured MVPA for a given study participant likely differed (higher or lower) from their habitual MVPA by an average of 29%, even in the most compliant subjects. In terms of sample size, to detect a difference in MVPA between 40- to 49-year-old women (n = 258; mean = 19.9 min·d^{-1}) and men (n = 259; mean = 34.7 min·d^{-1}) at a power of 0.9, a standard deviation of 15.6, and $\alpha = 0.05$, only 44 study subjects were needed (22 per group). However, when comparing 20 to 59-year-old Non-Hispanic white men (n = 465; mean = 34.6 min·d^{-1}) and Non-Hispanic black men (n = 174; mean = 37.9 min·d^{-1}) at a power of 0.9, a standard deviation of 15.6, and $\alpha = 0.05$, 942 subjects (471 per group) were needed to detect the difference. So, in the latter comparison, it could be argued that this detectable difference could have been statistically significant had more Non-Hispanic black men had been included in the sample. In addition, far fewer subjects would have been required for either comparison if the data had been log transformed.

In conclusion, the current study provides a number of insights into understanding the nature of habitual physical activity. However, it is important to note there are a number of issues to take into consideration when applying these results. Given that the study subjects were middle-aged with an average BMI greater than 30, the within- and between-subject variance estimates could be different in other populations. Although the average TPA and MVPA were lower on Sundays, there is considerable variation in day-of-week effects among study subjects. Therefore, it is important to capture as many different days of the week of data as possible for each subject, as opposed to rigidly requiring Sunday data collections for all study subjects. Another important question is how many days of data collection are required to capture habitual TPA and MVPA with more accuracy than the lowest estimate in Table 4? Using log-transformations greatly reduced the number of days required, whereby less than a week of data collection

appeared adequate for TPA. Since the study subjects only wore the accelerometers over 7 consecutive day periods, we cannot reliably estimate habitual TPA or MVPA for studies conducted longer than 7 consecutive days (thus we can't provide the number of additional days that would be necessary for very accurate estimates). Lastly, the results of this study are from a group of highly-adherent study subjects (an average of 17 hrs/day), therefore the inference space of these analyses differ from studies reporting results from less adherent participants.

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References

1. Donnelly JE, Blair SN, Jakicic JM, Manore MM, Rankin JW, Smith BK. American College of Sports Medicine Position Stand. Appropriate physical activity intervention strategies for weight loss and prevention of weight regain for adults. *Med Sci Sports Exerc*. 2009;41(2):459–471. PubMed doi:10.1249/MSS.0b013e3181949333
2. Troiano RP, Berrigan D, Dodd KW, Masse LC, Tilert T, McDowell M. Physical activity in the United States measured by accelerometer. *Med Sci Sports Exerc*. 2008;40(1):181–188. PubMed doi:10.1249/mss.0b013e31815a51b3
3. Trost SG, McIver KL, Pate RR. Conducting accelerometer-based activity assessments in field-based research. *Med Sci Sports Exerc*. 2005;37(11, Suppl):S531–S543. PubMed doi:10.1249/01.mss.0000185657.86065.98
4. Troiano RP. A timely meeting: objective measurement of physical activity. *Med Sci Sports Exerc*. 2005;37(11, Suppl):S487–S489. PubMed doi:10.1249/01.mss.0000185473.32846.c3
5. Matthews CE, Ainsworth BE, Thompson RW, Bassett DR, Jr. Sources of variance in daily physical activity levels as measured by an accelerometer. *Med Sci Sports Exerc*. 2002;34(8):1376–1381. PubMed doi:10.1097/00005768-200208000-00021
6. Coleman KJ, Epstein LH. Application of generalizability theory to measurement of activity in males who are not regularly active: a preliminary report. *Res Q Exerc Sport*. 1998;69(1):58–63. PubMed doi:10.1080/02701367.1998.10607667
7. Levin S, Jacobs DR, Jr, Ainsworth BE, Richardson MT, Leon AS. Intra-individual variation and estimates of usual physical activity. *Ann Epidemiol*. 1999;9(8):481–488. PubMed doi:10.1016/S1047-2797(99)00022-8
8. Buchowski MS, Choi L, Majchrzak KM, Acra S, Mathews CE, Chen KY. Seasonal changes in amount and patterns of physical activity in women. *J Phys Act Health*. 2009;6(2):252–261. PubMed
9. Gretebeck RJ, Montoye HJ. Variability of some objective measures of physical activity. *Med Sci Sports Exerc*. 1992;24(10):1167–1172. PubMed doi:10.1249/00005768-199210000-00016
10. Baranowski T, Masse LC, Ragan B, Welk G. How many days was that? We're still not sure, but we're asking the question better! *Med Sci Sports Exerc*. 2008;40(7, Suppl):S544–S549. PubMed doi:10.1249/MSS.0b013e31817c6651
11. Paul DR, Kramer M, Stote KS, et al. Estimates of adherence and error analysis of physical activity data collected via accelerometry in a large study of free-living adults. *BMC Med Res Methodol*. 2008;8:38. PubMed doi:10.1186/1471-2288-8-38
12. SAS Version 9.3. Cary, NC, USA.
13. Paul DR, Kramer M, Moshfegh AJ, Baer DJ, Rumpler WV. Comparison of two different physical activity monitors. *BMC Med Res Methodol*. 2007;7:26. PubMed doi:10.1186/1471-2288-7-26
14. Evenson KR, Buchner DM, Morland KB. Objective measurement of physical activity and sedentary behavior among US adults aged 60 years or older. *Prev Chronic Dis*. 2012;9:E26. PubMed
15. Vallance JK, Winkler EA, Gardiner PA, Healy GN, Lynch BM, Owen N. Associations of objectively-assessed physical activity and sedentary time with depression: NHANES (2005-2006). *Prev Med*. 2011;53(4-5):284–288. PubMed doi:10.1016/j.ypmed.2011.07.013
16. Hansen BH, Kolle E, Dyrstad SM, Holme I, Anderssen SA. Accelerometer-determined physical activity in adults and older people. *Med Sci Sports Exerc*. 2012;44(2):266–272. PubMed doi:10.1249/MSS.0b013e31822cb354
17. Castelloe JM. *Sample size computations and power analysis with the SAS system*. SAS Institute Inc; 2002.
18. Matthews CE, Hagstromer M, Pober DM, Bowles HR. Best practices for using physical activity monitors in population-based research. *Med Sci Sports Exerc*. 2012;44(1, Suppl 1):S68–S76. PubMed doi:10.1249/MSS.0b013e3182399e5b