Best Practices in the Data Reduction and Analysis of Accelerometers and GPS Data

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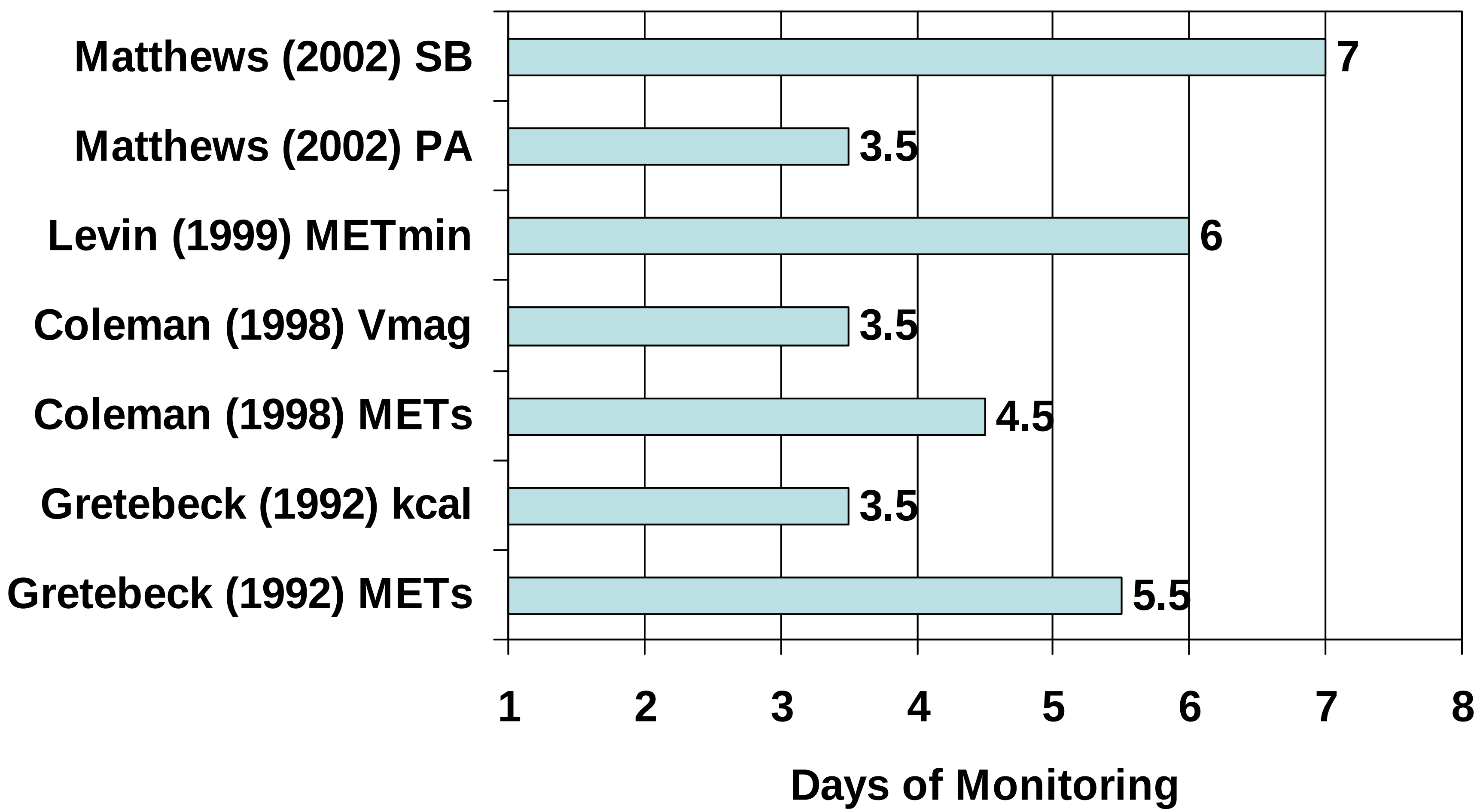
Key Planning Issues

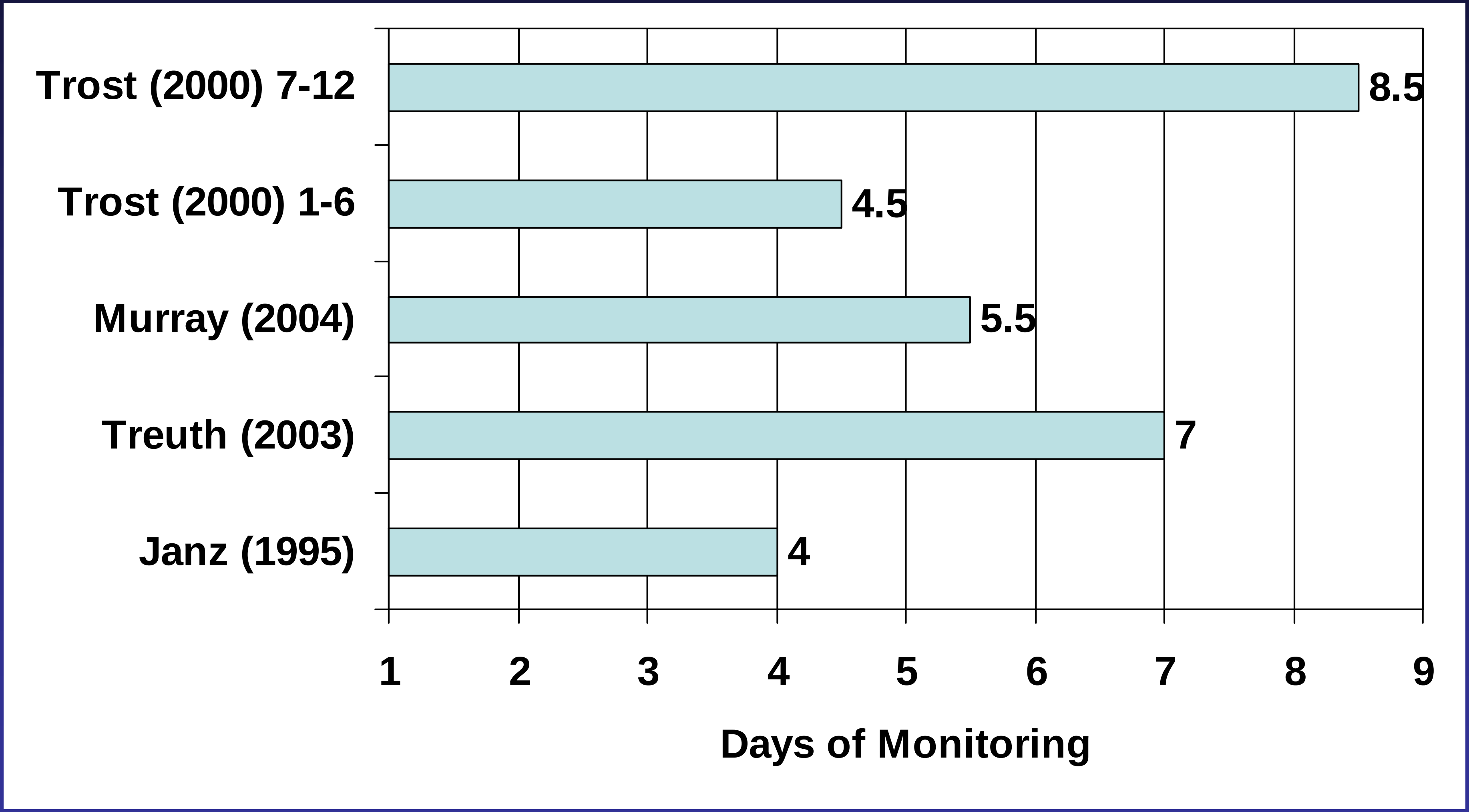
- Number of Days of Monitoring
- Epoch Length
- Monitor Distribution and Collection
- Promoting Compliance

Days of Monitoring – Adult Studies



Trost, McIver, Pate. Med Sci Sports Exerc 2005:37(11, Suppl):S531-S543

Days of Monitoring – Youth Studies



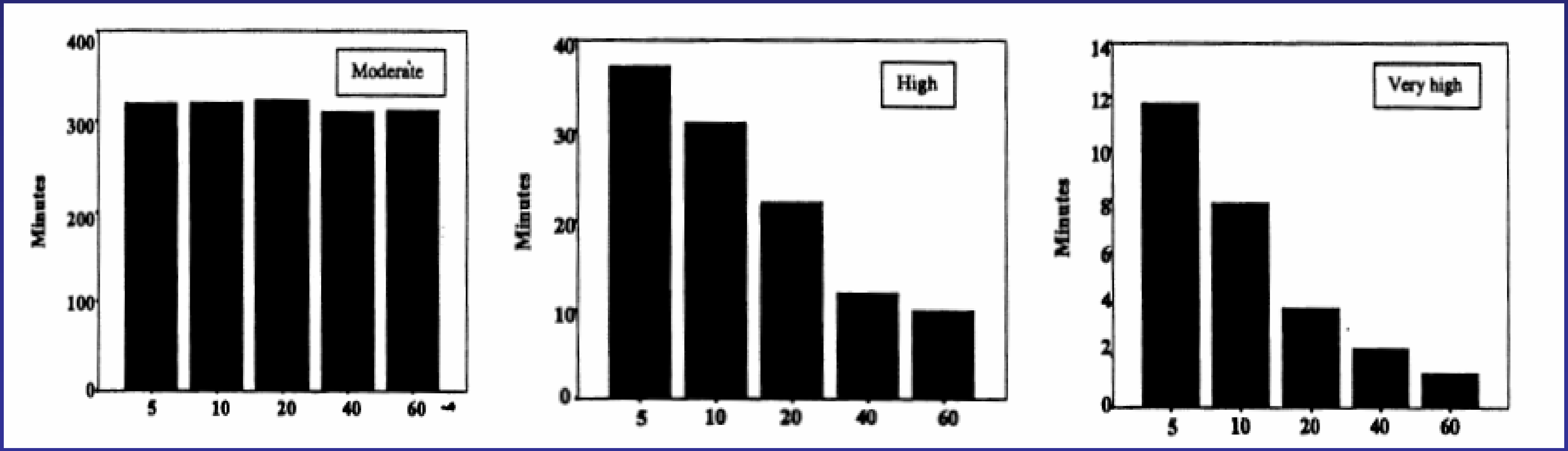
Trost, McIver, Pate. Med Sci Sports Exerc 2005:37(11, Suppl):S531-S543

Effect of Epoch Length

- Cut-points based on 1-min epochs could significantly underestimate children’s highly sporadic and intermittent activity patterns.
- Over the 1-min period, bursts of vigorous activity and brief periods of inactivity are averaged
- Vigorous activity becomes “masked”
- Unexplored issue in the adult population

Effect of Epoch Length

- 16 children (mean age 7.5 ± 0.3 y)
- Wore monitor on right hip and lower back
- 4 monitoring days, 5-second epoch
- Mins of PA estimated via Freedson adult cut-points



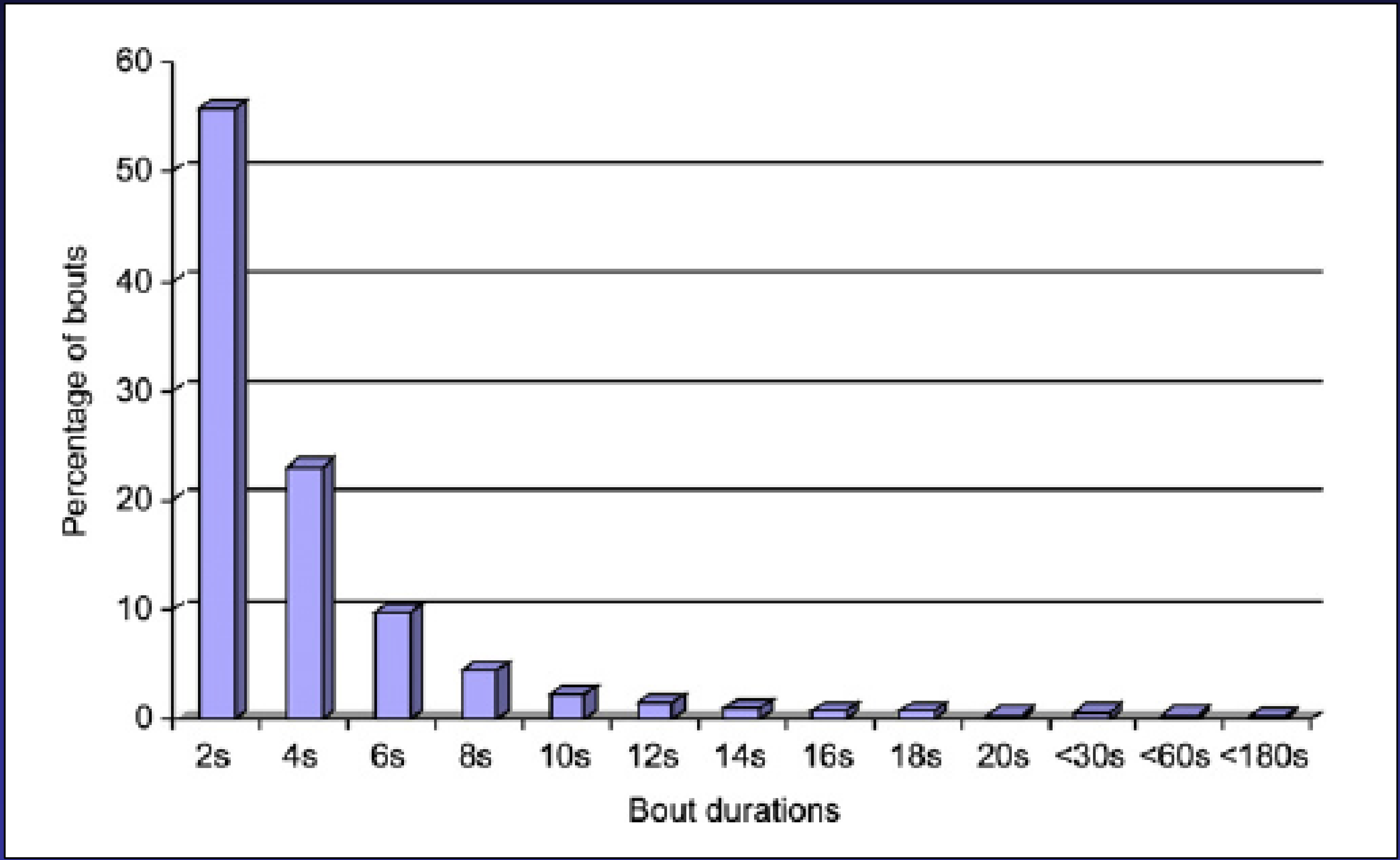
Nilsson, Ekelund, Yngve,& Sjostrom (2002) *Pediatric Exercise Science*,14,87-96

Effect of Epoch Length

- Baquet et al. (2007)
- 26 children (mean age 9.95 ± 0.99 y)
- Epoch set for 2-seconds
- Minutes of PA estimated via Freedson adult cut-points
  - LPA – 70.8 ± 13.2 seconds
  - MPA – 9.0 ± 2.8 seconds
  - VPA – 4.7 ± 1.2 seconds
- 80% of MPA bouts, 93% of VPA bouts lasted < 10 seconds

Baquet, Stratton, Van Praagh, Berthoin *Preventive Medicine* 2007;44:143-147

Effect of Epoch Length



Baquet, Stratton, Van Praagh, Berthoin *Preventive Medicine* 2007;44:143-147

Epoch and Cut-Points

TABLE 2. Descriptive statistics, root mean squared error (RMSE), and significant of differences between direct observation (DO) and AG accelerometer derivations of MVPA by epoch.

Intensity Derivation	Mean MVPA (s)	Median MVPA (25th, 75th percentile) (s)	MVPA Range (s)	RMSE (s)	Significance (DO vs AG Epoch)
DO	522 ± 48	521 (487, 559)	420–632	NA	NA
Treuth					$F = 103$, $P < 0.001$
T_5	318 ± 87	310 (265, 370)	100–470	218	$P < 0.001$*
T_10	309 ± 87	310 (250, 370)	30–490	231	$P < 0.001$*
T_15	289 ± 99	285 (225, 345)	30–465	249	$P < 0.001$*
T_20	277 ± 107	260 (220, 320)	20–500	263	$P < 0.001$*
T_30	242 ± 97	240 (80, 300)	0–450	293	$P < 0.001$*
T_60	246 ± 146	240 (120, 360)	0–540	310	$P < 0.001$*
Mattocks (4 MET)					$F = 174$, $P < 0.001$
M_5	248 ± 80	250 (205, 295)	40–400	284	$P < 0.001$*
M_10	230 ± 92	220 (180, 300)	20–420	304	$P < 0.001$*
M_15	214 ± 97	210 (135, 270)	0–405	320	$P < 0.001$*
M_20	207 ± 104	200 (140, 260)	0–440	328	$P < 0.001$*
M_30	183 ± 85	180 (120, 240)	0–360	350	$P < 0.001$*
M_60	137 ± 121	120 (16, 180)	0–420	405	$P < 0.001$*
Freedson (4 MET)					$F = 1.3$, $P = 0.275$
F_5	488 ± 91	490 (445, 545)	260–655	91	NA
F_10	506 ± 101	510 (460, 570)	260–680	93	NA
F_15	504 ± 113	510 (450, 570)	195–675	108	NA
F_20	506 ± 117	520 (460, 580)	180–700	112	NA
F_30	495 ± 129	480 (450, 570)	150–750	122	NA
F_60	525 ± 179	540 (420, 720)	60–780	161	NA

MVPA, moderate-to-vigorous physical activity. T_, M_, and F_ 5, 10, 15, 20, 30, and 60 correspond to specific epoch lengths (in seconds) for Treuth et al. (26), Mattocks et al. (10), and Freedson et al. (6) children's activity count cutpoints:
* Significantly different based on alpha of 0.008 (i.e., Bonferroni alpha correction for multiple comparisons).

McClain et al. Med Sci Sports Exerc 2008;40:2080-2087

Distribution & Collection

- Face to face at home, school or other community setting – collection the same.
- Mail to subject and return via mail.
- Combination of distributing face-to-face by returning via mail.
- Postage or shipping option viable.
- Compensation contingent upon the safe return of monitor.
- This has not been systematically studied

Promoting Compliance

- Multiple single day monitoring
- Frequent contacts during the monitoring period
- Written materials/ flyers
- Logs – promotes self-monitoring
- Apply “relapse prevention model”
- Giving them options for wearing under clothes
- Educate teachers, coaches, referees, and other sport officials
- Show participants graphical display of data
- Providing incentives contingent on compliance – money, gift certificates, coupons, extra credit.

Key Data Reduction Issues

- Minimal wear requirements / a valid day
- Identifying spurious data
- Computing summary variables
  - Calibration of accelerometer output
- Extracting bouts
- Imputing data

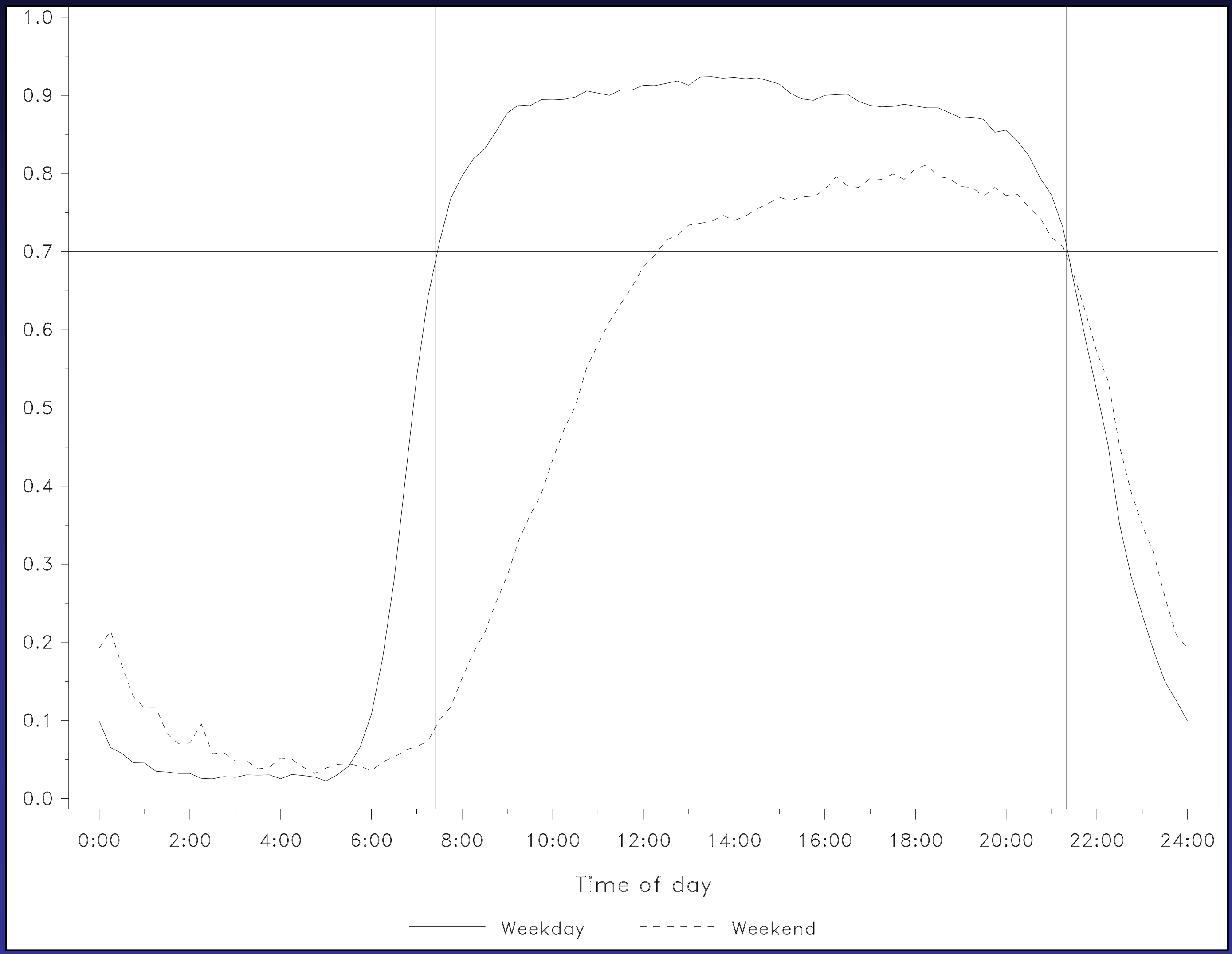
What is a complete day ?

- Zero Count method
  - Counting strings of consecutive 0 counts
  - 60-minutes
  - 20-minutes
  - 10-minutes
- Compared to criterion for “registered counts”
  - 720 - 840 1-min epochs
  - 12 -14 hours per day of wearing time
  - “Bouts” of zero strings > 3 bouts indicate non-wearing

Cut-off for "complete" day

- 70/80 rule
  - Find 70th percentile of on and off times
  - Define adherence as 80% of the difference in on/off times.
- Weekdays
  - on: 7:15 AM; off: 9:15 PM (14 hrs)
  - Adherence 11.2 hours
- Weekends
  - on: 12:15 PM; off: 9:15 PM (9 hrs)
  - Adherence 7.2 hours

What is a complete monitoring day ?



Sample Data Approach used in the TAAG intervention study

Identifying Spurious Data

- Variety of criteria have been used
- ≥ 16,000 - 20,000 counts
- Percentile Approach
- # of SD's
- Should also screen for negative counts strings of identical counts
- Possible with ActiGraph software

Computing Summary Variables

- Usually calculated for each monitoring day
- Total Counts
- Average counts per minute?
- Time spent in sedentary, light, moderate, and vigorous physical activity
- Meeting guidelines
- Based on the average or aggregate?
- # of valid days makes a big difference

Calibration of Activity Monitors

- Numerous equations exist!!!
- Early studies were treadmill-based.
- More recent studies use “free living” non-ambulatory activities plus locomotor activity.
- Predictive validity in field settings remains a question.
- NB: None appear to be valid for individual level prediction of PAEE.

Lots of Equations!

TABLE 1. Description of existing ActiGraph prediction equations and cut points.

	Source Activities				Prediction Equation					Cut Points		
Reference	Sit Rest	Walk	Run	Mixed Dynamic-Static	Units	Intercept	Slope	R^2	SEE	Inactive/Light	Moderate	Vigorous
Freedson (11) *N* = 50; men/women (avg ~24 yr)		2	1		METs	1.439	0.000795	0.82	1.12	0–1951	1952	5725
Nichols (28) *N* = 30; men/women (18–35 yr)		2	1		METs[a]	1.731	0.0007271	0.89	1.06	0–1576[b]	3285[b]	5677[b]
Yngve (42) *N* = 28; men/women (avg ~23 yr) (see equation code below)[c]		2	1		METs	0.751	0.0008198	0.86	1.10	0–2742	2743	6403
					METs	1.136	0.0008249	0.85	1.14	0–2259	2260	5896
					METs	1.004	0.0007587	0.89	0.96	0–2630	2631	6585
					METs	1.762	0.0007371	0.86	1.09	0–1679	1680	5750
Brage (7) *N* = 12; men (23–30 yr)		2	2		METs[a,d]	2.886	0.0007429 −0.02 ($\dot{V}O_2$)	0.89	0.91	0–1809	1810	5850
Hendelman (14) *N* = 25; men/women (30–50 yr)		4			METs	1.602	0.000638	0.59	0.87	0–2190	2191	6893
		4		6	METs	2.922	0.000409	0.35	0.96	0–190	191	7526
Swartz (34) *N* ~10/activity; men/women (19–74 yr)		4		24	METs	2.606	0.0006863	0.32	1.16	0–573	574	4945
Leenders (18) *N* = 28, men/women (avg ~24 yr)		5			METs	2.240	0.0006	0.74	0.53	0–1266	1267	6252

NHANES Cutpoints for Adults

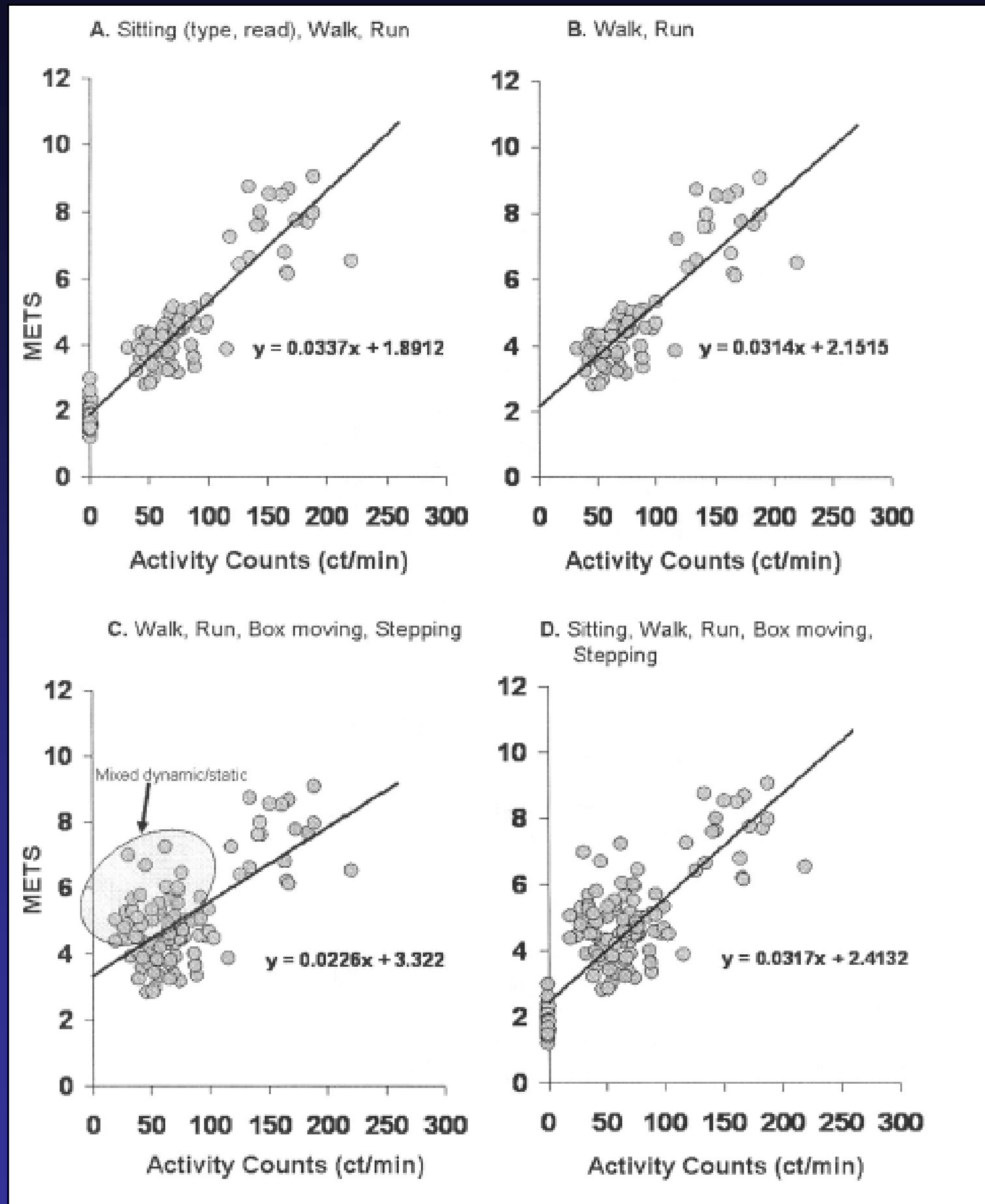
Author		Moderate	n		Vigorous	n	
Freedson	Treadmill	1952	50	668.49	5725	50	1960.62
Yngve	Track	2743	28	526.05	6403	28	1227.97
	Treadmill	2260	28	433.43	5896	28	1130.74
Brage	Treadmill	1810	12	148.77	5850	12	480.82
Leenders	Treadmill	1267	28	242.99	6251	28	1198.82
				2019.7			**5999.0**

Note heterogeneity among studies in cut-points, especially for moderate activities.

Decision: weighted average of these studies.

Slide courtesy of Rick Troiano NCI

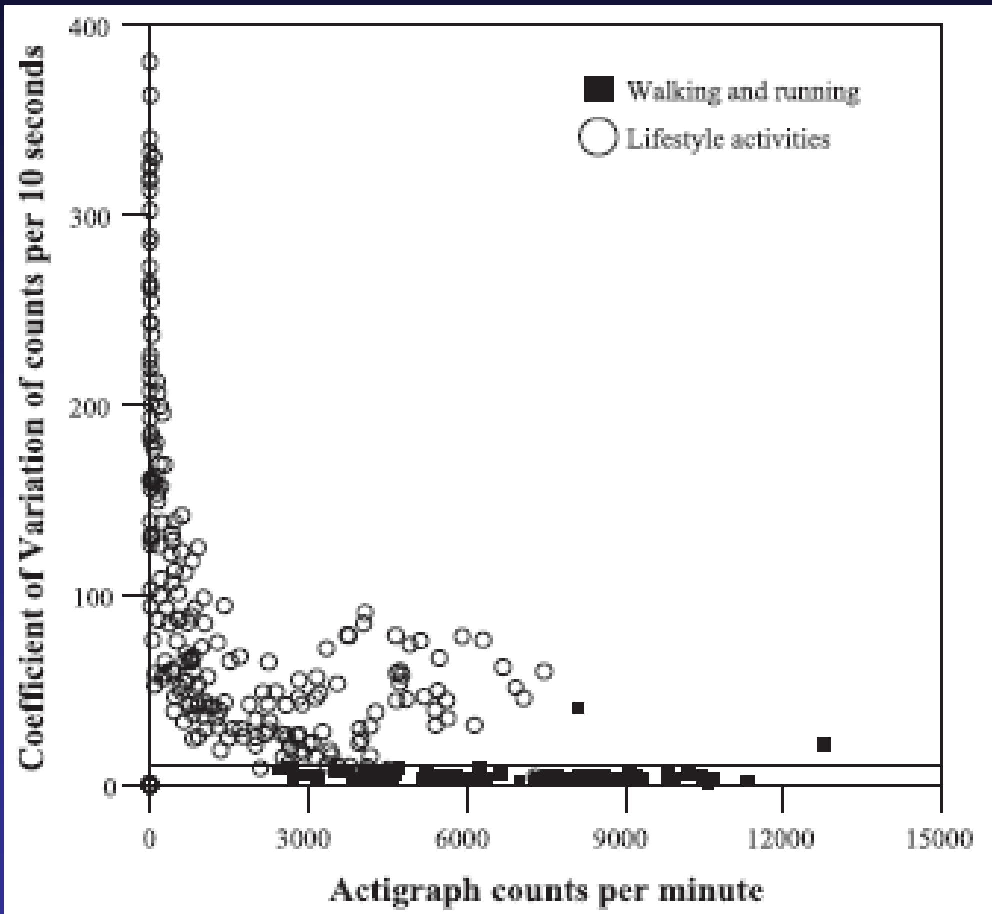
Why do the cut-points differ so much?

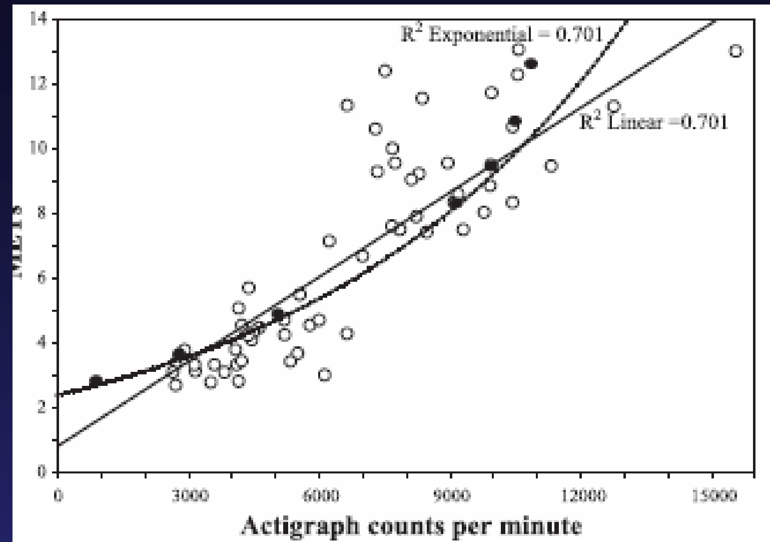


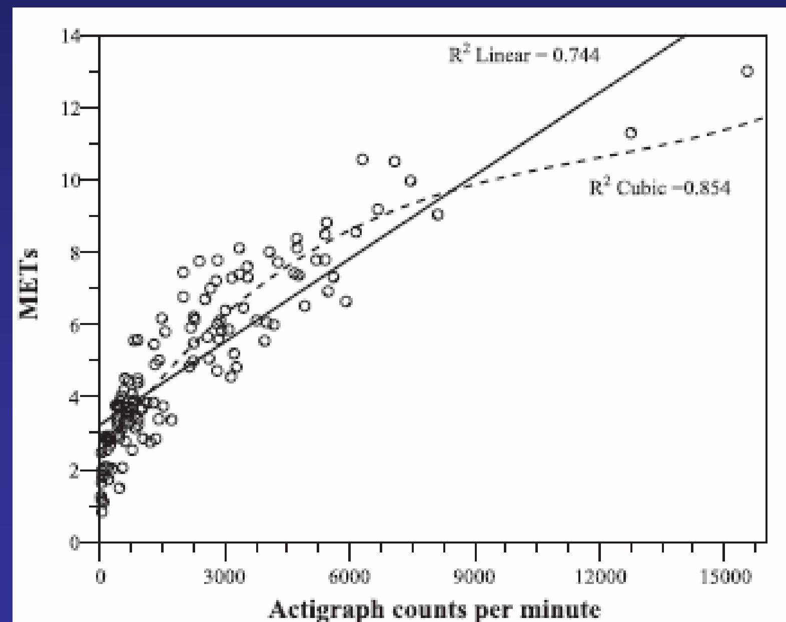
Matthews CE. Med Sci Sports Sci 2005 37(11 Suppl):S512-522

A step forward – 2 regression model

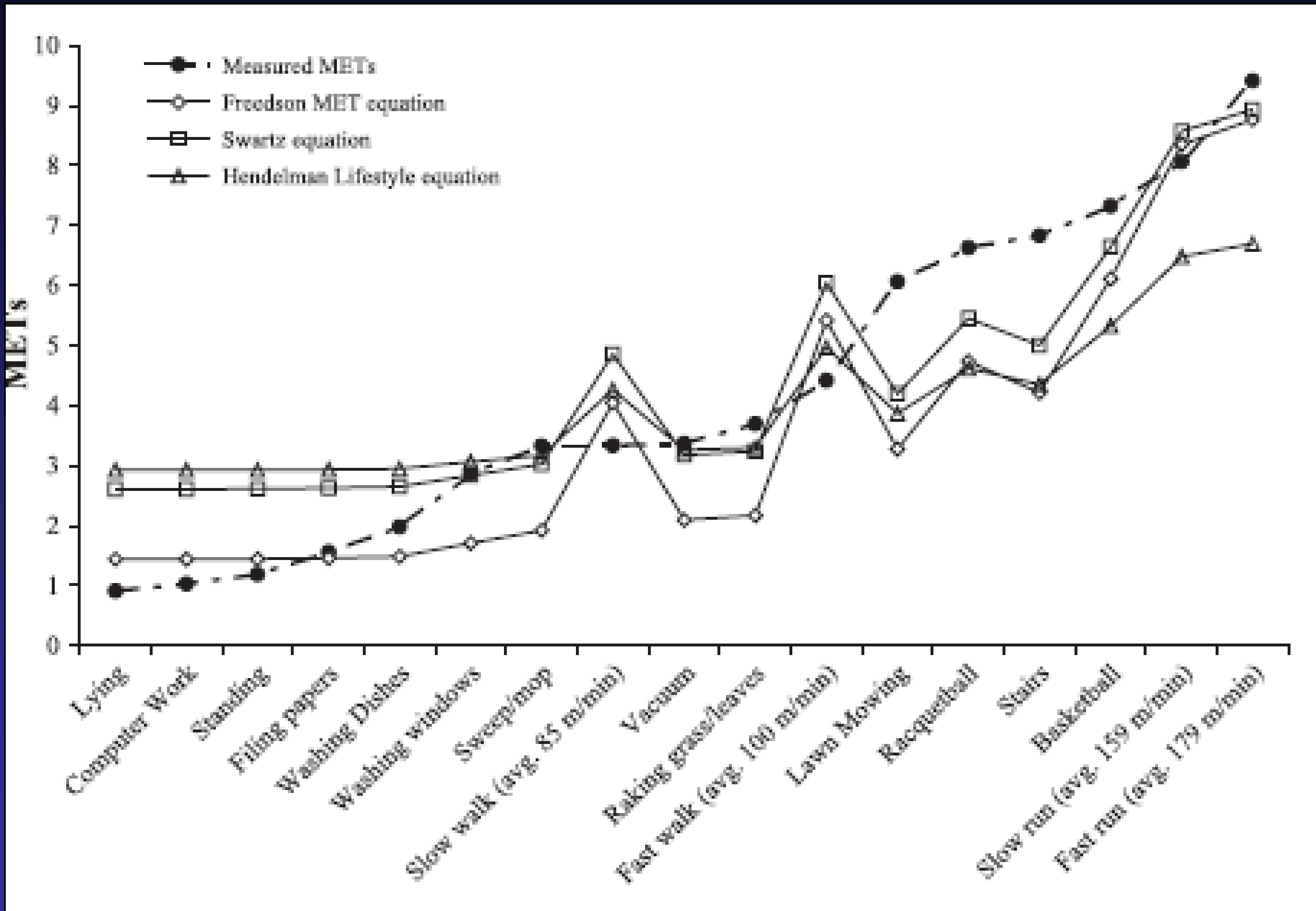
- Crouter et al. *JAP* 100:1324-1331
- Background
  - No single equation line is able to accurately predict EE or time spent in different intensity categories across a wide range of activities
  - Overestimation of walking and running
  - Underestimation of lifestyle activities
  - Hypothesized that walking and running can be distinguished from other activities on the basis of variability in counts







Crouter, Clowers, Bassett *J Appl Physiol* 2006;100:1324-1331



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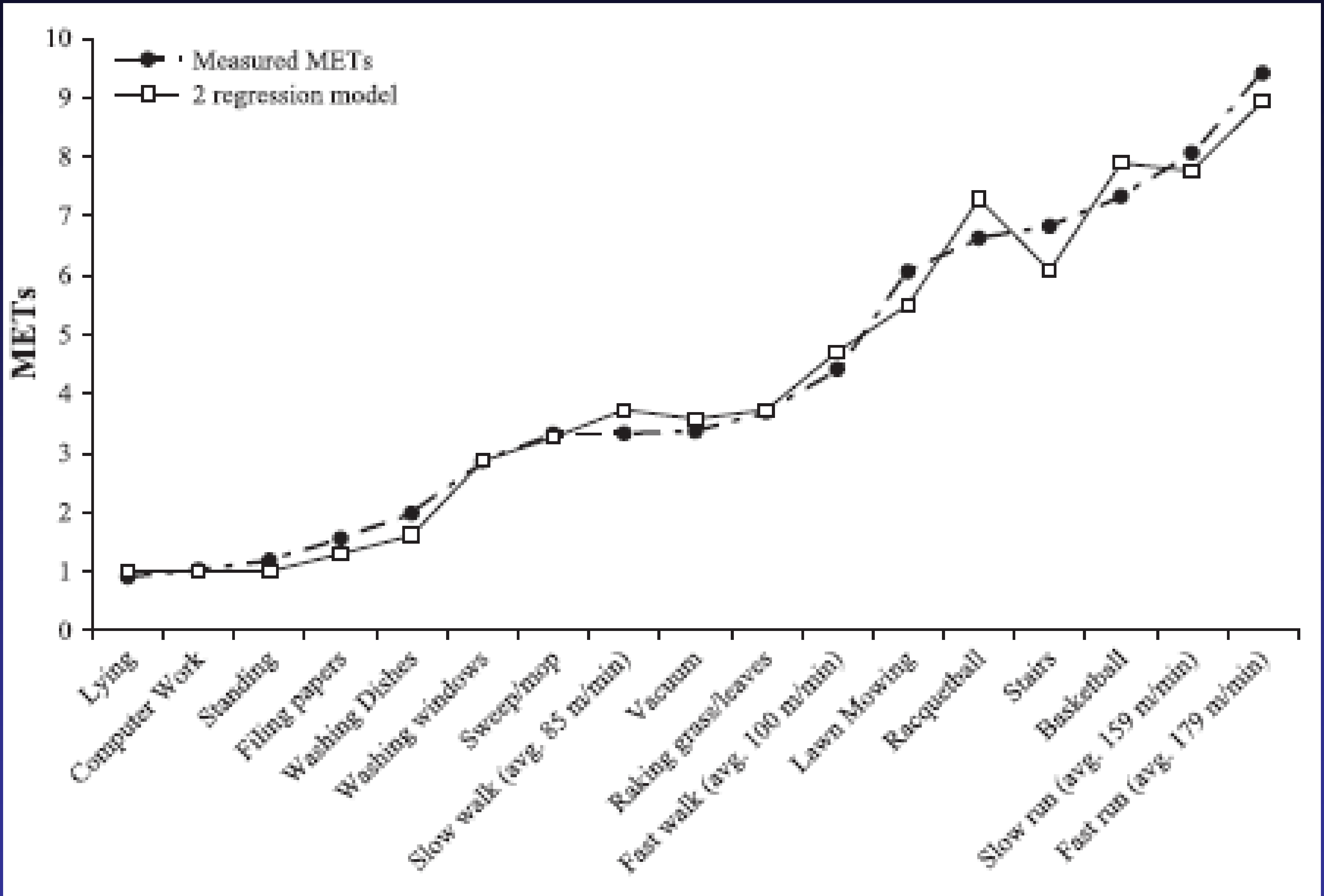
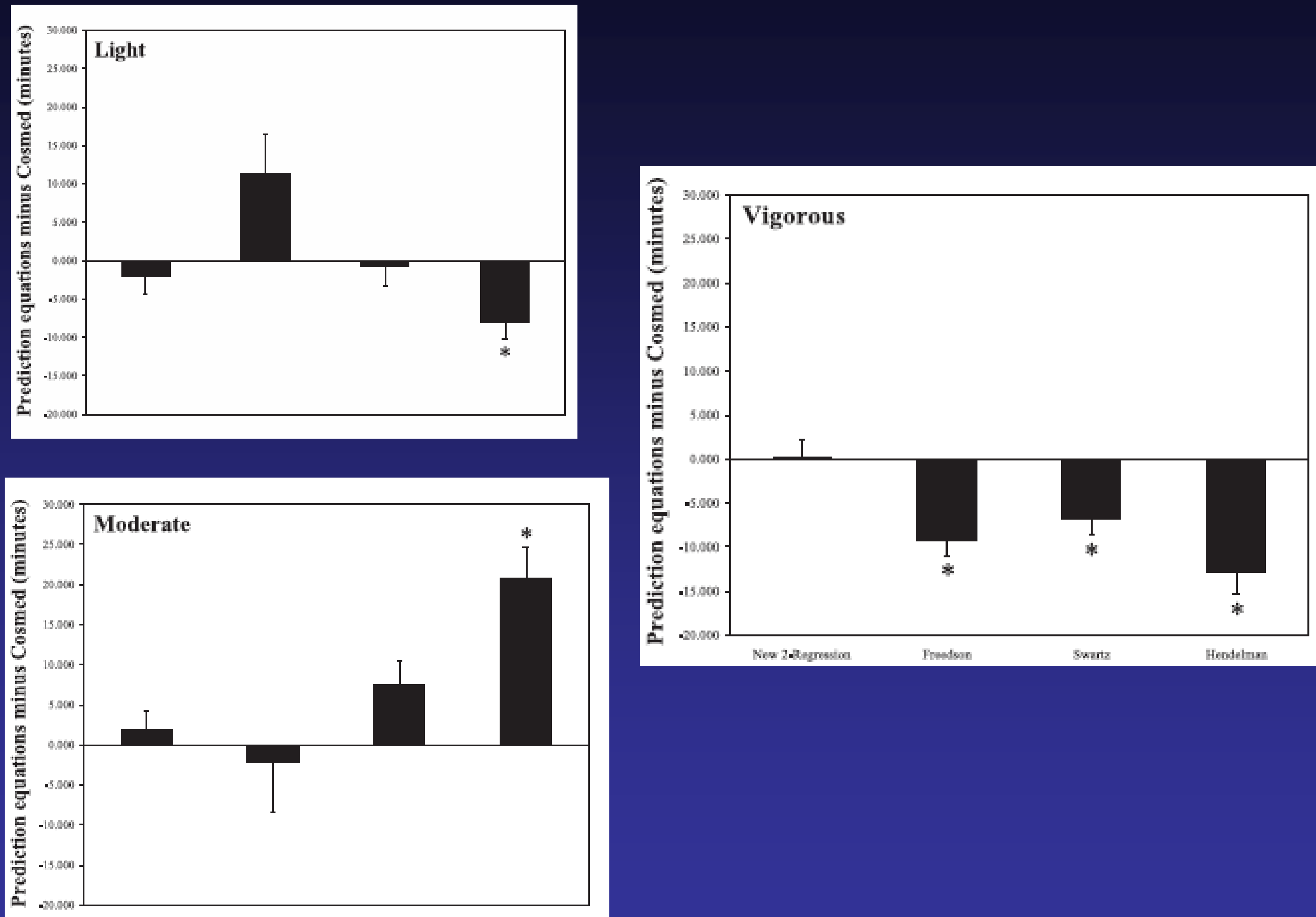


Crouter, Clowers, Bassett *J Appl Physiol* 2006;100:1324-1331



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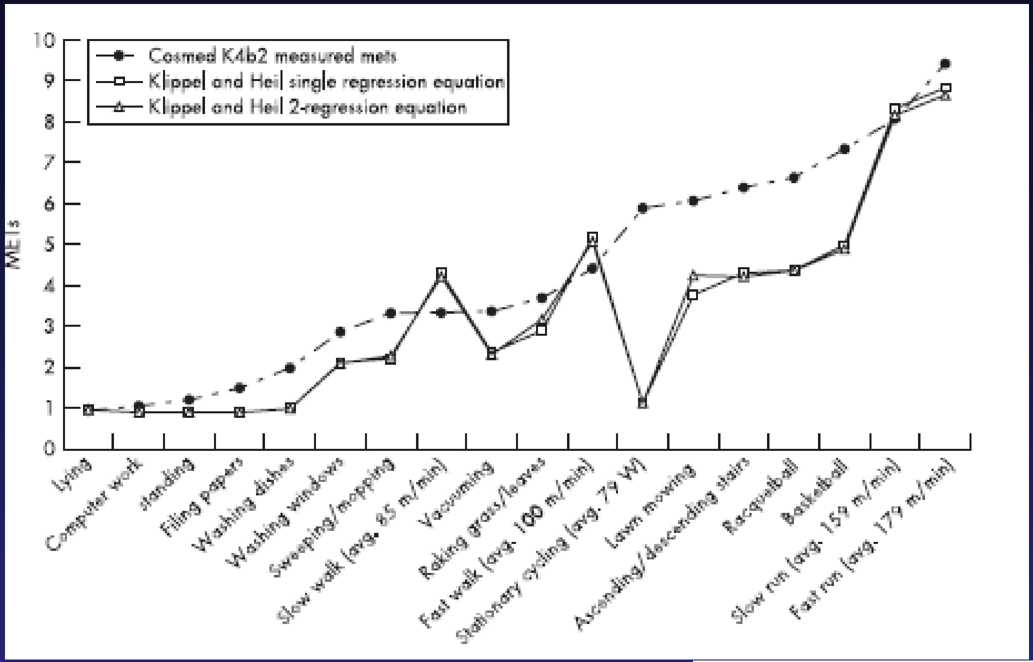
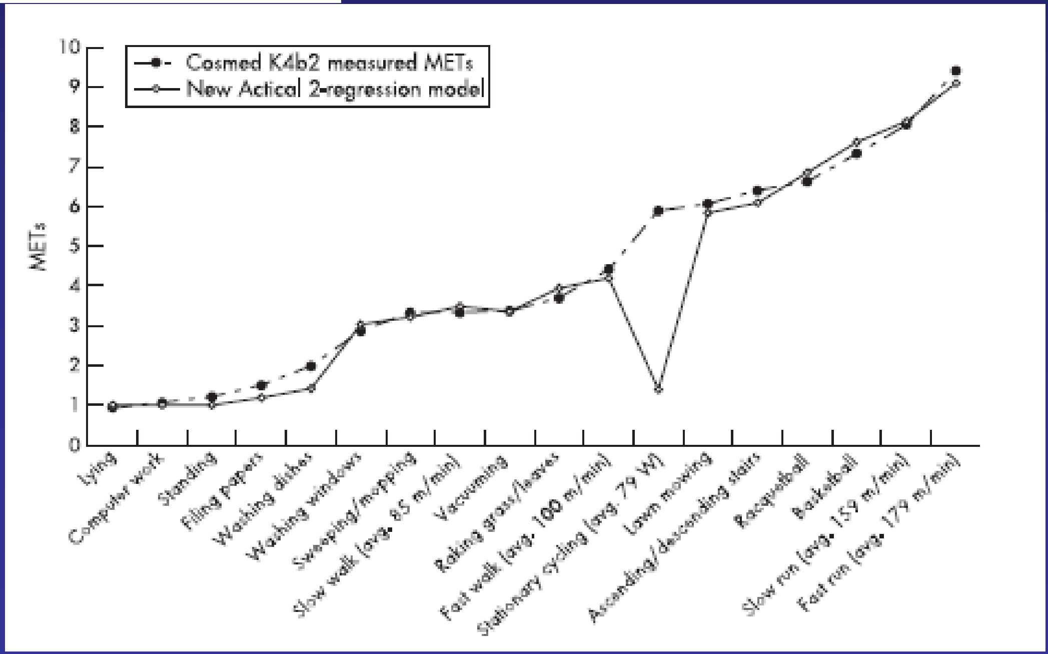




Br. J. Sports Med. 2008;42;217-224;

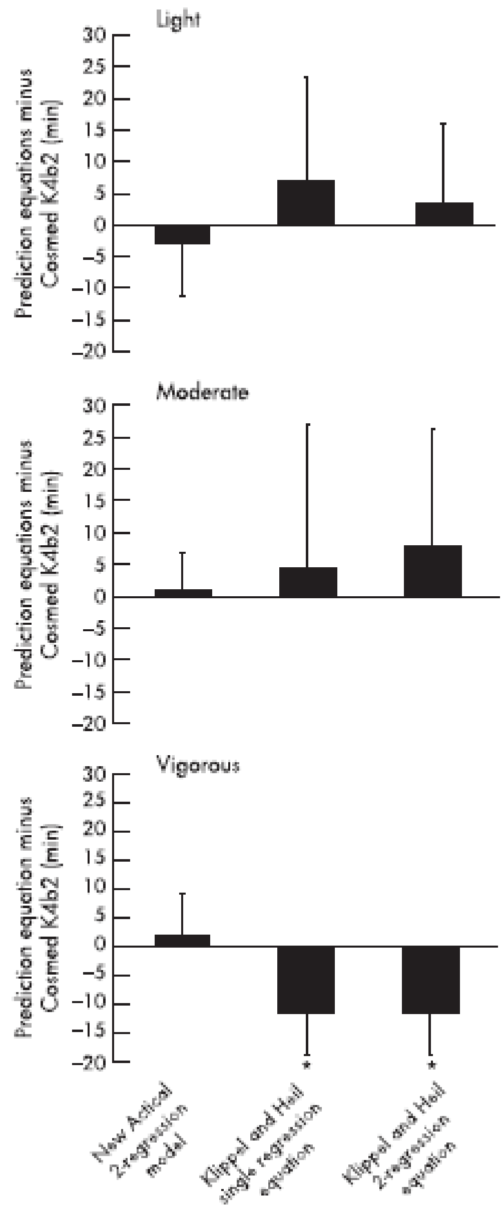


Figure 7 Mean error scores (prediction minus actual) for minutes spent in light (<3 METs), moderate (3–5.99 METs) and vigorous (≥6 METs) physical activity, in the cross-validation group. Values are mean (SE); *Significantly different from criterion ($p<0.05$).

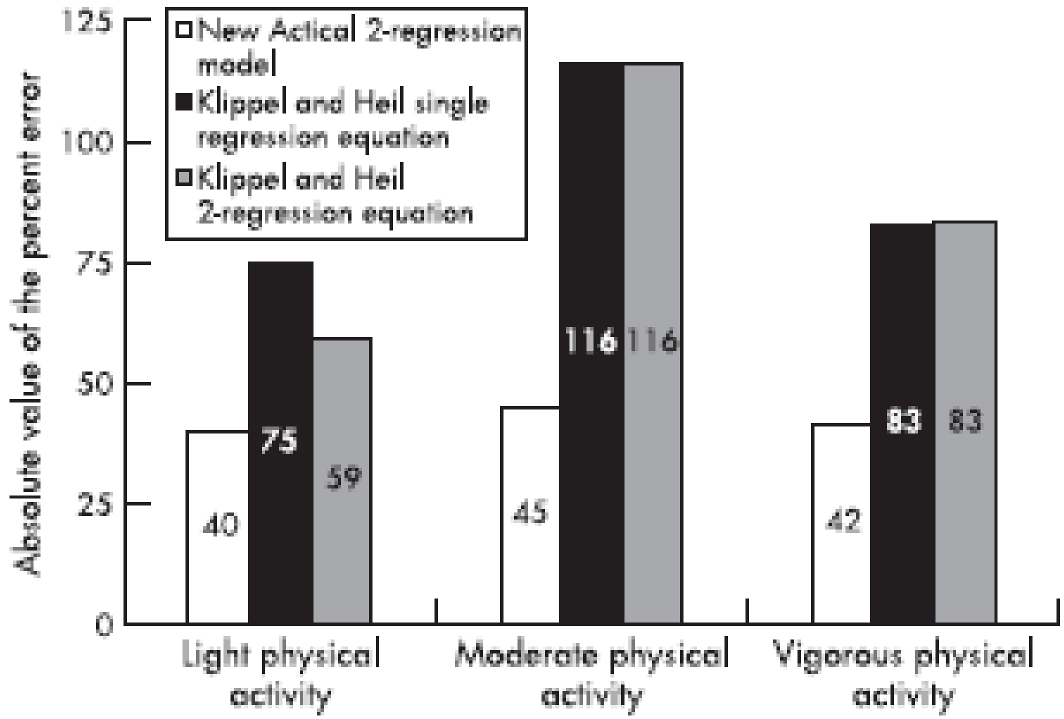


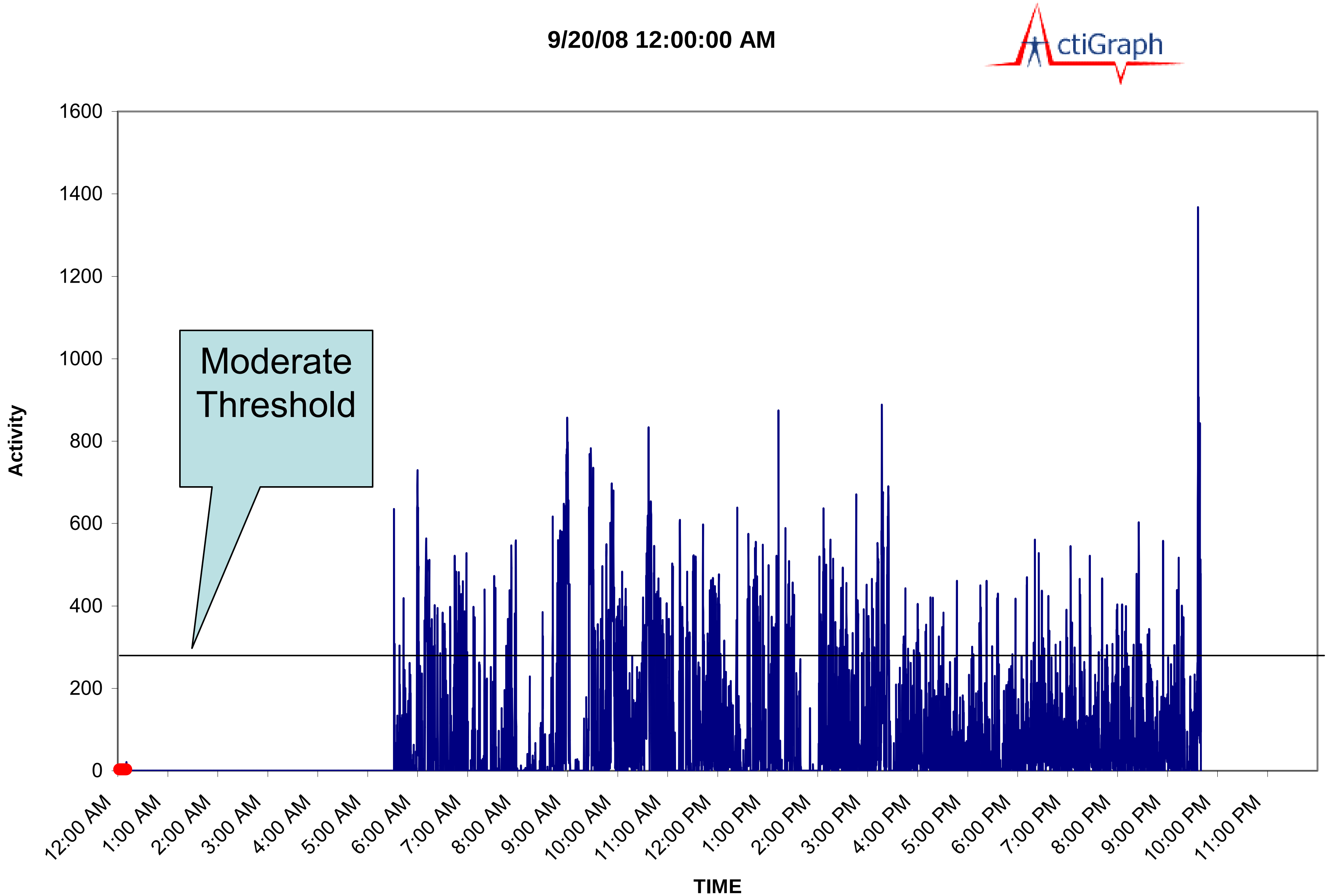
Figure 8 Absolute per cent difference between the Cosmed K4b² and each prediction equation for time spent in light (<3 METs), moderate (3–5.99 METs) and vigorous (≥6 METs) physical activity, in the cross-validation group.

Br. J. Sports Med. 2008;42;217-224;

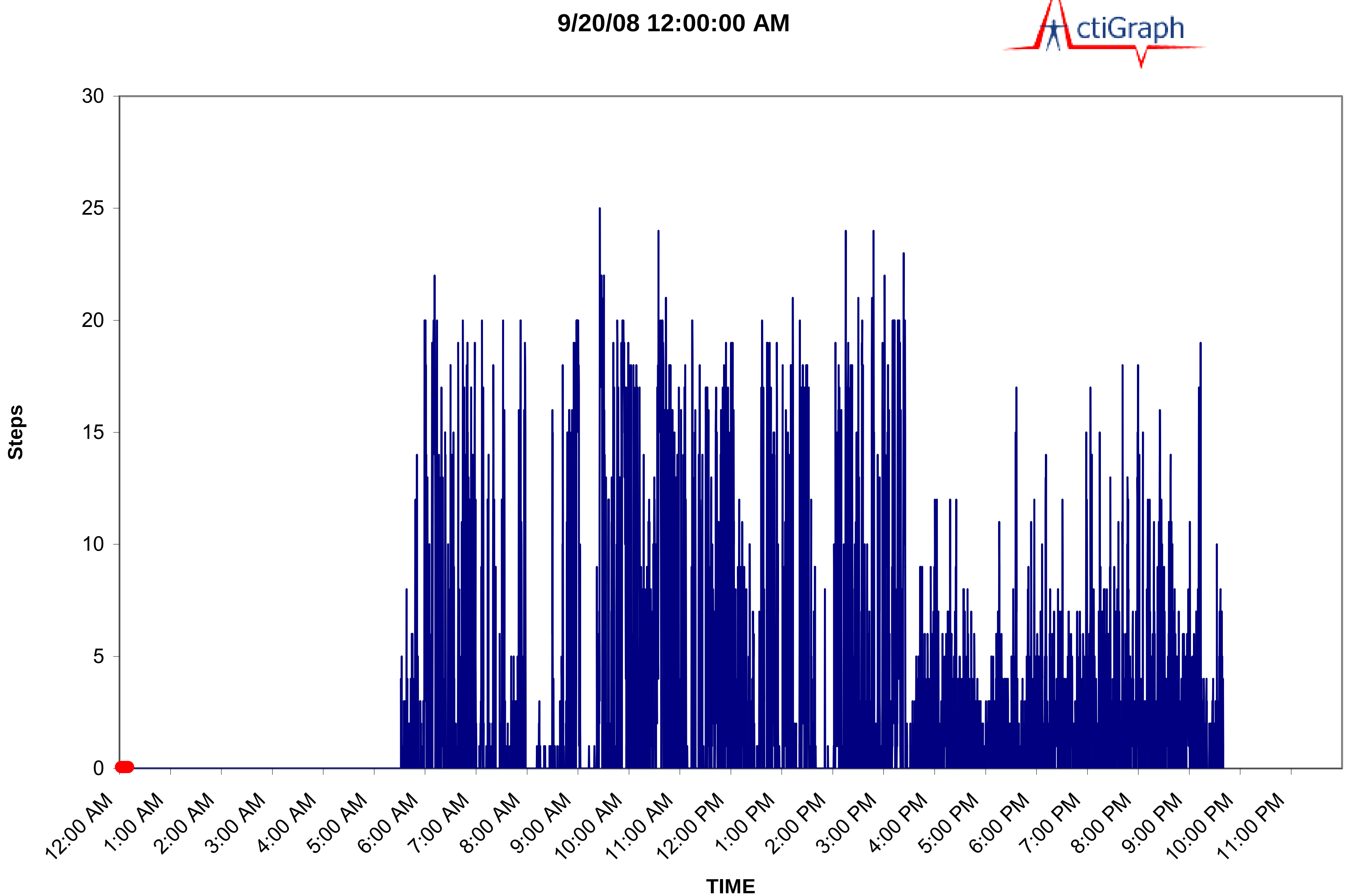
Physical Activity at Work – Lauren

- Wore the Actigraph GT1M accelerometer for the entire work day starting at 6:00 am
- Downloaded at the bar at ~9:45 pm
- Accumulated 18,481 steps
  - 83 min of MVPA (through walking at work)
  - Note: 31 min of MVPA in bouts >= 10 mins
  - 440 min of Light Intensity activity
  - 418 min of Sedentary activity
  - Crouter 479 mins of MVPA (only 5 mins walking)

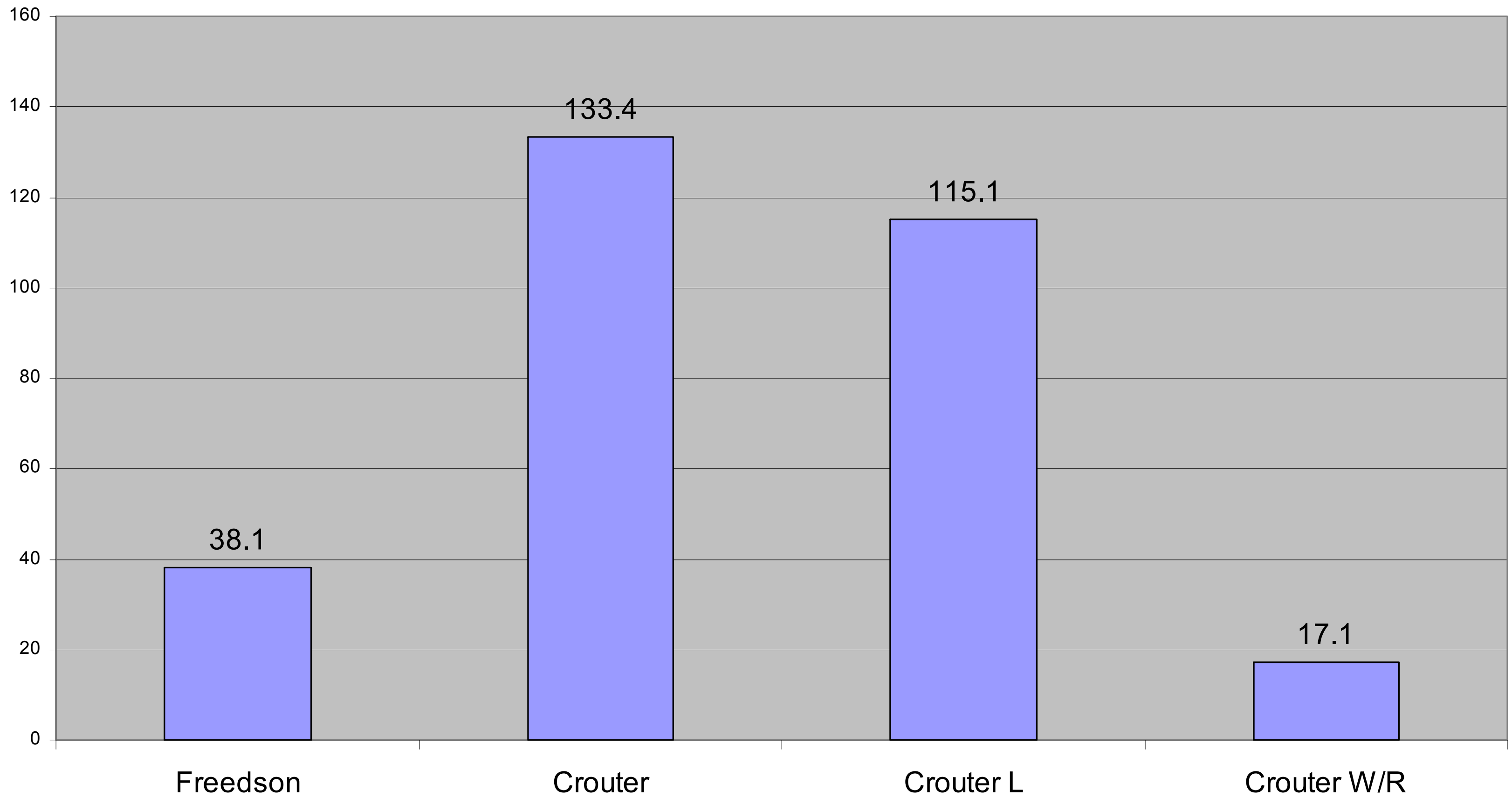
Activity Counts – Moderate Intensity Activity = 325 counts per 10 s



of Steps per 10 sec: 18,481 steps total

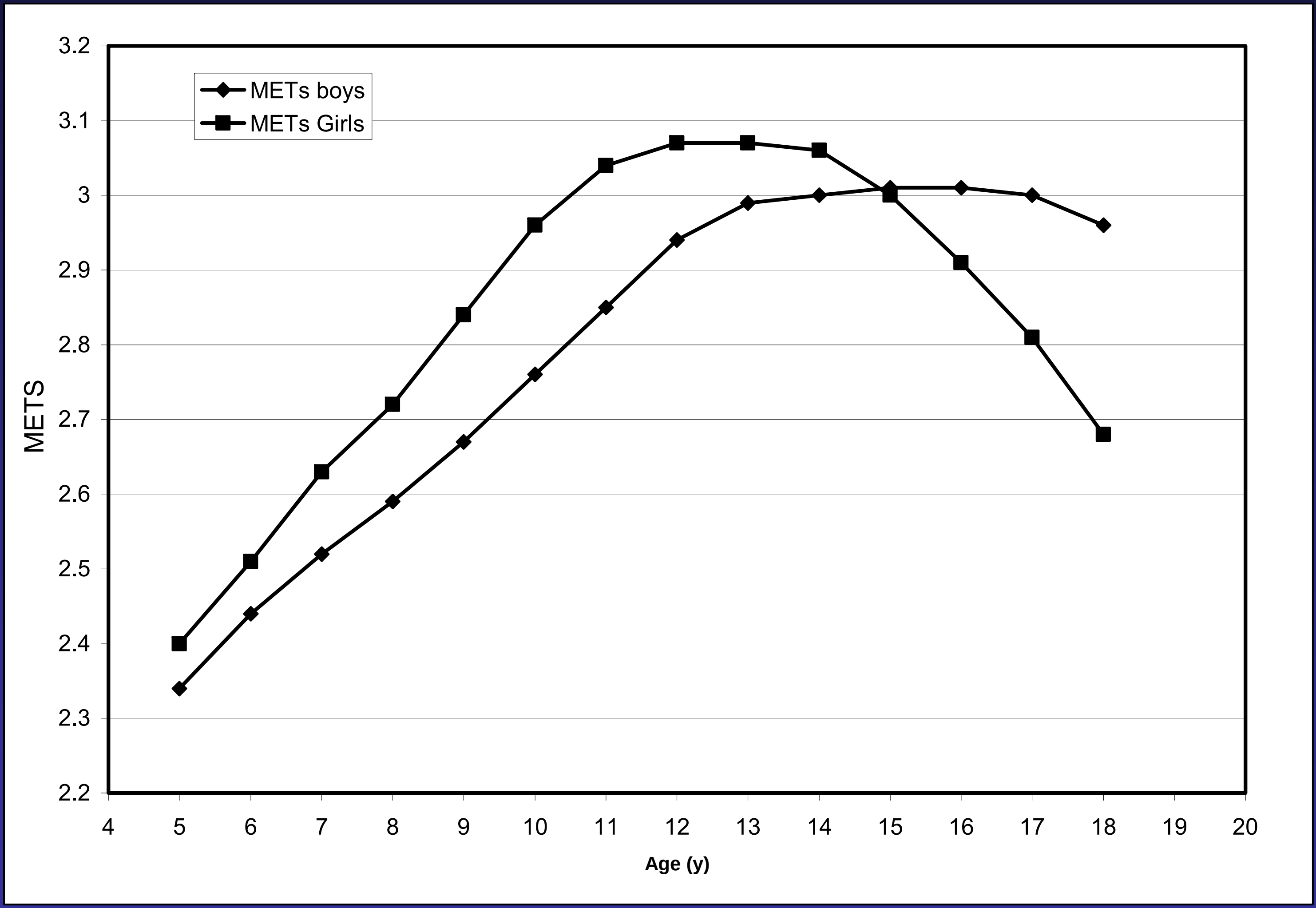


Freedson vs. C2R



Calibration in Children and Youth

Effects of Growth and Development of MET level during walking 2.5 mph



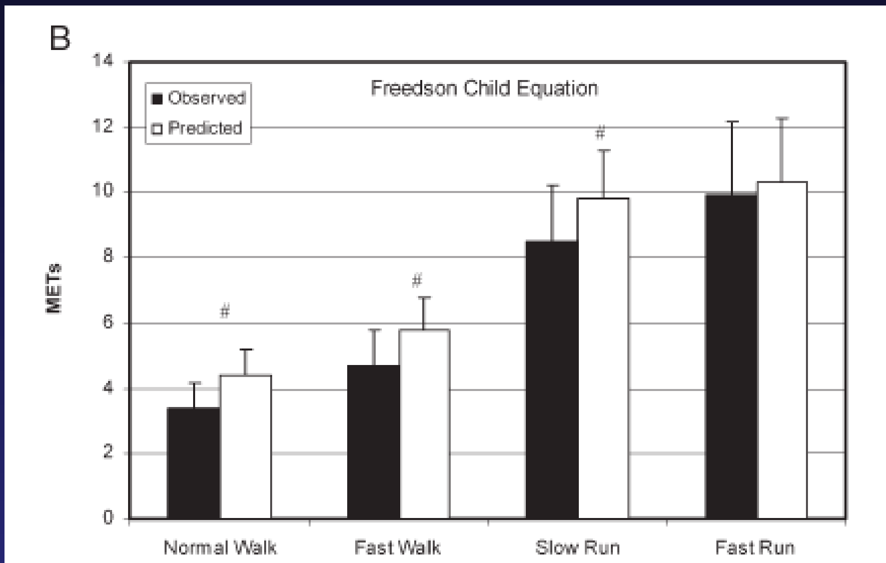
Calibration of Activity Monitors - Youth

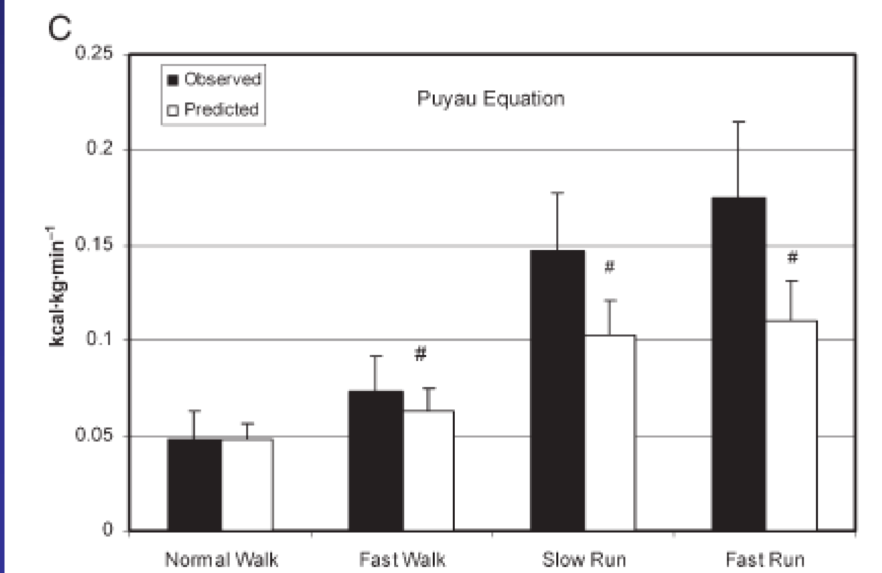
Table 2.

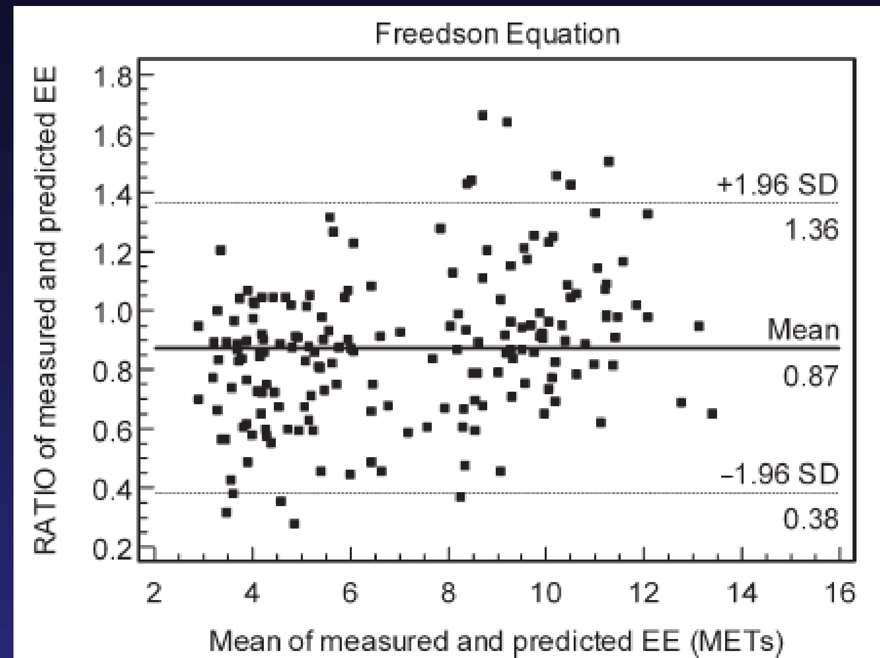
Youth-Specific Calibration Equations and Cut Points for the Actigraph, Actical, and RT3 Accelerometers

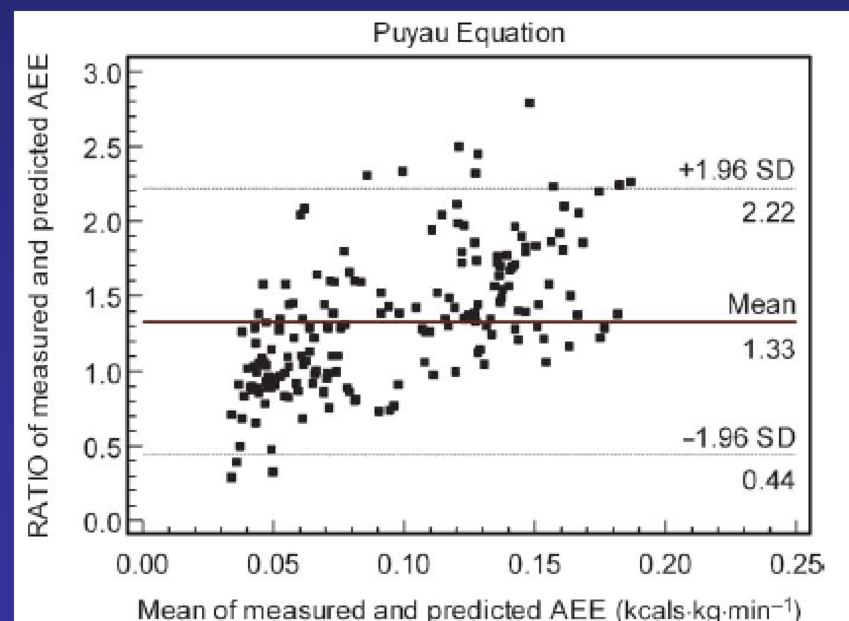
Author	Sample	Activities	Equation/Cut Points	Error
Actigraph				
Freedson et al[29]	N = 80 Range: 6-18 y Mean age: 11.3 y 41 girls, 39 boys Grades 1-2, n = 17 Grades 3-6, n = 19 Grades 7-9, n = 24 Grades 11-12, n = 20	TM walk and run. 1 common speed: 4.4 km/h; other 2 speeds varied for age (5.6-9.7 km/h)	METs = 2.757 + (0.0015 × cnts/min) − (0.08957 × age [y]) − (0.000038 × cnts/min × age [y]) Cut points are age dependent For a 12-year-old: SED: (<1.5 METs) < 100 counts/min LIGHT: (1.5 METs) = 100 cnts/min MPA: (3 METs) = 1263 counts/min VPA: (6 METs) = 4136 counts/min	SEE = 1.19 METs Rxy = 0.94 Mean bias: −0.05 ± 0.11 METs
Puyau et al[34]	N = 26 Range: 6-16 y Mean age: 10.7 y 12 girls, 14 boys	Walk, run, free-living activities such as computer games, playing with toys, aerobics, skipping, jump rope, soccer	AEE = 0.0183 + 0.000010 (cnts/min) SED: <800 cnts/min LIGHT: (AEE = 0.01) = 800 cnts/min MPA: (AEE = 0.05) = 3200 cnts/min VPA: (AEE = 0.10) = 8200 cnts/min	SEE = 0.0172 kcals/kg/min No cross-validation data are presented.
Treuth et al[58]	N = 74 Range: 13-14 y Girls only	Walk, run, free-living activities such as computer games, household chores, aerobics, shooting baskets	METs = 2.01 + 0.000856 cnts/min METs = 2.01 + 0.00171 cnts/30 s SED: < 100 cnts/min LIGHT: 100 cnts/min MPA: 3000 cnts/min VPA: 5000 cnts/min	Concordance correlation: 0.84 SEE = 1.36 METs 95% CI for misclassification 2.8%-6.5% in validation sample

Trost SG. Am J Lifestyle Med 2007;299-314









Trost et al. MSSE 2006

Classification Accuracy

TABLE 4. Percent agreement, sensitivity (Se), specificity (Sp), and area under the receiver operating characteristic (ROC) curve (AUC) for each equation by intensity level.

		Moderate PA			Vigorous PA		
Equation	Alignment (%)	Se (%)	Sp (%)	AUC	Se (%)	Sp (%)	AUC
Trost	83.9	83.7	85.0	0.84	95.5	88.0	0.92
Freedson	75.6	68.4	82.7	0.76	93.3	71.4	0.82
Puyau	71.1	87.5	58.0	0.73	63.6	95.7	0.80

PA, physical activity.

Trost Equation (MSSE 1998;30:629-633

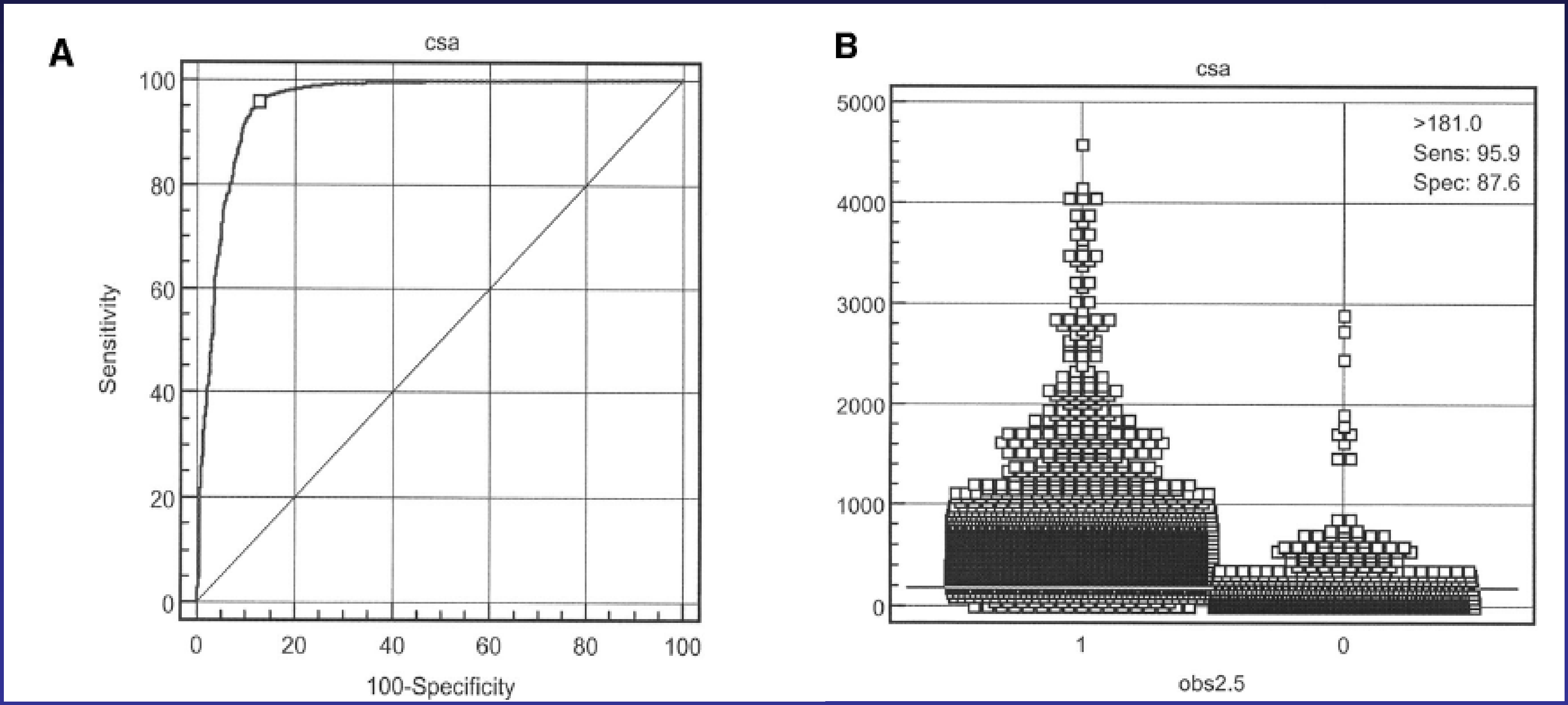
Kcal/min = -2.23 + 0.0008 counts/min

Trost et al. MSSE 2006

ROC Curve Approach

- A graphical representation of the trade offs between sensitivity and specificity for different cut-points
- False positive rate on x-axis
- True positive rate on y-axis
- Determine the cut-point that yields the fewest misclassifications
- Maximizes AUC (mean of Se & Sp)

ROC Curve Approach



Area under the ROC Curve

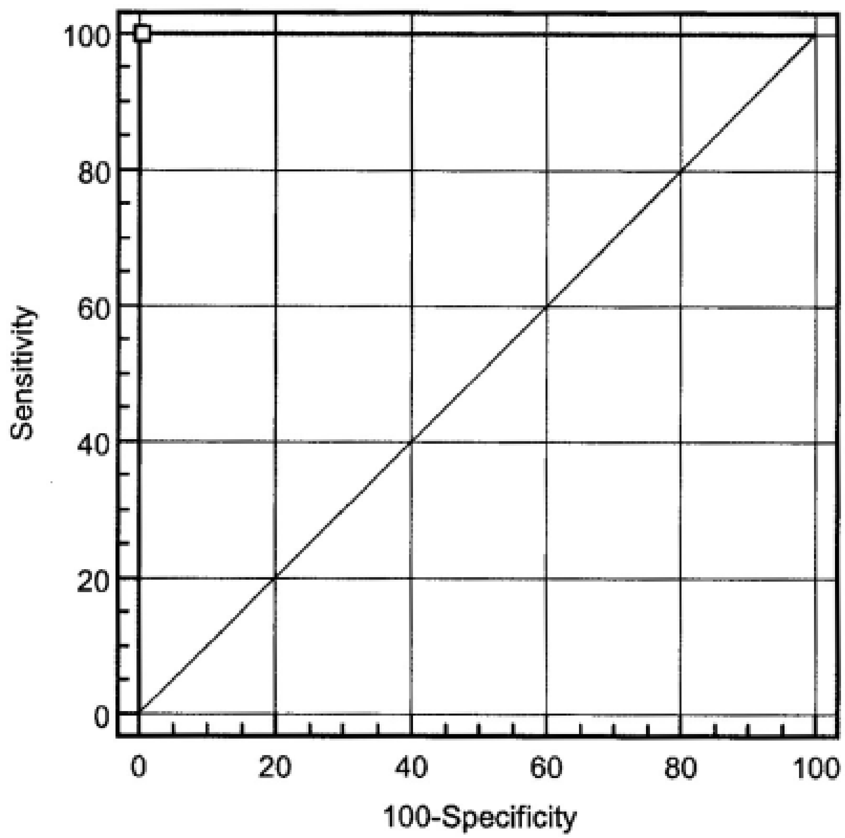


FIGURE 1—Hypothetical ROC curves. The *dark line* shows the best case scenario (perfect sensitivity and specificity) and the *dotted line* shows the worst case scenario (any increase in sensitivity is matched by a reduction in specificity).

Values

- > .90 Excellent
- .80 - .90 Good
- .70 - .80 Fair
- < .70 Poor

Evenson et al. (2008) J Sport Sci 26;1557-1565

Table II. The activities each participant performed at the two measurement visits by intensity level.

Intensity	Visit	Type of activity	Description
Sedentary	2	Rest	Sit in a reclining chair, awake and still
	3	Watch a DVD	Sit in chair and watch DVD
	3	Colouring books	Sit in chair and colour in books using crayons
Light	3	Slow walk	Walk at 2 mph on treadmill
Moderate	2	Stair climbing	88 bpm on the metronome
	2	Dribble basketball	Dribble around obstacle course
	3	Brisk walk	Walk at 3 mph on treadmill
Vigorous	2	Bicycling	Bicycle on stationary bike (60 bpm – double time)
	3	Jumping jacks	Jumping jacks at 126 bpm with the metronome
	3	Running	Running at 4 mph on treadmill

Note: bpm = beats per minute.

Table V. Sensitivity, specificity and area under the ROC curve and 15-s count cutoffs that maximised sensitivity and specificity* for the ActiGraph and Actical.

	Sensitivity (%)	Specificity (%)	Area under the ROC curve (95% CI)	Count 15 s^{-1}
ActiGraph				
Sedentary	95	93	0.98 (0.95–0.99)	0–25
Light	NA	NA	NA	26–573
Moderate	77	81	0.85 (0.80–0.90)	574–1002
Vigorous	68	89	0.83 (0.78–0.88)	≥1003
Actical				
Sedentary	97	98	0.99 (0.97–1.00)	0–11
Light	NA	NA	NA	12–507
Moderate	78	79	0.86 (0.81–0.90)	508–718
Vigorous	77	79	0.86 (0.81–0.90)	≥719

Notes: NA, not applicable using ROC curve analysis.
*Defined as the count that gave equal weight to sensitivity and specificity.

Predictive Validity – ActiGraph Equations

Equation	SED			LIGHT			MVPA		
	Se%	**Sp%**	**AUC**	**Se%**	**Sp%**	**AUC**	**Se%**	**Sp%**	**AUC**
Freedson	100	75.1	0.88	42.7	91.5	0.67	87.9	92.0	0.90
Puyau	100	73.5	0.87	38.5	65.6	0.52	52.0	99.0	0.76
Treuth	98.2	89.1	0.94	65.1	89.7	0.77	83.2	91.1	0.87
Mattocks	100	76.7	0.88	53.7	67.0	0.60	57.0	99.6	0.78
Evenson	100	75.4	0.88	44.7	91.0	0.68	87.3	93.1	0.90

Extracting Bouts

- Guideline driven
- Adults studies typically specify that activity be counted only in 10-min bouts
- Has a huge impact on the estimated amount of moderate physical activity
- Definition of a bout

Extracting Bouts

- Strict definition of a bout.
- Minutes are accumulated if and only if they were performed as part of a 10-min or longer bout in which 10 or more consecutive 1-min epochs were above the count cutoff for moderate intensity activity (3 METs).
- The bout, and hence the accumulation of MVPA minutes, ends as soon as the program encounters a single count below the moderate cut-point.

Extracting Bouts

- Variety of approaches are possible
- Need for ecologically validity
  - Interruption Interval - Counts are permitted to dip below the count cut-point for 1-min
  - The bout and hence the accumulation of MVPA minutes will continue if the program encounters a count above the threshold *immediately* after reading the last count below threshold.

Imputation of Missing Data

- Observed data values are used to predict missing values.
- Accuracy will depend on the number of predictors available, correlation with missing variable, amount of missing data, and pattern of missing values.
- Multiple Imputation methods could be used to predict missing values for segments within a day or the entire day. Proc MI in SAS
- See Catellier et al. MSSE NOV 2005 Suppl.

The Future -Pattern Recognition?

Development of Novel Techniques to Classify Physical Activity Mode Using Accelerometers

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ABSTRACT

POBER, D. M., J. STAUDENMAYER, C. RAPHAEL, and P. S. FREEDSON. Development of Novel Techniques to Classify Physical Activity Mode Using Accelerometers. *Med. Sci. Sports Exerc.*, Vol. 38, No. 9, pp. 1626–1634, 2006. **Purpose:** Use of accelerometers to assess physical activity (PA) is widespread in public health research, but their utility is often limited by the accuracy of data-processing techniques. We hypothesized that more sophisticated approaches to data processing could distinguish between activity types based on accelerometer data, providing a more accurate picture of PA. **Methods:** Using data from MTI Actigraphs worn by six subjects during four activities (walking, walking uphill, vacuuming, working at a computer), quadratic discriminant analysis (QDA) was performed, and a hidden Markov model (HMM) was trained to recognize the activities. The ability of the new analytic techniques to accurately classify PA was assessed. **Results:** The mean (SE) percentage of time points for which the QDA correctly identified activity mode was 70.9% (1.2%). Computer work was correctly recognized most frequently (mean (SE) percent correct = 100% (0.01%)), followed by vacuuming (67.5% (1.5%)), uphill walking (58.2% (3.5%)), and walking (53.6% (3.3%)). The mean (SE) percentage of time points for which the HMM correctly identified activity mode was 80.8% (0.9%). Vacuuming was correctly recognized most frequently (mean (SE) percent correct = 98.8% (0.05%)), followed by computer work (97.3% (0.7%)), walking (62.6% (2.3%)), and uphill walking (62.5% (2.3%)). In contrast to a traditional method of data processing that misidentified the intensity level of 100% of the time spent vacuuming and walking uphill, the QDA and HMM approaches correctly estimated the intensity of activity 99% of the time. **Conclusion:** The novel approach of estimating activity mode, rather than activity level, may allow for more accurate field-based estimates of physical activity using accelerometer data, and this approach warrants more study in a larger and more diverse population of subjects and activities. **Key Words:** ACTIGRAPH, CLASSIFICATION, HIDDEN MARKOV MODEL, QUADRATIC DISCRIMINANT ANALYSIS