ACCELEROMETERS IN THE CONTEXT OF INTAKE-BALANCE ASSESSMENTS

FINDINGS, STRATEGIES, AND RESOURCES

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UI Health | UIC

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WHAT'S AHEAD

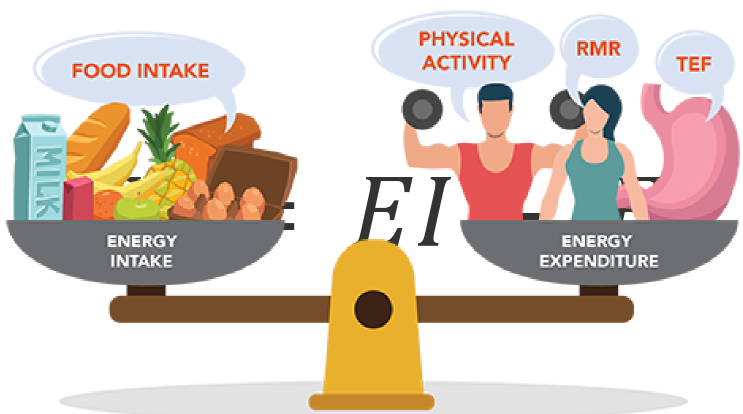
- Overview of the intake-balance method
- Intro to accelerometer-based intake-balance methods
  - Validation methods
  - Prior findings
- Strategies and resources for implementing accelerometer-based intake-balance methods

2

OVERVIEW OF THE INTAKE-BALANCE METHOD

3

WHAT IS THE INTAKE-BALANCE METHOD?



activehealth.sg

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WHAT IS THE INTAKE-BALANCE METHOD?

stableisotope.tn-sanso.co.jp

deutramed.com

$$EI = \Delta ES + EE$$

ksimg.com

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INTRO TO ACCELEROMETER-BASED INTAKE-BALANCE ASSESSMENTS

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WEARABLES FOR INTAKE-BALANCE

stableisotope.tn-sanso.co.jp

deutramed.com

$$EI = \Delta ES + EE$$

ksimg.com

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WEARABLES FOR INTAKE-BALANCE

$$EI = \Delta ES + EE$$

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ACCELEROMETRY FOR INTAKE-BALANCE

British Journal of Nutrition (2023), 130, 344–352 doi:10.1017/S0007114522003312
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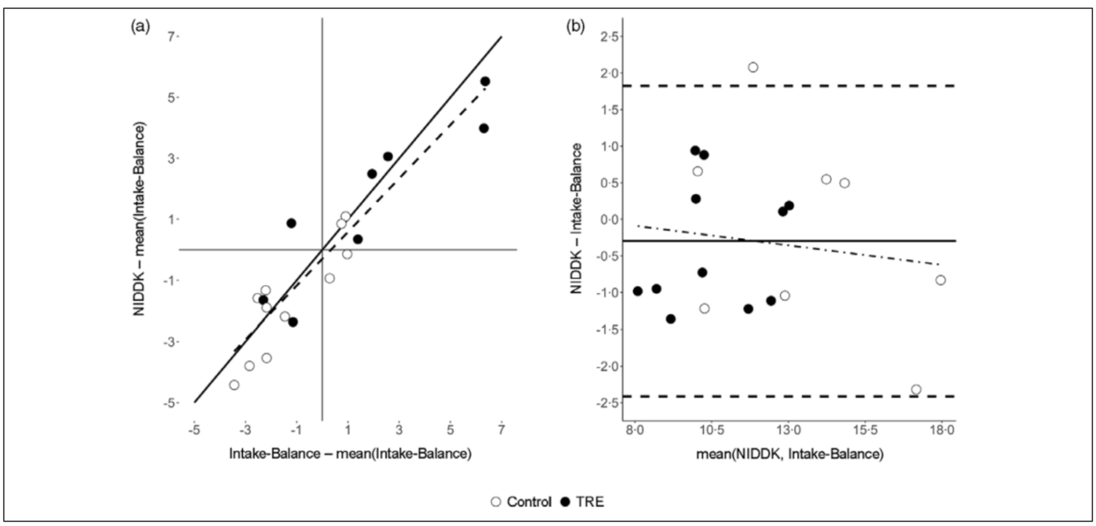
Predicting energy intake with an accelerometer-based intake-balance method

Paul R. Hibbing[1]*, Robin P. Shook[1,2], Satchidananda Panda[3], Emily N. C. Manoogian[3], Douglas G. Mashek[4] and Lisa S. Chow[4]

DOI: 10.1017/S0007114522003312

ACCELEROMETRY FOR INTAKE-BALANCE



DOI: 10.1017/S0007114522003312

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Wawa®
NOT TREATED WITH rBST*
*No significant difference has been shown between milk derived from rBST-treated and non-rBST-treated cows.

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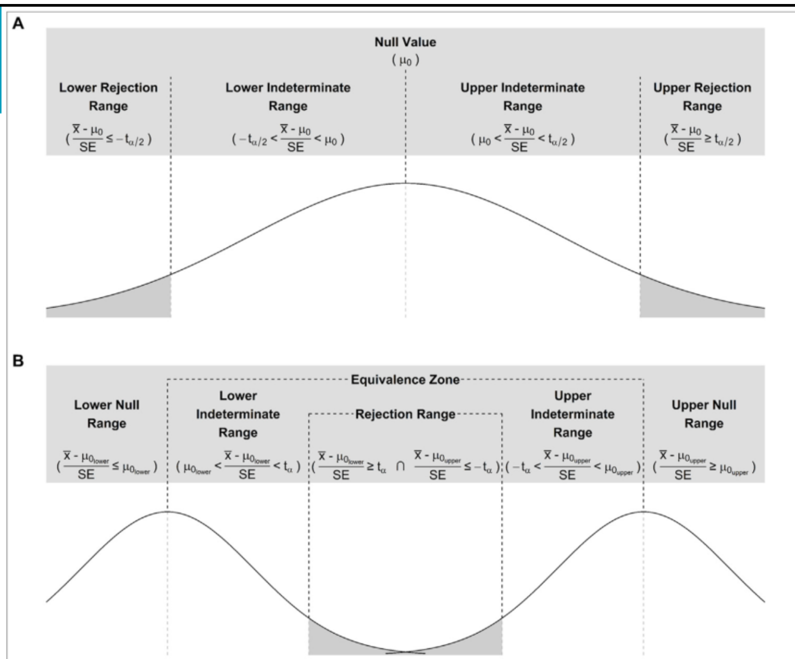

DOI: 10.1016/j.ajcnut.2024.12.017

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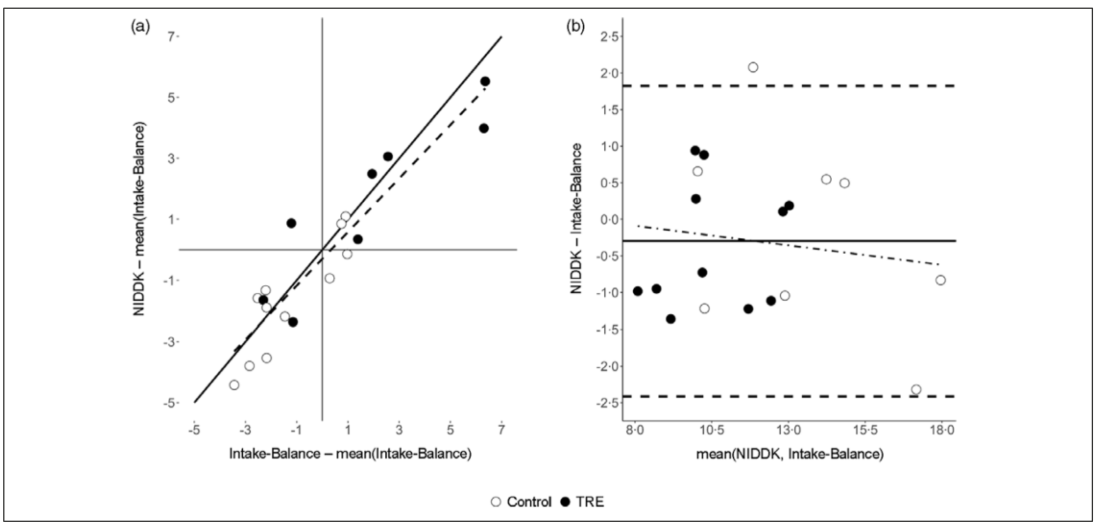

DOI: 10.1017/S0007114522003312

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Hibbing *et al. Int J Behav Nutr Phys Act* (2023) 20:115
https://doi.org/10.1186/s12966-023-01515-0

International Journal of Behavioral Nutrition and Physical Activity

METHODOLOGY **Open Access**

Criterion validity of wrist accelerometry for assessing energy intake via the intake-balance technique

Paul R. Hibbing[1,2*], Gregory J. Welk[3], Daniel Ries[4], Hung-Wen Yeh[5,6] and Robin P. Shook[2,6]

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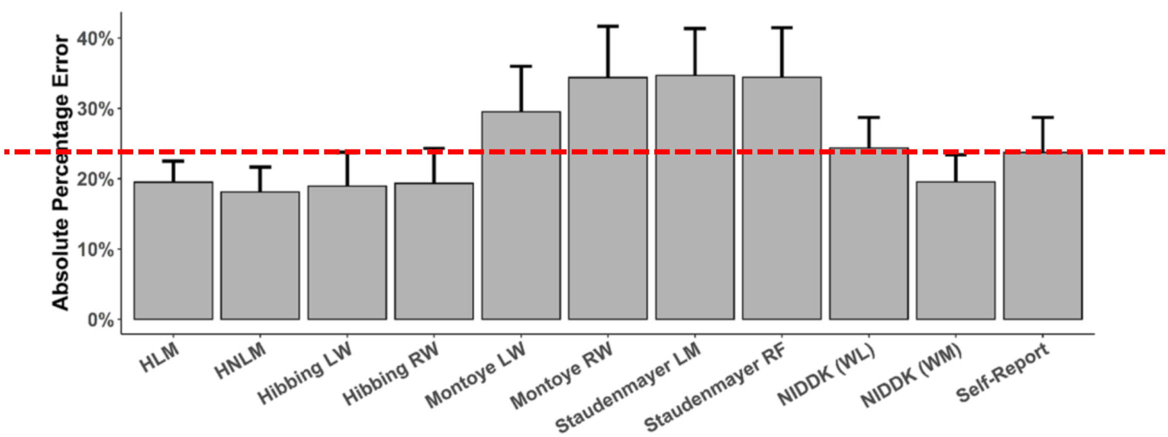
ACCELEROMETRY FOR INTAKE-BALANCE



DOI: 10.1186/s12966-023-01515-0

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BIGGER PICTURE

- Accelerometer methods can be improved over time
- Accelerometers can measure and record continuously

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STRATEGIES & RESOURCES

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CONSUMER-GRADE TECHNOLOGY

$$EI = \Delta ES + EE$$

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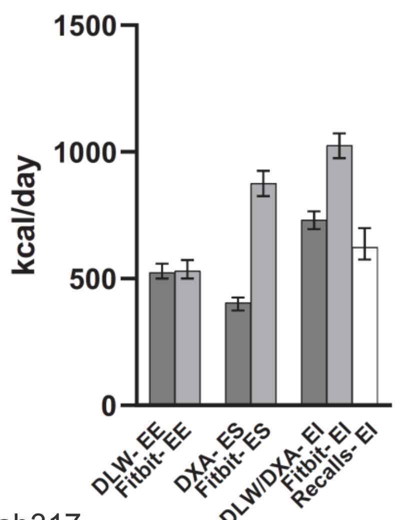
CONSUMER-GRADE TECHNOLOGY



DOI: 10.1093/jn/nxab317

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RESEARCH-GRADE (ACCELEROMETER) TECHNOLOGY: ROADMAP

- (Choose a device and protocol; collect data)
- Pick and apply an EE algorithm
  - https://sites.google.com/view/accelerometerrepository
- Account for non-wear time (and sleep?)
- Determine final EE
- Then proceed to ES data and calculation of EI

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TWO VIGNETTES

- paulhibbing.com/TREaccel (basic)
- paulhibbing.com/IntakeBalance (enhanced)

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APPLYING EE ALGORITHMS

- Read files into R
  - Helpful packages: read.gt3x, GENEAread, GGIRread, AGread
- Pre-process data (format it according to algorithm's demands), apply the algorithm, and (if applicable) post-process the data, e.g., by averaging estimates every minute
  - For a number of algorithms, this can be done in one big step using the accelEE package

ACCOUNTING FOR NON-WEAR

- Run a non-wear detection algorithm
  - Useful packages are PhysicalActivity (Choi algorithm) and GGIR
  - Ahmadi et al. have also tested some useful algorithms for raw acceleration
- Overlay non-wear data on EE data, and exclude EE estimates from non-wear periods
- If desired, use imputation to compensate for the lost data (e.g., by assigning resting EE to non-wear periods as a conservative measure)
  - The PAutilities package has functions to estimate basal/resting EE using, e.g., Harris-Benedict and Schofield equations, etc.

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DETERMINE FINAL EE

Date	total_minutes	total_hildebrand_linear	total_is_Sleep	total_is_NonWear
9/18/2019	1440	2.536927	828	490
9/19/2019	1440	2.512302	816	500

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CALCULATING EI

PID	fm_start	fm_end	ffm_start	ffm_end	ee	n_days
001	50.5	50.7	75.1	74.9	1950	14
002	70.2	70.0	90.3	90.3	2473	14

Now let's calculate EI:

```
## Generate the result
df_result <- IntakeBalance::IntakeBalance(

  ## These arguments still refer to the same information outlined previously,
  ## but now we have added a layer of abstraction to reference the names of
  ## columns where that information is stored, rather than providing the
  ## values themselves
  fm_start = "fm_start",
  fm_end = "fm_end",
  ffm_start = "ffm_start",
  ffm_end = "ffm_end",
  ee_per_day = "ee",
  n_days = "n_days",

  ## The trick is to pass in a data frame via this extra argument. That's how R
  ## knows to interpret the other variables as column names rather than raw values
  df = info

)

## Show the result
knitr::kable(df_result)
```

PID	fm_start	fm_end	ffm_start	ffm_end	ee	n_days	delta_ES	EI
001	50.5	50.7	75.1	74.9	1950	14	121.1429	2071.143
002	70.2	70.0	90.3	90.3	2473	14	-135.7143	2337.286

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ZOOMING BACK OUT

- (Choose a device and protocol; collect data)
- Pick and apply an EE algorithm
  - https://sites.google.com/view/accelerometerrepository
- Account for non-wear time
- Determine final EE
- Then proceed to ES data and calculation of EI

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CONCLUSION

- Accelerometer-based intake-balance methods are one of several ways to assess EI, and suitability may vary by study
- Limitations apply
- Teamwork advised
- Lots of questions still to be answered!

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THANK YOU

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PRECISION OF MEASUREMENT

$$Calculated\ EI = 1020\frac{\Delta FFM}{\Delta t} + 9500\frac{\Delta FM}{\Delta t} + EE$$

DOI 10.1093/jn/nxx029

PRECISION OF MEASUREMENT

$$Calculated\ EI = 1020\frac{\Delta FFM}{\Delta t} + 9500\frac{\Delta FM}{\Delta t} + EE$$

DOI 10.1093/jn/nxx029

Table 1. Participant characteristics and sample descriptives. Accelerometer-derived variables are grand averages across participants

	Control (*n* 8)*				TRE (*n* 11)†			
	Pre		Post		Pre		Post	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Body mass (kg)	103·6	26·8	102·7	25·8	94·0	21·6	90·9	21·3
Fat mass (kg)	48·8	19·7	48·1	19·4	41·1	16·8	39·4	16·4
Fat-free mass (kg)	54·9	9·3	54·6	8·4	52·9	10·3	51·5	10·3

DOI 10.1017/S0007114522003312

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PRECISION: VARIOUS METHODS

TABLE 2 Absolute and relative test–retest reliability of the three body composition measurement devices

Measurement device	Absolute reliability: %BF Mean differences (Trial 1–Trial 2) [95% CI]	p-value[a]	SEM (%BF)	MD (%BF)	Relative reliability: $ICC_{2,1}$ [95% CI]
Skinfold callipers	0.54 [0.22, 0.87]	<0.001	0.63	1.74	0.991 [0.979, 0.995]
Ultrasound	0.17 [−0.25, 0.58]	0.43	0.78	2.16	0.988 [0.979, 0.993]
3DPS	−0.01 [−0.43, 0.40]	0.96	0.67	1.84	0.983 [0.968, 0.991]

DOI 10.1111/cpf.12716

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PRECISION: BIOELECTRICAL IMPEDANCE ANALYSIS

TABLE 3 Test–retest reliability and variability of key bioelectrical impedance analysis (BIA) measurements.

			Variability between				
Measurement	Mean	SD	Participant	Day	Test	Range	ICC
Body fat (% body mass)	17.6	7.4	7.3	0.6	0.3	1.9 ± 0.9	0.998

DOI 10.3389/fnut.2024.1491931

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PRECISION: AIR DISPLACEMENT PLETHYSMOGRAPHY

Table 4. Statistical measures of test–retest reliability of %BF and FFM measurements.

	Protocol	%BF (%)				FFM (kg)			
		TEM [1]	SEM	MDC	ICC(2,1) [2]	TEM	SEM	MDC	ICC(2,1)
All	Single	1.00	1.00	2.77	0.9914	0.675	0.673	1.867	0.9974
	Collins	0.69	0.69	1.91	0.9960	0.507	0.506	1.403	0.9985
	Tucker	0.70	0.70	1.93	0.9959	0.515	0.513	1.422	0.9985
	Median	0.62	0.62	1.72	0.9967	0.457	0.456	1.264	0.9988
Men	Single	0.88	0.88	2.44	0.9898	0.683	0.679	1.883	0.9934
	Collins	0.66	0.66	1.82	0.9944	0.552	0.549	1.522	0.9957
	Tucker	0.69	0.69	1.91	0.9938	0.576	0.573	1.588	0.9953
	Median	0.60	0.60	1.67	0.9953	0.510	0.508	1.407	0.9963
Women	Single	1.11	1.10	3.05	0.9866	0.668	0.664	1.840	0.9885
	Collins	0.72	0.71	1.98	0.9944	0.457	0.455	1.261	0.9948
	Tucker	0.71	0.71	1.96	0.9945	0.444	0.442	1.225	0.9951
	Median	0.64	0.63	1.76	0.9956	0.397	0.395	1.095	0.9961

DOI 10.3390/ijerph182010693

PRECISION: DXA

Table 2. Mean (±SD) weight and precision (% CV) of whole-body bone mineral, lean tissue, and fat tissue

Measurement site	BMC g	BMC % CV	Lean g	Lean % CV	Fat g	Fat % CV
Month 0						
Arms	254 ± 80	1.7 ± 0.7	3,837 ± 605	3.7 ± 1.7	2,421 ± 1,040	6.7 ± 1.7
Legs	783 ± 197	1.1 ± 0.5	13,675 ± 2,313	1.5 ± 0.6	8,460 ± 1,689	2.5 ± 1.2
Trunk	624 ± 202	2.4 ± 0.9	18,451 ± 2,380	1.3 ± 0.4	7,423 ± 2,603	4.1 ± 1.1
Total body	2,132 ± 522	0.8 ± 0.4	38,372 ± 5,213	1.1 ± 0.5	19,723 ± 5,497	2.7 ± 0.8
Month 9						
Arms	265 ± 85	2.0 ± 0.8	3,862 ± 721	2.9 ± 1.3	2,570 ± 1,010	4.3 ± 1.6
Legs	799 ± 193	1.2 ± 0.7	12,977 ± 2,249	1.7 ± 0.6	8,322 ± 1,217	2.4 ± 1.0
Trunk	653 ± 203	2.8 ± 1.2	17,380 ± 2,627	1.4 ± 0.2	7,634 ± 2,014	2.8 ± 0.6
Total body	2,184 ± 520	1.2 ± 0.6	36,570 ± 5,593	1.0 ± 0.5	19,981 ± 4,394	1.7 ± 0.5

DOI: 10.1007/BF02556113

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PRECISION: DXA

Table 2
Total Body and Regional Body Precision Acquired by Lunar iDXA

Region	Variables	Mean (range)	RMS-SD	CV (%)	LSC
Total body	BMC (g)	2622 (1595−3766)	12.2	0.5	33.9
	Fat mass (kg)	17.3 (7.9−36.7)	0.18	1.0	0.49
	Lean mass (kg)	45.92 (32.60−72.70)	0.22	0.5	0.61
	Region % fat	27.2 (13.1−45.3)	0.25	—	0.68
	Tissue % fat	28.3 (13.7−46.6)	0.26	—	0.72

DOI: 10.1016/j.jocd.2012.02.009

PRECISION: ENERGY EXPENDITURE

- DLW generally ~6% (± ~2%), based on mean absolute errors from DOI 10.1038/s41430-019-0492-z
- For accelerometer-based measures, depends on the specific method, monitor, and population
  - Values of 10% to ≥30% are common (e.g., DOIs 10.1038/s41598-021-97299-z and 10.1016/j.jsams.2014.10.002)
  - Repeatability is not an issue; given the same data, the algorithms will produce the same output