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Original article

Leg to leg bioelectrical impedance analysis of percentage fat mass in obese patients—Can it tell us more than we already know?

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Abstract

Background: Bioelectrical impedance analysis (BIA) is well tolerated, inexpensive, and readily available, but can it be used to detect with clinical precision aberrant changes in the proportion of fat mass to fat-free mass during weight loss?

Objectives: To assess the variance in percentage body fat mass explained by the readily available inputs and assess residual variance provided by leg-to-leg BIA scales.

Methods: Using cross-sectional data from a cohort of 665 patients of Indian ethnicity presenting for bariatric surgery, we examine the determinants of percentage body fat as provided by leg-to-leg output from Tanita SC-330 BIA scales.

Results: Four input factors—sex, weight, height, and age—contributed to provide 92% and 95% explanation in output variance for percentage fat mass (%FM) and actual fat mass, respectively, in 665 patients. Body mass index alone explained 89% and 81% of variance in %FM output for women and men, respectively. Neither weight distribution, as indicated by waist and hip circumference or waist to hip ratio, nor plasma lipids or markers of glucose metabolism contributed additional variance in %FM when controlled for the 4 key inputs.

Conclusions: Simple, known input variables dominate the leg-to-leg BIA output of %FM, and this may compromise the detection of aberrant changes in %FM and fat-free mass with substantial weight loss. For clinical research, validated methods not largely dependent on known inputs should be used for evaluating changes in body composition after substantial weight loss. (Surg Obes Relat Dis 2016;▮:00–00.)

Key Words: Weight loss; Obese; Obesity; Severe obesity; Bariatric-metabolic surgery; Bariatric; Metabolic; Surgery; Health; Quality of life; Mortality; Chronic disease; Body fat; Fat loss; Fat-free mass; Resting energy expenditure; Weight regain; Strength; Function; Sarcopenia; Dual-energy x-ray absorptiometry (DXA); Bioelectrical impedance analysis (BIA); Co-morbidity; Foot-to-foot BIA.

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Intentional weight loss is recommended for obese individuals, especially those with clinically severe obesity. Bariatric-metabolic surgery is currently our best therapy for generating and sustaining substantial weight loss in clinically severe obesity. Accompanying the weight loss are major improvements in health, quality of life, and reduced

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overall mortality [1]. However, it is important when treating a chronic disease with long-term therapy, which is usually the intent of bariatric metabolic surgery, to look at any downside of chronic therapy with the view to attenuating any risk [2]. The most commonly performed conventional bariatric procedures provide 15% to 30% sustained weight loss, raising concerns about long-term body composition. Of particular importance has been the aim of maximizing fat loss and attenuating the loss of fat-free mass (FFM), as this is important for maintaining resting energy expenditure (possibly providing some insurance against weight regain), strength, and function as well as preventing sarcopenia and frailty with aging [3].

When and how to measure body composition presents a practical challenge in clinical practice where availability of sophisticated and well-validated body composition methods are time consuming, sometimes physically challenging, and expensive. We have recently shown in an obese European white population that sex, weight, height, and age can together provide 90% of the variance in dual-energy x-ray absorptiometry (DXA), estimated body fat mass (BFM) and 78% of percent body fat (%BF) [4]. Bioelectrical impedance analysis (BIA) is the most commonly reported method for reporting percentage body fat in journals focusing specifically on bariatric-metabolic surgery.

Leg-to-leg bioimpedance measures are obtained when the subject stands with bare feet on scales that incorporate input and output electrodes on the standing platform; additional information such as height, sex, age, level of fitness, and build are manually entered. BIA is well tolerated, cheap, easy to use, readily available, and requires minimal training, but it is unclear how much of its estimate of BFM or %BF is driven by the input variables that have been shown themselves to be critically related to the outcome-independent DXA-derived estimate of %BF. Can the BIA-estimated %BF provide useful additional information about a patient's co-morbidity or metabolic factors before surgery?

We hypothesised that 1) readily available input factors in the BIA algorithm will dominate the %BF output, allowing very limited remaining variance to be influenced by the impedance measures, and 2) the value of BIA beyond the input factors provides no additional insights into cardiometabolic risk and co-morbidity. Therefore, the aim of this analysis was to 1) assess how input factors weight, height, sex, and age are related to the output measure of %BF derived from foot-to-foot BIA in a population of Indian ethnicity, and 2) control for these input factors and then assess any additional value of BIA-derived percentage body fat in predicting obesity-related metabolic factors and obesity-related co-morbidity.

Methods

Patients presenting at the Indian Centre for Obesity & Digestive Surgery (Gamdevi, Mumbai, India) were carefully evaluated before surgery. Assessment included anthropometric measures of height, weight, waist and hip circumference, and waist-to-hip ratio. Obesity-related co-morbidities were detailed, and biochemical analyses included fasting plasma glucose, insulin, lipid panel, liver function, and thyroid function.

BIA analysis was performed using the Body Composition analyzer SC-330 (Tanita Corp, Tokyo, Japan). The analyzer required age, build, sex, and height before analysis of %BF could be provided using the weight measured by the instrument's scales. The instrument provided a 3-compartment body composition model of fat mass, muscle mass (FFM), and bone mass, adding up to the scale-measured weight. The manufacturer also indicated that factors such as exercise, time of day, posture, food and drink intake, foot surface condition, urinary bladder status, ambient temperature and humidity, and transmitter electrical interference may influence the accuracy of measurements. Constant conditions are recommended for taking measurements.

Statistical analyses

The group's characteristics are summarized and presented in Table 1 as n (%), mean (standard deviation), and median (interquartile range) as appropriate. The analysis was performed using linear regression analysis using the BIA-estimated %BF or BFM as the dependent variable. Regression models were assessed entering all variables simultaneously, together with stepwise loading and stepwise removing. Assessment of the variance provided by the 4 individual BIA input factors was performed using a block method after controlling for the other 3 factors. B values and 95% confidence intervals are provided, and individual adjusted R^2 values and cumulative R^2 values are presented along with percentage variance explained. All analysis was performed using SPSS Statistics version 22 (IBM Corp. Armonk, NY).

Results

The characteristics of the 665 adults of Indian ethnicity presenting for weight loss therapy are shown in Table 1. Linear regression analysis was used to assess input measures for their association with the BIA-derived %BF output as the dependent variable.

Using the combined cohort of both men and women, all 4 input factors (sex, weight, height, and age) each contributed to providing the explained variance of the percentage body fat and together contributed 92% ($R^2 = 0.92$) of the variance, leaving 8% for other inputs (Table 2 and Fig. 1A). When combining weight and height as one variable—body mass index (BMI)—the 3 input variables contributed to 93% ($R^2 = 0.93$) of variance. The adjusted R^2 values for each of the 4 input variables (each adjusted for the other 3) are presented in Table 2, and the stepwise build order and additional variance provided with the

Table 1
Characteristics of all participants (N = 665) when attending for baseline study examinations at the Centre for Obesity and Digestive Surgery

Characteristic	Women	Men
Number (%)	375 (55%)	290 (45%)
Age (yr)	41.4 (12.0)	41.5 (12.3)
	Range 19–72	Range 17–70
Anthropometric and body composition		
Weight (kg)	106.4 (21.0)	130.1 (24.2)
	Range 54–190	Range 72–203
Height (m)	1.58 (.06)	1.72 (.07)
BMI (kg/m^2)	42.9 (8.2)	44.1 (7.7)
	Range 22–71	Range 27–55
Total body fat (kg)	60.1 (20.1)	55.2 (17.7)
	Range 16–137	Range 18–136
Waist circumference (cm)	121.2 (17.8)	136.1 (14.7)
	Range 49–181	Range 52–179
Total body fat free mass (kg)	43.4 (4.8)	70.9 (8.8)
	Range 27–74	Range 36–100
Percent fat mass	55.1 (8.6)	41.6 (6.2)
	Range 26–75	20–69
Co-morbidity		
Hypertension	38.4%	53.4%
Type 2 diabetes	27.2%	40.3%
Obstructive sleep apnea	38.1%	58.3%
Dyslipidemia	20.4%	31%
Polycystic ovary syndrome	22%	-
Hypothyroidism	28%	8.3%
Joint pain	31%	21%
Biochemistry		
F plasma glucose mmol/l	6.25 (2.8)	6.5 (2.6)
F plasma insulin × μIU/mL (median, IQR)	17.3 (12.0, 25.2)	22.6 (15.6, 34.2)
Total cholesterol (mmol/l)	4.82 (1.02)	4.46 (.92)
Triglyceride (mmol/l)	1.6 (.7)	1.6 (.7)
HDL cholesterol (mmol/l)	1.15 (.26)	1.00 (.21)
LDL cholesterol (mmol/l)	3.0 (.9)	2.7 (.9)
Uric acid (μmol/l)	312.9 (80.3)	358.8 (99.9)

BMI = body mass index; HDL = high-density lipoprotein; IQR = interquartile ratio; LDL = low-density lipoprotein
The only co-morbidity to show additional explained variance in %BF was joint pain in men.

Table 2
Stepwise regression models show the influence of key input variables on the BIA output of estimated percentage body fat in men and women of Indian ethnicity. Residual variance in BIA estimated percentage body fat not explained by the input variables is provided.

	Whole Group N = 665	Women n = 375	Men n = 290
Sex (male = 1)	B = -13.7 (–14.4, –13.0)		
	Adjusted R^2 = .20		
Weight (kg)	B = .322 (.311, .332)	B = .387 (.374, .400)	B = .254 (.242, .267)
	Adjusted R^2 = .46	Adjusted R^2 = .84	Adjusted R^2 = .81
	Combined R^2 = .79	Unadjusted R^2 = .71	Unadjusted R^2 = .60
Height (m)	B = –52.5 (–56.1, –48.9)	B = –55.5 (–60.0, –51.1)	B = –47.1 (–51.5, –42.7)
	Adjusted R^2 = .10	Adjusted R^2 = .15	Adjusted R^2 = .23
	Combined R^2 = .91	Combined R^2 = .90	Combined R^2 = .83
Age (yr)	B = .092 (0.074, .111)	B = .086 (0.063, .110)	B = .066 (0.033, .090)
	Adjusted R^2 = .01	Adjusted R^2 = .01	Adjusted R^2 = .02
	Combined R^2 = 0.92	Combined R^2 = .91	Combined R^2 = .85
Remainder of variance for % body fat	.08 or 8% of overall variance	.09 or 9% of overall variance	.15 or 15% of overall variance

Adjusted R^2 values are adjusted for each of the remaining input variables.
Combined R^2 values show the overall variance in %FM explained with stepwise inclusion of variables.
B Values represent those of the combined model for each variable after controlling for the other input factors. Individual estimated %BF = 99.73 + .092 × age (yr) – 13.7 × 1 (male) – 52.5 × height (m) + .322 × weight (kg).

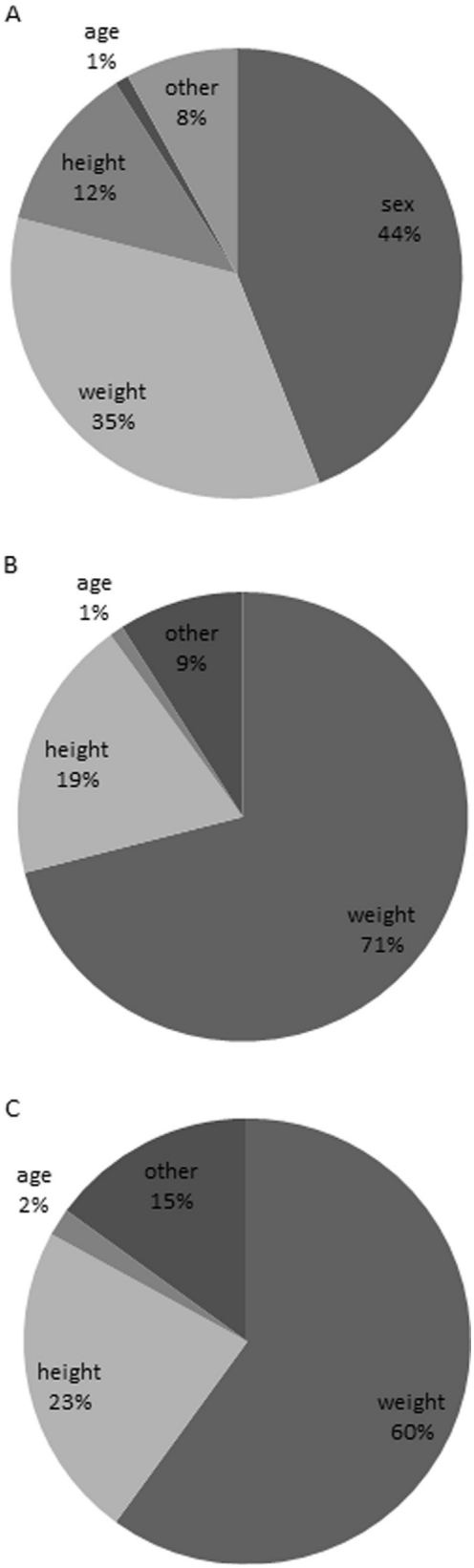

Fig. 1. The proportion of variance in the bioelectrical impedance analysis (BIA) derived percentage body fat explained by inputs into the BIA analysis. (A) The whole group (N = 665), (B) female participants (n = 375), and (C) male participants (n = 290).

inclusion of the next variable shown in Fig. 1A. The equation for estimating any individual's %BF is 99.73 + .092 × age (years) − 13.7 × 1 (male) − 52.5 × height (meters) + .322 × weight (kg). The factors provided a robust regression model with stepwise inclusion, stepwise removal, and entering all factors simultaneously provided the same overall result.

Sex was the first factor entered, explaining 44% of overall variance, followed by weight, height, and age. However, when adjusted for the other input variables, weight explained 45% of overall variance and, together with sex, accounted for 79% of overall variance (Table 2). The 4 input factors explained 95% of variance in fat mass, 93% in muscle mass (FFM), and 87% variance in bone mass with the 3 compartments that total measured weight. When simple anthropometric measures of waist and hip circumference, or waist-to-hip ratio, were added to the 4 input variables, no additional variance of BIA %BF was provided. BMI alone explained 89.4% and 80.6%, and waist circumference alone explained 56.6% and 60.4%, of variance in %BF in women and men, respectively.

When women and men were assessed separately, the input factor order for explaining variance in %BF was weight, height, and age for both; together, these explained 91% and 85% of total variance, respectively (Table 2, Figs. 1B, C). This left 9% and 15% of overall variance unexplained in women and men, respectively. Weight alone provided 71% of variance in women and 60% in men, and BMI provided 89% and 81% of variance, respectively (Fig. 2). When BMI was adjusted for age, 91% and 83%, respectively. Waist and hip measures did not add additional waist and hip circumferences and waist to hip ratio for either sex. Co-morbidity was documented at the time of initial assessment and presented in Table 1. Of these co-morbidities, only one influenced variance in %BF after controlling for age, weight, and height; that was joint pain in men only, but it only added an additional .4% of variance. Men reporting joint pain (n = 62) had a mean %BF of 43.1% compared with 41.1% for those not reporting joint pain (n = 228). None of the metabolic markers listed in Table 1 explained any variance in %BF.

Discussion

Input variables sex, weight, height, age, and ethnicity explain approximately 90% of the variance in measures of body fat mass and 78 %BF using validated measures of body composition such as DXA and whole-body magnetic resonance imaging (MRI), yet these 2 methods do not rely on these key factors being provided [4]. In essence DXA and MRI, which concur well in their fat mass estimates [5], do so by providing 100% of output variance. Our analysis indicates that 92% of %BF and 95% BIA-estimated fat mass variance in this Indian ethnic obese cohort is explained by readily available input measures. This raises

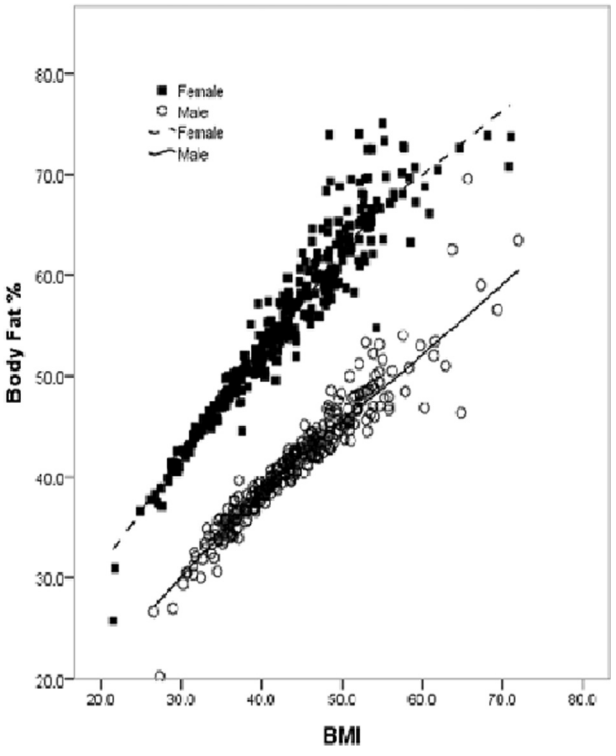

Fig. 2. The relationship between the percentage body fat output from leg-to-leg bioelectrical impedance analysis scales and body mass index for men and women.

concern about how valuable the remaining 5%–8% is in allowing the detection of aberrant baseline body composition or aberrant changes with substantial weight loss. Our data suggest that readily available input variables may saturate the algorithms used to calculate FFM from BIA. Thus, BIA may not provide useful information regarding body composition above and beyond what clinicians and researchers can glean from a patient's age, sex, height, and weight. For example, if patient losses 30 kg, it is likely that the body composition estimates from BIA will be driven primarily by the 30-kg weight loss, sex, and height of the participant, and clinicians will not be able to assess if this weight loss is well tolerated in terms of losing of fat mass and preserving lean mass. If, for example, the 30-kg weight loss was associated with a tolerable, expected 25%–30% proportional loss of FFM, how well would the BIA estimates enable the detection of a highly favorable loss of just 15% or a problematic loss of 40%? Therefore, validation of BIA for the clinical ability to detect meaningful perturbations in body composition, beyond that driven by readily available inputs, is critical to clinical utility beyond acting as a body composition calculator using inputs alone. This is important, as 67% (30/52) of the body composition studies reporting total body %FM in the bariatric surgery–focused journals [*SOARD* and *Obesity Surgery*]) used BIA as the method of measurement (author review 2006–2015, conducted 16 December 2015).

Multiple large studies have compared leg-to-leg BIA and DXA assessments of body composition. A total of 591 Canadian volunteers underwent the 2 assessments, one immediately after the other. The BIA measure of %BF explained 72% and 61% of variance in DXA %BF values, for men and women respectively, but it particularly underestimated fat mass in obese individuals [6]. A recent Taiwanese study of 554 healthy patients aged 16 to 75 years found BIA estimates of body fat explained 79%–86% and 76%–88% of variance of DXA-estimated %FM in women and men, respectively [7]. A large French study of 5740 consecutive obese patients found BIA-estimated %FM only provided 50% of explained variance of DXA %FM in both men and women [8]. Lack of precision throughout the range of weights and broad limits of agreement with DXA are often reported [8,9].

We have previously reported in a study of obese women that the output provided by 2 widely used BIA algorithms failed to provide greater explanation of DXA-measured % FM variance than was provided by BMI alone. Indeed, the more the BIA algorithm relied on the external readily available inputs, the better it reflected DXA %FM [9]. We have recently shown that sex, weight, height, and age can predict 90% of DXA measured body fat mass variance in Caucasian patients with obesity [4]. Therefore, leg-to-leg BIA as a comparator to DXA assessments would seem to provide an explanation of variance similar to those provided by the available input variables within an algorithm developed for use in a specific ethnic population. Of course, the BIA output therefore would understandably correlate significantly with the DXA output as it is driven by input factors known to have a dominant influence on body composition. However, the BIA output may not provide a clinically meaningful appraisal of any aberrant outcome. Andreu et al from Barcelona provide a good example of the different results obtained when using BIA and DXA to examine the effect of protein intake on changes in FFM after gastric bypass and sleeve gastrectomy. Their initial publication using BIA reported no effect of protein intake on change in the proportion of FFM with weight loss [10]; however, when DXA was used in a later study, the relationship between protein intake and preservation of FFM was clear and clinically relevant for gastric bypass but less clear for sleeve gastrectomy where a greater overall proportion of FFM was lost [11].

Our analysis also found that the BIA-estimated %BF in the Indian population was not associated with fat distribution as indicated by waist-to-hip ratio, cardiometabolic biochemical risk factors, or patient-reported co-morbidity with the exception of joint pain in men. A Swedish study of 136 obese middle-aged women found estimates of %BF measured with BIA or DXA were disappointing in providing clinically useful information about cardiometabolic inflammatory markers and recommended the continued use of BMI and waist circumference [12]. A large US

analysis based on 8773 adults in the National Health and Nutrition Examination Survey (1999–2004) found that readily available measures of BMI and waist circumference were of a value similar to DXA-measured BFM and %FM in their associations with obesity-related biomarkers and the prevalence of metabolic syndrome [13]. An analysis of data from the Melbourne Collaborative Cohort Study found the waist-to-hip ratio was more predictive of all-cause mortality than measures of BMI and BIA estimates of BFM or %BF and suggested that the use of BIA as a predictor was unjustified [14]. Therefore, it would appear that simple anthropometric measures of BMI, as well as waist and hip circumference, provide the necessary impetus to formally measure key biochemical measures of cardiometabolic risk.

Many studies have presented body composition outcomes using leg-to-leg BIA before and after bariatric surgery [10,15,16], and some validation studies have been performed [9,17–20]. The studies indicate strong correlations with DXA and total body water measures but do not indicate greater explanation of variance than expected for the input parameters [9,19]. In addition, BIA can underestimate fat mass and overestimate FFM compared with DXA [18], and wide 95% limits of agreement between individuals restrict the clinical utility and precision of standard leg-to-leg BIA assessment [9,17,21]. Other broader limitations of leg-to-leg BIA include the need for algorithms appropriate for the population being examined and immediate factors that may influence the accuracy of the result, including time of day, posture, food and drink intake, foot surface condition, exercise, ambient temperature, and humidity.

Conclusion

As a measure of body composition, leg-to-leg BIA has limitations that are likely to restrict its clinical utility. For clinical research purposes, well-validated and reliable techniques such as DXA, whole-body MRI, air displacement plethysmography, and underwater weighing provide methods to assess and detect changes in 2 compartments of—fat and FFM—body composition after weight loss. The simple and easily available parameters of BMI and waist-to-hip ratio remain clinically useful tools in estimating body fat percentage and cardio-metabolic risk.

Disclosures

The authors have no commercial associations that might be a conflict of interest in relation to this article.

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