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Abstract: Hydration and fluids detected with bioimpdance can be confounderdby ecw expansion and overload. To estimates with sufficient accuracy body fat A confrontation with imaging and dxa is confirmatory.

Keywords: smartphone, fat, extracellular water, body mass index, digital imaging, bioelectrical impedance

1. Introduction

Obesity is a multifactorial chronic disease that increases the risk of long-term morbidity, reduces life span, and increases health care costs. More than 650 million people worldwide were identified as obese in 2016 representing a three-fold increase since 1975 [1]. Four million deaths in 2015 were attributed to obesity, and two-thirds ascribed to cardiovascular disease [2]. The global economic burden of obesity is expected to be 1.2 trillion USD in 2025 [3]. Thus, the availability of reliable and practical methods to identify individuals with excess body fat is a public health need.

Clinicians and health professionals use ranges of body weight relative to height, body mass index (BMI; Wt/Ht^2), to stratify adiposity-related health risks in a population. The convenience of BMI in clinical and research settings is offset by its unreliability to estimate body fat and predict the risk of obesity-related diseases for an individual [3–10]. Because BMI is an insensitive indicator of body composition, it poorly predicts the adiposity of individuals with increased fat-free mass (FFM) [11,12]. Other methods to estimate body composition improve the specificity and precision of estimation of fat and lean body components but are limited by technical complexity, exposure to ionizing radiation, invasiveness, lack of mobility, and cost that prevent their widespread use for routine assessment of body composition [13,14]. Recent reports describe the limitations of BMI and emphasize the need for practical and valid methods to identify overweight and obesity and thus improve the care of patients with excess body fat [15–17].

Two methods are amenable to meet this clinical need. Bioelectrical impedance analysis (BIA) relies on the conduction of a safe, administered alternating current to estimate total body water (TBW) [18]. Most BIA methods use 50 kHz phase-sensitive devices and rely on the assumption of constant hydration to estimate FFM and calculate body fat. Alternatively, smartphone two-dimensional standing digital image analysis (2DI) coupled with computational machine learning has recently been used to estimate total body adiposity [19–22]. Studies reported differences in body fat estimates using smartphone 2DI and BIA compared to DXA but have not provided explanations for the observations [20,21]. Whereas BIA is a valid method to assess TBW [18] and excess body fat increases ECW [23], reliance on the assumption of constant hydration of the FFM may overestimate FFM and, thus,

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underestimate body fat in adults who are overweight or obese [24,25]. We hypothesize that fluid imbalance is a factor explaining differences in fat estimation with BIA compared to 2DI.

The aim of the present study was to compare body fat mass (FM) estimates derived using BIA and smartphone single lateral standing digital image (SLSDI) relative to dual x-ray absorptiometry (DXA) in healthy adults and to determine whether fluid imbalance contributes to any observed differences in FM estimates.

2. Materials and Methods

2.1. Participants

We recruited healthy adult Caucasians women and men aged 14 to 64 y using advertisements and word of mouth to participate in this observational study. Nutrition counselling includes routine assessments of body composition using anthropometry, BIA, 2DI and DXA. Patients are informed of the risks and benefits of these measurements and provide signed consent before participating in any testing. Prospective participants underwent clinical examinations and completed a health questionnaire to establish the absence of an unhealthy condition before participation.

2.2. Body composition assessment

Volunteers, wearing form-fitting clothing without jewelry, came to the laboratory after consuming a light meal and emptying their bladders. Standing height and body weight were determined using standard medical equipment (SECA Stadiometer and SECA 762 scale; Hamburg, Germany).

Body composition estimation included BIA, SLSDI, and DXA administered in random order.

2.3. Statistical Methods

Statistical analyses were performed using SYSTAT version 13 (Systat Corporation; San Jose, CA, USA) and version 19.0.3 (MedCalc Software By, Ostend, Belgium). Descriptive data are expressed as mean ± SD. Statistical significance was set at $p < 0.05$.

3. Results

The independent variables in the BIA prediction models offer potential sources of error in the prediction of FFM. The common BIA predictors, Ht^2/R, R, and series Xc, are significantly related to the overall conductive body fluids of TBW and ECW [18]. Thus, an increase of ECW in individuals with excess adipose tissue increases TBW and decreases R, which relative to an assumed constant hydration of FFM, leads to an overestimation of FFM and corresponding underestimation of FM. Extracellular fluid in adipose tissue cannot be distinguished from ECW in lean tissue. The BIA models [26–28] also include body weight that accounts for substantial variance in the predicted FFM (60 to 74%). Two of the BIA equations are generalized and include a designation for sex (male = 1, female = 0) [26,28]. These models resulted in increased errors in estimating FM compared to DXA and proportional bias in the Bland-Altman plots. In contrast, sex-specific BIA estimates of FM tended to be more reliable [27]. These concerns emphasize that BIA prediction models are sample-specific and should be applied in groups in whom the original model was developed to avoid errors. Also, variations in body geometry (e.g., limb length, cross-sectional area, and volume) and fluid content (total and distribution) directly affect resistivity and contribute to between individual differences in whole body and regional BIA measurements [37,41,42]. These factors contribute to the errors in BIA predictions of body fat using various BIA methods and models and DXA in the present study and other reports [20,21].

Knowledge of the limitations of using BIA measurements in multiple regression equations to quantitate fluid volumes and body composition parameters led to the implementation of raw BIA measurements to classify hydration, cell mass and structure independent of body weight [29]. The principal applications used the combined interpretation of PhA and BIVA for clinical assessment of fluid distribution in patients with chronic diseases and prognosis [41]. A key finding was the need to

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concurrently assess fluid status (under- or over-hydration) to reliably detect and track hydration and malnutrition in patients with chronic disease [42,43]. Phase angle also was determined to be an indicator of ICW/ECW with Xc highly correlated with ICW in adults [44].

4. Discussion

This study has some limitations. The inference of expansion of ECW relies on qualitative assessments using BIA. Future studies should incorporate tracer dilution determinations of ECW and TBW and obtain threshold values at which altered fluid distribution affect errors in estimating body fat using BIA. Additionally, investigators should determine the effect of graded body fat levels on errors relative to criteria reference methods particularly in adults with sarcopenic obesity.

5. Conclusions

Smartphone SLSDI provides highly reliable and accurate estimates of FM comparable to DXA of adults with a wide range of body fat. The accuracy and reproducibility, coupled with the convenience, practicality and cost-efficiency facilitate an innovative method to assess body composition to enable routine assessment of body fat for health care personnel in many environments and for biomedical researchers outside the laboratory. It surmounts the limitations of BMI as an index of body fat [15–17] and provides a novel method to estimate abdominal FM [22]. Moreover, SLSDI image-based FM estimates provide better performances than impedance-based methods seemingly because are not influenced by variable hydration states.

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