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ORIGINAL ARTICLE

Accuracy of body fat percentage measurements from a smartphone-based 3D application compared to a bioelectrical impedance analyser

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ABSTRACT

Conventional methods of assessing body composition are accurate but may not be accessible beyond clinical settings. While technological advances have led to the development of more convenient alternative measures, their accuracy has yet to be determined. The present investigation assessed the accuracy of a smartphone-based 3D application's measurements of body fat percentage in comparison to a bioelectrical impedance analyser (BIA), a well-established criterion measure. Sixty-nine apparently healthy, college-aged adults had their body fat percentage measured with BIA followed by the smartphone-based application. Spearman's rank correlation was calculated to be 0.98 (95% CI: 0.92, 0.99), indicating a very strong correlation between the two BF percentage measures. The bias observed between the two devices was low (0.2% [95% CI: -0.1, 0.5]) with limits of agreement spanning from -2.9% (95% CI: -3.4, -2.3) to 3.2% (95% CI: 2.7, 3.8). Given the strong overall agreement between the two modalities, this smartphone-based application may have the potential to make accurate body fat measurements more accessible. Further validation is needed in more diverse populations and against other criterion measures, such as dual-energy x-ray absorptiometry (DXA).

Keywords: Sport medicine, Body fat percentage, Bioelectrical impedance analyser, Smartphone application.

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INTRODUCTION

Body composition is a valuable metric for evaluating comprehensive health and fitness, providing insight into acute and long-term responses to dietary modifications and physical activity (Castro et al., 2020). Standard assessments of body composition measure total body mass using a two-category model: fat mass (FM) and fat-free mass (FFM), which comprises muscle, water, organs, and bones (Holmes & Racette, 2021). Adverse changes in body composition, such as muscle wasting and elevated adiposity, are associated with poor clinical outcomes and a higher risk of mortality (Santanasto et al., 2017). Most relevant to public health at the global scale, however, is the development of obesity, which carries significant cardiometabolic risk and may lead to downstream health complications (Bray et al., 2018).

Considering the importance of body composition in both clinical and fitness contexts, numerous methods are available for its measurement. Self-weighing with commercially available scales can provide a general, albeit limited, indication of overall body composition through body weight (Zheng et al., 2014). Body mass index (BMI) measures weight relative to height but fails to differentiate between FM and FFM. Resultantly, reliance on BMI measures alone can contribute to discrepancies in obesity diagnoses (Okorodudu et al., 2020). Alternative measures include abdominal circumference measurement, waist-to-hip ratio, and skinfold measurements, all of which are subject to considerable variability in execution and interpretation (Duren et al., 2008). Well-validated measures, such as dual-energy x-ray absorptiometry (DXA), bioelectrical impedance analysers (BIA), computed tomography, and magnetic resonance imaging, may offer more accurate assessments of body composition. However, these methods are limited by high cost, time consumption, the need for expert involvement, and their applicability to specific demographics. Furthermore, these methods may not be accessible beyond laboratories or clinics, consequently limiting their practicality and feasibility for home-based use.

Recent technological advancements have been leveraged to facilitate digitally based anthropometric measurements, improving accessibility to body composition assessments. From three-dimensional imaging scans (Tinsley et al, 2024; Florez et al., 2024) to integrated two- and three-dimensional modelling (Neufeld et al., 2020), these modern alternatives have demonstrated promising results in accurately evaluating body composition. Overall, these app-based measurements have shown relative agreement with traditional methods, including DXA and BIA. However, given that these platforms are still in their nascent stages, further validation is necessary to ensure their accuracy. This present study assesses the accuracy and validity of *Visualize Me* (Visualize Inc., Tokyo, Japan), a smartphone-based application that uses depth mapping and infrared scanning for detailed body composition analysis, against criterion-BIA measurements.

METHODS

Participants

A total of eighty-eight apparently healthy participants (60 male, aged 20.1 ± 1.1 yrs; BMI 23.2 ± 1.2 kg/m^2) from the University of California, Los Angeles (UCLA) community volunteered to participate in this study. Sixty-nine participants were included in the final analysis (Figure 1). Written informed consent and ethical approval (IRB:11-003190) was obtained from all pilot participants for a priori power analysis determination at UCLA. Off-site participants gave written consent and approval from a single IRB (sIRB: BRANY, NY, USA) for all data collection. Research practices were conducted in accordance with the ethical principles documented in the Declaration of Helsinki.

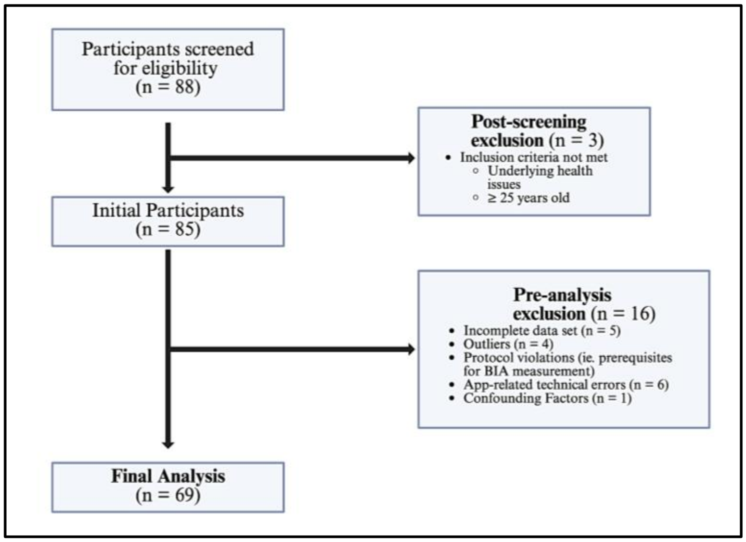

Figure 1. Schematic outlining the exclusion parameters for the final data set used for analysis. Made with Biorender (2025).

Testing procedures

Body mass and height

Body mass was measured on a calibrated medical scale (accuracy ±0.1 kg), and height was determined using a precision stadiometer (Seca, Hanover, MD, United States; accuracy ±0.01 m). In a fasted state and after voiding their bladder, participants were instructed to remove unnecessary clothing and accessories prior to being weighed, as well as remove their shoes prior to taking height measurements.

Criterion measure

A validated octipolar, multi-frequency, multi-segmental bioelectrical impedance analyser (BIA) was used as the criterion measure for assessing body composition (InBody Co., Seoul, Korea Republic) (Dolezal et al., 2013). To ensure accuracy, participants adhered to standard pre-measurement BIA guidelines recommended by the American Society of Exercise Physiologists (Heyward, 2001). Briefly, the test was performed after at least 3 hours of fasting and voiding, with participants instructed to remain hydrated and not exercise 2 hours before testing. After investigators explained the procedure, the participant stood upright with their feet on two metallic footpads while holding a handgrip with both hands. The instrument measured resistance and reactance using proprietary algorithms. Measurements were conducted in triplicate and averaged.

Mobile application

Following the BIA measurements, body fat percentage was determined using a smartphone-based application ("*Visualize Me*", Visualize Inc., Tokyo). This application employs the True Depth camera system (Apple Inc., Cupertino, CA) to obtain body measurements through a combination of depth mapping and infrared scanning technologies (Figure 2). According to the company, a 30-second scan facilitates measurements of the user's neck, chest, waist, and hip circumferences, which are subsequently processed through proprietary AI models to validate measurement accuracy. Body fat percentage is then calculated by incorporating these measurements into the circumference-based formula utilized by various arms of the United States military (Taylor et al., 2024).

Participants began by removing any loose upper-body clothing, excluding bras and tight-fitting shirts, for the measurements. The smartphone equipped with the application was initially provided by the staff to the participant. Once prompted, the participant entered their sex and height, then pressed the 'scan' button. Subsequently, the app delivered an instructional audio prompt. Two photographs were then taken: a front profile with the smartphone held in both hands to capture the shoulders and waist (excluding the face), and a side profile with the smartphone held in one hand to capture the side of the shoulder and waist. Participants subsequently adjusted a circle on the screen to mark the position of their belly button on the frontal image. To ensure impartiality, neither the staff nor the participants were permitted to access their body fat percentage results from this measurement or the subsequent BIA assessment. The test was conducted three consecutive times, with results documented by an independent, unblinded associate.

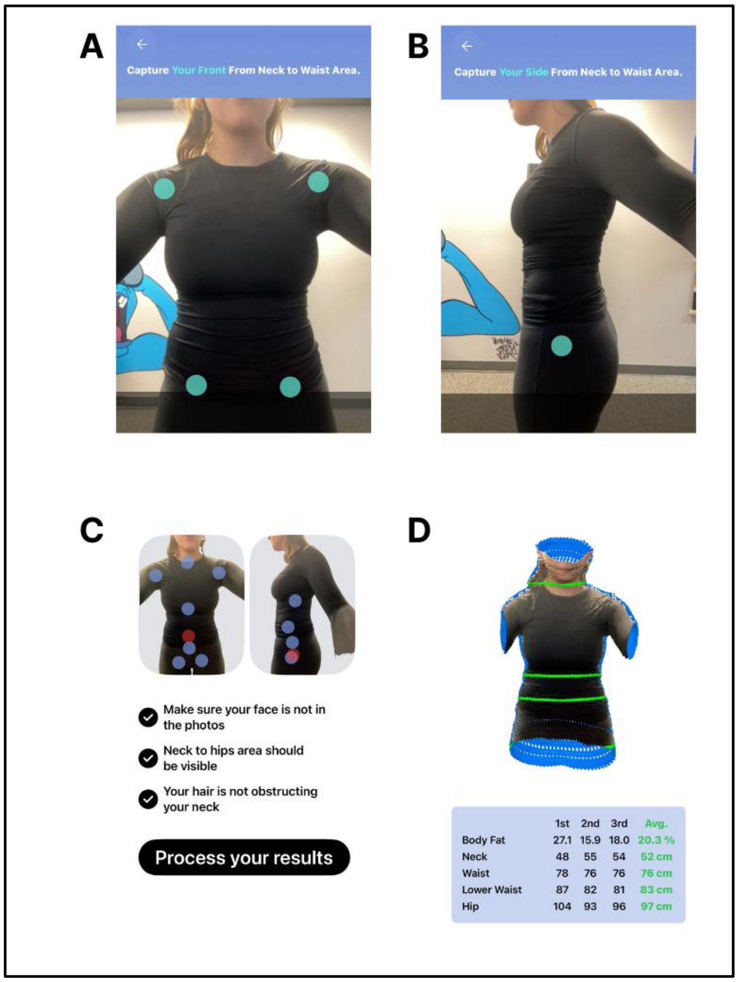

Figure 2. Depiction of front view (A) and side view (B) postures for thorough body composition evaluation via the smartphone application. Quality assurance and precise measurement guidelines are provided during the assessment process (C). Triplicate measurements are averaged using proprietary software to produce an estimation of body fat percentage (D).

Data analysis

Group agreement between each measurement pair (*i.e.,* smartphone application versus BIA) was determined through bias and limits of agreement (LoA) (Bland & Altman, 1986). The former evaluates the average difference between concurrent measurements across a sample, whereas the latter indicates the outer extremes for the potential difference between two measurements (i.e. 95% LoA) (Giavarina, 2015; Bland & Altman, 1999). Normality assessment was conducted using Shapiro-Wilk tests (Ghasemi & Zahediasl, 2012), followed by determination of the Spearman rank correlation coefficient to identify monotonic association (Schober et al., 2018). The threshold for a strong correlation between two measurements corresponds to a correlation coefficient ≥ .90.

RESULTS

Of the 85 initial participants, data from 69 of these participants was used for final analysis. Shapiro-Wilk tests demonstrated that both distributions deviate significantly from normality. Spearman's rank correlation coefficient was calculated due to non-normal distributions and calculated to be 0.98 (95% CI: 0.92, 0.99) (Figure 2), indicating a very strong correlation between the two BF percentage measures. The bias observed between the two devices, represented by a Bland-Altman plot (Figure 3), was 0.2% (95% CI: -0.1, 0.5) with LoA spanning from -2.9% (95% CI: -3.4, -2.3) to 3.2% (95% CI: 2.7, 3.8). These findings support a strong overall agreement between both modalities.

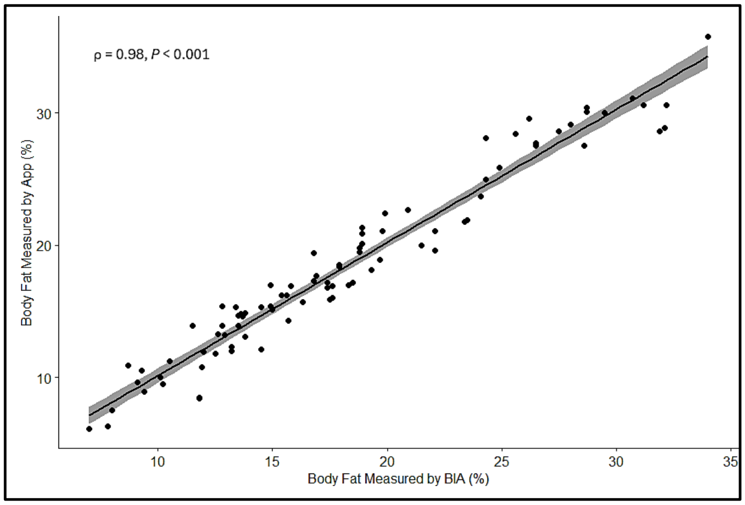

Figure 3. Correlation between body fat measurements with the criterion BIA measure and the smartphone application.

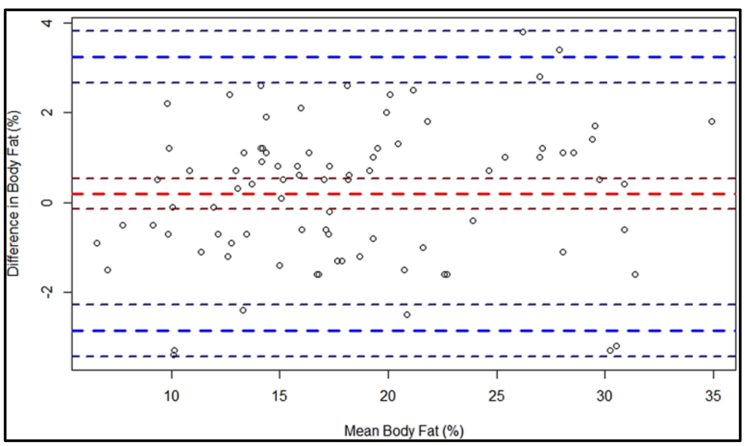

Figure 4. The Bland-Altman plot demonstrates the difference in body fat measurements between the app and criterion methods versus the average of the two modalities. The smaller dashed lines next to each larger dashed line indicate the 95% confidence interval.

DISCUSSION

The primary objective of this study was to assess the validity of a novel smartphone application's body fat (BF) measurements in comparison to a criterion BF measure (BIA). These results indicate that BF measurements were highly comparable between both methods. Spearman's rank correlation exceeded the threshold of 0.90, demonstrating a very strong correlation in BF percentage between the *Visualize Me* smartphone application and criterion BIA. Additionally, there was negligible bias and a small error margin of less than 2.5% between the measurements. These findings highlight the potential of this application to provide accurate and accessible body composition assessments.

Previous efforts have been made to simplify body composition assessment, but oversimplification may compromise accuracy. Frija-Masson and colleagues evaluated the accuracy of body composition assessments from three commercially available smart scales in comparison to DXA (Frija-Masson et al., 2021). Despite accurate measurements of body weight, notable discrepancies were observed in regard to body fat and muscle mass. Body fat was underestimated across all three scales, with absolute errors of -2.2 kg (IQR: -5.8, 1.3), -4.4 kg (IQR: -6.6, 0), and -3.7 kg (IQR: 8.0, 0.3), respectively. Similarly, variability in the assessment of muscle mass was characterized by absolute errors of 4.5kg (IQR: 0.4, 7.3), -6.6 kg (-9.4, -3.6), and 4.0 kg (IQR: 0.1, 7.6), respectively. The authors posited that these inconsistencies could have been attributed to a variety of factors, including foot position, inadvertent leg flexion, and varied electrode contact due to differing foot dimensions. Ultimately, this variability suggests that accurate estimations of body composition may not be achievable with contemporary scales and may therefore require alternative, more sophisticated methods.

Recent advancements in anthropometric measurements via digital platforms have demonstrated promising preliminary results, although absolute accuracy has yet to be achieved. For instance, mobile phone-based three-dimensional (3D) optical imaging has been used to measure abdominal circumference, which can be incorporated into a single-site BF estimation equation devised by the United States military (Florez et al., 2024). When compared to DXA, measurements of BF percentage, fat mass (FM), and fat-free mass (FFM) revealed no significant discrepancies between the two methods. Nevertheless, notable proportional bias was detected among participants with exceptionally low or high BF percentages. Another application, which reconstructed 3D avatars based on smartphone camera scanning, showed a strong correlation with DXA measurements (r = 0.90) without proportional bias (Tinsley et al., 2024). Unlike the one-site method, this application utilized a range of visual data through a full 360-degree rotation of the subject. Indeed, the multiple angles and comprehensive visual detail captured through this method may have enhanced the assessment's accuracy. While the present study's application only captured front and side views of each participant, its accurate estimation of BF percentage relative to BIA suggest that this approach may still be sufficient for proper assessment.

3D body scanning without the use of smartphone imaging has also been shown to produce reliable measurements, especially when compared to manual anthropometric measurements (Medina-Inojosa et al., 2016; Pepper et al., 2010; Derouchey et al., 2020). A recent review found that numerous 3D body scanning modalities have demonstrated strong agreement with other criterion measures, including DXA and air displacement plethysmography (ADP) (Porterfield et al., 2024). For instance, the Styku S100 scanner has been able to produce estimations of FFM and FM with minor differences compared to DXA (1.2 ± 3.4 kg and 1.3 ± 3.4 kg, respectively) (Bennett et al., 2022). Concordance correlation coefficients further validated the accuracy of FFM and FM estimations, which were calculated to be 0.97 (95% CI: 0.96-0.98) and 0.95 (95% CI: 0.94-0.97), respectively. Other 3D body scanning methods, such as the Size Stream SS20 3D optical system (Harty et al., 2020) and the Fit 3D body scanner (Ng et al., 2019), have been used in conjunction with advanced prediction equations to yield body composition estimates concordant with DXA. The former predicted body fat percentage with an R^2 value of .78, whereas the latter produced estimates of FM and visceral fat with R^2 values of .88 and .67 in males, in addition to .93 and .75 in females, respectively. Altogether, these results support the efficacy of 3D body scanning to accurately assess body composition.

However, two-dimensional (2D) images can still be utilized to produce accurate estimations of body composition. A recently developed visual body composition method, which uses 2D images captured via smartphone in conjunction with convolutional neural networks, was able to produce accurate and unbiased body fat estimates concordant with DXA (Majmudar et al., 2022). Notably, this method also outperformed home-based BIA modalities and ADP. Other 2D body scanning platforms have also shown the ability to produce accurate anthropometric measurements of the torso, waist, and both upper and lower extremities (Anisuzzaman et al., 2019; Foysal et al., 2021; de Souza et al., 2020). While 3D scanners have been validated in larger and more diverse populations, they may be less accessible than 2D scanners. Unlike 3D scanners that cost hundreds to thousands of dollars (Daanen et al., 2013), the majority of available 2D body scanners are generally inexpensive and simple to operate. 2D body scanning is typically conducted with smartphone technology, offering a low-cost alternative to 3D scanning and other clinic-based methods (i.e.. DXA). At least 85% of the United States population owns a smartphone, whether it be for personal, work-related, and/or social media purposes (Schuster et al., 2022). Therefore, smartphone-based applications may be more widely accessible compared to other 3D scanning modalities. It is important to acknowledge that the application utilized in the present study is both smartphone-based and utilizes 3D scanning, which may support its accessibility and accuracy compared to alternative methods.

Aside from the methodological and practical challenges of assessing BF percentage, the variable distribution of adipose tissue also warrants consideration. Adipose tissue primarily resides beneath the skin, known as subcutaneous adipose tissue (SCAT), and around internal organs, referred to as visceral adipose tissue (VAT) (Frank et al., 2018). While women tend to have more SCAT, concentrated mainly in the gluteofemoral region, men have higher levels of VAT located predominantly around their abdominal organs (Fried et al., 2015; Link et al., 2017). These sex-related dimorphisms, however, are temporospatial. Girls typically have less waist fat and more peripheral hip fat than boys during prepubescence, whereas boys tend to have more trunk fat. Such regional differences become more pronounced over time and become particularly apparent during the transition between late puberty and early adulthood (Taylor et al., 2012). Age, while still important in both sexes, is a critical factor for women. Postmenopausal women generally lose the protective effects of oestrogen that mitigate weight gain, resulting in a more central accumulation of adipose tissue (Ley et al., 1992). Consequently, the age- and sex-related differences in regional concentrations of adipose tissue should be considered for the proper assessment of body composition.

The limitations of this study include the homogeneity of participant demographics and potential user errors with the application. Since the data was collected exclusively from college-aged, apparently healthy individuals, interpretations should be confined to this specific population. Further validation of measurement accuracy is required across a broader and more diverse population, including paediatric and geriatric subjects. To this end, additional research is necessary to compare this application’s accuracy with that of DXA, which is widely considered the gold standard for body composition assessments. The majority of previous validation studies use DXA as the criterion measure for comparison, which may also limit our findings in comparison to other studied modalities. Although the application provides audible measurement guidelines, camera angles and user errors in positioning may have led to some discrepancies in data capture.

CONCLUSION

The application utilized in this study facilitated accurate body fat measurements relative to a criterion BF method (BIA). A strong correlation was observed between both modalities, along with overall agreement and negligible bias. This efficient, smartphone-based application has the potential to make body fat assessments more accessible in public health and fitness landscapes. Further research is warranted to assess the accuracy of this application compared to alternative methods, such as DXA, as well as in more diverse populations.

AUTHOR CONTRIBUTIONS

The study was conceived and designed by T.Y. and B.A.D. D.C., A.M., J.J.B., and B.A.D. performed data collection. T.Y., E.V.N., and B.A.D. completed data analysis. T.Y., E.V.N., and B.A.D. interpreted data and composed the manuscript while D.C., A.M., J.J.B., and E.V.N. made crucial edits. All authors have read and agreed to the published version of the manuscript.

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DISCLOSURE STATEMENT

No potential conflict of interest was reported by the authors.

ETHICS COMMITTEE APPROVAL

This study was performed in accordance with the ethical standards of the Helsinki Declaration and was approved by the UCLA Institutional Review Board (#11-003190). All participants provided written informed consent.

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