Obesity Facts

Research Article

Obes Facts 2026;19:12–21
DOI: 10.1159/000546820

Received: February 7, 2025
Accepted: May 28, 2025
Published online: June 12, 2025

Body Composition and Function in Patients with Obesity in Clinical Practice: Beyond the Body Mass Index

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Keywords

Obesity · Morphofunctional assessment · Nutritional ultrasound · Bioelectrical impedance analysis · Handgrip strength dynamometry

Abstract

Introduction: Assessing the nutritional and morphofunctional status of patients with obesity (PwO) is essential for optimizing their management. Nutritional ultrasound (NU) is a noninvasive, portable technique that offers insights into muscle and adipose tissue status. Combining NU with bioelectrical impedance analysis (BIA) and handgrip strength (HGS) may improve the assessment of body composition and muscle functionality. This study aimed to evaluate the usefulness of NU as a primary tool for morphofunctional assessment in PwO while comparing and complementing it with BIA and HGS. ***Methods:*** A cross-sectional observational study was conducted including 178 PwO. Body composition was assessed using NU, single-frequency BIA, and HGS dynamometry. Correlations and multiple linear regression models were used to evaluate associations between NU, BIA, and HGS parameters. ***Results:*** Significant correlations were found between NU-measured quadriceps rectus femoris-cross-sectional area (RF-CSA) and BIA-derived fat-free mass markers, such as body cell mass (BCM) ($r = 0.638$, $p < 0.001$) and appendicular skeletal muscle mass ($r = 0.591$, $p < 0.001$). Additionally, leg subcutaneous adipose tissue measured by NU was highly correlated with BIA-calculated fat mass ($r = 0.656$, $p < 0.001$). Linear regression analyses further confirmed the importance of RF-CSA as a strong predictor of BCM, along with HGS and body mass index, explaining 78.2% of the variability in BCM ($R^2 = 0.782$, Akaike Information Criterion = 672). ***Conclusion:*** These findings suggest that NU, combined with BIA and HGS, provides a comprehensive, practical tool for assessing body composition and muscle function in obesity management, with the potential for routine application in clinical settings.

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Plain Language Summary
Obesity can increase the risk of several health problems. To better understand and manage obesity, our study looked at new ways to measure both body composition (the amount of muscle and fat) and muscle function (strength). We worked with 178 adults who have obesity. We used three main techniques: nutritional ultrasound, a simple, noninvasive tool that shows muscle size and fat thickness. One key measure is the size of the area of the rectus femoris muscle in the thigh, which can reflect overall muscle health; bioelectrical impedance analysis (BIA), a quick and simple test that sends a weak electrical current through the body to estimate resistance and reactance, fat mass, muscle mass, and other important markers like body cell mass (BCM) (the "active" cells in your body), and handgrip strength (HGS), a simple device to measure muscle strength in the hands and forearms, which also hints at overall muscle function of the patients. We found that a larger thigh muscle area measured by ultrasound was strongly linked to higher BCM from BIA and better HGS. In addition, thicker leg fat measured by ultrasound was linked to higher body fat from BIA. By using these methods (morphofunctional assessment) together, healthcare providers can get a better picture of both muscle and fat in patients with obesity, potentially improving individualized treatment plans.

Introduction

Obesity is a pathological condition. When not managed correctly, it may predispose patients to an increased risk of cardiorenal, metabolic, and other complications, thus compromising their life expectancy and quality of life. Morphofunctional assessment, which includes bioimpedanciometry, nutritional ultrasound (NU), and handgrip strength (HGS), of nutritional status and body composition is required to determine the appropriate treatment for patients with obesity (PwO) [1]. Body mass index (BMI), although enlightening, does not provide information regarding either body composition or visceral adiposity, thus increasing the risk of misleading diagnoses and favoring the so-called obesity or BMI paradox [2]. Dual-energy X-ray absorptiometry (DXA) is the reference method for evaluating body composition indicators such as fat mass (FM), fat-free mass (FFM), or bone mineral content [3, 4]. Although DXA is considered the reference method for body composition assessment, its use in routine clinical practice is limited due to safety concerns regarding radiation exposure, high costs, and the need for technical expertise, particularly in patients with severe obesity [5]. For this reason, other procedures have been applied and validated to assess body composition and muscle function, namely, bioelectrical impedance analysis (BIA) and HGS dynamometry. BIA is based on the different impedance for an electric current presented by the body's water and cell mass, which allows the calculation of FM and FFM [5]. BIA is not as expensive as DXA and does not require specific training. BIA has shown good consistency for FM and FFM assessment in healthy subjects and PwO [6–8], although the results are influenced by the hydration level of the patient and measurements of body composition are indirect, which requires the use of prediction equations [9]. HGS is a reliable indicator of muscle condition and muscle functionality. HGS has been found to be associated with body composition parameters [10], and the procedure has been used to assess the risk of disease-related malnutrition [11], metabolic syndrome [12], abdominal obesity [13], and sarcopenic obesity (SO) [14].

NU evaluates body compartments, such as muscle, adipose, connective, vascular and bone tissue, to assess ultrasound-based body composition. This procedure is emerging as a cheap, portable, noninvasive, widely available, and easy-to-use procedure for morphofunctional assessment [15]. NU consists of two dimensions to assess FFM and FM. Many NU procedures involve the anterior rectum area of the quadriceps, the so-called rectus femoris (RF). Its composition changes in malnutrition states are well defined [14, 15]. Thus, RF-cross-sectional area (RF-CSA) and RF-Y-axis values have been shown to be reliable indicators of strength and functional performance [16–18]. NU also yields valuable information regarding subcutaneous fat in the leg (L-SAT), as well as abdominal fat, either subcutaneous or visceral (VAT) [19].

We have previously demonstrated the potential usefulness of NU to predict malnutrition-related mortality in cancer patients [20] and sarcopenia in post-critical COVID-19 and colorectal cancer patients [19, 21]. The aim of this study was to evaluate the usefulness of the advance techniques for morphofunctional assessment (BIA, HGS, and NU) in PwO in clinical practice, complementing and comparting it with classical tools like BMI and anthropometric measurements, and also to explore the suitability of NU to analyze the nutritional status of PwO.

Methods

Study Design

This cross-sectional study was conducted between November 2021 and November 2022 at the Obesity Unit at Quirónsalud Hospital of Málaga, Spain. Consecutive adult patients with a diagnosis of obesity, either attending for the first time or for routine follow-ups, were included. This consisted of assessing the morphofunctional status of patients by using functional procedures to measure muscle quality (HGS), as well as by applying BIA- and NU-based procedures to determine body composition. All patients underwent standard clinical assessment, including a complete blood test panel comprising basic biochemical parameters, fasting glucose and insulin, HOMA-IR index, and their obesity status was determined according to the American Association of Clinical Endocrinologists (AACE) guidelines [22].

Inclusion criteria were age ≥18 years old and either BMI ≥30 kg/m^2 or BMI ≥27 kg/m^2 and at least one comorbidity associated with body weight (prediabetes or type 2 diabetes, hypertension, dyslipidemia, obstructive sleep apnea, cardiovascular disease). Exclusion criteria included age under 18 years, BMI <27 kg/m^2, refusal or inability to provide written informed consent, the presence of neurological conditions that could interfere with study participation, and any physical limitation that prevented the completion of the morphofunctional assessment procedures.

Data anonymization was guaranteed. All patients gave written informed consent. The study was conducted in accordance with the ethical principles of the Declaration of Helsinki and started once the Provincial Research Ethic Committee (CEI) of Málaga had approved the study protocol. Study code was 1168-N-23.

Morphofunctional Assessment

Bioelectrical Impedance Analysis

The bioimpedance measurements were performed using a phase-sensitive single-frequency analyzer (NUTRILAB, Akern® Srl, Pontassieve, Italy), as previously described [20]. In brief, the device applies an alternating sinusoidal electric current of 400 µA at 50 kHz (±0.1%; resolution Rz: ±1%, Xc: ±1%, coefficients of variation <2%). Standard whole-body tetrapolar measurements were performed, with the patient in a supine position with a leg opening of 45° compared to the median line of the body and the upper limbs 30° away from the trunk. One Ag/AgCl very low-impedance electrode was placed on the back of the right hand and another electrode on the corresponding foot, each one of them including a sensor and injector area separated by 5 cm (BIVATRODES, Akern® Srl) [23]. The patient was advised to abstain from food and drink for >2 h before the test to warrant proper fluid distribution.

The device directly measured raw bioelectrical parameters, including resistance (R), reactance (Xc), and phase angle (PhA), without the need for vectorial graphical representation. These raw parameters reflect the cellular and fluid status of the body and are particularly useful for assessing hydration and cellular integrity. While PhA was obtained directly from the device, the rest of the body composition estimations, such as FFM, body cell mass (BCM), and skeletal muscle mass (SMM), were derived from predictive equations based on the raw electrical data.

Nutritional Ultrasound

A comprehensive NU study was performed, as previously described [24], to take advantage of the two dimensions of the procedure which allow the assessment of FFM and FM in RF, as well as of abdominal FM [15, 19–21]. A Mindray® Z60 ultrasound analyzer was used with frequency range of 10–12 MHz (Mindray, Madrid, Spain). The patient was relaxed in a supine position, lying with the knee fully extended. The anatomical site for quadriceps RF measurement was standardized following the protocol proposed by García-Almeida et al. [15], locating the distal third of the distance between the anterosuperior iliac spine and the upper edge of the patella, using a flexible, nonelastic measuring tape. RF-CSA, circumference of the quadriceps RF, RF-X axis, and RF-Y axis, i.e., the linear measurement of the distance between the muscular limits of the RF (lateral and anteroposterior), as well as L-SAT, were determined [15, 25]. Scans corresponding to abdominal adipose tissue ultrasound were also taken at the midpoint between the xiphoid appendix and the navel on the midline (total subcutaneous abdominal fat [T-SAT], superficial subcutaneous abdominal fat [S-SAT], preperitoneal or visceral fat [VAT]) (shown in Fig. 1).

All ultrasound examinations were performed by a trained healthcare technician with specialized training in NU. Each measurement took about 3 min to complete. To minimize intraobserver variability, each session was monitored by a second trained clinician, and the results were reviewed jointly. This protocol was designed to ensure reliability and reproducibility of the ultrasound measurements, as indicated by prior studies demonstrating good intra- and interobserver agreement in similar settings.

Functional Outcome

HGS was determined by using the JAMAR-Dynamometer (J.A. Preston Corporation, New York, NY, USA). Patients were sitting with the

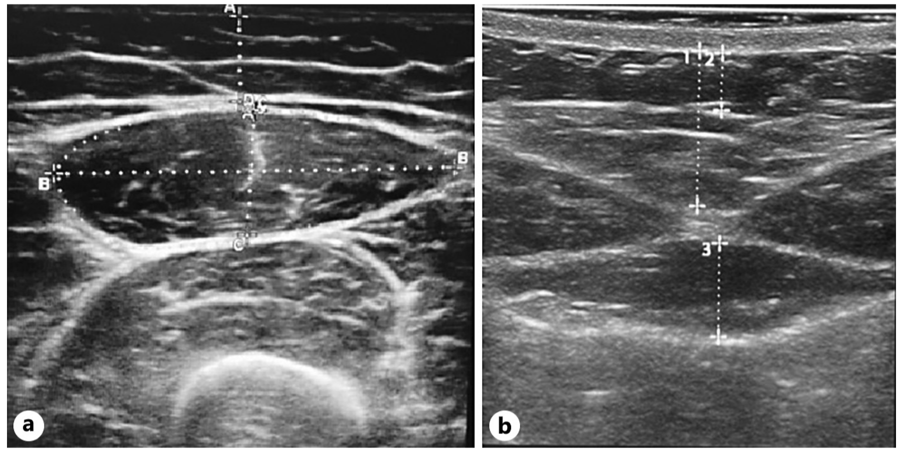

Fig. 1. Nutritional ultrasound. **a** RF muscle ultrasound: (A) L-SAT, (B) RF-X axis, (C) RF-Y axis, (D) RF-CSA and RF-CIR. **b** Abdominal adipose tissue ultrasound: (1) T-SAT, (2) S-SAT, (3) VAT.

shoulder adducted and the elbow flexed at 90° with the forearm and wrist of the dominant arm in a neutral position. Three measurements were obtained, and the average value was considered as the result [26].

Statistical Analyses

For descriptive purposes, the mean (standard deviation [SD]) was used for quantitative, normally distributed variables. The two-tailed unpaired t test, with Welch's correction if variances were significantly different, was used to compare quantitative variables between female and male patients. The Fisher's exact test was used to compare qualitative variables. To compare the suitability of the different procedures to assess the morphofunctional status of PwO, the one-tailed Pearson test was used to analyze correlations between functional/body composition variables determined by BIA, NU, or HGS.

Additionally, linear regression analyses were performed to examine the relationships between key morphofunctional variables. A first model was built to assess the relationship between the RF-CSA, age, BMI, and BCM. A second model evaluated the relationship between BCM and RF-CSA, HGS, and BMI. Model performance was assessed using the coefficient of determination (R^2) to quantify the proportion of variability in the dependent variable explained by the predictors and the Akaike Information Criterion (AIC) to evaluate the balance between model fit and complexity, with lower values indicating a better fit.

Statistical significance was set at $p < 0.05$. All calculations were performed using JAMOVI, version 2.3.22 for macOS.

Results

Baseline Features

Two hundred patients attended the Obesity Unit during the scheduled study period. Fifteen of them had not the complete assessment with BIA, HGS, and NU. Outlier detection was performed using scatterplots and boxplots of key variables (RF-CSA, BCM, HGS). Seven patients were excluded due to extreme values inconsistent with the physiological range of the population, likely reflecting measurement or data entry errors. Thus, 178 patients, 69.7% of whom were female, were finally recruited for morphofunctional assessment (shown in Table 1). Compared to female, weight, BMI, and waist circumference (WC) were significantly higher in male patients (average weight was 24 kg higher, and BMI and WC were 2.6 kg/m^2 and 15 cm higher, respectively). HbA1c values were close to the lower limit of the range of prediabetes. Accordingly, fasting circulating glucose levels were also close to the upper range of normality, and the HOMA insulin resistance index (HOMA-IR) was elevated, being higher in males. More than 80% of patients presented with at least one obesity-related complication. Total cholesterol and triglycerides were within normal range, which was partly explained by the widespread use of statins (not shown).

Morphofunctional Assessment

Morphofunctional assessment measurements using BIA, NU, and HGS are shown in Table 2. Significant differences between female and male patients were observed independently of the methods used to assess body composition and muscle strength.

Given the well-established physiological differences in body composition between men and women, gender-specific analyses were conducted to ensure accurate interpretation of the morphofunctional assessments. Higher

Table 1. Baseline characteristics of the recruited population

Variables	Patient cohort			*p* value
	overall (*n* = 178)	male (*n* = 54)	female (*n* = 124)	
Demographic				
Age, years	46.6 (12.5)	45.7 (12.3)	47.0 (12.3)	0.517
Sex (female), *n* (%)	124 (69.7)	n.a.	n.a.	n.a.
Weight, kg	102.0 (21.1)	119.0 (21.3)	94.7 (16.3)	<0.001
Height, cm	166.2 (9.2)	175.9 (6.6)	162.0 (6.7)	<0.001
BMI, kg/m^2	36.7 (6.2)	38.5 (7.5)	35.9 (5.4)	0.028
WC, cm	115.7 (14.4)	126.0 (13.0)	111.0 (12.3)	<0.001
Hip circumference, cm	123.0 (11.3)	123.0 (13.0)	123.0 (12.3)	0.879
Obesity stage according to AACE[a], *n* (%)				0.046[b]
Stage 0	28 (15.7)	4 (7.4)	24 (19.3)	0.046
Stage 1	78 (43.8)	26 (48.1)	52 (41.9)	0.512
Stage 2	72 (40.4)	24 (44.4)	48 (38.7)	0.509
Biochemical				
Glucose, mg/dL	97.4 (25.5)	105.1 (36.2)	93.8 (17.8)	0.058
HbA1c, %	5.61 (0.79)	5.76 (1.15)	5.53 (0.53)	0.223
HOMA-IR, median (IQR)	2.90 (1.88, 4.38)	3.72 (1.87, 6.14)	2.73 (1.86, 4.06)	0.037
Total cholesterol, mg/dL	186.6 (39.0)	179.7 (38.8)	189.7 (38.8)	0.181
Triglycerides, mg/dL	111.8 (60.5)	139.3 (81.9)	99.8 (44.0)	0.007
25-hydroxyvitamin D, ng/mL	22.7 (9.2)	21.4 (7.0)	23.3 (10.1)	0.211

Data are mean ± standard deviation, except where otherwise indicated. The two-tailed unpaired *t* test was used to compare quantitative variables between male and female patients, with Welch's correction in the event that variances were significantly different, except in the case of HOMA-IR, for which the two-tailed Mann-Whitney U test was used. The two-tailed Fisher's exact test was used to compare qualitative variables between male and female patients. AACE, American Association of Clinical Endocrinologists; BMI, body mass index; HbA1c, glycosylated hemoglobin; HOMA-IR, HOMA insulin resistance index; IQR, interquartile range; n.a., not applicable. [a]Stage 0: BMI ≥30 kg/m^2, no obesity-related complications; stage 1: BMI ≥25 kg/m^2, presence of one or more mild to moderate obesity-related complications; stage 2: BMI ≥25 kg/m^2, presence of one or more severe obesity-related complications [22]. [b]For this analysis, male and female patients were grouped according to whether they were at stage 0 vs. at either stage 1 or stage 2.

values in muscle composition and muscle functionality variables were observed in men and, conversely, the proportion of abdominal and limb adipose tissue was higher in women. Accordingly, there were significant differences in BCM between men and women.

More interestingly, there was a fair correlation between the different methods used to analyze body composition, as well as between these and functional assessment by HGS. A highly significant correlation was observed between BIA functional and muscle markers such as BCM, FFM, or ASMM, and the NU parameter that best represents strength and functional performance, namely, RF-CSA. The association between the rest of the BIA and NU functional and muscle measurements was always significant or highly significant. A low, still significant correlation was observed between BIA PhA and NU muscle markers. A correlation was also observed between BIA and NU when body composition estimates reflecting fat status were analyzed, especially between NU-measured leg FM, estimated by L-SAT, and BIA-measured body FM. An association between abdominal FM as estimated by NU- and BIA-measured FM was also detected. Interestingly, there was a highly significant direct correlation between the reference procedure to assess functional status and NU-measured muscle markers, as well as a highly significant inverse correlation between the former and NU-measured leg fat. Finally, a medium or high correlation was assessed between HGS and body composition parameters estimated by BIA (shown in Tables 3, 4).

A linear regression analysis was conducted to evaluate the relationship between the RF-CSA and the following predictors: age, BMI, and BCM. The model showed a moderate fit (R^2 = 0.509, AIC = 447), explaining 50.9% of the variability in RF-CSA.

This regression model shows that BCM is the strongest predictor of RF-CSA, with a significant positive association. Both age and BMI have a negative effect on RF-CSA. These

Table 2. Body composition and functional assessment

Variables	Cohort			*p* value
	overall (*n* = 178)	male (*n* = 54)	female (*n* = 124)	
BC assessment (BIA)				
PhA, °	6.17 (0.79)	6.40 (0.96)	6.08 (0.70)	0.019
SPA, °	0.33 (0.69)	0.12 (0.68)	0.41 (0.68)	0.016
BCM, kg	31.9 (8.5)	42.4 (7.8)	27.6 (3.6)	<0.001
FFM, kg	58.6 (13.6)	76.4 (10.3)	51.2 (5.6)	<0.001
FFMI, %	22.1 (14.9)	24.6 (3.5)	21.0 (16.8)	0.153
FM, kg	43.7 (13.3)	44.2 (15.3)	43.5 (12.4)	0.760
FM, %	42.5 (7.2)	35.9 (6.5)	45.2 (5.5)	<0.001
FMI, %	16.3 (7.3)	14.3 (5.3)	17.2 (7.9)	0.022
SMI, cm^2/m^2	9.26 (2.03)	11.50 (1.78)	8.32 (1.21)	<0.001
ASMM, kg	23.8 (6.1)	31.3 (5.0)	20.6 (3.1)	<0.001
SMM/kg	25.4 (4.9)	30.2 (4.8)	23.3 (3.3)	<0.001
BC assessment (NU)				
RF-CSA, cm^2	4.94 (1.52)	6.11 (1.70)	4.42 (1.10)	<0.001
RF-CIR, cm	9.10 (1.38)	10.0 (1.41)	8.68 (1.15)	<0.001
RF-X axis, cm	3.68 (0.74)	4.10 (0.91)	3.50 (0.57)	<0.001
RF-Y axis, cm	1.69 (0.36)	1.93 (0.39)	1.59 (0.30)	<0.001
L-SAT, cm	1.81 (0.72)	1.34 (0.79)	2.02 (0.56)	<0.001
RF-CSA/kg	4.96 (1.43)	5.31 (1.51)	4.80 (1.36)	0.036
RF-Y axis/kg	1.70 (0.37)	1.66 (0.33)	1.72 (0.39)	0.361
T-SAT, cm	3.09 (0.96)	2.83 (1.15)	3.20 (0.84)	0.019
S-SAT, cm	1.59 (0.58)	1.41 (0.58)	1.67 (0.56)	0.007
VAT, cm	1.12 (0.54)	1.20 (0.65)	1.08 (0.48)	0.188
Functional assessment				
HGS, kg	27.1 (11.0)	39.9 (9.3)	20.9 (5.2)	<0.001

Body composition was assessed by both BIA and NU, and skeletal muscle function was assessed by HGS. Results are expressed as mean (SD). The two-tailed unpaired *t* test was used to compare quantitative variables between male and female patients, with Welch's correction in the event that variances were significantly different. ASMM, appendicular skeletal muscle mass; BC, body composition; BCM, body cell mass; BIA, bioelectrical impedance analysis; CE, creatine excretion; FFM, fat-free mass; FFMI, fat-free mass index; FM, fat mass; FMI, fat mass index; HGS, handgrip strength; IQR, interquartile range; L-SAT, leg subcutaneous adipose fat; SD, standard deviation; NU, nutritional ultrasound; PhA, phase angle; RF-CIR, rectus femoris quadriceps circumference; RF-CSA, rectus femoris-cross-sectional area; Rz, resistance; SMI, skeletal muscle index; SMM, skeletal muscle mass; SPA, standardized phase angle; S-SAT, superficial abdominal subcutaneous adipose fat; T-SAT, total abdominal subcutaneous adipose fat; Xc, reactance; VAT, visceral adipose tissue.

results reinforce the idea that a higher BCM and younger age are associated with better muscle status, as reflected by larger RF-CSA, in PwO. Additionally, the negative impact of BMI suggests that greater adiposity is linked to reduced muscle size in this population (shown in Table 5). A second linear regression analysis was performed to assess the relationship between BCM and the following predictors: RF-CSA, HGS, and BMI. The model showed a strong fit (R^2 = 0.782, AIC = 672), explaining 78.2% of the variability in BCM.

This regression model demonstrates that RF-CSA is the strongest predictor of BCM, followed by HGS and BMI. The positive association between RF-CSA and BCM highlights the importance of muscle size in determining BCM. Additionally, higher HGS and BMI are positively associated with increased BCM, indicating that both muscle functionality and adiposity contribute to overall BCM in PwO (shown in Table 6).

Although BMI was a positive predictor of BCM, it showed a negative association with RF-CSA in the first regression model. This apparent contradiction highlights the complexity of BMI as a measure that combines both fat and FFM. In PwO, a higher BMI may be associated with

Table 3. Correlations between NU and BIA

NU	BIA						
	PhA, °	BCM, kg	FFM, kg	SMM, kg	SMI, cm^2/m^2	SMM/kg	ASMM, kg
RF-CSA, cm^2	0.338***	0.638***	0.597***	0.466***	0.505***	0.487***	0.591***
RF-CIR, cm	0.308***	0.530***	0.491***	0.346***	0.401***	0.474***	0.479***
RF-X axis, cm	0.200**	0.412***	0.395***	0.302***	0.296***	0.358***	0.385***
RF-Y axis, cm	0.338***	0.582***	0.540***	0.446***	0.448***	0.277***	0.531***
NU	**BIA**						
	PhA, °	FM, kg	FM, %				
L-SAT, cm	−0.317***	0.560***	0.656***				
T-SAT, cm	−0.004	0.360***	0.357***				
S-SAT, cm	0.025	0.325***	0.342***				
VAT, cm	0.134*	0.234**	0.101				

Cells with no color indicate no correlation or weak correlation (<0.200). Cells with pale wintergreen color indicate low correlation (0.200–<0.400). Cells with baby blue color indicate medium correlation (0.400–<0.700). *p < 0.05, **p < 0.01, ***p < 0.0001.

Table 4. Correlations between NU, BIA, and HGS

	NU							
	RF-CSA, cm^2	RF-CIR, cm	RF-X axis, cm	RF-Y axis, cm	L-SAT, cm	T-SAT, cm	S-SAT, cm	VAT, cm
HGS, kg	0.536***	0.520***	0.423***	0.429***	−0.416***	−0.069	−0.045	0.246**
	BIA							
	PhA, °	BCM, kg	FFM, kg	SMM, kg	ASMM, kg	FM, kg	FM, %	
HGS, kg	0.281**	0.753***	0.745***	0.556***	0.714***	0.030	−0.529***	

Cells with no color indicate no correlation or weak correlation (<0.200). Cells with pale wintergreen color indicate low correlation (0.200–<0.400). Cells with baby blue color indicate medium correlation (0.400–<0.700). Cells with dark blue color indicate high correlation or very high correlation (0.700–1). **p < 0.01, ***p < 0.001.

increased total FFM, including BCM. However, this does not necessarily indicate a greater amount of quadriceps muscle or improved muscle function, as assessed NU.

Discussion

To the best of our knowledge, this is the first study to validate the use of advanced techniques, such as NU, BIA, and HGS, over traditional approaches like BMI and WC in the clinical practice. These new tools provide crucial data on body composition and functionality, offering a more comprehensive and precise assessment of the nutritional and morphofunctional status of PwO. This paradigm shift enhances the understanding of obesity beyond classical anthropometric parameters, paving the way for more effective and individualized patient management strategies.

While BMI and WC offer a global and estimated assessment of adiposity, they do not provide specific or localized information on body composition. In contrast, BIA – although based on predictive models – can estimate total body fat content and lean mass distribution, while NU

Table 5. Linear regression model predicting RF-CSA based on age, BMI, and BCM

Model	R		R^2	AIC
Model 1	0.714		0.509	447
Predictor	Estimator	SE	t	p value
Constant	4.1071	0.70119	5.85	<0.001
Age	−0.0281	0.00736	−3.82	<0.001
BMI	−0.0542	0.01687	−3.21	0.002
BCM	0.1328	0.01245	10.66	<0.001

BMI, body mass index; BCM, body cell mass; RF-CSA, rectus femoris-cross-sectional area.

Table 6. Linear regression model predicting BCM based on RF-CSA, HGS, and BMI

Model	R		R^2	AIC
Model 1	0.884		0.782	672
Predictor	Estimator	SE	t	p value
Constant	−3.473	2.3880	−1.45	0.149
RF-CSA	1.815	0.2610	6.95	<0.001
HGS	0.393	0.0376	10.43	<0.001
BMI	0.427	0.0598	7.13	<0.001

HGS, handgrip strength; BCM, body cell mass; RF-CSA, rectus femoris-cross-sectional area.

allows for the direct visualization and differentiation of fat compartments, such as subcutaneous and visceral adipose tissue at the abdominal level. This multidimensional approach enables a much more precise and clinically useful assessment of body composition and muscle health in PwO.

The size and location of quadriceps RF allows for an easy, time-saving way to perform NU procedures in routine clinical practice. Among NU-measured variables, RF-CSA is essential for clinical application, and it has been associated with muscle strength [27]. We observed a relevant, significant association between RF-CSA and BIA estimates of nonfat variables such as BCM, FFM, SMI, and ASMM. The noteworthy correlation found between RF-CSA and BCM is of interest since the latter provides information about the number of metabolically active cells in the body and has been suggested to be a reliable marker of malnutrition [28]. An association between RF-CSA and other BIA-measured variables such as FFM or ASMM in the presence of other clinical conditions has also been reported [19, 21].

On the other hand, according to the previous findings, RF-CSA also showed a high correlation with HGS dynamometry, thus suggesting that the former can also reflect the muscle functionality of PwO. Muscle circumference as well as transverse and longitudinal axis are also highly informative NU-measured variables [15]. In our sample, they were also directly correlated with muscle-related BIA and HGS parameters. Finally, the close association found between muscle-related BIA variables and HGS dynamometry results, which has been previously reported [29, 30], further validates the methods used to assess body composition in our cohort of PwO.

Although the correlations between BIA and HGS may appear stronger in some specific parameters, each of the three methods evaluated – NU, BIA, and HGS – captures different aspects of the morphofunctional profile. BIA estimates body composition parameters based on electrical properties, HGS measures muscle strength as a functional parameter, and NU provides direct, anatomical assessment of muscle, and adipose tissue. Therefore, rather than being redundant, these techniques are complementary. Their combined use enables a multidimensional evaluation – quantitative, structural, and functional – offering a more complete picture of the nutritional and muscle health status of PwO.

When focusing on the assessment of FM body composition markers, we also found a fair correlation between NU-measured L-SAT and FM as estimated by BIA, in accordance with our previous observations in a cohort of patients with colorectal cancer [19]. Therefore, subcutaneous fat of RF also provides reliable information regarding the fat status of PwO. Furthermore, NU can provide a more complete picture since it can distinguish between limb and VAT, which has a great impact on health risks [31], while BIA provides an overall, indirect estimation of body fat obtained by applying mathematical modeling [23]. NU-measured VAT has been previously associated with metabolic syndrome features in PwO [32]. On the other hand, remarkably, L-SAT showed an inverse correlation with HGS measurements. Dynamometry is a powerful predictor of disability, frailty, morbidity, and mortality [33]. Thus, the close alignment between HGS and both muscle and fat RF markers reinforces the potential usefulness of NU to assess the nutritional status of PwO.

Our study has some limitations. The proportion of male and female patients is not balanced, and the sample size of the cohort precludes a reliable analysis after stratifying by sex. We have not performed repeated measurements to estimate variability. The cross-sectional nature of the study does not allow us to test the validity of the method to monitor changes in body composition after treatment initiation/change, lifestyle changes, and so on, an issue that will be addressed in ongoing studies. Other potential limitation of this study is the inherent operator dependency of NU. Although ultrasound provides a noninvasive and valuable tool for assessing body composition and muscle health, its accuracy can be influenced by the skill and experience of the clinician performing the measurement. To minimize variability, all ultrasound assessments in this study were conducted by trained clinicians specialized in NU.

Additionally, each measurement was verified by a second clinician, and any discrepancies were resolved through joint review. These steps were taken to ensure the reliability and reproducibility of the measurements. Despite these efforts, small variations in measurement technique may still occur, and future studies should consider further standardization and automation where possible. Finally, although BIA and HGS are accepted methods for assessing nutritional status, DXA is the gold standard, and a direct comparison between NU and DXA was not performed.

Conclusions

Our findings suggest that the combination of the advance techniques for morphofunctional assessment, NU, BIA, and HGS, provides a practical and reliable approach for the assessment in PwO. By supplementing classical measures like BMI and WC, these morphofunctional tools contribute to a more individualized and precise assessment strategy that can enhance the clinical management and follow-up of PwO.

NU proved useful as a valid tool for assessing muscle size and fat distribution, with significant associations between RF-CSA and BCM and between L-SAT and body fat calculated by BIA. This combination offers a noninvasive, efficient means of evaluating both body composition and muscle functionality, essential for an optimal management of obesity. Given its affordability, portability, and ease of use, NU has potential for routine implementation in clinical and primary care settings to facilitate the continuous monitoring of morphofunctional changes, thereby enhancing individualized patient management, intervention, and outcomes in obesity care. Future research should further validate these findings against gold-standard methods and explore the utility of these techniques in tracking treatment-related changes over time.

Statement of Ethics

This study was performed in accordance with the Declaration of Helsinki. This human study was approved by Declaration of Helsinki and was approved by the Ethics Committee of Málaga, approval: 1168-N-23. All adult participants provided written informed consent to participate in this study.

Conflict of Interest Statement

The authors have no conflicts of interest to declare.

Funding Sources

This research was funded by Novo Nordisk. The APC was funded by Novo Nordisk. The funder had no role in the design, data collection, data analysis, and reporting of this study.

Author Contributions

Conceptualization: J.M.G.A.; methodology: J.M.G.A., M.G.O., L.D.R., R.F.J., and C.H.A.; formal analysis: M.G.O., R.F.J., and J.M.G.A.; investigation and project administration: J.M.G.A., M.G.O., L.D.R., and R.F.J.; resources and supervision: J.M.G.A., M.G.O., and L.D.R.; data curation: J.M.G.A., M.G.O., R.F.J., and C.H.C.; writing – original draft preparation: J.M.G.A. and M.G.O.; and review: J.M.G.A., L.D.R., R.F.J., J.A.F., V.M.J., and F.H.S. All authors have read and agreed to the published version of the manuscript.

Data Availability Statement

All data generated or analyzed during this study are included in this article. Further inquiries can be directed to the corresponding author.

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