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Statistical Medical Pattern Recognition for Body Composition Data Using Bioelectrical Impedance Analyzer

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Abstract: Identifying patterns, recognition systems, prediction methods, and detection methods is a major challenge in solving different medical issues. Few categories of devices for personal and professional assessment of body composition are available. Bioelectrical impedance analyzer is a simple, safe, affordable, mobile, non-invasive, and less expensive alternative device for body composition assessment. Identifying the body composition pattern of different groups with varying age and gender is a major challenge in defining an optimal level because of the body shape, body mass, energy requirements, physical fitness, health status, and metabolic profile. Thus, this research aims to identify the statistical medical pattern recognition of body composition data by using a bioelectrical impedance analyzer. In previous studies, a pattern was identified for four indicators that concern body composition (e.g., body mass index (BMI), body fat, muscle mass, and total body water). The novelty of our study is the fact that we identified a recognition pattern by using medical statistical methods for a body composition that contains seven indicators (e.g., body fat, visceral fat, BMI, muscle mass, skeletal muscle mass, sarcopenic index, and total body water). The youth that exhibited the body composition pattern identified in our study could be considered healthy. Every deviation of one or more parameters outside the margins of the pattern for body composition could be associated with health issues, and more medical investigations would be needed for a diagnosis. BIA is considered a valid and reliable device to assess body composition along with medical statistical methods to identify a pattern for body composition according to the age, gender, and other relevant parameters.

Keywords: Statistical method; pattern recognition; body composition; assessment

1 Introduction

In recent years, people became more interested in assessing and diagnosing their health status. Nowadays, many medical devices are available, thereby allowing the assessment and screening of one's health. Identifying patterns, recognition systems [1], prediction methods [2], detection methods [3–6], and benchmark methods [7] to solve different medical issues is a major challenge [8,9]. For body composition there are few categories of devices for personal and professional assessment: dual-energy X-ray absorptiometry (DXA), magnetic resonance imaging (MRI), and bioelectrical impedance analyzer (BIA).

DXA is used to assess the bone mineral density and body composition. The body measurement must be taken by a licensed radiological technician, and a complete scan lasts for 5 minutes [10–12]. MRI is a non-invasive technology that produces three-dimensional (3D) images for soft body tissues. This technology does not use ionizing radiation and allows the detection of changes in the protons found in the water of the human body. Special software processes the image pixels. MRI is considered a reference method for body composition assessment along with DXA [12–14].

BIA is considered a valid method for the assessment of body composition, and its reliability could be influenced by several factors, such as device, operator, subject, and environment [15]. Furthermore, it is a simpler, safer, more affordable, mobile, non-invasive, and less expensive alternative than other devices or methods used for body composition assessment [16]. BIA allows the selection of standard or athletic mode, gender, age, and height. Nevertheless, statistically significant differences are observed among BIAs because of calibration, different electric current frequencies, and different numbers of electrodes [12,17].

The novelty of this research is that we will determine the pattern recognition for body composition data by using BIA and statistical medical methods for at least seven parameters (e.g., body fat, visceral fat, body mass index (BMI), muscle mass, skeletal muscle mass, sarcopenic index, and total body water). The medical technology evolves rapidly, and new functions are available for use. However, each person is unique because although their age, height, and weight are the same, their body shapes, body composition, energy requirements, physical fitness, health status, and metabolic profiles are different. Establishing a pattern for body composition related to the age and gender is necessary.

A synaptic overview of the different devices used to assess the body composition in the analyzed studies is presented in Tab. 1.

Table 1: Previous studies that used devices to assess body composition

Authors	Device	Collected data	Statistics
Matias et al. [18]	Tanita MC-180MA	Total body water (TBW) Extracellular (ECW) Intracellular water (ICW)	Bland-Altman analysis
Vasold et al. [19]	RJL, Omron, and Tanita	Fat-free mass	Pearson correlation
Isaev et al. [20]	Tanita BC-418AA	Muscle mass Fat mass BMI	Analysis of variance

(Continued)

Table 1: Continued

Authors	Device	Collected data	Statistics
Ciplak et al. [21]	Tanita BC-418	Body weight Body Mass Index (BMI) Body fat	Pearson correlation
Guedes et al. [22]	Tanita MC-980U InBody 770 whole-body spectral techniques (Xitron 4200)	Fat-free mass (FFM) Fat mass (FM) Body fat percentage (BF%)	Pearson correlation Bland-Altman's analysis
Siddiqui et al. [23]	Tanita MC-180MA	Total fat Visceral fat Muscle mass BMI	Regression
Verney et al. [11]	Dual-energy X-ray absorptiometry (DXA)—QDR4500A scanner Tanita MC780	Fat Mass Fat-Free Mass	Intra-class correlation coefficient Bland and Altman
Kutac and Kopecky [17]	Tanita 418 MA, InBody 720 InBody R20 and Omron BF 300	Total body water (TBW) Body fat	Pearson correlation Bland-Altman's analysis
Wang et al. [12]	HBF 359 (Omron), BC 532 (Tanita), standard dual energy X-ray absorptiometry (DXA) and magnetic resonance imaging (MRI)	Body fat percentage (BF) Skeletal muscle mass percentage (or fat-free mass) Visceral fat (VF)	Intraclass correlation analysis Paired *t*-test
Dixon and Andreacci [24]	Tanita TBF-300A and Tanita BC-418	Body fat	Mean±SD Analysis of variance
Demura et al. [25]	Tanita BC-118 Dual-energy X-ray absorptiometry (DXA)	Percent total body fat (% TBF) Percent segmental fat (% SF)	Intra-class correlation
Cable et al. [26]	Tanita body fat analyzer, TBF 105	Body mass index Body fat Fat-free Mass	Bland-Altman

Many of the previously analyzed studies used Pearson correlation and Bland–Altman analysis, but some of them used the analysis of variance (ANOVA) and paired t-test [12,20,24].

The statistical expression for ANOVA is:

$$\mathrm{SST}: \sum_{i=1}^{m}\sum_{j=1}^{n}\left(X_{ij}-\overline{X}_{\cdot\cdot}\right)^2 \tag{1}$$

$$\mathrm{SSE} = \sum_{i=1}^{m}\sum_{j=1}^{n}\left(X_{ij}-\overline{X}_{i\cdot}\right)^2 \tag{2}$$

$$\mathrm{SS(Tr)} = n\sum_{i=1}^{m}\left(\overline{X}_{i\cdot} - \overline{X}_{\cdot\cdot}\right)^2 \tag{3}$$

$$\sum_{i=1}^{m}\sum_{j=1}^{n}\left(X_{ij} - \overline{X}_{\cdot\cdot}\right)^2 = \sum_{i=1}^{m}\sum_{j=1}^{n}\left(X_{ij} - \overline{X}_{i\cdot}\right)^2 + n\sum_{i=1}^{m}\left(\overline{X}_{i\cdot} - \overline{X}_{\cdot\cdot}\right)^2 \tag{4}$$

SST—Sum of Squares – Total
SSE—Sum of Squares – Error
SS(Tr)—Sum of Squares – Treatment/case
m—Number of samples
n—Total size of all the samples.

Finally, with previous data, determining the value of F is possible:

$$F = \frac{SS\,(Tr)\,/\,(m-1)}{SSE/(m\,(n-1)} \triangleq \frac{MS\,(Tr)}{MSE} \sim F\,[m-1, m\,(n-1)]\,. \tag{5}$$

MS—Mean square.

A synthetic view for all this operation to determine F by using analysis of variance (ANOVA) is shown in Tab. 2.

Table 2: Summary table of one-way ANOVA

Source	Sum of squares (SS)	Df	Mean square (MS)	F
Between	SS_{tr}	Df_{tr}	MS_{tr}	F
Within	SS_{e}	Df_{e}	MS_{e}	
Total	SS_{t}	Df_{t}		

The statistical significance of at least $p < 0.05$ is required for ANOVA and paired t-test according to the number of cases/subjects.

The paired t-test statistic value is calculated by using the following formula:

$$t = \frac{m}{s/\sqrt{n}} \tag{6}$$

m—Mean differences
n—Sample size
s—Standard deviation.

Also, these studies allow us to identify a pattern because analyzed data concerning body composition are presented in Tab. 3.

According to the data from other studies, we identified the patterns for youth by using the statistical data for body composition in Tab. 4.

Identifying the body composition pattern of individuals with different age and gender is a major challenge in defining an optimal level because of the differences in their body shape, body mass, energy requirements, physical fitness, health status, and metabolic profile. These patterns allow the identification of possible health issues or disorders very easily and encourage people to have a healthy lifestyle along with a very good quality of life.

Studies on different age categories with various numbers of subjects and genders were identified by reviewing literature concerning the topic, and their components were analyzed using different kinds of devices for body mass composition. For youth, we identified a pattern for four body composition parameters in previous studies. By using a BIA device and statistical medical methods, we aim to establish a pattern for body composition for youth that comprises more parameters to identify the healthy profile particular for that age.

Table 3: Patterns for body composition identified by analyzing other studies

Authors	Collected data	Age, gender
Matias et al. [18]	Total body water (TBW)—3.1–5.1 kg Extracellular (ECW)—5.0–2.3 kg Intracellular water (ICW)—2.5–9.6 kg	18.5 ± 4.1 years 17 males 19 females
Vasold et al. [19]	Fat-free mass males—75.6 ± 9.4 kg Fat-free mass males—59.8 ± 7.6 kg	19.1 ± 1.2 years 31 males 46 females
Isaev et al. [20]	Muscle mass—52.4%–58.9% Fat mass—9%–10.2% BMI—25.64	14–17 years 15 males
Ciplak et al. [21]	Body weight—65.6 ± 7.9 kg Body Mass Index (BMI)—21.4 ± 2.3 Body fat—22.9 ± 3.6%	15–17 years 103 females
Guedes et al. [22]	Fat-free mass (FFM)—0.98–1.69 kg Fat mass (FM)—1.91–3.93 kg Body fat percentage (BF%)—3.86%–5.28% Limits of agreement	18–28 years 117 subjects
Siddiqui et al. [23]	Males BMI—22.80 ± 3.83 Total fat—22.03 ± 6.33% Visceral fat—5.91 ± 3.78% Muscle mass—74.05 ± 6.23% Females BMI—22.38 ± 5.05 Total fat—32.17 ± 9.03% Visceral fat—4.54 ± 4.11% Muscle mass—63.46 ± 8.72%	17–24 years 32 males 53 females
Verney et al. [11]	Fat mass males—14.3 ± 3.2 kg Fat mass females—23.7 ± 5.5 kg Fat-free mass males—60.9 ± 8.2 kg Fat-free mass females—44.1 ± 5.22 kg	22.7 ± 3.5 years 36 males 35 females
Kutac and Kopecky [17]	Males Total body water (TBW)—65.6 ± 3.0%/49.3 ± 4.8 kg Body fat—10.6 ± 4.0%/8.0 ± 3.4 kg Females Total body water (TBW)—55.2 ± 2.9%/33.1 ± 3.7% Body fat—23.6 ± 5.1%/14 ± 3.5 kg	70 males 20.2 ± 1.1 years 55 females 19.8 ± 1.2 years
Dixon and Andreacci [24]	Body fat females—25.5 ± 7.3% Body fat males—18.8 ± 7.9%	52 females 40 males
Cable et al. [26]	Body mass index—26 ± 4 Body fat—18.1 ± 8.9% Fat-free mass—66.2 ± 7.7 kg	39 ± 11.68 years

Table 4: Body composition pattern for youth

Body composition parameters	Males	Females
Body mass index	19–26.6	17.3–27.4
Body fat (%)	10.9–26.7	20.5–33.5
Muscle mass or fat-free mass (%)	68–80	55–72
Total body water (%)	62–69	52–58

This research is organized as follows. Section 2 presents the methodology. Section 3 presents the results collected by BIA and analyzed by statistical medical methods. Section 4 analyzes the results and identifies the pattern recognition for the body composition of males and females. Section 5 presents the conclusions and prospects for future work.

2 Materials and Methods

This research aims to identify the statistical medical pattern recognition for body composition data by using BIA.

2.1 Participants

The research subjects include students who provided written informed consent prior to the research. The protocol was approved by the University Ethic Research Committee. The body characteristics and age averages by gender are presented in Tab. 5.

Table 5: Body characteristics of the subjects

Body pattern/Subjects	Males	Females
Height	177.40 ± 6.96 cm	163.67 ± 8.80 cm
Weight	77.95 ± 11.41 kg	59.25 ± 10.72 kg
Body mass index	24.67 ± 2.40	21.94 ± 2.17
Age	22.65 ± 6.24	20.60 ± 1.12 years

The BMI is a parameter that allows determining the body composition very easily:

$$\mathrm{BMI} = \frac{\mathrm{W\,(kg)}}{\mathrm{H}^2(m)}. \tag{7}$$

The normal index must be between 18.5 and 25 points, the people who are in this range are considered to have a normal weight, and their health status is usually optimal. A point that falls below 18.5 are considered underweight, and an individual health status could be affected in this situation. Values over 25 points suggests an overweight level and over 30 corresponds to obesity, that is, the health status of an individual is deteriorating with poor effects at the physical and physiological level. Along with the health issues, the people who are in these categories (over 25 or 30) are also affected at the psychological level, because they cannot perform their daily tasks. The BMI is moderately correlated to the level of body fat [27,28].

2.2 Materials

The subjects followed four hours of physical activities according to their curricula and additional 4 to 8 hours of extracurricular physical activities weekly. The assessments were made throughout the first and in the last week of the research during the same day and at the same hour.

2.3 Procedure

In this research, we used a BIA (Tanita MC-780 MA) to assess body composition with high-frequency current (50 Khz, 90 μA) and eight electrodes that allow the current to flow into the upper and lower limbs (tetrapolar). All subjects in the standard mode were selected. The assessment protocol by BIA is shown in Fig. 1.

Figure 1: Assessment protocol using BIS (Tanita MC-780 MA)

The descriptive statistics, including Pearson correlation and Bland–Altman analysis, were calculated on the basis of the collected data by using IBM SPSS version 26. To achieve statistical significance, the value was set at $p < 0.05$.

Pearson correlation formula was applied to determine the concordance between data sets.

$$r = \frac{n\sum xy - \left(\sum x\right)\left(\sum y\right)}{\sqrt{n\left(\sum x^2\right) - \left(\sum x\right)^2}\sqrt{n\left(\sum y^2\right) - \left(\sum y\right)^2}} \tag{8}$$

r = Pearson r correlation coefficient
n = number of observations/cases
x = individual value group 1
y = individual value group 2.

The value of r ranges between +1 and −1. If the correlation coefficient is −1, then a strong negative connection exists, and it is a perfect negative connection between the variables. If the correlation coefficient is 0, then there is no connection. If the correlation coefficient is 1, then a strong positive connection exists. A level of confidence of 95% was established by the Bland–Altman analysis, and we obtained a bias and lower and upper limits of agreement (LOA).

3 Results

In our research, data concerning body composition (body fat, visceral fat, BMI, muscle mass, skeletal muscle mass, sarcopenic index, and total body water) were collected. The collected data were analyzed separately for each gender because differences concerning body composition are observed, as shown in Tabs. 6 and 7.

Table 6: Statistical analysis for body composition (males)

Body composition parameters	Pre-test (X ± SD)	Post-test (X ± SD)	Correlation	Bland Altman confidence 95% ($p < 0.05$)	
				Bias	Limits
Body fat (%)	19.99 ± 3.764	19.57 ± 3.504	0.976	−0.42	−2.06–1.22
Visceral fat (%)	4.05 ± 2.373	4.10 ± 2.292	0.948	0.05	−1.44–1.54
Body mass index	24.67 ± 2.401	25.01 ± 2.323	0.982	0.34	0.46–1.24
Muscle mass (%)	76.02 ± 3.550	76.57 ± 3.312	0.952	0.55	1.09–2.69
Skeletal muscle mass (%)	44.61 ± 4.333	44.70 ± 3.036	0.890	0.09	2.14–4.28
Sarcopenic index	8.48 ± 0.817	8.73 ± 0.734	0.918	0.25	0.32–0.88
Total body water (%)	56.68 ± 4.450	56.87 ± 3.428	0.918	0.20	1.93–3.97

By applying ANOVA and paired t-test at each gender and for each parameter of the body composition between pre and post-test, the statistical significance of 10 out of 14 indicators were not achieved (Tab. 8). These results confirm that BIA is a reliable device in assessing body composition, and its results could be used at the benchmark to determine pattern recognition.

The average values for each body composition parameters did not show any significant differences between pre and post-test at males (Fig. 2) and females (Fig. 3). These aspects confirm that BIA had an excellent accuracy for assessing body composition.

Table 7: Statistical analysis for body composition (females)

Body composition parameters	Pre-test (X ± SD)	Post-test (X ± SD)	Correlation	Bland Altman confidence 95% ($p < 0.05$)	
				Bias	Limits
Body fat (%)	23.97 ± 5.246	23.26 ± 5.432	0.927	−0.71	−4.73–3.32
Visceral fat (%)	1.40 ± 0.737	1.33 ± 0.617	0.942	−0.07	−0.57–0.44
Body mass index	21.94 ± 2.168	21.87 ± 1.984	0.979	−0.07	−0.98–0.84
Muscle mass (%)	72.13 ± 4.950	72.85 ± 5.175	0.928	0.73	−3.08–4.53
Skeletal muscle mass (%)	38.36 ± 6.065	38.41 ± 6.607	0.976	0.05	−2.86–2.97
Sarcopenic index	6.36 ± 0.506	6.46 ± 0.341	0.755	0.10	−0.55–0.75
Total body water (%)	51.29 ± 5.541	51.45 ± 5.790	0.982	0.16	−2.01–2.33

Table 8: Statistical analysis for body composition (paired t-test, ANOVA)

Body composition parameters	Males				Females			
	Paired t-test		ANOVA		Paired t-test		ANOVA	
	t	p*	F	p**	t	p***	F	p****
Body fat (%)	2.24	<0.05	0.13	0.72	1.33	>0.05	0.13	0.72
Visceral fat (%)	−0.29	>0.05	0.01	0.95	1.00	>0.05	0.07	0.79
Body mass index	−3.33	<0.05	0.21	0.65	0.56	>0.05	0.01	0.93
Muscle mass (%)	−2.25	<0.05	0.26	0.62	−1.45	>0.05	0.15	0.70
Skeletal muscle mass (%)	−0.19	>0.05	0.01	0.94	−0.14	>0.05	0.01	0.98
Sarcopenic index	−3.39	<0.05	1.00	0.32	−1.17	>0.05	0.39	0.54
Total body water (%)	−0.45	>0.05	0.02	0.88	−0.56	>0.05	0.01	0.94

Critical value for: p*—1.73; p**—4.10; p***—1.76; p****—4.20.

4 Discussions

For Pearson correlation, at males, 6 out of 7 values were over 0.900 and that means a strong positive correlation and for one indicator the value was 0.890. For females, one indicator has a value of 0.755, and the six other indicators have values over 0.900, indicating a strong positive correlation. According to the data collected from BIA (Tanita MC 780 MA) and by applying Bland–Altman analysis (Figs. 2 and 3) and Pearson correlation, we determined the body composition pattern of the subjects involved in our study (males and females) and compared them with our previous studies. The body composition pattern of males is shown in Tab. 9, and the distribution of values is shown in Fig. 4.

The body composition pattern of females is shown in Tab. 10, and the distribution according to Bland Altman analysis is presented in Fig. 5.

For body fat (BF%), at males, there was obtained a value of 0.976 at Pearson correlation, that means a strong positive correlation; at Bland–Altman analysis the bias was −0.42, and the LOA were −2.06 (lower) and +1.22 (upper). For females, a strong positive correlation was also recorded; the bias value was −0.71, and the LOA were −4.73 and +3.32. The visceral fat (VF%) for both genders exhibited a strong positive correlation (males—0.948, females—0.942).

The Bland–Altman analysis for males shows that the lower and upper LOA were −1.44 and +1.54, respectively; whereas those for females were −0.57 and +0.44, respectively [17,24,25,29–32].

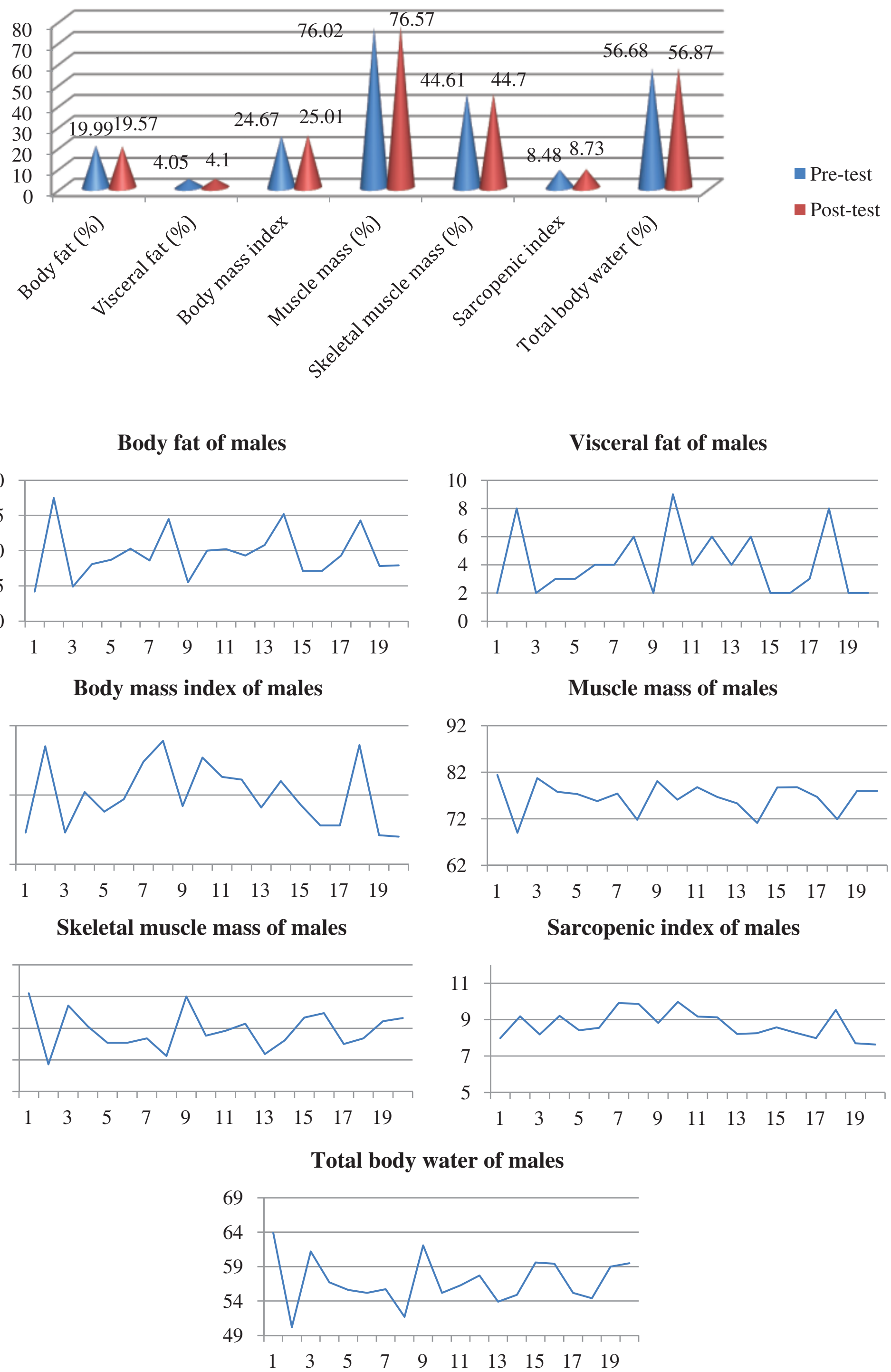

Figure 2: Assessment results using bioelectrical impedance analyzer (males)

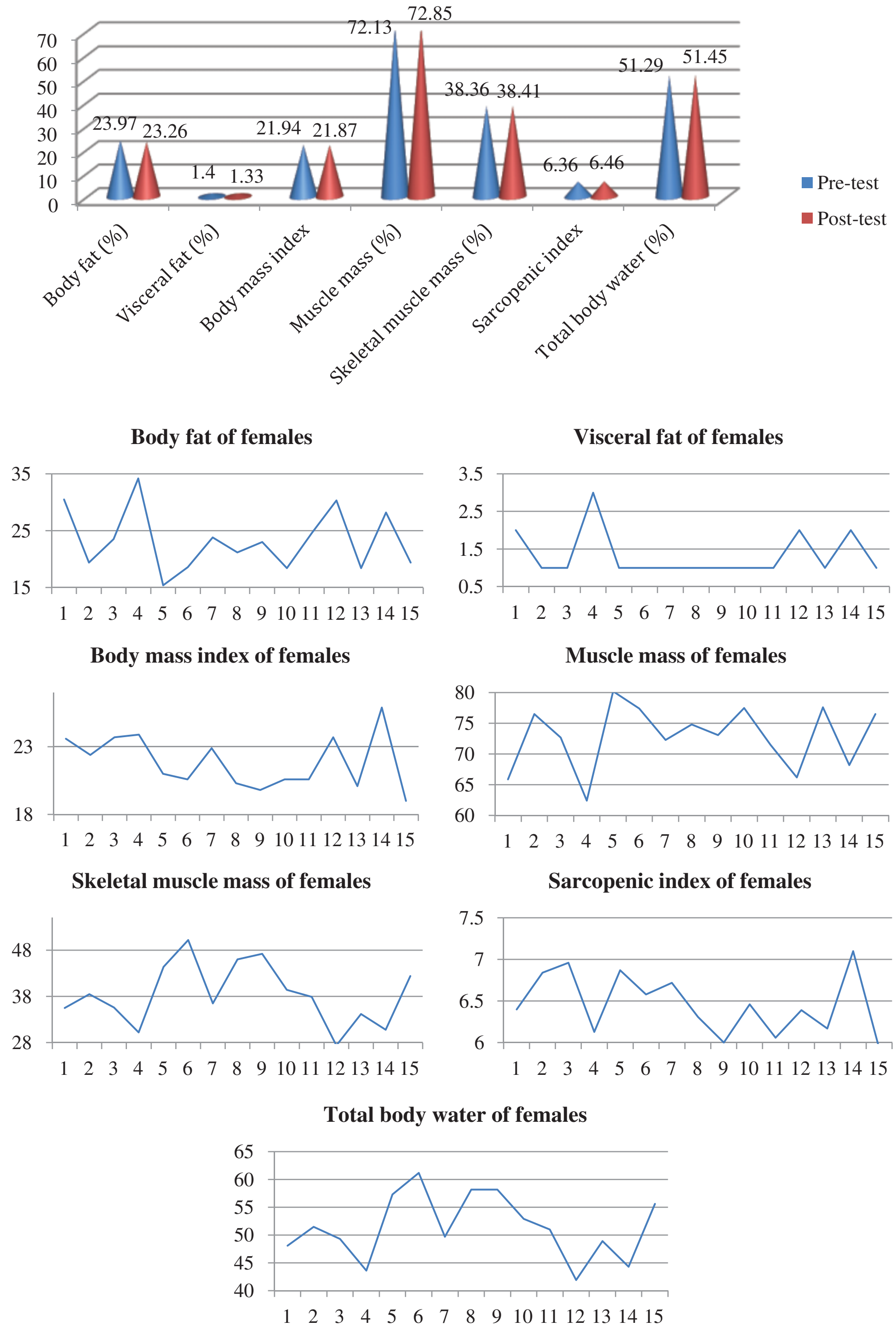

Figure 3: Assessment results using BIA (females)

Table 9: Male body composition pattern

Body composition indicator	Limits of agreement (Bland Altman analysis)
Body fat (%)	17.72–21
Visceral fat (%)	2.63–5.61
Body mass index	24.38–26.08
Muscle mass (%)	75.21–78.99
Skeletal muscle mass (%)	42.52–48.94
Sarcopenic index	8.29–9.49
Total body water (%)	54.85–60.75

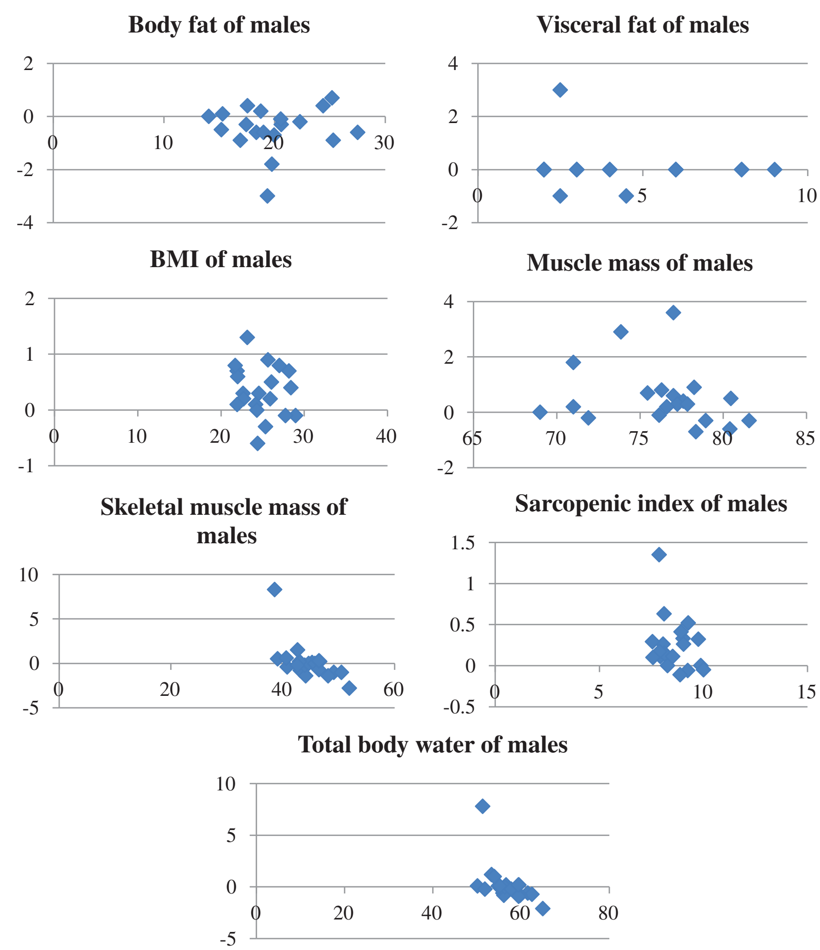

Figure 4: Bland–Altman plot for male body composition parameters

At BMI, the correlations were strong for both genders. The LOA for males and females at the Bland–Altman analysis was +0.46 and +1.24 and −0.98 and +0.84, respectively. The upper limit for the BMI of males is 26.08, which indicates a tendency for being overweight; the same situation is also observed in previous studies [26,32,33]. The correlations concerning the muscle mass and skeletal muscle mass for females were strong, and those for the muscle mass and skeletal muscle mass (0.890) of males are strong and moderate to strong, respectively. The LOA for the muscle mass and skeletal muscle mass of females were −3.08 and +4.53 and −2.86 and +2.97, respectively. For males The LOA for the muscle mass and skeletal muscle mass of males were +1.09 and 2.69 and +2.14 and +4.28, respectively [16,34,35].

Table 10: Female body composition pattern

Body composition indicator	Limits of agreement after analysis
Body fat (%)	18.88–26.93
Visceral fat (%)	0.80–1.81
Body mass index	20.93–22.75
Muscle mass (%)	69.41–77.02
Skeletal muscle mass (%)	35.53–41.36
Sarcopenic index	5.86–7.60
Total body water (%)	49.36–53.70

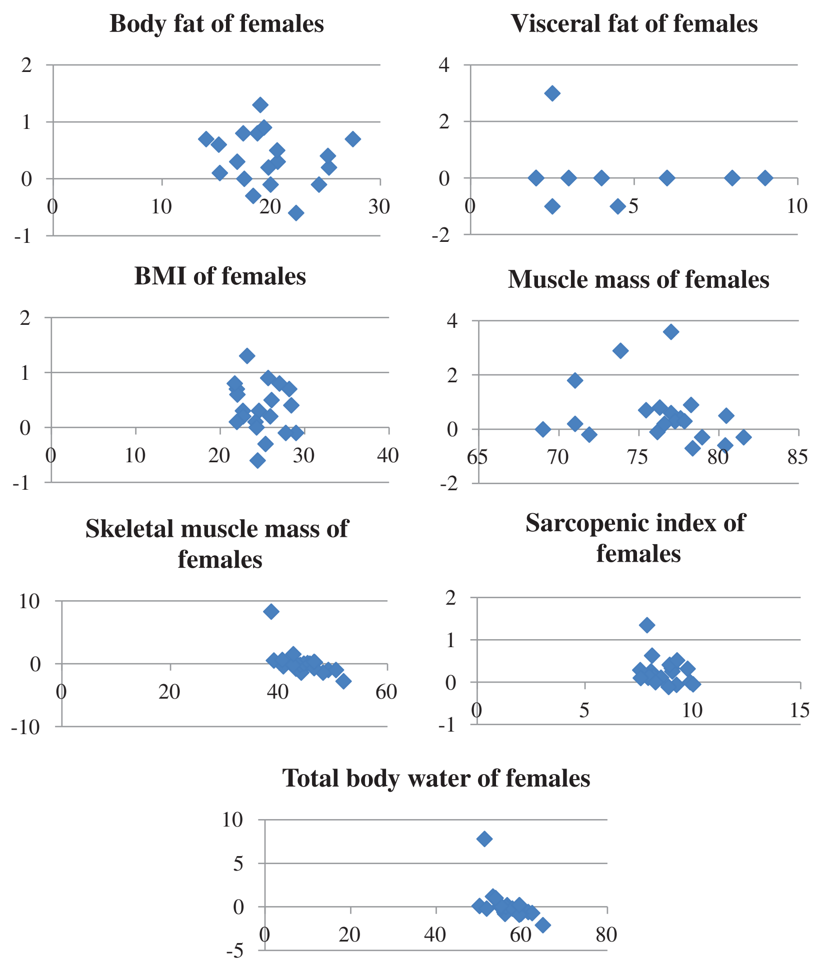

Figure 5: Bland–Altman plot for female body composition parameters

At sarcopenic index, the bias for males and females was 0.25 and 0.10, respectively. The LOA for males and females was +0.32 and +0.88 and −0.55 and +0.75, respectively [36–38]. For total body water (TBW%), the Pearson correlation was strong for both genders, and the LOA for males and females was +1.93 and +3.97 and −2.01 and 2.34, respectively [18,39–41].

This research is subjected to several limitations, including the number of participating subjects, the device settings, and the software algorithms used. The reason is that a wide range of BIA is available on the market, and differences are observed among them.

5 Conclusion

In previous studies, a pattern was identified for the four indicators that concern body composition (e.g., BMI, body fat, muscle mass, and total body water). The novelty of our study is the fact we identified a recognition pattern by using medical statistical methods for a body composition that contains seven indicators (e.g., body fat, visceral fat, BMI, muscle mass, skeletal muscle mass, sarcopenic index, and total body water). To statistically validate the pattern for the body composition obtained in our study for males and females, we used four different statistical methods (e.g., Bland–Altman analysis, paired t-test, ANOVA, and Pearson correlation). The limits of agreement allowed us to establish the margins for every analyzed indicator for each body composition. The statistical methods used confirmed the reliability of the device utilized in the research. Our results are in the margins of previous studies for both genders, except for the total body water (TBW), wherein the data were at a lower limit and below. The youth that possesses the body composition pattern identified in our study could be considered healthy. Every deviation of one or more parameters outside the margins of the pattern for body composition could be associated with health issues and more medical investigations would be needed for diagnosis. BIA is considered a valid and reliable device to assess body composition along with medical statistical methods to identify a pattern for body composition according to the age, gender, and other relevant parameters. Other studies that involve more subjects are needed to determine the pattern of body composition for different ages, weights, and physical activity levels.

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