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Validation and diagnostic accuracy of a multi-frequency bioelectrical impedance analysis device with dual-energy X-ray absorptiometry (DXA) for estimating body composition among healthy Malaysian adults

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Background: Precise assessment of body composition is critical for managing obesity and sarcopenia, both of which are rising health concerns around the globe. While dual-energy X-ray absorptiometry (DXA) remains the gold standard, its high cost and limited accessibility hinder large-scale application. Multi-frequency bioelectrical impedance analysis (MF-BIA) shows promise as an alternative method, but validation in specific populations remains necessary.
Objectives: This study aimed to validate and evaluate the diagnostic accuracy of the InBody 970S MF-BIA device in estimating body composition parameters against DXA among healthy Malaysian adults.
Methods: A prospective validation study was conducted among 148 healthy adults aged 20–45 years. Participants underwent standardised assessments using MF-BIA (InBody 970S) and full-body DXA. Linear regression, paired t-tests, Bland–Altman plots, and diagnostic performance indices (sensitivity, specificity, PPV, NPV) were used to evaluate the agreement between methods for fat mass (BFM), lean body mass (LBM), fat-free mass (FFM), percent body fat (PBF), bone mineral content (BMC), and skeletal muscle mass index (SMI).
Results: MF-BIA showed strong correlations with DXA across all parameters (R^2 = 0.72–0.97). The predictive models for BFM, LBM, and PBF demonstrated high accuracy (e.g., BFM: R^2 = 0.96; LBM: R^2 = 0.96; FFM: R^2 = 0.97). Diagnostic agreement was particularly strong for sarcopenia (sensitivity = 95.1%, NPV = 98.0%) and obesity classification (specificity and PPV = 100%), though obesity sensitivity was lower (75.2%). Bland–Altman analysis confirmed acceptable limits of agreement.
Conclusion: MF-BIA offers a clinically valid, non-invasive, and accessible method for body composition assessment in Malaysian adults. Its utility in identifying obesity and sarcopenia risk supports its integration into routine clinical practice

and public health screening, especially in resource-limited settings. Future work should explore ethnic-specific calibration to enhance its diagnostic precision across diverse populations.

KEYWORDS

body composition, diagnostic accuracy, dual-energy x-ray absorptiometry, InBody 970S, multi-frequency bioelectrical impedance analysis, obesity, sarcopenia

1 Introduction

Accurate assessment of body composition is essential for assessing nutritional status, managing chronic diseases, and assessing the effectiveness of health interventions. Traditional anthropometric measures, such as body mass index (BMI), while commonly used, often fall short in distinguishing between fat mass and lean mass, thus limiting their utility in both clinical and research settings. Globally, over one billion people are affected by obesity, including 650 million adults, and the trend is rising sharply in Southeast Asia due to urbanization, dietary changes, and sedentary lifestyles (Safiri et al., 2025; Nickerson, 2018). This surge contributes to the growing prevalence of metabolic diseases such as type 2 diabetes and cardiovascular conditions.

In the ASEAN region, Malaysia reports one of the highest adult obesity rates (>15%), followed by Thailand and Indonesia (10%–12%), with countries like the Philippines and Vietnam also seeing a steady rise in overweight populations (Safiri et al., 2025). These rising burdens of obesity underscore the need for precise, reliable, and accessible methods to quantify body composition across diverse populations.

Dual-energy X-ray absorptiometry (DXA) is widely regarded as a gold standard for body composition analysis due to its high accuracy and ability to differentiate between bone mineral content, lean tissue mass, and fat mass (Slart et al., 2025). However, its high cost, limited availability, and requirement for specialized personnel and equipment pose practical limitations, especially in large-scale epidemiological studies and community health settings.

Bioelectrical impedance analysis (BIA) has become a practical alternative; it offers several advantages, including portability, non-invasiveness, ease of use, and lower cost. BIA estimates body composition by measuring the resistance and reactance of body tissues to a small electrical current (Bosy-Westphal et al., 2008). Multi-frequency BIA (MF-BIA) devices, such as the InBody 970S, represent a significant advancement in this technology. These devices utilize multiple electrical frequencies to improve the accuracy of total body water estimation, which in turn enhances fat-free mass and fat mass calculations (Looney, 2024). Additionally, the InBody 970S offers segmental analysis, allowing for more detailed assessments of body composition (Looney, 2024).

Many BIA devices are initially calibrated using Western populations, which may limit their validity for other populations (Merrigan et al., 2022). This is particularly relevant in Malaysia, a country with a multiethnic population comprising Malays, Chinese, Indians, and indigenous groups, each with distinct anthropometric characteristics and body composition profiles. Accumulating evidence suggests that Asian populations exhibit distinct body composition characteristics, including higher body fat percentages and greater visceral adiposity at lower BMI values compared with Western populations. In addition, differences in body build, limb length proportions, and fat distribution patterns may influence impedance-derived estimates (Zulfarina, 2022). This represents an important knowledge gap, as the accuracy of impedance-derived estimates cannot be assumed across populations with differing anthropometric and fat distribution profiles.

To our knowledge, this is the first study to validate the InBody 970S against DXA in the Malaysian adult population. This study aims to assess the accuracy of the InBody 970S in estimating fat mass, fat-free mass, and body fat percentage by comparing it with DXA measurements in healthy Malaysian adults. The findings will inform the clinical utility and potential limitations of using the InBody 970S for body composition assessment in the Malaysian context.

2 Methodology

2.1 Study design

The present study was a prospective validation study conducted at a tertiary hospital, specifically Damansara Specialist Hospital (DSH), between April 2024 and February 2025. The study was approved by the KPJ Clinical and Research Ethics Review Committee (CRERC) (ID KPJ 037/24), and it complies with the Declaration of Helsinki.

We recruited potential participants through the dissemination of posters at the site and on social media. KPJ CRERC approved written informed consent was obtained for all study participants before study participation. Interested individuals contacted the designated enumerator for this study, who then performed pre-screening, evaluating eligibility via a Google form. Inclusion criteria included healthy adults aged 20–45 years. Exclusion criteria included those with implanted metal devices other than dental work (e.g., pacemakers, deep brain stimulators), those with chronic diseases such as cancer, diabetes, or cardiovascular conditions known to affect body composition, pregnant women, individuals within 6 months postpartum, and those with physical amputations. All female participants of childbearing potential who reported a delayed menstrual period exceeding 28 days were required to undergo pregnancy tests, with only those who tested negative permitted to proceed with the assessments.

Suitable participants were invited to register using a standardised form, after which they were scheduled for specific appointment dates to undergo both tests. Notifications were sent at least 1 week before the appointment to ensure participants had adequate time to prepare and comply with the test requirements. The requirements included abstaining from strenuous exercise, alcohol, and caffeine for 24 h before testing. Additionally, they were also informed that the test would only be conducted at least 3–4 h post-prandial and following bladder voiding. They were also

advised to wear light clothing and avoid wearing jewelry on the day of the assessments. In addition to the pre-test behavioural restrictions, hydration status was controlled through standardised scheduling and preparation procedures. All participants were assessed in a rested state, at least 3–4 h post-prandial and after bladder voiding, to minimise acute fluid shifts. Participants were instructed to maintain their usual fluid intake the day before testing and to avoid excessive fluid consumption immediately before assessment. Although direct biochemical measures of hydration (e.g., urine specific gravity) were not performed, these standardised preparation protocols are consistent with best practices in body composition and metabolic testing to enhance the accuracy and reliability of results (Prado et al., 2025).

Sample size was calculated using StatsDirect software (Version 4.0.3) for estimating a single correlation coefficient with 90% power at an alpha level of 5%. Assuming a true correlation of r = 0.30 (conservative, two-sided), an estimation of 140 subjects was required for this study. More subjects were enrolled to allow for potential exclusions.

2.2 Body composition measurement

All assessments were performed in a controlled clinical environment during the morning hours to minimise diurnal variation in body composition. Ambient temperature and humidity were maintained within recommended ranges to reduce environmental influences. Standing height was measured using a calibrated digital stadiometer (BSM170) and recorded manually for both MF-BIA and DXA assessments. Participants removed all metallic objects before testing to avoid interference.

Body composition analysis was conducted in a standardised sequence, beginning with the InBody 970S multi-frequency bioelectrical impedance analyser (MF-BIA), followed by a full-body DXA scan. Participants rested quietly for 10 min before each measurement to ensure physiological stability.

To minimise potential measurement and observer bias, a double-blind procedure was implemented. The operator conducting the DXA assessment was blinded to the BIA results, and the operator performing the BIA measurement was blinded to the DXA findings. Data extraction and statistical analyses were performed only after completion of all measurements.

2.2.1 Multi-frequency bioelectrical impedance analysis (MF-BIA)

MF-BIA measurements were obtained using the InBody 970S (InBody Asia Sdn. Bhd., Kuala Lumpur, Malaysia), with participants standing barefoot and grasping the hand electrodes in accordance with the manufacturer's protocol. The device utilises eight tactile electrodes (two on the palms, two on the thumbs, and four on the soles) to introduce and detect current. Impedance values were collected across five body segments (right arm, left arm, trunk, right leg, left leg) using multiple frequencies (5, 50, 250, 500, 1000, and 3000 kHz). Proprietary algorithms embedded in the InBody 970S firmware were then applied to derive estimates of fat mass, fat-free mass, lean body mass, percent body fat, bone mineral content, and skeletal muscle index. Raw impedance (R/Xc) and segmental data were exported and archived. Measurement reports were automatically generated and stored in the cloud system, with a printed copy provided to each participant. The measurements were performed twice consecutively for each participant under the same standardised conditions, and the mean value was used for subsequent analysis to improve measurement reliability.

2.2.2 Dual-energy X-ray absorptiometry (DXA)

Whole-body DXA scans were performed using a dual-energy X-ray absorptiometry system (Hologic Discovery W/88,685, Hologic Inc., Marlborough, Massachusetts, USA), with participants lying supine on the scanning table. A dual-energy X-ray beam (high and low energy levels) was transmitted through the body, and tissue-specific absorption was detected by a sensor array positioned above the participant. This allowed the quantification of multiple body composition parameters, including fat mass (FM), fat-free mass (FFM), lean body mass (LBM), bone mineral content (BMC), percent body fat (PBF), and appendicular lean mass indices relevant for skeletal muscle estimation. A uniform scanning protocol and X-ray dose were applied to all participants to ensure measurement reliability and data homogeneity.

2.3 Statistical analysis

Data were presented as mean ± standard deviation (SD), and a two-sided $p < 0.05$ was considered statistically significant. Independent *t*-test and paired *t*-test were used after checking normality of the differences (Shapiro–Wilk) to assess differences between gender and differences in body composition measurements between DXA and MF-BIA, respectively. Comparing both methods, the ordinary least squares (OLS) models were fit with DXA as the dependent variable and BIA as the predictor to summarise R^2adj, RMSE, and mean absolute error (MAE). We performed general linear model (GLM) diagnostics, including linearity (scatter/loess), Q–Q plots of standardised residuals with Shapiro–Wilk, residuals-vs-fitted for homoscedasticity. All assumptions were checked and not violated. Bland–Altman (BA) analysis estimated the mean bias and 95% limits of agreement (LoA = bias ±1.96 × SD), each with 95% confidence intervals (CI). Proportional bias was tested by regressing (DXA − BIA) on the within-subject mean. If heteroscedasticity was present, log-scale BA was performed, and the reported ratio LoA (%) after back-transformation. All statistical analyses were conducted using SPSS software version 30.0 (IBM SPSS Inc., USA).

2.4 Diagnostic accuracy for risk of obesity and sarcopenia

Classification of obesity using PBF was derived based on the World Health Organization (WHO) general recommendation, which defines normal PBF as <25% for men and <35% for women. Individuals exceeding these thresholds were classified as obese. Sarcopenia risk categorisation followed the criteria recommended by the ASEAN Working Group on Sarcopenia (AWGS), where appendicular skeletal muscle mass index (SMI) values of <7.0 kg/m^2 for men and <5.7 kg/m^2 for women indicate a higher risk of sarcopenia.

The diagnostic accuracy of the multi-frequency bioelectrical impedance analysis (MF-BIA) device (InBody 970S) against the gold standard dual-energy X-ray absorptiometry (DXA) was

TABLE 1 Baseline characteristics.

Variable	Male (n = 61), mean	Female (n = 87), mean	*p*-Value[a]
Age (year)	28.1	28.4	0.13
Height (cm)	168.7	155.7	0.44
Weight (kg)	69.9	57.7	0.82
BMI (kg/m^2)	24.6	23.8	0.63

[a]independent t-test; significant level at $p < 0.05$.
BMI: body mass index.

evaluated. The classification outcomes were tabulated as true positives (TP), false positives (FP), true negatives (TN), and false negatives (FN). These indicators quantify the MF-BIA's performance in correctly identifying individuals at risk of obesity and sarcopenia, compared to DXA. Hence, the following metrics were calculated:

$$\textit{Sensitivity} = TP \,/\, (TP + FN)$$

$$\textit{Specificity} = TN \,/\, (TN + FP)$$

$$\textit{Positive Predictive Value}\ (\textit{PPV}) = TP \,/\, (TP + FP)$$

$$\textit{Negative Predictive Value}\ (\textit{NPV}) = TN \,/\, (TN + FN)$$

3 Results

A total of 155 individuals volunteered to participate in the study; however, only 148 were selected after screening for eligibility. Baseline subject characteristics are detailed in Table 1. There were no significant differences in the general characteristics between different sexes. Overall, the mean age was 28.3 ± 5.4 years, mean body mass index (BMI) was 24.1 ± 4.1. According to BMI categories following the Asia-Pacific BMI (Lim et al., 2017), 64 (43.2%) subjects were normal, 61 (41.2%) were overweight, and 23 (15.5%) were obese.

Statistically significant differences were observed across all body composition parameters when comparing MF-BIA and DXA measurements, both overall and by sex ($p < 0.001$; Table 2). These results suggest that, although the values differ between methods, the differences are systematic and not due to random variation.

For all models, linearity was supported, and residuals were approximately normal (Shapiro–Wilk $p > 0.05$ for BFM, LBM, FFM, BMC; borderline for PBF and SMI). Breusch–Pagan indicated mild heteroscedasticity for PBF and SMI ($p < 0.05$). Three observations ($k = 3$) were flagged as influential, but exclusion or robust SE did not alter inference (slopes shifted by <0.03, R^2 unchanged).

Linear regression analyses (Table 3) demonstrated strong correlations between the MF-BIA (InBody 970S) and DXA measurements across all parameters. The coefficient of determination (R^2) ranged from 0.72 to 0.97, indicating that 72%–97% of the variance in DXA-measured values could be explained by the MF-BIA device. These findings reflect a strong and consistent relationship between the two measurement methods. The root mean square error (RMSE) for the linear regression model across all parameters corresponds to <10% of the mean DXA values, indicating high predictive accuracy of the MF-BIA device.

TABLE 2 Comparison between MF-BIA and DXA in different sexes.

Parameter	BIA (mean ± SD, 95% CI)	DXA (mean ± SD, 95% CI)	*p*-value[a]
BFM (kg) Overall Male Female	19.70 ± 7.66 (95% CI: 18.46–19.70) 17.33 ± 7.33 (95% CI: 17.28–20.43) 21.37 7.48 (95% CI: 19.77–22.96)	20.59 ± 6.61 (95% CI: 19.51–21.66) 18.85 ± 6.15 (95% CI: 17.28–20.43) 21.80 ± 6.68 (95% CI: 20.38–23.22)	$p < 0.001$ $p < 0.001$ $p < 0.001$
LBM (kg) Overall Male Female	36.32 ± 9.05 (95% CI: 34.85–37.80) 45.09 ± 5.74 (95% CI: 43.62–46.56) 30.17 ± 4.93 (95% CI: 29.13–31.23)	35.35 ± 8.87 (95% CI: 33.90–36.79) 43.54 ± 6.24 (95% CI: 41.95–45.14) 29.60 ± 5.12 (95% CI: 28.51–30.70)	$p < 0.001$ $p < 0.001$ $p < 0.001$
FFM (kg) Overall Male Female	43.02 ± 9.95 (95% CI: 41.40–44.63) 52.53 ± 6.61 (95% CI: 50.83–54.23) 36.34 ± 5.42 (95% CI: 35.19–37.50)	40.43 ± 9.47 (95% CI: 38.89–41.97) 49.17 ± 6.59 (95% CI: 47.48–50.86) 34.30 ± 5.54 (95% CI: 33.12 35.49)	$p < 0.001$ $p < 0.001$ $p < 0.001$
PBF (%) Overall Male Female	31.20 ± 8.94 (95% CI: 29.74–32.65) 24.07 ± 7.40 (95% CI: 22.18–25.97) 36.20 ± 6.09 (95% CI: 34.90–37.50)	33.70 ± 7.55 (95% CI: 32.48–34.93) 27.19 ± 5.77 (95% CI: 25.72–28.67) 38.27 ± 4.81 (95% CI: 37.24 39.29)	$p < 0.001$ $p < 0.001$ $p < 0.001$
BMC (kg) Overall Male Female	2.54 ± 0.51 (95% CI: 2.46–2.63) 2.98 ± 0.41 (95% CI: 2.87–3.08) 2.24 ± 0.31 (95% CI: 2.18–2.31)	2.32 ± 0.42 (95% CI: 2.25–2.39) 2.62 ± 0.38 (95% CI: 2.52–2.71) 2.11 ± 0.31 (95% CI: 2.04–2.18)	$p < 0.001$ $p < 0.001$ $p < 0.001$
SMI (kg/m^2) Overall Male Female	6.57 ± 1.20 (95% CI: 6.38–6.77) 7.67 ± 0.73 (95% CI: 7.48–7.85) 5.81 ± 0.80 (95% CI: 5.64–5.98)	6.85 ± 1.43 (95% CI: 6.62–7.08) 8.01 ± 1.07 (95% CI: 7.73–8.29) 6.04 ± 1.03 (95% CI: 5.82–6.26)	$p < 0.001$ $p < 0.001$ $p < 0.001$

[a]paired t-test; significant level at $p < 0.05$.
BFM: body fat mass; LBM: lean body mass; FFM: fat-free mass; PBF: percent body fat; BMC: bone mineral content; SMI: skeletal muscle mass index.

TABLE 3 Correlations between parameters by BIA and DXA.

Parameter	Constant	B	R^2	RMSE	*p*-Value[a]
BFM (kg)	3.96	0.84	0.96	1.39	$p < 0.001$
LBM (kg)	0.50	0.96	0.96	1.39	$p < 0.001$
FFM (kg)	0.13	0.94	0.97	1.65	$p < 0.001$
PBF (%)	8.38	0.81	0.92	2.1	$p < 0.001$
BMC (kg)	0.52	0.71	0.73	0.22	$p < 0.001$
SMI (kg/m^2)	−0.61	1.14	0.90	0.45	$p < 0.001$

Model: DXA, intercept + slope x (BIA). Slopes/intercepts are from Deming regression unless stated; OLS, shown in sensitivity analyses. R^2adj and RMSE, are from OLS, for comparability. BFM: body fat mass; LBM: lean body mass; FFM: fat-free mass; PBF: percent body fat; BMC: bone mineral content; SMI: skeletal muscle mass index.

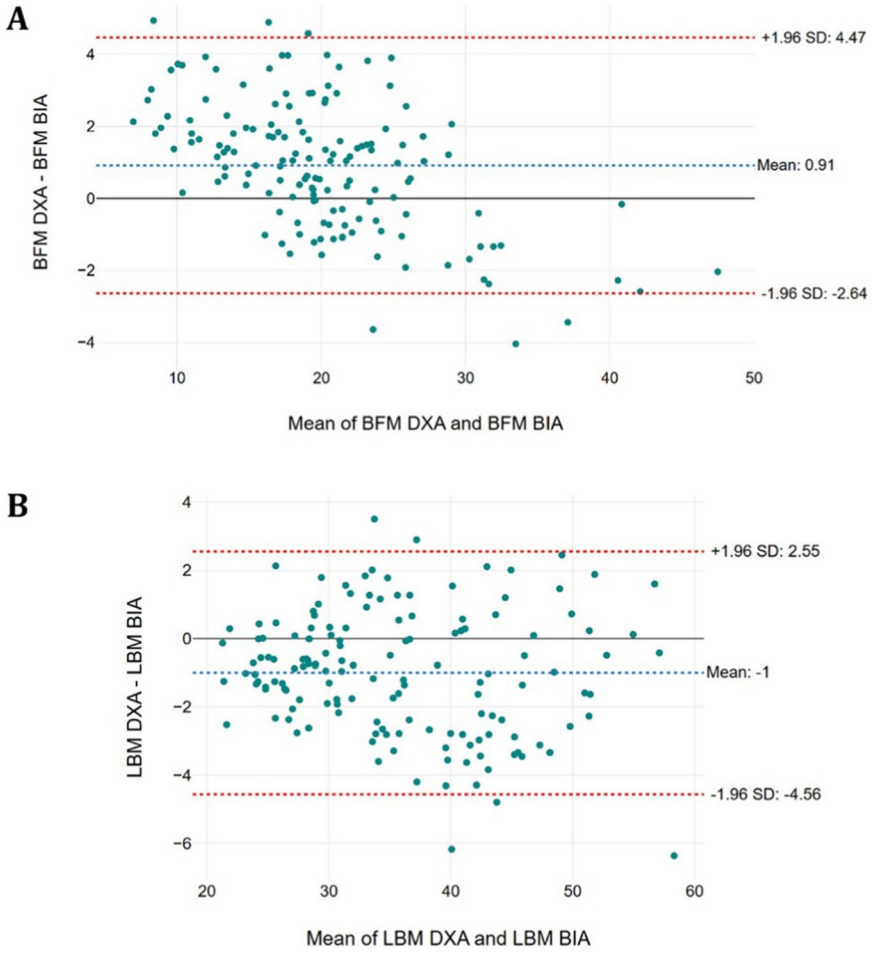

FIGURE 1
(A) Bland–Altman plot for BFM comparing BIA and DXA. The solid line represents the mean bias 0.91 kg), and the dotted lines represent the upper (+4.47 kg) and lower (−2.64 kg) limits of agreement (LoA) with difference range of 7.11. **(B)** Bland–Altman plot for LBM comparing BIA and DXA. The solid line represents the mean bias (−1.00 kg), and the dotted lines represent the upper (+2.55 kg) and lower (−4.56 kg) LoA with difference range of 7.11 kg.

Further agreement analysis using the Bland–Altman method (Figure 1; Figure 2; Figure 3) revealed acceptable limits of agreement for all parameters. While some proportional bias was observed in certain variables, the mean differences (bias) between methods were within clinically acceptable ranges. This supports the potential use of MF-BIA as a valid alternative to DXA in estimating body composition among healthy adults.

Based on the Bland-Altman plot for BFM (Figure 1A), there is no strong visual evidence of proportional bias, but the clustering of differences around lower mean values and increasing scatter at

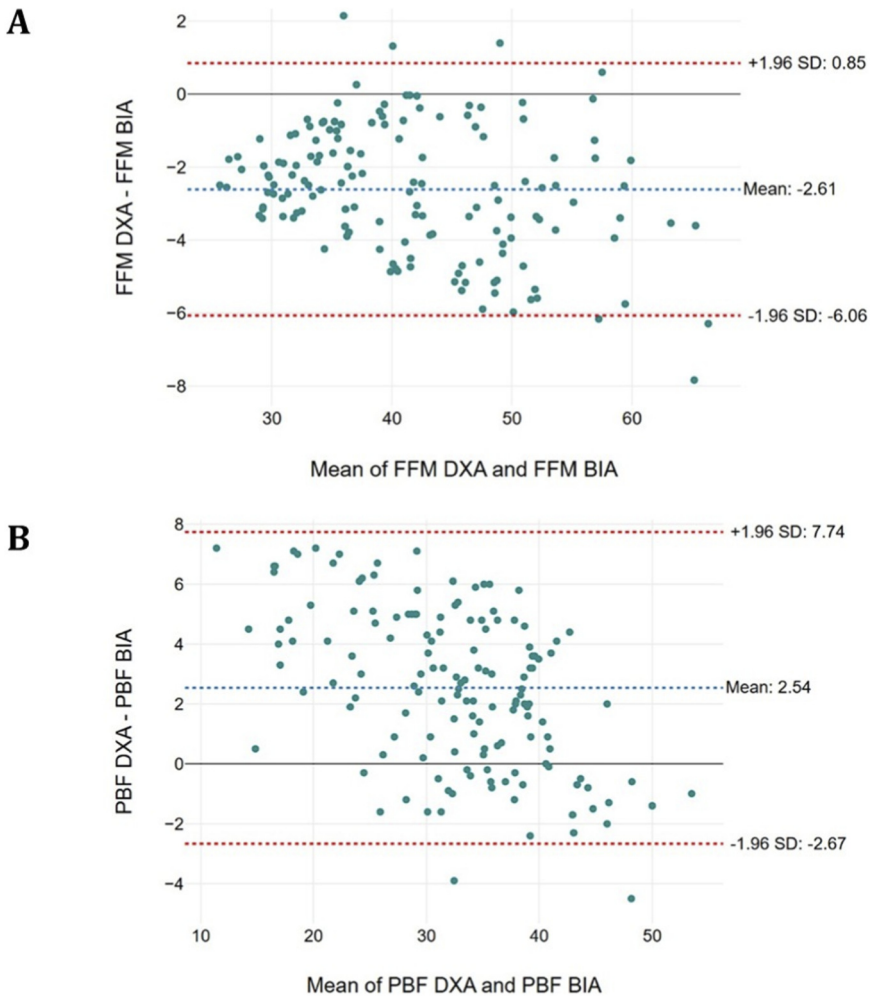

FIGURE 2
(A) Bland–Altman plot for FFM comparing BIA and DXA. The solid line indicates the mean bias (−2.61 kg), while the upper (+0.85 kg) and lower (−6.06 kg) LoA with difference range of 6.91 kg. **(B)** Bland–Altman plot for PBF comparing BIA and DXA. The solid line indicates the mean bias (2.54 %), while the upper (+7.74 %) and lower (−2.67 %) LoA with difference range of 10.41%.

higher values could suggest a slight tendency for disagreement in individuals with higher BFM. Following the analysis of BFM, Figure 1B revealed that most data points for LBM were distributed symmetrically around the mean bias, with no obvious pattern indicating proportional bias. The agreement between BIA and DXA was generally consistent across the range of LBM values, although some variability was observed at both lower and higher ends of the distribution. The FFM values indicated in Figure 2A showed that increased variability was observed among participants with lower FFM values, suggesting some reduction in agreement precision in that subgroup. Nevertheless, the overall LoA was acceptable for use in healthy adult populations. Similarly, in Figure 2B (PBF), the variability shown in the analysis suggests cautious interpretation for individuals with very low or very high PBF. Figures 3A, B analyse the BMC and SMI, respectively. The data points for BMC values (Figure 3A) were tightly clustered around the mean, and minimal variability was observed, suggesting a high level of agreement between methods for estimating BMC. In contrast, the analysis for SMI (Figure 3B) showed wider variability, with the majority of the points falling within the agreement limits, hence indicating that the MF-BIA provides an acceptable LoA with DXA in estimating SMI.

Table 4 describes the diagnostic performance of MF-BIA in classifying obesity and sarcopenia and was evaluated against DXA as the reference standard. The results indicate that MF-BIA is particularly accurate in identifying individuals without obesity and those not at risk of sarcopenia, while maintaining good overall detection rates for both conditions.

4 Discussion

This study found that approximately 56.7% of participants were classified as overweight or obese, mirroring national statistics (Salam, 2022). While Malaysia currently records the highest prevalence of overweight and obesity in the ASEAN region, countries such as Brunei, Singapore, and Thailand are exhibiting similar upward trends. These increases are driven by common

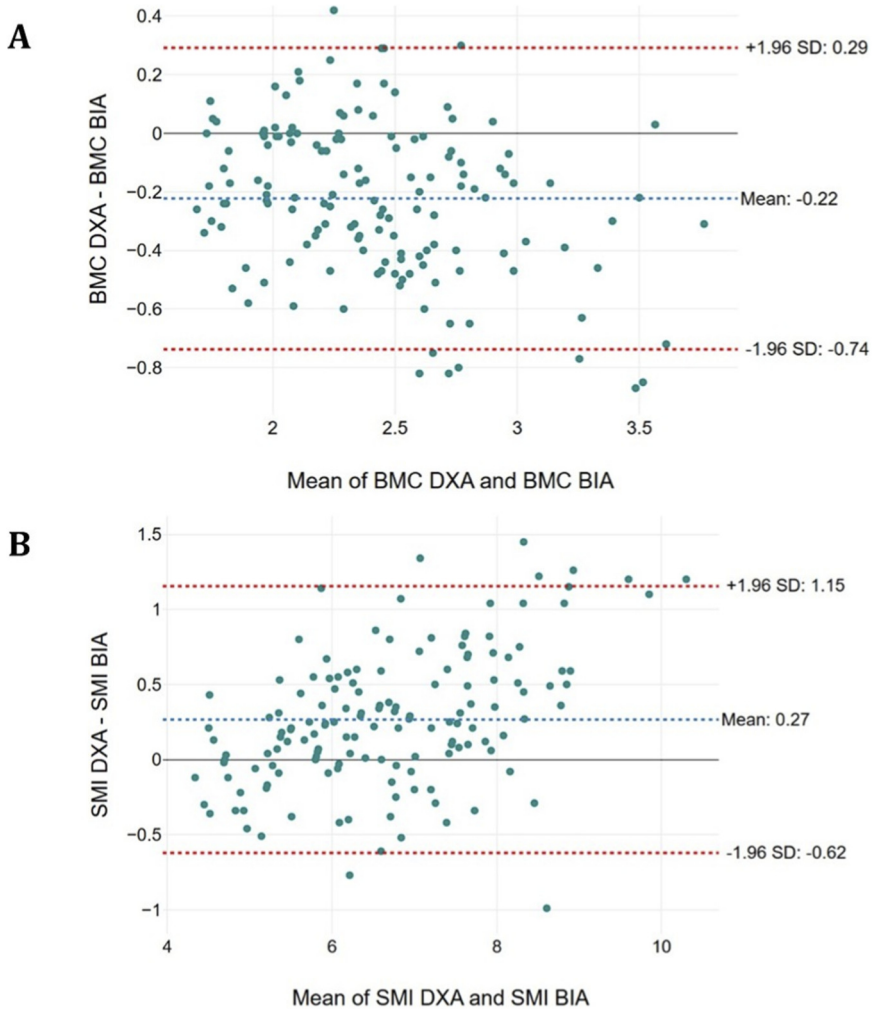

FIGURE 3
(A) Bland–Altman plot for BMC comparing BIA and DXA. The solid line indicates the mean bias (–0.22 kg), while the upper (+0.29 kg) and lower (–0.74 kg) LoA with difference range of 1.03. **(B)** Bland–Altman plot for SMI comparing BIA and DXA. The solid line indicates the mean bias (0.27 kg/m^2), while the upper (+1.15 kg/m^2) and lower (–0.62 kg/m^2) LoA with difference range of 1.77.

TABLE 4 **Diagnostic accuracy of MF-BIA in determining obesity and risk of sarcopenia.**

Metric	Obesity (PBF thresholds)	Sarcopenia (SMI thresholds)
True positive (TP)	79	39
False positive (FP)	0	8
True negative (TN)	43	99
False negative (FN)	26	2
Sensitivity	75.2%	95.1%
Specificity	100.0%	92.5%
Positive predictive value (PPV)	100.0%	83.0%
Negative predictive value (NPV)	62.3%	98.0%

PBF: percent body fat; SMI: skeletal muscle mass index.

factors, including rapid urbanization, rising income levels, sedentary lifestyles, and greater consumption of calorie-dense, processed foods. Alarmingly, the rise in obesity is also evident among children in these nations, signaling a widespread and growing public health concern across generations (Tee and Voon, 2024). These trends collectively highlight the urgent need for accessible and accurate body composition screening tools to facilitate early detection and intervention across all population groups.

While the MF-BIA demonstrated a tendency to slightly underestimate body fat mass (BFM) and lean body mass (LBM) compared to DXA, this discrepancy was systematic and not due to random error. Importantly, strong and consistent predictive relationships were observed between MF-BIA and DXA for both parameters. The regression model for BFM (BFM_{DXA} = 3.96 + 0.84×BFM_{BIA}) can explain 97.7% of its variance, and LBM (LBM_{DXA} = 0.503 + 0.959×LBM_{BIA}) explains 96% of its variance. Some studies among the elderly (Meier et al., 2020; van den Helder et al., 2022), gender (Nickerson, 2018), and different ethnicities (Nickerson et al., 2018) found similar results with the current study. The findings support the use of MF-BIA as a practical and reasonably accurate tool for large-scale body composition assessment. The regression model for FFM (FFM_{DXA} = 0.13 + 0.94×FFM_{BIA}) also demonstrated excellent predictive capacity for the consistent underestimation by MF BIA. The strong correlation between both methods, R^2 = 0.97 support the clinical utility of the MF-BIA for estimating FFM in the healthy population. In contrast, PBF tended to be slightly overestimated by MF-BIA; the corresponding regression model (PBF_{DXA} = 8.38 + 0.81×PBF_{BIA}) still explained 92.4% of the variance, indicating a strong linear relationship. These results differ from Achamrah et al. (2018), whose analysis of 3,655 paired MF-BIA and DXA scans showed MF-BIA overestimated fat-free mass by 3.4–8.3 kg and underestimated fat mass by 2.5–5.7 kg in adults with BMI 18.5–40 kg m^{-} (Achamrah et al., 2018). Notably, previous studies highlighted that the discrepancies between both methods were more pronounced in individuals with higher body fat percentages, those with short stature, and the elderly. Suggesting that impedance-based methods may be less accurate in cases of excessive adiposity (Achamrah et al., 2018; Velázquez-Alva et al., 2022).

Both BMC and SMI suggest corresponding regression models of BMC_{DXA} = 0.516 + 0.708×BMC_{BIA} and SMI_{DXA} = −0.608 + 1.135×SMI_{BIA} respectively. The narrow range and consistent spread of differences of both parameters for the MF-BIA and DXA method, with small systematic differences, indicate good agreement at the individual level, thus supporting the utility of MF-BIA in estimating the parameters. Similarly to this study, Achamrah et al. (2018) suggested that the small bias between BIA and DXA methods may allow for comparable use at the population level; however, caution is warranted when interpreting individual-level measurements (Achamrah et al., 2018).

The present study demonstrates that MF-BIA shows strong diagnostic agreement with DXA, particularly in the identification of sarcopenia risk. The high sensitivity (95.1%) and NPV (98.0%). These metrics underscore its effectiveness as a non-invasive screening tool, especially in primary care and community settings where early detection is crucial, and DXA access is limited. This is aligned with findings from data collected for the recruitment of clinical trial participants at Wonju Severance Christian Hospital, which reported high predictive accuracy of BIA for sarcopenia diagnosis, despite slight overestimations of muscle mass (Lee et al., 2024). Furthermore, a systematic review on cancer patients supported the viability of BIA as a substitute for DXA and CT in assessing muscle mass, highlighting its potential even in clinical populations with altered body composition (Aleixo et al., 2020). In the regional context, the Singapore Clinical Practice Guidelines for Sarcopenia (2022) explicitly recommend BIA as a frontline tool for sarcopenia screening in older adults, emphasizing its integration into routine clinical assessments due to its convenience, cost-efficiency, and acceptable accuracy (Reliability and Validity of Contemporary, 2022).

In the classification of obesity, MF-BIA exhibited perfect specificity and PPV (100%), confirming its utility in correctly identifying individuals with elevated body fat percentages. However, the moderate sensitivity (75.2%) and relatively moderate NPV (62.3%) indicate a tendency to underestimate certain cases of obesity, potentially due to variability in fat distribution or hydration status influencing impedance measurements. Similar findings among the Pakistani population found that hand-to-foot BIA achieved 90.1% sensitivity and 100% specificity, outperforming BMI in identifying overweight and obese individuals (Anwer et al., 2023). Meanwhile, a cohort study in Romania highlighted that although BMI showed superior overall predictive accuracy for obesity, BIA offered better specificity in identifying obesity-related risk factors, hence, reinforcing the complementary role of BIA in targeted risk stratification (Pescari et al., 2024). Moreover, a recent systematic review emphasized that device model, prediction algorithm, population age, and health status significantly influence the diagnostic accuracy of BIA. This further explains variability in sensitivity observed across different studies and supports the need for population-specific calibration or adjustment factors when applying BIA clinically (Campa et al., 2024).

Collectively, these comparisons affirm that while MF-BIA may not be optimal for standalone obesity screening due to moderate sensitivity, it remains a highly specific and practical tool for confirming obesity diagnoses and assessing associated metabolic risk, particularly in community-based and resource-limited settings.

This study has several limitations. First, it was conducted at a single centre, which may limit generalisability to broader Malaysian populations. Second, the age range of participants was relatively narrow and comprised primarily healthy adults, thereby limiting extrapolation to older individuals or those with chronic conditions. Finally, the proprietary nature of device-specific prediction algorithms may introduce systematic bias that cannot be fully evaluated. These factors should be considered when interpreting the findings.

5 Conclusion

This study reinforces the clinical relevance of MF-BIA, demonstrating that it is not merely a rapid and convenient tool, but a scientifically validated method capable of providing body composition estimates that show strong agreement with DXA., particularly in the assessment of obesity and sarcopenia risk. Despite some limitations in sensitivity, MF-BIA exhibited strong

predictive accuracy and high specificity across multiple body composition parameters, affirming its reliability for population-level assessments and supportive use in individual evaluations. Its non-invasive nature, portability, and efficiency make it exceptionally well-suited for integration into routine practice across diverse healthcare settings, from primary care clinics to public health outreach and wellness programs. Importantly, the findings support the incorporation of MF-BIA into broader risk stratification frameworks, where timely identification of body composition abnormalities can facilitate early interventions and preventive strategies (Kafri et al., 2014; Farbo and Rhea, 2021; Thajer et al., 2025). As Malaysia and other ASEAN countries face a growing burden of lifestyle-related diseases (Si et al., 2025), MF-BIA offers a scalable, accessible solution to support health monitoring in both clinical and community-based environments. Future efforts to refine device-specific prediction models for different ethnic groups may further enhance their diagnostic precision and clinical impact (Campa et al., 2024).

Data availability statement

The original contributions presented in the study are included in the article; further inquiries can be directed to the corresponding author.

Ethics statement

The studies involving humans were approved by KPJ Clinical and Research Ethics Review Committee (CRERC) of KPJ Healthcare University (Approval ID: KPJ 037/24, date 15 July 2024). The studies were conducted in accordance with the local legislation and institutional requirements. The participants provided their written informed consent to participate in this study.

Author contributions

NJ: Conceptualization, Formal Analysis, Methodology, Validation, Visualization, Writing – original draft, Writing – review and editing. MZ: Conceptualization, Project administration, Writing – original draft, Writing – review and editing. SM: Conceptualization, Writing – original draft, Writing – review and editing. HH: Project administration, Writing – original draft, Writing – review and editing. MR: Methodology, Writing – original draft, Writing – review and editing. MI: Funding acquisition, Writing – original draft, Writing – review and editing. SF: Project administration, Writing – original draft, Writing – review and editing. NH: Writing – original draft, Writing – review and editing. SA: Supervision, Writing – original draft, Writing – review and editing.

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Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

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