Combination of DXA and BIS predicts jump power better than traditional measures of sarcopenia

Benjamin Rush, MPH¹, A, Neil Binkley, MD², Diane Krueger, BS², Yosuke Yamada, PhD³, Adam J. Kuchnia, PhD¹

¹ Department of Nutritional Sciences, University of Wisconsin-Madison, Madison, WI, USA
² University of Wisconsin Osteoporosis Clinical Research Program, Madison, WI, USA
³ Department of Physical Activity, National Institute of Health and Nutrition, National Institutes of Biomedical Innovation, Health and Nutrition, Japan, 1-23-1 Toyama, Shinjuku-ku, Tokyo 162–8636, Japan.

Running Title: DXA and BIS predicts function

^ Corresponding author. Rush4@wisc.edu

Main text word count: 4055

Data elements: 5
Abstract

**Background** Traditional diagnostic criteria for sarcopenia use Dual-energy X-ray Absorptiometry (DXA) measured appendicular lean mass (ALM), normalized to height (ALM/ht²) or body mass index (ALM/BMI) to define low muscle mass. However, muscle function declines with aging before the loss of muscle mass is detected by ALM. This is likely due, in part, to qualitative muscle changes such as extracellular and intracellular fluid compartment shifts uncaptured by DXA. We propose combining bioimpedance spectroscopy (BIS), which estimates extracellular and intracellular compartment volume, with DXA to more accurately predict muscle function. This combination may help incorporate muscle quality, thereby improving sarcopenia diagnosis.

**Methods** We cross-sectionally analyzed data from 248 Black and White participants aged 25-75 from the Midlife in the United States Refresher Cohort. We proposed two novel muscle measures: ALM corrected by the BIS-derived whole body extracellular to intracellular fluid ratio (E/I) and leg lean mass corrected by leg specific E/I creating (ALM/(E/I)w) and (LLM/(E/I)L), respectively. We compared the associations of traditional muscle measures, ALM/(E/I)w, and LLM/(E/I)L with grip strength and lower limb power using jumping mechanography.

**Results** LLM/(E/I)L explained jump power best at R²=0.803 compared to ALM/(E/I)w (p<0.0001) and all other measures. ALM/(E/I)w explained jump power second best (R²=0.759) but significantly better than traditional muscle measures. No muscle measure performed better than covariates when predicting handgrip strength.

**Conclusions** LLM/(E/I)L outperformed ALM/ht² and ALM/BMI when predicting jump power. We propose LLM/(E/I)L is a powerful and clinically relevant method that accounts for muscle quality.
Key Words Dual Energy X-Ray Absorptiometry (DXA); Bioimpedance spectroscopy (BIS); Sarcopenia; Muscle Function; Muscle Quality

Conflict of Interest

None to disclose.

Funding

Publicly available data from the MIDUS study was used for this research. The MIDUS study has been funded by John D. and Catherine T. MacArthur Foundation Research Network and the National Institute on Aging (P01-AG020166 and U19-AG051426). BR was supported in part by the National Institute of Food and Agriculture, United States Department of Agriculture Hatch project (1023263) DK and NB were supported in part by the National Institute on Aging (P01-AG020166).
Introduction

Sarcopenia, the progressive loss of muscle mass and function, puts older individuals at higher risk of immobility, quality of life decline, and mortality (1–6). In addition, sarcopenia increases healthcare cost (7,8). Although sarcopenia is becoming a major public health burden, it is clinically virtually unacknowledged and underdiagnosed, thereby impairing care of older adults (5).

According to the updated 2019 European Working Group on Sarcopenia in Older Adults guidelines, the first indications of sarcopenia are low muscle strength and function and later confirmed by low muscle mass measurement (1). Low muscle function, often assessed by handgrip strength, is traditionally associated with low muscle mass estimated by appendicular lean mass (ALM) (9). ALM is the sum of lean mass in the arms and legs typically measured by dual-energy X-ray absorptiometry (DXA) to estimate appendicular muscle mass (1,9). To account for variation in the size of individuals, ALM is normalized by height (ALM/ht^2) or body mass index (BMI; ALM/BMI) (1,9).

Although frequently used in sarcopenia diagnosis, DXA is limited in that it measures three compartments: bone, fat, and all others (generally referred to as lean mass, which includes muscle tissue) (10). Muscle tissue contains fluid compartments, which are major contributors to ALM (11). As people age, the fluid compartments within muscle tissue change with the preservation or slight increase of extracellular fluid (ECF) but a decline in intracellular fluid (ICF) (11,12). However, this loss of ICF and conservation of ECF with aging results in a higher ECF to ICF (E/I) ratio within muscle, which is significant because reduced ICF is associated with the loss of muscle function with age (11,13,14). The retention of ECF is also thought to mask
true muscle atrophy when measuring ALM because DXA cannot distinguish between ICF and ECF and instead categorizes both as lean mass (13).

Conversely, bioimpedance spectroscopy (BIS) can distinguish between ICF and ECF (14). Furthermore, BIS-derived ICF and ECF can be segmentally assessed in the arms and legs, yielding both whole-body and regional ratios of ICF to ECF (11). Decline in leg specific BIS measures are more strongly associated with age than DXA derived leg lean mass and thus may prove useful for assessing muscle mass (11). However, BIS becomes less accurate at higher or lower BMI as the assumptions used for body size modeling do not account for all sizes (12). To account for the variation from BMI, BIS derived ICF and ECF can be adjusted for differences in BMI, yielding a corrected whole body E/I ratio ((E/I)w) (12).

To mediate the limitations of DXA and incorporate the benefits of BIS to predict muscle function, we propose novel measures using a combination of DXA and BIS, which incorporate both muscle mass and muscle quality. Muscle quality encapsulates the physiological and metabolic state of muscle tissue, and is theorized to explain the loss of muscle function before the loss of muscle mass (15,16). No consensus measures of muscle quality exist; however, fatty or connective tissue infiltration within muscle tissue have been proposed as measures of muscle quality (1,17,18). We propose BIS derived E/I as another measure of muscle quality.

In a previous study, we tested a novel measure of DXA derived ALM adjusted for BIS derived E/I against the traditional mass only measures ALM/ht² and ALM/BMI. We showed that ALM/(E/I)w is more highly associated with handgrip strength and jump power than ALM/ht² and ALM/BMI in an older, mostly White cohort (16). Both handgrip strength and jump power are measurements of muscle function; however, jump power declines more with age than hand grip strength does with age and thus is possibly a better method of assessing muscle function when...
diagnosing sarcopenia (19). Jump power assesses an individual’s power generated from a dynamic, coordinated jump registered by a force plate using multiple muscle groups and is thought to be a more comprehensive muscle function test than handgrip strength (20,21). Because both diminished lower leg strength and sarcopenia are associated with a higher risk of falls, predicting leg muscle function specifically may better determine those at higher risk of falls (22,23). Therefore, we propose another measure of DXA-derived leg muscle mass which incorporates a surrogate of muscle quality measured by adjusting leg lean mass (LLM) for the BIS derived, leg specific ratio of extracellular to intracellular fluid, or LLM/(E/I)l..

We hypothesize our novel measures of muscle, which incorporate a surrogate of muscle quality and muscle mass, are more associated with muscle function compared to traditional muscle mass-based measures. The purpose of this study is to further explore ALM/(E/I)w and LLM/(E/I)l as improved measures of muscle by determining their associations with muscle function compared to ALM/ht² and ALM/BMI in a larger, more diverse population, furthering our understanding of sarcopenia.

**Methods**

We tested our hypothesis in volunteers participating in the Midlife in the United States (MIDUS) Refresher cohort. MIDUS is a multisite, national prospective cohort study which began in 1995 (24). Due to loss of follow-up, the MIDUS Refresher cohort was established as a separate cohort and enrolled additional participants ages 25-75 starting in 2011. The University of Wisconsin Health Sciences Institutional Review Board approved this study and researchers conducted the study in compliance with global, national, and local regulations. We cross-sectionally analyzed data from the first study visit from MIDUS Refresher participants who...
completed their study visit at the Osteoporosis Clinical Research Center in Madison, Wisconsin as this was the only MIDUS site to conduct both DXA and BIS (n = 267). We further restricted our analysis to participants who identified their race as Black or White (n=248) for an adequate statistical comparison between racial groups.

Demographic and anthropomorphic measures

Demographic data including race, age, and sex were collected during a phone interview. Height measured by calibrated Harpenden wall mounted stadiometer (Holtain, Crymych Wales, UK) and weight using a calibrated analog scale were collected during the research study visit. BMI was calculated using weight in kilograms divided by height in meters squared (kg/m²). We generated age categories because age was non-normally distributed after transformation. The age categories were based on mean age quartiles and grouped from 25-40, 41-50, 50-61, and 61 and older. Physical activity was assessed by self-reported metabolic equivalent of tasks (METs). METs were calculated by multiplying the minutes of each exercise activity by intensity (6 METS for vigorous, 3 METs for moderate, and 1.1 METs for light) and by the frequency of each activity per week. Because of a non-normal distribution in METS after transformation, physical activity was converted from continuous to dichotomous with a participant labelled “non-sedentary” if that participant self-reported METs greater than 0.

Muscle function measures

All muscle function measures were collected during the research study visit. Handgrip strength was measured using a Jamar handheld dynamometer (JLW Instruments, Chicago, Illinois) and jump power was determined using a jump mechanography force plate (Leonardo,
Novotec, Pforzheim, Germany) following established standard operating procedures. To obtain handgrip strength, we used each participant’s maximum of 3 grip trials by their non-dominant hand while sitting and flexing their elbow 90° according to established protocol \(^{(25,26)}\). To obtain jump power, each participant performed 3 countermovement jumps on a force plate; the jump with the maximal power from the highest jump was used according to established protocol \(^{(20)}\). Leonardo software 4.2 calculated the maximum jump power. We defined jump power as maximum jump power because it captures a measurement of individuals not able to fully be airborne when jumping and is a measurement of the countermovements assessed by the force plate \(^{(27)}\).

**Lean mass and quality measures**

All muscle measures were collected during the research study visit. DXA measurements were acquired and analyzed using a Lunar iDXA densitometer with enCORE software v17 (GE Healthcare, Madison, Wisconsin) by International Society for Clinical Densitometry certified technologists following manufacturer recommendations. Scans were autoanalyzed by the software and manually adjusted when errors were identified. ALM is the sum of lean tissue mass from each individual arm and leg. Likewise, LLM is the sum of the lean mass in both legs. We calculated ALM/ht² and ALM/BMI by dividing ALM by height squared or BMI, respectively.

Participant BIS exams were performed using an ImpediMed SFB7 (Impediimed, Pinkenba, Queensland, Australia). For whole-body measurement, the current injecting electrodes were placed on the left side of the body on the dorsal surface of the hand and foot proximal to the metacarpal-phalangeal and metatarsal-phalangeal joints, respectively. The sensing electrodes
were placed medially between the distal prominences of the radius and ulna at left wrist and between the medial and lateral malleoli at the left ankle (16). Left leg only measurements were performed by placing the current injecting electrodes on the left side of the body on the dorsal surface of the hand and foot identical to the whole-body measurement. The sensing electrodes were placed on each ankle (11,28). These measurements yielded whole body and left leg ICW and ECW through Impedimed proprietary algorithms using Hanai’s mixture conductivity theory previously described elsewhere (12).

To generate our ALM/(E/I)w measure, we normalized ALM by the whole-body ratio of extracellular to intracellular fluid corrected by BMI ((E/I)w). Further details about the calculation of ALM/(E/I)w are described elsewhere (13,16). To produce our LLM/(E/I)l measure, we adjusted LLM by the leg specific ratio of left leg extracellular fluid to left leg intracellular fluid. We assumed the ratio of left leg extracellular to left leg intracellular fluid is equal for both legs. From herein, we include ALM, ALM/ht2, ALM/BMI, (E/I)w, ALM/(E/I)w, LLM, and (E/I)l , LLM/(E/I)l when referring to muscle measures.

Statistical analysis

We performed all data cleaning and analysis using SAS software Version 9.4 (Copyright © 2016, SAS Institute Inc. SAS and all other SAS Institute Inc. product or service names are registered trademarks or trademarks of SAS Institute Inc., Cary, NC, USA). Frequencies, means, and standard deviations were calculated for categorical and continuous variables, respectively. We conducted descriptive statistics and Spearman’s ranked order correlation to assess bivariate correlations before transforming variables or the deletion of any outliers. We conducted a Shapiro-Wilks test of normality, examined skewness, and calculated kurtosis for each continuous
variable. If the variable was non-normally distributed based on the Shapiro-Wilks test at $\alpha=0.05$, the variable was transformed once and tested again for normality. If non-normality remained, the variable was converted into a categorical variable, except for ALM/BMI to compare between other muscle measures. Univariate outliers were defined as having $z$-scores of greater than 3.29 and were then deleted from further analysis. Normality for each continuous variable was checked again once the univariate outliers were deleted. To remove the impact of multivariate outliers, we converted SAS software generated leverage from proc reg for all continuous variables of interest into Mahalanobis distances for each participant. We determined a participant to be a multivariate outlier if their Mahalanobis distance was greater than 27.88 based on a Chi-square distribution with an $\alpha=0.001$. After data cleaning, we tested the predictive abilities of traditional muscle mass measures (ALM, ALM/ht$^2$, ALM/BMI), BIS-derived fluid ratios [(E/I)$_W$ and (E/I)$_L$], and our novel muscle quality measures (ALM/(E/I)$_W$ and LLM/(E/I)$_L$) on handgrip strength and jump power using multiple linear regression with sex, age, race, BMI, and physical activity as covariates. We also tested for interactions between sex, race, and all muscle measures using multiple linear regression. Significance levels for the multiple linear regressions were set as $\alpha=0.05$.

Lastly, we tested the difference in model prediction effectiveness, or $R$ from each multiple regression and subsequently $R^2$, between each of the muscle measures in predicting handgrip strength and jump power to determine if one muscle measure predicted handgrip strength or jump power best using Steiger’s method. Steiger’s method is used to compare how groups of different independent variables predicts the same dependent variable based on the difference in $R^2$. We tested sequentially in order of lowest to highest $R^2$ values. Significance levels for model comparisons were adjusted with a Bonferroni correction because we compared
6 models to one another using Steiger’s methods yielding an $\alpha=0.008^{(32)}$. We conducted post-hoc power analyses for the multiple regression models for handgrip strength and jump power. Our power analyses suggest that all models had a power greater than 0.80. We used G*Power (Version 3.1.9.7, Düsseldorf, Germany) for all power analyses $^{(33)}$.

**Results**

Our cohort had 248 participants, of which 100 (40.3%) were Black and 144 (58.1%) were women. The average age and BMI of the sample were 49.25 years (SD ±12.95 years) and 31.37 kg/m$^2$ (SD ±7.97 kg/m$^2$). Sixty-one (24.6%) participants were between the ages of 25-40, while 58 (23.4%) were ages 41-50, 65 (26.2%) were ages 51-60, and 64 (25.8%) were ages 61 or older. Non-sedentary adults comprised 147 (59.3%) of the sample. The averages of handgrip strength, jump power, ALM, ALM/ht$^2$, ALM/BMI, ALM/(E/I)$_w$, LLM, and LLM/(E/I)$_L$ are detailed in **Table 1**. Technical challenges prevented 5 subjects from having valid LLM measurement, consequently, leg specific ECF and ICF data were unavailable. All continuous variables were natural log transformed except for handgrip strength which was square root transformed to obtain a normal distribution.

Spearman’s rank order analysis of bivariate correlations using the entire sample (n=248) is presented in **Table 2**. Most importantly, handgrip strength was not associated with age ($\rho=0.006$, $p=0.92$), while jump power had a moderate negative association with age ($\rho=-0.423$, $p<0.001$). ALM/ht$^2$ was not associated with age ($\rho=-0.083$, $p=0.194$), while ALM/BMI and ALM/(E/I)$_w$ had slight negative associations with age ($\rho=-0.140$, $p=0.028$; $\rho=0.163$, $p<0.001$, respectively). LLM/(E/I)$_L$ had the greatest association with age out of all muscle measures with ALM included ($\rho=-0.413$, $p<0.001$). The BIS-derived ratios of (E/I)$_w$ and (E/I)$_L$ were also
correlated with age with \((E/I)_L\) most strongly associated with age \((p=0.247, p<0.001; p=0.559, p<0.001, \text{ respectively})\).

We identified and removed 3 univariate outliers after transformations to obtain normality and found 0 multivariate outliers when testing Mahalanobis distances. This yielded \(n=245\) for all multivariate analyses. The multiple regression models show that each muscle measure was associated with handgrip strength (Table 3). Sex also consistently predicted handgrip strength across all models, with females having lower handgrip strength. Race was associated with handgrip strength in models with muscle measures, except for the LLM/(E/I)_L model. BMI was associated with handgrip strength among all muscle measures models largely with a greater BMI predicting lower handgrip strength. Conversely, age was not associated with handgrip strength in any model which included a muscle measure. Overall, the prediction models of covariates, all muscle measures, and BIS-derived fluid ratios captured between 46.5 to 51.4 percent of the variance in handgrip strength.

The multiple regression models predicting jump power also showed that each muscle measure was associated with jump power (Table 4). Unlike handgrip strength, sex was significantly associated with jump power in only the covariate ALM/ht^2, LLM, and LLM/(E/I)_L models. Age was associated with jump power across all models in a dose respondent manner with greater age associated with lower jump power. Race was associated with jump power only in the ALM/ht^2 model. BMI was associated with jump power in all muscle measure models except for the ALM/(E/I)_w models. No interaction terms between muscle measures and sex or muscle measures and race were significant when predicting jump power. The covariate model explained 60.2% of the variance in jump power. The addition of muscle measures to the covariate model increased the amount of variance in jump power explained, with \((E/I)_w\)
explaining 65.3%, (E/I)w explaining 69.5%, ALM explaining 73.2%, ALM/ht² explaining 71.2%, ALM/BMI explaining 73.8%, ALM/(E/I)w explaining 75.9%, LLM explaining 72.2%, and LLM/(E/I)ₗ explaining 80.3% of the variance in jump power.

When we used Steiger’s test to compare handgrip strength model differences in R², no significant differences were found between the covariate model and models with the addition of ALM, ALM/ht², ALM/BMI, LLM, ALM/(E/I)w or LLM/(E/I)ₗ (covariate model: vs ALM p=0.293; vs ALM/ht² p=0.615; vs ALM/BMI p=0.319; vs ALM/(E/I)w p=0.293; vs LLM p=0.380; vs LLM/(E/I)ₗ p=0.584). No significant differences in handgrip strength models between ALM/(E/I)w and ALM/ht², ALM/(E/I)w and ALM/BMI, or ALM/(E/I)w and LLM/(E/I)ₗ were found (p=0.673, p=0.914, and p=0.614, respectively).

In contrast, the Steiger’s test for jump power showed model differences in R² for all muscle measures significantly explained more variance in jump power than the covariate model alone (p<0.001). When comparing ALM, ALM/ht², ALM/BMI, LLM, and ALM/(E/I)w, only ALM/ht² and ALM/(E/I)w significantly differed with ALM/(E/I)w explaining more jump power variance than ALM/ht² when α=0.05, however the difference in R² between ALM/ht² and ALM/(E/I)w was no longer significant after the Bonferroni correction of α=0.008 for multiple comparisons. Our new measure of LLM/(E/I)ₗ significantly explained the most variance in jump power and differed from ALM/(E/I)w after the Bonferroni correction (p<0.001; Figure 1).

Discussion

This study validates ALM/(E/I)w as an improved muscle measure over ALM/ht² and introduces LLM/(E/I)ₗ, which outperformed all traditional measures of muscle. In this cohort, LLM/(E/I)ₗ, which includes a surrogate of muscle quality, predicts jump power better than
ALM/ht², ALM/BMI, and ALM/(E/I)w. ALM/(E/I)w predicted a large amount of variation in jump power but did not significantly outperform ALM/ht² or ALM/BMI when adjusted for multiple comparisons. The normalization of LLM or ALM by the ratio of extracellular to intracellular fluid adjusts for fluid distribution changes seen with aging, which is not accounted for by either ALM/ht² or ALM/BMI. We suggest that these novel measures be utilized in larger and more diverse studies. If our results are validated, the BIS adjustment of ALM should receive consideration of inclusion as a component of future sarcopenia diagnostic parameters.

Our results demonstrate that these novel muscle measures, which incorporate both muscle mass and muscle quality, outperform the prediction of muscle function based on tradition muscle measures that assess mass alone. Although no consensus definition of muscle quality exists, working definitions include contractile area, fat infiltration, and in this present study, fluid volume distribution (15–17,34). Regardless, muscle quality predicts muscle function, recovery, and mortality yet clinicians do not currently assess quality attributes (18,35–37). Though ambiguous, muscle quality provides an explanation for the large drop in muscle function with age that cannot be explained by the loss of muscle mass alone (15,38). Incorporating muscle quality into the definition of sarcopenia may improve the utility of its diagnosis. The characterization of muscle quality may also identify those individuals with adequate muscle mass but low muscle quality. Reduction in muscle quality likely occurs before any appreciable loss of mass can be measured, which also supports the higher association of muscle quality with age (15). Utilizing a muscle quality measure may then serve as an early detection of sarcopenia and provide an opportunity for timely interventions needed to mitigate consequential outcomes. Our results support the use of combining DXA and BIS for two improved measure of muscle, LLM/(E/I)L and LLM/(E/I)L, for predicting muscle function.
When examining the statistical comparisons of muscle measures, handgrip strength is not strongly predicted by ALM, ALM/ht², ALM/BMI, (E/I)w, ALM/(E/I)w, LLM, (E/I)l, or LLM/(E/I)l in the present study. Although all muscle measures seem to predict jump power, our results do not suggest these muscle measures are meaningfully associated with handgrip strength. Our multivariate models, using any of our muscle measures predicting handgrip strength, explained only 2.3 to 4.9 percent more than the multivariate model which included only covariates. This suggests the muscle measures only added a clinically irrelevant amount of explanation of handgrip strength.

In contrast, our results suggest jump power is better associated with age and instrumental muscle measures in bivariate and multivariate models. This supports the use of jump power as an alternative, more appropriate method to determine muscle function than handgrip strength, especially in relation to age (19–21). Assessing jump power requires both legs and coordinated movement, which can be seen as an indicator of muscle motor units function and electrophysiological health, instead of only handedness or individual muscle groups in handgrip strength (39). Indeed, lower leg strength is associated with falls and fractures, both of which are outcomes of sarcopenia (22,23).

In all our multivariate models, categories of increasing age negatively impacted jump power, providing evidence jump power is negatively associated with age in an expected physiological way. Because jump power is significantly associated with age in a dose-responsive manner across all muscle measures, LLM/(E/I)l is associated with age, and LLM/(E/I)l best predicts jump power, we recommend jump power in conjunction with LLM/(E/I)l as appropriate diagnostic measures for sarcopenia diagnosis. In addition, because the ALM/(E/I)w model explained a large amount of variation in jump power and did not have sex or BMI as significant
covariates, this novel measure may also lead to a more clinically useful approach of measuring muscle health.

Although these results are promising, this study does have several limitations. Our study population included only participants who identified as Black or White, limiting its applicability in other races/ethnicities, which do show average differences in skeletal muscle mass and difference in skeletal muscle mass decline (40). Our cross-sectional study design is not able to use any muscle mass or quality measure to prospectively predict health outcomes, and at this point, the associations are based on correlations. Being non-sedentary is likely not a predictor in many of our models because we used a dichotomous variable indicating “yes or no” for being non-sedentary because of the lack of individuals who reported any METS, which is not a real world scenario as the lowest level of METS measure oxygen consumption levels in a sedentary state (41). Other studies have shown that increased resistance training increases muscle mass and muscle quality (42–46), suggesting physical activity may be a modifier in the relationship between these muscle measures and muscle function. Because of the non-normal distributions, we used transformations of each continuous variable, which make the interpretability of results difficult. Our transformations did not produce a normal distribution for ALM/BMI, which had a tendency towards a bimodal distribution though non-normality was slightly significant based on the Shapiro-Wilk test (p=0.018). Our novel method also requires both DXA and BIS, versus the current diagnosis of sarcopenia using DXA to diagnose muscle mass, which may limit the applicability of our method in a clinical setting.

However, our study does have substantial strengths including the large number of individuals who completed both DXA, BIS, and jump power. Other studies which have assessed BIS and DXA have had limited sample numbers (11,16,47). The present study also includes Black
and White individuals ages 25-75 with variations in BMI and age expanding upon results from our initial study examining the potential of ALM/(E/I)w conducted within an older, White population \(^{16}\). In our present study, we show jump power is associated with age regardless of the muscle measure across various ages, including those who would not be traditionally targeted for sarcopenia interventions. We show ALM/(E/I)w may be unbiased when assessing muscle between sexes which would be advantageous in a clinical setting, though LLM/(E/I)L does not account for sex. Both ALM/(E/I)w and LLM/(E/I)L are not affected by race, though more research is needed to expand ALM/(E/I)w and LLM/(E/I)L into more racially and ethnically diverse populations. In addition, our results suggest our measure of LLM/(E/I)L is clinically relevant because of the high R\(^2\) value when predicting jump power using a combination of two non-invasive techniques.

Future studies should use ALM/(E/I)w and LLM/(E/I)L to predict health outcomes including falls, fractures, disability, quality of life, and mortality. Research examining the associations between ALM/(E/I)w and LLM/(E/I)L and chronic diseases, such as diabetes or congestive heart failure, may also support the use of our novel muscle measures predictors of chronic disease severity. Muscle function and muscle quality are consistently predictors of mortality, though muscle mass is only an occasional predictor of mortality \(^{48-51}\), however, ALM/(E/I)w and LLM/(E/I)L remain to be tested as a predictor of mortality. Longitudinal studies will elucidate the connection between the changes in muscle quality and muscle function. Studies with higher sample sizes and more diverse study populations will be able to explore more minute differences in health outcomes between muscle quality and muscle mass, leading to better evidence to define sarcopenia.
Conclusion

Our novel measure, LLM/(E/I)L, outperformed traditional sarcopenia diagnosis measures, specifically ALM/ht^2 and ALM/BMI, when predicting jump power. Additionally, we previously observed ALM/(E/I)W outperformed ALM/ht^2 in an older, White population, when predicting muscle function, and now have demonstrated expanded utility in a larger, more age and racially diverse population. Future research into the predictive capabilities of ALM/(E/I)w and LLM/(E/I)L on health outcomes, including falls and fractures, among large samples is necessary. Our muscle measures are improved measures of muscle and should be considered for the identification of sarcopenia.
Acknowledgements

We thank the Midlife in the United States (MIDUS) research team for their time and efforts collecting the data used. The MIDUS study has been funded by John D. and Catherine T. MacArthur Foundation Research Network and the National Institute on Aging (P01-AG020166 and U19-AG051426). We also thank all the participants in the MIDUS Refresher Cohort. We also thank Dale Schoeller for his review and discussion of the manuscript.

This material is based upon work supported by the National Institute of Food and Agriculture, United States Department of Agriculture, Hatch project [1023263].

Authors Roles: Data collection: NB, DK. Data interpretation: BR, NB, DK, AK. Drafting manuscript: BR, AK. Revising manuscript content: BR, NB, DK, YY, AK. Approving final version of manuscript: BR, NB, DK, YY, AK. BR takes responsibility for the integrity of the data analysis.

Author Contributions: BR: conceptualization, data curation, methodology, statistical analysis, data visualization, writing original draft, writing review and editing, project management. NB: conceptualization, data collection, review and editing, funding acquisition. DK: conceptualization, data collection, review and editing, funding acquisition. YY: conceptualization, review and editing. AK: conceptualization, methodology, writing original draft, review and editing, project management supervision, funding acquisition.
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<td>41-50</td>
<td>58 (23.4)</td>
<td>33 (22.9)</td>
<td>25 (24.0)</td>
</tr>
<tr>
<td>51-61</td>
<td>65 (26.2)</td>
<td>43 (29.9)</td>
<td>22 (21.2)</td>
</tr>
<tr>
<td>&gt;61</td>
<td>64 (25.8)</td>
<td>28 (19.4)</td>
<td>36 (34.6)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Sedentariness</th>
<th>Total (n=248)</th>
<th>Female (n=144)</th>
<th>Male (n=204)</th>
</tr>
</thead>
<tbody>
<tr>
<td>METs = 0</td>
<td>101 (40.7)</td>
<td>59 (41.0)</td>
<td>42 (40.4)</td>
</tr>
<tr>
<td>METs greater than 0</td>
<td>147 (59.3)</td>
<td>85 (59.0)</td>
<td>62 (59.6)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Total (n=248)</th>
<th>Female (n=144)</th>
<th>Male (n=204)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Mean (SD)</td>
<td>Mean (SD)</td>
<td>Mean (SD)</td>
</tr>
<tr>
<td>BMI (kg/ht(^2))</td>
<td>31.37 (7.97)</td>
<td>31.82 (8.01)</td>
</tr>
<tr>
<td>Age (years)</td>
<td>49.25 (12.95)</td>
<td>47.79 (12.50)</td>
</tr>
<tr>
<td>Handgrip strength (kg)</td>
<td>30.56 (11.85)</td>
<td>23.83 (7.52)</td>
</tr>
<tr>
<td>Jump power (kW)</td>
<td>2.62 (0.96)</td>
<td>2.17 (0.63)</td>
</tr>
<tr>
<td>ALM (kg)</td>
<td>23.89 (6.08)</td>
<td>20.82 (4.56)</td>
</tr>
<tr>
<td>ALM/ht(^2) (kg/ht(^2))</td>
<td>8.33 (1.99)</td>
<td>7.77 (1.55)</td>
</tr>
<tr>
<td>ALM/BMI (kg/(kg/ht(^2)))</td>
<td>0.78 (0.18)</td>
<td>0.67 (0.11)</td>
</tr>
<tr>
<td>ALM/(E/I)(_L) (kg)</td>
<td>62.67 (14.95)</td>
<td>53.88 (9.62)</td>
</tr>
<tr>
<td>LLM (kg)</td>
<td>17.77 (4.33)</td>
<td>15.84 (3.50)</td>
</tr>
<tr>
<td>LLM/(E/I)(_L) (kg)(^\wedge)</td>
<td>6.7 (2.41)</td>
<td>5.91 (1.96)</td>
</tr>
</tbody>
</table>

Note. METs= metabolic equivalent of task, ALM= appendicular lean mass, ALM/ht\(^2\) = ALM divided by height squared, ALM/BMI = ALM divided by body mass index, (E/I)\(_L\) = BMI correct ratio of extracellular to intracellular fluid, LLM= leg lean mass, E/I\(_L\) = ratio of leg extracellular fluid to leg intracellular fluid. \(^\wedge\)n=243 for LLM/(E/I)\(_L\).
Table 2. Spearman’s correlations between non-transformed continuous variables (n=248).

<table>
<thead>
<tr>
<th></th>
<th>Age</th>
<th>BMI</th>
<th>HGS</th>
<th>JP</th>
<th>ALM</th>
<th>ALM/h²</th>
<th>ALM/BMI</th>
<th>(E/I)w</th>
<th>ALM/(E/I)w</th>
<th>LLM</th>
<th>(E/I)L²</th>
<th>LLM/(E/I)L²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Age</td>
<td>0.063</td>
<td>0.006</td>
<td>-0.423</td>
<td>-0.099</td>
<td>-0.083</td>
<td>-0.140</td>
<td>0.247</td>
<td>-0.163</td>
<td>0.559</td>
<td>-0.413</td>
<td></td>
<td></td>
</tr>
<tr>
<td>BMI</td>
<td>0.063</td>
<td>-0.070</td>
<td>0.169</td>
<td>0.538</td>
<td>0.757</td>
<td>-0.384</td>
<td>0.904</td>
<td>0.289</td>
<td>0.577</td>
<td>0.035</td>
<td>0.382</td>
<td></td>
</tr>
<tr>
<td>HGS</td>
<td>0.006</td>
<td>-0.007</td>
<td>0.502</td>
<td>0.500</td>
<td>0.292</td>
<td>0.607</td>
<td>-0.177</td>
<td>0.595</td>
<td>0.444</td>
<td>-0.162</td>
<td>0.391</td>
<td></td>
</tr>
<tr>
<td>JP</td>
<td>-0.423</td>
<td>0.169</td>
<td>0.502</td>
<td>0.740</td>
<td>0.599</td>
<td>0.633</td>
<td>-0.077</td>
<td>0.817</td>
<td>0.717</td>
<td>-0.548</td>
<td>0.837</td>
<td></td>
</tr>
</tbody>
</table>

*Note. BMI= body mass index, HGS = handgrip strength, JP= jump power, ALM= appendicular lean mass, ALM/h² = ALM divided by height squared, ALM/BMI = ALM divided by BMI, (E/I)w = BMI correct ratio of extracellular to intracellular fluid, LLM= leg lean mass, (E/I)L² = ratio of leg extracellular fluid to leg intracellular fluid. a n=243 for LLM/(E/I)L². b p<0.05, c p<0.001.*
Table 3. Results of the multiple regression models showing the association between handgrip strength, a covariate only model, and muscle measure [ALM/ht², ALM/BMI, ALM/(E/I)_W, LLM, and LLM/(E/I)_L] models with covariates. Each muscle measure and BMI are log-transformed (n=245).

<table>
<thead>
<tr>
<th>Model</th>
<th>Intercept</th>
<th>Muscle Measure</th>
<th>Sex</th>
<th>Age 40 and less than 50</th>
<th>Age 50 and less than 61</th>
<th>Age 61 and older</th>
<th>Race</th>
<th>BMI</th>
<th>Non-sed</th>
<th>R²</th>
</tr>
</thead>
<tbody>
<tr>
<td>Covariates only</td>
<td>7.829⁠¹</td>
<td>-1.452⁠³</td>
<td>0.029</td>
<td>-0.187</td>
<td>-0.309⁠⁹</td>
<td>-0.160</td>
<td>0.042</td>
<td>0.147</td>
<td>0.465</td>
<td></td>
</tr>
<tr>
<td>ALM</td>
<td>7.433⁠⁴</td>
<td>0.820⁠³</td>
<td>0.082</td>
<td>-0.060</td>
<td>-0.240⁠⁹</td>
<td>-1.320⁠⁹</td>
<td>0.066</td>
<td>0.512</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ALM/ht²</td>
<td>7.696⁠⁹</td>
<td>1.993⁠⁹</td>
<td>-0.749⁠³</td>
<td>0.077</td>
<td>-0.160</td>
<td>-0.287⁠⁹</td>
<td>-1.273⁠⁹</td>
<td>0.090</td>
<td>0.488</td>
<td></td>
</tr>
<tr>
<td>ALM/BMI</td>
<td>5.259⁠⁹</td>
<td>1.945⁠⁹</td>
<td>-1.078⁠⁰</td>
<td>0.096</td>
<td>-0.059</td>
<td>-0.242⁠⁹</td>
<td>0.644⁠⁵</td>
<td>0.062</td>
<td>0.510</td>
<td></td>
</tr>
<tr>
<td>ALM/(E/I)_W</td>
<td>1.454</td>
<td>1.937⁠⁹</td>
<td>-0.763⁠³</td>
<td>0.096</td>
<td>-0.059</td>
<td>-0.258⁠⁹</td>
<td>-0.747⁠⁹</td>
<td>0.051</td>
<td>0.514</td>
<td></td>
</tr>
<tr>
<td>LLM</td>
<td>6.180⁠⁹</td>
<td>1.761⁠⁹</td>
<td>-0.911⁠⁰</td>
<td>0.111</td>
<td>-0.013</td>
<td>0.026</td>
<td>-0.212⁠⁹</td>
<td>-1.193⁠⁹</td>
<td>0.066</td>
<td>0.505</td>
</tr>
<tr>
<td>LLM/(E/I)_L</td>
<td>7.910⁠⁹</td>
<td>0.774⁠⁹</td>
<td>-1.146⁠³</td>
<td>0.144</td>
<td>-0.017</td>
<td>0.031</td>
<td>-0.199</td>
<td>-0.557⁠⁹</td>
<td>0.067</td>
<td>0.491</td>
</tr>
</tbody>
</table>

Note. Non-sed= non-sedentary, BMI= body mass index, Non-sed=non-sedentary, ALM= appendicular lean mass, ALM/ht² = ALM divided by height squared, ALM/BMI = ALM divided by BMI, (E/I)_W = BMI correct ratio of extracellular to intracellular fluid, LLM= leg lean mass, (E/I)_L = ratio of leg extracellular fluid to leg intracellular fluid. ^n=243 for LLM/(E/I)_L. ⁠ᵇp<0.05, ⁠ᶜp<0.01, ⁠ᵈp<0.001.
Table 4. Results of the multiple regression models showing the association between jump power, a covariate only model, and muscle measure [ALM/ht\(^2\), ALM/BMI, ALM/(E/I)\(_W\), LLM, and LLM/(E/I)\(_L\)] models with covariates. Each muscle measure and BMI are log-transformed (n=245).

<table>
<thead>
<tr>
<th>Model</th>
<th>Intercept</th>
<th>Muscle Measure</th>
<th>Sex</th>
<th>Age 40 and less than 50</th>
<th>Age 50 and less than 61</th>
<th>Age 61 and older</th>
<th>Race</th>
<th>BMI</th>
<th>Non-sed</th>
<th>R(^2)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Covariates only</td>
<td>0.372</td>
<td>-0.478(\text{a})</td>
<td>-0.127(\text{a})</td>
<td>-0.239(\text{a})</td>
<td>-0.491(\text{a})</td>
<td>0.020</td>
<td>0.420(\text{b})</td>
<td>0.069(\text{c})</td>
<td>0.602</td>
<td></td>
</tr>
<tr>
<td>ALM</td>
<td>0.148</td>
<td>0.464(\text{b})</td>
<td>-0.080</td>
<td>-0.098(\text{c})</td>
<td>-0.167(\text{c})</td>
<td>-0.340(\text{c})</td>
<td>-0.026</td>
<td>-0.350(\text{c})</td>
<td>0.023</td>
<td>0.732</td>
</tr>
<tr>
<td>ALM/ht(^2)</td>
<td>0.273</td>
<td>1.475(\text{b})</td>
<td>-0.201(\text{b})</td>
<td>-0.092(\text{d})</td>
<td>-0.171(\text{d})</td>
<td>-0.381(\text{d})</td>
<td>-0.075(\text{d})</td>
<td>-0.553(\text{d})</td>
<td>0.027</td>
<td>0.712</td>
</tr>
<tr>
<td>ALM/BMI</td>
<td>-1.149(\text{e})</td>
<td>1.150(\text{e})</td>
<td>-0.070</td>
<td>-0.088(\text{e})</td>
<td>-0.163(\text{e})</td>
<td>-0.337(\text{e})</td>
<td>-0.029</td>
<td>0.777(\text{e})</td>
<td>0.019</td>
<td>0.738</td>
</tr>
<tr>
<td>ALM/(E/I)(_W)</td>
<td>-3.491(\text{f})</td>
<td>1.174(\text{f})</td>
<td>-0.038</td>
<td>-0.078(\text{f})</td>
<td>-0.133(\text{f})</td>
<td>-0.288(\text{f})</td>
<td>-0.040</td>
<td>-0.058</td>
<td>0.011</td>
<td>0.759</td>
</tr>
<tr>
<td>LLM</td>
<td>-0.599(\text{h})</td>
<td>1.037(\text{h})</td>
<td>-0.159(\text{h})</td>
<td>-0.087(\text{h})</td>
<td>-0.167(\text{h})</td>
<td>-0.346(\text{h})</td>
<td>-0.011</td>
<td>-0.307(\text{h})</td>
<td>0.021</td>
<td>0.722</td>
</tr>
<tr>
<td>LLM/(E/I)(_L)(^A)</td>
<td>0.388(\text{h})</td>
<td>0.717(\text{h})</td>
<td>-0.190(\text{h})</td>
<td>-0.039</td>
<td>-0.074(\text{h})</td>
<td>-0.162(\text{h})</td>
<td>0.000</td>
<td>-0.125(\text{h})</td>
<td>-0.020</td>
<td>0.803</td>
</tr>
</tbody>
</table>

Note. Non-sed= non-sedentary, BMI= body mass index, Non-sed=non-sedentary, ALM= appendicular lean mass, ALM/ht\(^2\) = ALM divided by height squared, ALM/BMI = ALM divided by BMI, (E/I)\(_W\) = BMI correct ratio of extracellular to intracellular fluid, LLM= leg lean mass, (E/I)\(_L\) = ratio of leg extracellular fluid to leg intracellular fluid. \(^A\) n=243 for LLM/(E/I)\(_L\). \(^\text{b}\) p<0.05, \(^\text{c}\) p<0.01, \(^\text{d}\) p<0.001.
Figure 1. The results from Steiger’s model comparison test. When comparing R² values between models, each muscle measure model explained significantly higher variance in jump power. Among the muscle measure models, appendicular lean mass (ALM) adjusted for height squared (ALM/ht²), leg lean mass (LLM), ALM, ALM adjusted for BMI (ALM/BMI), and ALM adjusted for the BMI corrected ratio of extracellular to intracellular fluid (ALM/(E/I)W) were not significantly different in the amount of jump power variance they explained when significance levels were adjusted using a Bonferroni correction. LLM/(E/I)L significantly explained the highest amount of variance in jump power with an R² value of 0.803. Brackets indicate comparisons between models with p-values of those comparison indicated on each bracket.