International Journal of EXERCISE SCIENCE

Original Research

Predictive Accuracy of the Nelson Equation via BodPod Compared to Commonly Used Equations to Estimate Resting Metabolic Rate in Adults

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ABSTRACT

International Journal of Exercise Science 14(2): 1166-1177, 2021. Indirect calorimetry (IC) is considered the gold standard for assessing resting metabolic rate (RMR). However, many people do not have access to IC devices and use prediction equations for RMR estimation. Equations using fat free mass (FFM) as a predictor have been developed to estimate RMR, as a strong relationship exists between FFM and RMR. One such equation is the Nelson equation which is used by the BodPod (BP). Yet, there is limited evidence whether the Nelson equation is superior to other common equations to predict RMR. To examine the agreement between predicted RMR from common RMR equations and the BP, and RMR measured via IC. Data from 48 healthy volunteers who completed both the BP and IC were collected. Agreement between RMR measured by BP, common regression equations, and indirect caloriometry was evaluated using repeated measures ANOVA, Bland-Altman analysis and root mean square error (RMSE). Predicted RMR values from common equations and BP were significantly different from IC with the exception of the World Health Organization (WHO) equation. Large limits of agreement and RMSE values demonstrate a large amount of error at the individual level. Despite the use of FFM, the Nelson equation does not appear to be superior to other common RMR equations. Although the WHO equation presented the best option within our sample, all equations performed poorly at the individual level. Clinicians should be aware that prediction equations may significantly under- or overestimate RMR compared to IC and when an accurate value of RMR is required, IC is recommended.

KEY WORDS: Resting metabolic rate, indirect calorimetry, body composition, fat-free mass, prediction equation

INTRODUCTION

Resting metabolic rate (RMR) is the measure of energy required for the body to sustain essential physiological processes while in a rested state and is generally within ± 10% of basal metabolic rate (26). Used in clinical and research settings, RMR is a valuable tool to estimate caloric needs, as well as to determine the effectiveness of nutritional interventions (1, 11, 12, 19). Accurate determination of energy needs is essential for nutritional assessment and clinical dietetics (11, 37), however, many factors influence RMR. These include age (21), gender (3), and body mass and composition (21). Currently, multiple approaches are used to measure RMR, with accuracy, reliability, complexity, and cost varying greatly across instruments (26).

In practice, a trade-off is often sought between accuracy, time, feasibility, and convenience in metabolic measurements (15). A convenient and inexpensive alternative to calorimetry to estimate RMR is the use of prediction equations. Proposed equations use demographic measures such as mass, height, age, and sex to predict RMR as these are all easily obtained. The most common examples include the Harris-Benedict (22), Mifflin-St Jeor (29), and World Health Organization (WHO) (24) equations. Despite their widespread use, low levels of agreement between predicted and measured (via indirect calorimetry) RMR has brought their validity into question (18, 20). Equations using fat free mass (FFM) as a predictor have been theorized as more accurate as prior studies have shown FFM to explain 53% to 88% of variance in RMR (14, 31).

More recently, technologies such as the BodPod (COSMED, Concord, CA) have provided a means for estimating RMR in addition to its primary purpose of estimating body fat percentage using a prediction equation utilizing FFM (31). Despite the inclusion of FFM, equations employing it as a predictor variable have fared no better compared to those using only demographic predictors in comparison studies (18). Results of multiple studies have showed that equations based on weight, sex, and age (Harris-Benedict, Mifflin-St Jeor, and WHO) have had better agreement with RMR measured via indirect calorimetry (IC) than those based on FFM (18, 19, 33, 38). These findings are unexpected as FFM has been reported to contribute approximately 13 kCal/kg/day to RMR (7). However, a limitation of these studies was their analysis was conducted using a cohort of both males and females and the sex-specific accuracy was not determined (18, 19). As males and females have significant differences in FFM and fat mass (FM) (23), these equations may perform better in sex-specific samples, rather than a mixed cohort.

While the BodPod is regarded as a valid method to assess body composition for various populations, its accuracy to estimate RMR via estimated FFM in a diverse sample of healthy adults requires further study (17). For convenience reasons many practitioners may default to using the RMR estimates provided by the BodPod and not consider obtaining an estimate of RMR using a different prediction equation. Therefore, the purpose of this study was to examine the agreement between predicted RMR from equations using demographic measures (Harris-Benedict, Mifflin St-Jeor, WHO) and the BodPod (via the Nelson equation) with measured RMR using indirect calorimetry (IC). Secondly, we assessed the sex-specific accuracy of these equations as previous literature is limited in regard to the accuracy of RMR prediction equations by sex.

METHODS

Participants

A cross-sectional design was used to collect data from a convenience sample of 50 individuals who had participated in both a BodPod (COSMED, Concord, CA, USA) and indirect calorimetry

(TrueOne2400, Parvo Medics, Salt Lake City, UT, USA) assessment at a sports performance clinic. The individuals completed the assessments for their own individual health and fitness reasons; however, we obtained permission to use the deidentified data for research purposes. To be eligible for the study, participants were required to be healthy, between the ages of 18 and 80, and free of any metabolic syndrome or condition that would significantly alter their metabolism. For the purposes of our assessments provided at the clinic, healthy is defined as 1) asymptomatic of cardiovascular, metabolic or renal disease, or 2) cleared for exercise and testing by their physician. Each test was performed between 8:00 and 9:00 A.M. with the participants rested and fasted for at least twelve hours. The BodPod and TrueOne 2400 metabolic cart were calibrated to manufacturer's specifications at least 30 minutes prior to testing. All experimental procedures were approved by the institutional review board and subjects signed an informed consent prior to participation. This research was carried out fully in accordance to the ethical standards of the International Journal of Exercise Science (30).

Protocol
Upon arrival, participants performed a body composition analysis using the BodPod. All participants wore tight compression shorts (and a sports bra if female) or a swimsuit. All jewelry was removed, and a swim cap was placed upon participants' heads. Height and mass were measured using a stadiometer and the BodPod calibrated scale, respectively. Participants then entered the BodPod and were instructed to sit still, breathe normally, and relax. Body density and volume were measured twice, with participants sitting motionless for approximately 50 seconds each test. If the second test was inconsistent (greater than 150 mL or 0.2 % difference in raw body volume between tests) with the first, a third test was conducted. All BodPod assessments used for this study had a minimum of two consistent tests. Thoracic gas volume (V_{TG}) was predicted for all participants and has previously been shown to be a reliable alternative to calculate body volume compared to direct measurement (16, 40). Body density was calculated from participants' mass and volume using the Siri equation (35). Measured FFM and FM were used to calculate estimated RMR using the Nelson equation [25.8 (FFM) + 4.04 (FM)] (31).

After completing the BodPod test, participants rested in a supine position for 20 minutes before RMR was measured using IC. The canopy was placed over the participants' heads, chest, and torso to limit gas escape. Participants were instructed to lay still, relax, but not to fall asleep during testing. Each test lasted approximately 30-45 minutes. Data from the last 15 minutes of testing was used for analysis. Gas analysis of the canopy hood and mixing chamber provided VO_2 and VCO_2 values for the modified Weir equation (RMR = [3.941 * VO_2] + [0.85 * 1.106 * VO_2]) to calculate RMR and respiratory exchange ration (RER) (39).

Resting metabolic rate was calculated using participant demographics (age, height, and weight) and FM and FFM taken from the BodPod. The equations used to estimate RMR are described in Table 1. These equations were selected as they showed the best agreement with measured RMR using indirect calorimetry in prior studies (18, 32).

Table 1. Summary of RMR prediction equations analyzed.

Method	Year Developed	Sample	Equation		
Harris-Benedict	1919	n = 239 (136 male, 103 female); mean age: males 27 y, females 32 y, mean body mass index for males 21.4, females 24.4	Male: RMR = 66.473 + (13.7516*W) + (5.0033*H) - (6.7550*A) Female: RMR = 655.0955 + (9.5634*W) + (1.8496*H) - (4.6756*A)		
Mifflin-St Jeor	1990	n = 498 (251 male, 247 female), 264 normal weight, 234 obese	RMR = (9.99*W) + (6.25*H)-(4.92*A) + (166*sex [males, 1; females,0]) - 161		
WHO	1981	Based on data > 114 studies and 7,000 subjects, ~ 33% female	Age:	Sex:	RMR:
			18 to 30 years	Male	0.063*W + 2.896
				Female	0.062*W + 2.036
			30 to 60 years	Male	0.048*W + 3.653
				Female	0.034*W + 3.538
			>60 years	Male	0.049*W + 2.450
				Female	0.038*W + 2.755
Nelson	1992	n = 212 (86 male, 126 female); 62% obese (males > 20% body fat, females > 30%)	RMR = 25.8*FFM + 4.04*FM		

Abbreviations: A, age; FFM, fat-free mass; FM, fat mass; H, height; RMR, resting metabolic rate; W, body weight.

Statistical Analysis

All statistical analyses were performed using R (R Core Team, Vienna, Austria) with alpha level set *a priori* at 0.05 (36). Data were normally distributed according to the Shaprio-Wilk's test ($p < 0.05$), and skewness and kurtosis were within normal values. Outliers were found using Tukey's method (either below or above 1.5 times the interquartile range) and removed. Descriptive statistics were calculated for age, height, mass, BMI, body fat percentage, FFM, FM, and RMR. Multiple repeated measures ANOVA were performed to determine if differences existed between all RMR measures (IC, Nelson, Harris-Benedict, Mifflin-St Jeor, WHO) across all participants, as well as split by sex. Where data violated the assumption of sphericity, Greenhouse-Geisser adjustment was used. Where results were significant, pairwise comparisons with Bonferroni corrections were conducted. To assess agreement, Bland-Altman plots were constructed between RMR measured via indirect calorimetry and RMR estimated from each prediction equation to detect systematic bias and error (6). Bias (measured RMR minus predicted) and limits of agreements (spread of the difference) were calculated to determine estimated limits of agreement (5). Proportional bias was assessed by correlation between the averages and the differences in the results obtained with each RMR measure. Furthermore, typical measurement error (standard deviation of residuals) was assessed with root mean square error (RMSE). Due to the utilization of a convenience sample a post-hoc power analysis for a medium effect at the 0.80 recommended power level (9) was conducted and suggested a minimum sample size of n = 40 was needed.

RESULTS

After removal of outliers, data from 48 participants were analyzed. Descriptive statistics of participants' demographics are presented in Table 2.

Table 2. Mean (SD) for demographic and body composition information for all participants and across sex.

	All (n = 48)	Female (n = 26)	Male (n = 22)
Age (years)	41.5 (12.1)	39.1 (11.0)	44.2 (13.0)
Height (meters)	1.7 (0.1)	1.6 (0.1)	1.8 (0.1)
Mass (kg)	79.6 (14.4)	74.2 (13.9)	85.8 (12.6)
BMI (kg/m^2)	27.5 (4.6)	27.5 (5.0)	27.4 (4.2)
Body Fat (%)	29.9 (11.8)	35.7 (10.7)	23.1 (9.3)
FFM (kg)	55.1 (11.2)	46.6 (5.8)	65.1 (6.9)
FM (kg)	24.4 (11.6)	27.6 (11.9)	20.7 (10.3)

Abbreviations: kg = kilograms; m^2 = meters squared.

The mean and range for RMR as measured via the metabolic cart was 1814 kcal and 816 kcal for males and 1472 kcal and 558 kcal for females. A significant difference was found between RMR values across measurement methods for all participants $F_{(2.19, 107.18)} = 100.88$, $p < 0.001$, as well as for females $F_{(2.13, 53.28)} = 98.05$ and males $F_{(1.95, 44.84)} = 104.62$. For all participants and female participants only, pairwise comparisons showed that all prediction equations were significantly different from RMR measured via IC, with the exception of the WHO equation. For all conditions, all but the WHO equation significantly underpredicted RMR as compared to RMR measured via IC . Bland-Altman analysis revealed that a large amount of bias was present in all equations aside from the WHO equation (Table 3).

Table 3. Mean (SD) for resting metabolic rate (RMR), and mean bias, lower (LLOA) and upper limits of agreement (ULOA, and root mean square error (RMSE).

Measure	Sample	RMR	Bias	LLOA	ULOA	RMSE	± 10% RMR measured with IC#
Indirect Calorimetry	All	1623 (242)					
	Female	1472 (155)					
	Male	1814 (188)					
Harris-Benedict	All	1225* (135)	404	49	759	442	4
	Female	1185* (130)	287	85	489	305	8
	Male	1272* (128)	542	240	845	563	0
Mifflin-St Jeor	All	1494* (169)	135	-155	425	199	56
	Female	1414* (151)	58	-143	258	116	81
	Male	1587* (140)	227	-51	506	266	27
WHO	All	1626 (244)	3	-276	282	141	75
	Female	1457 (119)	15	-222	252	120	77
	Male	1826 (198)	-12	-337	313	162	73
Nelson	All	1521* (283)	108	-109	325	154	67
	Female	1315* (162)	157	-8	323	178	42
	Male	1764 (183)	50	-169	270	120	95

1. Asterisks indicate significant differences between measured RMR via indirect caloriometry and RMR predicted by equations. 2. *Indicates $p < 0.05$ 3. #Values are percentage of subjects within ± 10% of RMR measured with indirect calorimetry.

Significant proportional bias was seen in all equations (Figure 1). The Harris-Benedict and Mifflin-St. Jeor equations increasingly overpredicted RMR for all participants as RMR values increased as seen by the positive slopes of the trend lines in Figure 1. Conversely, the lower the RMR value the more the Nelson equation overpredicted RMR in all participants as indicated by the negative slope of the trend line in Figure 1. In comparison, the WHO equation showed minimal proportional bias with a slope that was approximately 0 (flat) across the range of RMR values. RMSE ranged from 176.48 kcal in the Nelson equation to 438.19 in the Harris-Benedict equation (Table 3). The percentage of participants with accurate prediction of RMR (± 10% of IC) ranged from 0% for males using Harris-Benedict, to 95% for males using the Nelson equation, with the Harris-Benedict equation performing by far the most poorly for both sexes.

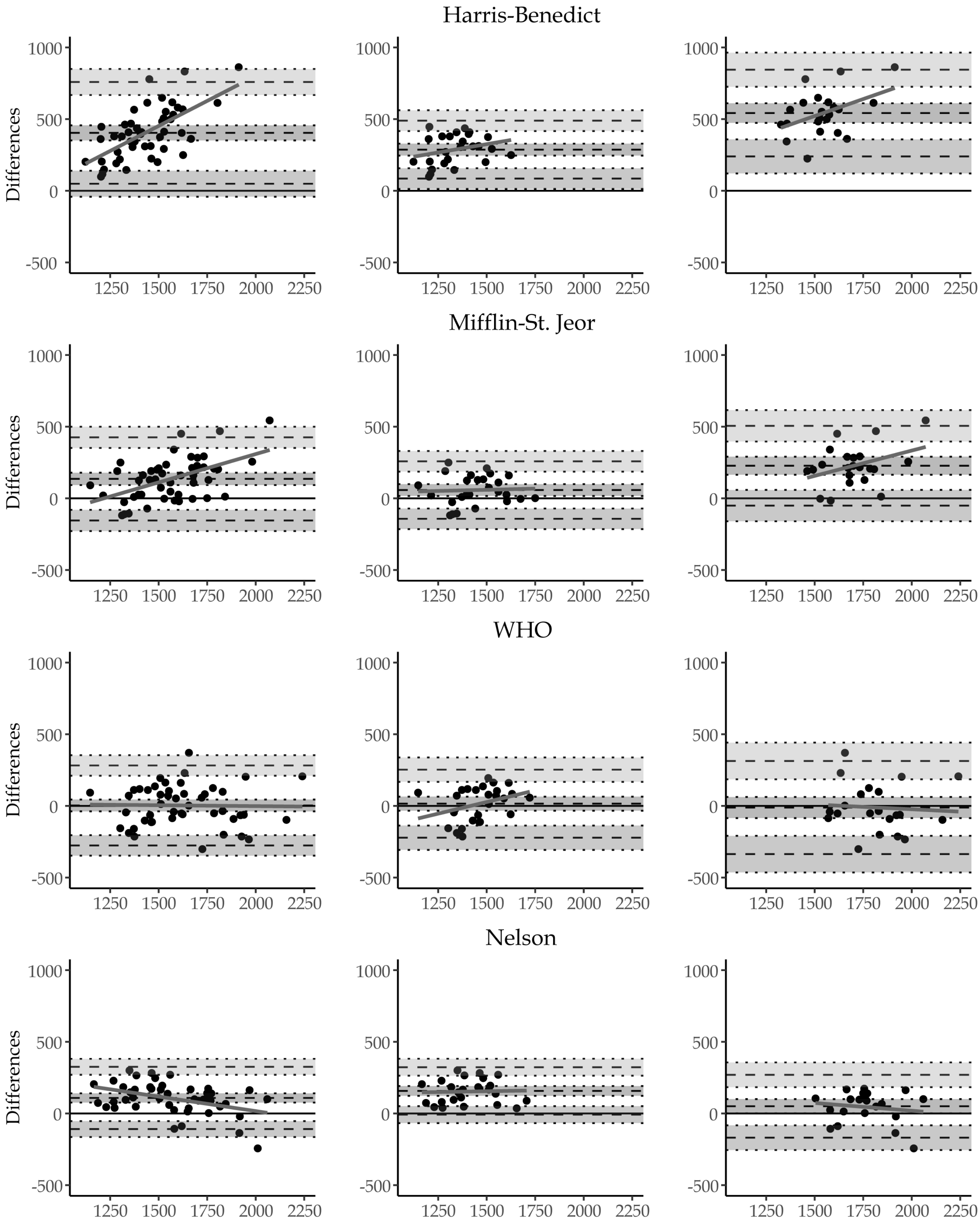

Figure 1. Bland-Altman plots for prediction equations using (A) all participants, (B) females, (C) males.

The vertical axes represent the difference in kCal measured using the TrueOne 2400 metabolic cart and kCal predicted by various equations. The horizontal axes represent the mathematical average for each participants' kCal measurements. The middle-dashed line represents bias, while the upper and lower dashed lines represents the upper (+ 2SD) and lower (- 2SD) limits of agreement. The dotted lines surrounding each dashed line represents the confidence intervals of the bias (middle), upper, and lower levels of agreement.

When split by sex, large limits of agreement were seen for both sexes. In both male and female participants, the Harris-Benedict and Mifflin St. Jeor equations were significantly different from indirect calorimetry, while the WHO was not. The Nelson equation was significantly different from indirect calorimetry in females but not in males. Males presented lower RMSE compared to females in the Nelson equation, while in all other equations RMSE was lower for females. Apart from the Nelson equation, females presented lower bias compared to males in all equations (Table 3).

DISCUSSION

The purpose of this study was to compare the level of agreement between measured RMR using IC, estimated RMR from three commonly used prediction equations using demographic predictors (i.e. gender, age, height and weight) and RMR estimated from the BodPod (via the Nelson equation) using FFM as a predictor. Significant differences between measured and predicted RMR were observed in all but the WHO equation with Bland-Altman analysis revealing a large degree of bias in each of the equations (again, with the exception of WHO). Moreover, RMSE values showed large residuals in all equations, while the percentage of participants with accurate predictions (± 10%) ranged from 4% to 75% with only the WHO equation predicting RMR accurately in over 70% of all participants. Lastly, the Nelson equation was the only equation which displayed better agreement to IC in males, while all other equations showed lower bias for females.

We demonstrated that at the group level the WHO equation, based on weight, sex, and age and stratified by both age and sex, had the greatest accuracy to predict RMR. However, large limits of agreement and high RMSE values revealed that all equations performed poorly on the individual level. For example, the average range between limits of agreements of all equations of 512 kcal found in this study makes it difficult to accurately determine caloric intake for weight loss if potential measurement error is larger than the 500-kcal deficit recommended by the NIH for incremental weight loss (34). Additionally, large proportional bias seen in the equations demonstrate that overprediction either increased (when using the Harris-Benedict and Mifflin-St. Jeor equations) or decreased (when using the Nelson equation) as measured RMR increased. These results support those of a recent study that compared the agreement of multiple prediction equations (Harris-Benedict (22), WHO (24), Mifflin-St Jeor (29), Nelson (31), Wang (38), and Sabounchi (33) with measured RMR in a sample of healthy individuals, finding that all studied equations also performed poorly at the individual level (18). For example, the above listed equations accurately predicted RMR (±10% of value measured with IC) between only 76.6% (Harris-Benedict) and 53.3% (Nelson) of participants (18). Therefore, although based on our data we would purport that the WHO equation best predicts RMR in a diverse sample, we agree with prior research in that predicted RMR should be used with caution when determining the caloric needs of individuals (18, 19).

Despite the relationship between FFM and RMR (14, 31), the Nelson equation used by the BodPod, did not perform better than the other equations investigated. Although the Nelson equation has been shown to be the most accurate when compared to other equations using FFM as a predictor (32), our results showed it was not as accurate as the WHO equation, greatly overpredicting RMR in mixed sex samples. These results have been replicated using FFM obtained from dual x-ray absorptiometry, wherein the Nelson equation produced poorer agreement with measured RMR compared to the Harris-Benedict, Mifflin-St. Jeor and WHO equations (18). Consistent with previous findings, we observed the Nelson equation to overpredict RMR in female participants (27). Thus while FFM and RMR have a strong relationship (14, 31) other factors (i.e. sex, body mass, age) influencing RMR appear to be needed in order to accurately predict RMR. Physiological differences likely play a role in the sex-specific accuracy of equations between those including FFM and those which do not. Males typically carry higher levels of muscle mass, which is included in FFM, while females have higher amounts of FM (2, 25). Another issue surrounding the sex-specific accuracy of equations to predict RMR in females is the inability of equations to account for phase of the menstrual cycle which has been shown to have a small effect on RMR (4). More generally, RMR has been shown to have a high degree of inter-individual variability which is influenced by intrinsic (i.e. hormones, genotype) and extrinsic factors (i.e. dietary intake, temperature) not accounted for in prediction equations (8). Given the limited number of predictors in the RMR prediction equations used in our study combined with the fact that none of the equations used both demographic and FFM predictors the overall accuracy we observed likely reflects these shortcomings of the equations.

This brings into question the utility of prediction equations based on FFM given the time, expertise, and expense needed to acquire accurate FFM values (i.e. dual x-ray absorptiometry, air-displacement plethysmography, or hydrodensitometry). Prior authors have demonstrated that weight provides a similar predictive ability for RMR as FFM can and that age and the inclusion of a greater constant term can account for a large portion of the FFM contribution to RMR (33). Our results support these findings as equations using FFM were no more accurate than those using age and weight. It may be argued that errors in the estimation of FFM by the BodPod induce errors in the predicted RMR; however, a number of studies have reported the accuracy of body composition measurements with the Bodpod to be valid and reliable in a variety of populations (17). Therefore based on our findings, estimated RMR via the Nelson equation used during BodPod analysis is no more accurate than prediction equations using demographic measures only and suffers from the same lack of predictive accuracy. Development of new RMR FFM-based prediction equations is an area of future work that we recommend at this time. More research is needed to confirm the underprediction of RMR with prediction equations using FFM in a diverse sample. Specifically, future research should investigate whether the worse predictive accuracy of the Nelson equation for females was truly a sex-related effect or was it due to body fatness as females are known to have greater bodyfat than males.

The strength of this study is the use of the BodPod to accurately calculate FFM and FM, and therefore, our ability to compare traditional prediction equations with those using FFM to RMR measured with the validated TrueOne 2400 metabolic cart (13). Although our sample was larger than those in some previous studies comparing predicted RMR via various equations to RMR measured via IC (18, 27), we did not believe it to be large enough to further investigate factors other than gender. Future research should attempt to obtain larger samples to analyze by further subgroups such as young vs old, overweight-obese vs normal-weight etc. Another potential limitation of our study was using predicted as opposed to measured lung volume during the body composition testing. While some literature (28) has reported a significant difference between the use of measured versus predicted lung volume values more recent literature has found no difference (10).

Individuals and practitioners should be aware that prediction equations may significantly under or overestimate RMR compared to IC. The inclusion of FFM through technology such as the BodPod does not appear necessary to predict RMR and does not improve predictive capacity beyond demographic measures. Specifically for females we found this to be the case. Based on our data, RMR estimations from prediction equations should be used with caution. More specifically, when an accurate RMR value is desired or necessitated per the specific clinical scenario, IC should be the method of choice

REFERENCES

1. Abdel-Hamid TK. Modeling the dynamics of human energy regulation and its implications for obesity treatment. Syst Dyn Rev 18(4): 431-71, 2002.

2. Abe T, Kearns C, Fukunaga T. Sex differences in whole body skeletal muscle mass measured by magnetic resonance imaging and its distribution in young Japanese adults. Br J Sports Med 37(5): 436-40, 2003.

3. Arciero PJ, Goran MI, Poehlman ET. Resting metabolic rate is lower in women than in men. J Appl Physiol 75(6): 2514-20, 1993.

4. Benton MJ, Hutchins AM, Dawes JJ. Effect of menstrual cycle on resting metabolism: A systematic review and meta-analysis. PLoS One 15(7): e0236025, 2020.

5. Bland JM, Altman D. Statistical methods for assessing agreement between two methods of clinical measurement. Lancet 327(8476): 307-10, 1986.

6. Bland JM, Altman DG. Applying the right statistics: Analyses of measurement studies. Ultrasound Obstet Gynecol 22(1): 85-93, 2003.

7. Bosy-Westphal A, Reinecke U, Schlörke T, Illner K, Kutzner D, Heller M, et al. Effect of organ and tissue masses on resting energy expenditure in underweight, normal weight, and obese adults. Int J Obes 28(1): 72-9, 2004.

8. Burton T, Killen S, Armstrong J, Metcalfe N. What causes intraspecific variation in resting metabolic rate and what are its ecological consequences? Proceedings of the Royal Society B: Biol Sci 278(1724): 3465-73, 2011.

9. Cohen J. Statistical power analysis for the behavioral sciences. 2nd ed. New York, NY: Routledge; 1998.

10. Collins A, McCarthy H. Evaluation of factors determining the precision of body composition measurements by air displacement plethysmography. Eur J Clin Nutr 57(6): 770-6, 2003.

11. Compher C, Frankenfield D, Keim N, Roth-Yousey L. Best practice methods to apply to measurement of resting metabolic rate in adults: A systematic review J Am Diet Assoc 106: 881-903, 2006

12. Cooper JA, Watras AC, O'Brien MJ, Luke A, Dobratz JR, Earthman CP. Assessing validity and reliability of resting metabolic rate in six gas analysis systems. J Am Diet Assoc 109(1): 128-32, 2009.

13. Crouter SE, Antczak A, Hudak JR, DellaValle DM, Haas JD. Accuracy and reliability of the ParvoMedics TrueOne 2400 and MedGraphics VO2000 metabolic systems. Eur J Appl Physiol 98(2): 139-51, 2006.

14. Cunningham JJ. A reanalysis of the factors influencing basal metabolic rate in normal adults. Am J Clin Nutr 33(11): 2372-4, 1980.

15. De Jesus S, Fitzgeorge L, McGowan E, Prapavessis H. Physical activity and body composition relations: Accurate and objective assessment of physical activity matters. Int J Body Comp Res 10: 73-8, 2012.

16. Dewit O, Fuller N, Fewtrell MS, Elia M, Wells J. Whole body air displacement plethysmography compared with hydrodensitometry for body composition analysis. Arch Dis Child 82(2): 159-64, 2000.

17. Fields DA, Goran MI, McCrory MA. Body-composition assessment via air-displacement plethysmography in adults and children: A review. Am J Clin Nutr 75(3): 453-67, 2002.

18. Flack KD, Siders WA, Johnson L, Roemmich JN. Cross-validation of resting metabolic rate prediction equations. J Acad Nutr Diet 116(9): 1413-22, 2016.

19. Frankenfield D, Roth-Yousey L, Compher C, Group EAW. Comparison of predictive equations for resting metabolic rate in healthy nonobese and obese adults: a systematic review. J Am Diet Assoc 105(5): 775-89, 2005.

20. Frankenfield DC, Rowe WA, Smith JS, Cooney R. Validation of several established equations for resting metabolic rate in obese and nonobese people. J Am Diet Assoc 103(9): 1152-9, 2003.

21. Fukagawa NK, Bandini LG, Young JB. Effect of age on body composition and resting metabolic rate. Am J Physiol Endocrinol Metab 259(2): e233-8, 1990.

22. Harris JA, Benedict FG. A biometric study of human basal metabolism. Proc Natl Acad Sci 4(12): 370, 1918.

23. He X, Li Z, Tang X, Zhang L, Wang L, He Y, et al. Age-and sex-related differences in body composition in healthy subjects aged 18 to 82 years. Medicine 97(25): e11152, 2018.

24. Joint F. Energy and protein requirements: Report of a joint FAO/WHO/UNU Expert Consultation: World Health Organization; 1985.

25. Karastergiou K, Smith S, Greenberg A, Fried S. Sex differences in human adipose tissues-the biology of pear shape. Biol Sex Differ 3(1): 13, 2012.

26. Levine JA. Measurement of energy expenditure. Public Health Nutr 8(7a): 1123-32, 2005.

27. Li AC, Tereszkowski CM, Edwards AM, Simpson JAR, Buchholz AC. Published predictive equations overestimate measured resting metabolic rate in young, healthy females. J Am Coll Nutr 29(3): 222-7, 2010.

28. McCrory MA, Molé PA, Gomez TD, Dewey KG, Bernauer EM. Body composition by air-displacement plethysmography by using predicted and measured thoracic gas volumes. J Appl Physiol 84(4): 1475-9, 1998.

29. Mifflin MD, St Jeor ST, Hill LA, Scott BJ, Daugherty SA, Koh YO. A new predictive equation for resting energy expenditure in healthy individuals. Am J Clin Nutr 51(2): 241-7, 1990.

30. Navalta JW, Stone WJ, Lyons TS. Ethical issues relating to scientific discovery in exercise science. Int J Exerc Sci 12(1): 1-8, 2019.

31. Nelson KM, Weinsier RL, Long CL, Schutz Y. Prediction of resting energy expenditure from fat-free mass and fat mass. Am J Clin Nutr 56(5): 848-56, 1992.

32. Otterstetter R, Miller B, Fridline M, Boltz M, Faciana C, Scanlon K, et al. RMR estimation model accuracy using air displacement plethysmography–derived body composition measures in young adults. J Am Coll Nutr 35(1): 68-74, 2016.

33. Sabounchi NS, Rahmandad H, Ammerman A. Best-fitting prediction equations for basal metabolic rate: informing obesity interventions in diverse populations. Int J Obes 37(10): 1364-70, 2013.

34. Services USDoHH. Aim for a healthy weight: Key recommendations: National Institutes of Health; Available from: https://www.nhlbi.nih.gov/health/educational/lose_wt/recommen.htm.

35. Siri WE. Body composition from fluid spaces and density: Analysis of methods. Nutrition 9(5): 480-91, 1993.

36. R Core Team. R: A language and environment for statistical computing. R Foundation for Statistical Computing; 2013.

37. Wang Z, Bosy-Westphal A, Schautz B, Müller M. Mechanistic model of mass-specific basal metabolic rate: Evaluation in healthy young adults. Int J Body Compos Res 9(4): 147, 2011.

38. Wang Z, Heshka S, Gallagher D, Boozer CN, Kotler DP, Heymsfield SB. Resting energy expenditure-fat-free mass relationship: new insights provided by body composition modeling. Am J Physiol Endocrinol Metab 279(3): e539-45, 2000.

39. Weir JdV. New methods for calculating metabolic rate with special reference to protein metabolism. J Physiol 109(1-2): 1-9, 1949.

40. Wells J, Douros I, Fuller N, Elia M, Dekker L. Assessment of body volume using three-dimensional photonic scanning. Ann NY Acad Sci 904(1): 247-54, 2000.