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Original Research

A Gender-agnostic Inclusive Estimation for Resting Metabolic Rate

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Abstract

International Journal of Exercise Science 19(2): 2019, 2026. Existing resting metabolic rate (RMR) prediction models do not accurately reflect the adult population because they do not include measures from individuals who are non-binary or gender diverse. The objective was to generate data for the purpose of deriving an inclusive, gender-agnostic equation for RMR estimation. Ninety-four individuals participated (gender diverse [transgender male-to-female, transgender female-to-male, genderqueer, gender nonconforming, neither exclusively female or male] n = 6, cisgender female n = 47, cisgender male n = 41). Participants reported to the laboratory between 0700 and 0830 for testing and circumference measurements and resting heart rate were obtained. RMR was measured via indirect calorimetry. Prediction equations were derived through stepwise multiple regression. The final model was RMR (kcal/day) = 14.708 x height (cm) + 10.421 x mass (kg) + 6.211 x resting heart rate − 2019.411 (R = 0.784, R^2 = 0.614, SEE = 207.32). This is the first study providing RMR prediction to include participants who do not identify as exclusively cisgender female or cisgender male. This equation may be used in an inclusive manner to estimate various caloric needs, including daily energy balance and dietary prescription.

Keywords: Resting energy expenditure, prediction equation, gender-inclusive, stepwise multiple regression, daily energy balance

Introduction

Resting metabolic rate (RMR) is the energy the body expends for essential functions while awake and at rest in a neutral temperature environment,[1] whereas basal metabolic rate (BMR) is collected under inactive conditions and a more stringent testing protocol.[2] The measure of RMR is considered to be more practical[3] and used to estimate caloric needs for a wide variety of applications, such as activities of daily living, daily energy balance, and evaluating lifestyles for disease risk such as metabolic syndrome.[4] The value of RMR, which accounts for 60–70% of total daily energy expenditure,[1] is critical to clinical, health, and athletic performance decision-making.[5] Because not all individuals have access to the laboratory equipment necessary to obtain this measure, prediction equations have been derived to provide estimates of RMR and BMR.[6-10]

Most RMR prediction equations currently in use were developed with underlying assumptions around the female/male sex binary. The driving assumption was that people who identify

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as male have a greater amount of muscle mass resulting in higher resting energy expenditure, and therefore necessitating separate estimation equations for female and male sexes.[6-10] Harris and Benedict assumed males burn between 140 to 240 kilocalories (kcal) more per day if all demographic parameters are the same, using published reference values for females (height = 163 cm, mass = 61 kg) and males (height = 176; mass = 76 kg).[6,11] The Owen equations take into account only body mass,[8,9] and similarly estimate between 270 to 315 greater kcal expenditure for males than females using reference values.[11] It should be noted that while other equations[7,12-15] consider only lean body mass or weight and not sex to estimate resting/basal metabolic rate, the estimates of lean body mass were derived using female-specific and male-specific equations,[13] or generated using male-only participants.[12,14] Thus, the assumption of a binary female/male identity is embedded into many algorithms for predicting RMR.

Our operational theory is that an RMR equation should reflect the population for which they are designed. This aligns with several population-specific RMR equations that exist, such as for professional cyclists,[16] elite athletes,[14] rugby players,[17] and physique athletes.[15] While some are generally applied to the overall population,[6,13] to our knowledge, no RMR prediction equation has been developed that included measures from individuals who are non-binary or gender diverse. Our prior work[18,19] and the broader literature[20,21] have shown that sport and exercise science research in particular often lacks gender diversity in its samples, undermining the generalizability of findings. Gender diversity includes, but is not limited to, a spectrum of identities including transgender (identity and/or role do not conform to what is typically associated with the sex assigned at birth),[22] non-binary (identity falls outside the binary categories of female and male) and genderqueer (may identify as both male and female at one time, as different genders at different times, or as no gender at all).[23] The overall population of individuals who identify as gender expansive in the U.S. has been estimated from 1%[24] to 5%,[25] but a larger proportion of younger individuals (25.3% of people who are transgender are between the ages of 13-17 years, and 28.9% are between the ages of 18-24 years)[26] desire to not be constrained into the female/male binary.[25] Because of this, there is a growing need for a gender-inclusive prediction equation for RMR that appropriately reflects current population demographics despite the growing tide of political and legislative attempts otherwise.

We have recently shown there may be systemic barriers to inclusion of the gender-diverse population in the very equipment used to obtain measurements of RMR since most systems only allow binary sex input.[27,28] Equitable health outcomes require that all individuals can fully navigate their environments,[29] which necessitates access to precise physiological assessments such as RMR. According to best practices it is important to collect data in a respectful and inclusive manner, allowing participants to self-identify when questions about gender identity are relevant to study objectives.[30] The aim of this study was to generate data for the purpose of deriving an inclusive equation for RMR estimation in a group of individuals that reflects the gender-diversity of the current population.

Methods

Participants

Utilizing data reported from 27 other RMR predictive equations,[31] where the lowest R^2 was 0.360 and the highest R^2 was 0.7396, it was determined that at least 11 to 35 participants would be needed, using an *a priori* power analysis completed in G*Power with the linear multiple regression function: fixed model, R^2 deviation from zero, an α error of probability of 0.05, and a power (1-β

error of probability) of 0.95 for 95% statistical power. Recruitment occurred through word of mouth, digital flyers, and messages posted to student and faculty announcement emails. The intention was to recruit up to 5% non-binary and gender-diverse participants,[25] with the remainder comprising cisgender female and cisgender male subsamples approximately equal in size to each other. One-hundred adults were tested. However, data from 6 individuals were removed due to missing predictor variables (*n* = 3, no waist girth, no hip girth, no resting heart rate), RMR values outside of the physiological range (*n* = 2; one individual returned an RMR more than two standard deviations below the mean [765 kcal/day], and the other individual returned an RMR more than three standard deviations below the mean [401 kcal/day]), or coefficient of variation not within the requisite 10% (*n* = 1).[32] Thus, 94 individuals were included in the present study (gender diverse [transgender male-to-female, transgender female-to-male, genderqueer, gender nonconforming, neither exclusively female or male] *n* = 6, cisgender female *n* = 47, cisgender male *n* = 41; age = 25.5±8.7 years [range = 18-68 years, median = 22 years]; height = 168.4±10.2 cm; mass = 71.7±14.3 kg). Some gender diverse participants did not have hormonal or surgical health care at the time the study was conducted. Other gender diverse participants had a combination of hormonal (estradiol/progesterone 2-5 years, valerate up to 1 year, testosterone up to 3 years) and surgical (top surgery 6 months-2 years, orchiectomy/vulvoplasty 2-4 years) health care.

The institutional review board approved the study (UNLV-2023-82) and participants provided written informed consent prior to completing any other aspects of the investigation. This research was carried out fully in accordance with the ethical standards of the *International Journal of Exercise Science*.[33] This phase of the investigation was part of a larger test battery which included an exercise component and more stringent inclusion and exclusion criteria than would be expected for an RMR study alone. Thus, people who were pregnant or thought they might be pregnant were not eligible to participate in the study. Additionally, participants were screened using the American College of Sports Medicine health screening algorithm,[34] and those deemed to not need medical clearance to perform moderate to vigorous exercise were allowed to progress with the remainder of the study procedures. Gender was self-reported using a two-step questionnaire: 1) sex assigned at birth, and 2) current gender identity, with an open-ended response option. For analysis, non-binary and gender-diverse participants were grouped together to protect confidentiality.

Protocol

Participants reported to the laboratory during the morning between 0700 and 0830 for a single session in which all measures were obtained. They were instructed to follow a typical diet for 48 hours prior, hydrate for 12 hours prior, not consume caffeine, alcohol, or nicotine for 12 hours prior, avoid high-intensity resistance training for 12 hours prior, and not introduce new exercises the day before testing. They were encouraged to arrive rested and relaxed, and to reschedule if they had a respiratory, gastrointestinal, or other illness within the previous two weeks.

Circumference measurements (waist girth and hip girth) were obtained using an anthropometric tape measure (Baseline Evaluation Instruments Gulick measurement tape, White Plains, NY). Waist girth was taken as the narrowest part between the lowest palpable rib and the suprailiac crest, as instructed by the Anthropometric Standardization Consensus Group.[35] Hip girth was obtained as the widest part around the gluteals at the level of the greater trochanter of the femur.

Height was measured to the nearest 0.1 cm using a stadiometer (SECA 213, Hamburg, Germany). Body mass was measured using a digital scale (SECA mb540, Hamburg, Germany) to the nearest 0.1 kg. Participants were measured while wearing workout clothes (t-shirt, shorts or leggings, sports bra) and without shoes or items in the pockets. No adjustment for clothing was included in the measurement of body mass.

A heart rate monitor (Polar H10, Polar Electro Inc., Kempele, Finland; sampling frequency 1000 Hz) was placed securely around the chest and connected to the metabolic analysis unit via Bluetooth. The resting heart rate measurement was taken as the arithmetic mean minus outlying values over the entire RMR session.

Resting metabolic rate was measured using indirect calorimetry (TrueOne 2400, Parvo Medics, Salt Lake City, UT, USA) with a mask over the nose and mouth attached securely to the head. Prior to the measurement period, the mask was checked for potential leaks and readjusted if necessary. Before each test, the flow meter was calibrated using a 3.0-L syringe and the gas analyzers were calibrated using verified gases of known concentrations. RMR was measured in a temperature-controlled room between 21°C and 24C° (mean = 22.2±0.7°C) with the participant in a semirecumbent position and lights off with the exception of one room in the laboratory. Because this was part of a multi-component study, RMR was completed first, for a period of 15-min, a duration that has been noted to provide accurate measures.[32,36] Participants were monitored to ensure they remained still and awake during the test period, and they were not allowed to use phones or other digital devices.

According to the recommendations of Compher et al, the first 5-minutes of the test were discarded before the data were processed in Google Sheets.[32] After assuring that the coefficient of variation was <10%, the lowest continuous 5-minute average VO_2 was used to determine the caloric expenditure. We then extrapolated the caloric expenditure in a 24-h period, and that value was taken as the RMR measurement from which the prediction equation was derived.

Furthermore, RMR measurements for participants were estimated using other prediction equations that are not constrained by the sex binary framework and shown in Table 1.

Table 1. Prediction equations which do not require the input of sex for RMR estimation.

Reference	Equation
De Lorenzo[12]	RMR (kcal/day) = 9 x weight (kg) + 11.7 x height (cm) − 857
Marra[14]	RMR (kcal/day) = 17.2 x weight (kg) − 5.95 x age (years) + 748
Mifflin-St Joer #2[7]	RMR (kcal/day) = 15.1 x weight (kg) + 371
Tinsley[15]	RMR (kcal/day) = 24.8 x weight (kg) + 10

RMR = resting metabolic rate

Statistical Analysis

Prediction equations were derived using the Linear Regression function in SPSS (Version 29.0.2.0, IBM Corporation, Armonk, NY) to perform stepwise multiple regression with the predictors of age, height, mass, waist girth, hip girth, waist-to-hip ratio, and resting heart rate. The following assumptions were determined: linearity, independence of observations, homoscedasticity, normality of residuals, and multicollinearity. If any of the assumptions were violated, the appropriate action was taken before performing the stepwise multiple regression (i.e., transformation of data, removal of collinear variables). Measured RMR was independently compared with RMR estimated using the newly developed equation and with RMR predicted by existing equations using a one-way ANOVA, with Tukey's post-hoc and effect partial eta squared (η^2) as the measure of effect size (interpreted as >0.01 = small, 0.06 = medium, and 0.14 =

large). Individual comparisons were reported through Cohen's *d* effect size and interpreted as 0.2 = small, 0.5 = medium, and 0.8 = large. Agreement between measured and predicted RMR was assessed via Bland–Altman analysis using the blandr function in Jamovi (version 2.6, Sydney, Australia).

Results

Table 2 displays the entire complement of variables initially used in the prediction equation. For model 1, $R = 0.796$, $R^2 = 0.634$, and standard error of the estimate (SEE) = 206.73. However, waist-to-hip ratio, waist girth, and hip girth were found to violate the multicollinearity assumption, and therefore waist-to-hip ratio was removed from the model (see model 2).

Table 2. Model 1: RMR multiple linear regression prediction with all variables included.

Model		*B*	Std. Error	*t*	Sig.
1	(Constant)	−924.537	3241.469	−.285	.776
	Age	−1.258	2.903	−.433	.666
	Height	10.581	3.832	2.762	.007
	Mass	19.727	5.610	3.516	<.001
	Waist Girth	−9.400	40.823	−.230	.818
	Hip Girth	−4.791	30.887	−.155	.877
	W-to-H Ratio	283.298	4169.582	.068	.946
	Resting HR	5.711	2.324	2.457	.016

RMR = resting metabolic rate, W-to-H Ratio = waist-to-hip ratio, HR = heart rate

When waist-to-hip ratio was removed, model 2 $R = 0.796$, $R^2 = 0.634$, and SEE = 205.54 (see Table 3). However only height (cm), mass (kg), and resting heart rate were significant.

Table 3. Model 2: RMR multiple linear regression prediction with multicollinear variable (waist-to-hip ratio) removed.

Model		*B*	Std. Error	*t*	Sig.
2	(Constant)	−711.867	837.615	−.850	.398
	Age	−1.219	2.828	−.431	.668
	Height	10.615	3.777	2.810	.006
	Mass	19.677	5.530	3.558	<.001
	Waist Girth	−6.652	5.468	−1.217	.227
	Hip Girth	−6.862	4.977	−1.379	.171
	Resting HR	5.676	2.254	2.518	.014

RMR = resting metabolic rate, HR = heart rate

Finally, in model 3 all nonsignificant variables were removed (see Table 4) including only height (cm), mass (kg), and resting heart rate. For this equation, $R = 0.784$, $R^2 = 0.614$, and SEE = 207.32. Thus, the inclusive prediction equation is as follows:
RMR (kcal/day) = 14.708 x height (cm) + 10.421 x mass (kg) + 6.211 x resting heart rate − 2019.411.

Table 4. RMR multiple linear regression prediction including only significant variables.

Model		*B*	Std. Error	*t*	Sig.
3	(Constant)	−2019.411	447.067	−4.517	<.001
	Height	14.708	2.714	5.420	<.001
	Mass	10.421	1.930	5.400	<.001
	Resting HR	6.211	2.148	2.892	.005

RMR = resting metabolic rate, HR = heart rate

Measured RMR was compared to estimates obtained from prediction equations and shown in Table 5 ($\eta^2 = 0.185$). Differences are present for equations designed for healthy participants,[7] general athletes,[12] elite athletes,[14] and muscular physique athletes.[15] A random sample of 42 participants from the current study was compared to the criterion RMR and no differences were observed (see Table 5).

Table 5. Comparison of measured and predicted RMR.

Equation	Mean±SD	Difference±SD	Lower 95% CI	Upper 95% CI	*p*	*d*
Criterion	1635±328					
De Lorenzo[12]	1758±223	−123±215	−167	−79	0.029	0.57
Marra[14]	1830±242	−194±242	−244	−145	<0.001	0.80
Mifflin-St Joer #2[7]	1453±216	182±240	133	231	<0.001	0.76
Tinsley[15]	1788±355	−153±273	−209	−97	0.002	0.56
Current (*N*=42)	1643±342	−8±215	−58	75	1.000	0.04

RMR = resting metabolic rate

The average bias for the current equation was small at 0.03 (upper 95% CI = 41.8, lower 95% CI = −41.7) kcal/day (see Figure 1). The upper limit of agreement was 399.78 (upper 95% CI = 471.4, lower 95% CI = 328.1), and the lower limit of agreement was −399.72 (upper 95% CI = −328.1, lower 95% CI = −471.4).

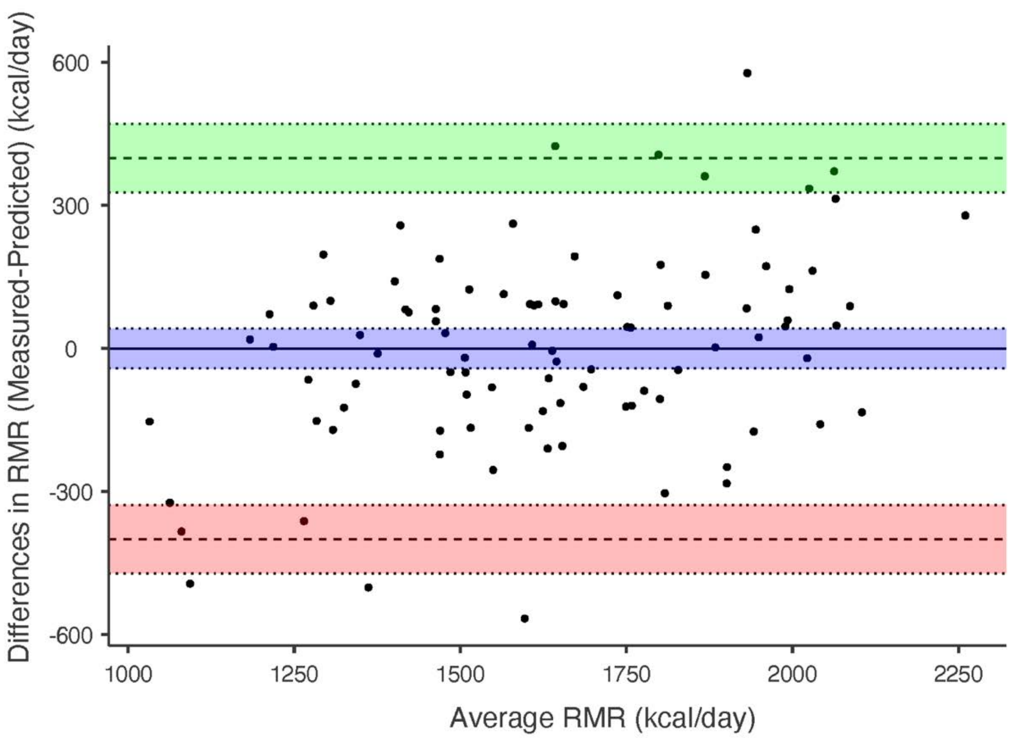

Figure 1. Differences between RMR measured via indirect calorimetry and estimated using the inclusive prediction equation (N = 94). RMR = resting metabolic rate.

We next removed gender diverse individuals from the dataset to determine what effect these individuals had on the model. For model 1 with the modified dataset, $R = 0.802$, $R^2 = 0.644$, and standard error of the estimate (SEE) = 204.79 (see table 1a in supplementary materials). Mass, waist-to-hip ratio, waist girth, and hip girth were found to violate the multicollinearity assumption, and waist-to-hip ratio was removed from the model like with the previous iterative procedure (see model 2 for this dataset and table 2a in supplementary materials), R = 0.802, R^2 = 0.644, and standard error of the estimate (SEE) = 203.48. Finally, in model 3 all nonsignificant variables were removed (see Table 3a in supplementary materials) including only height (cm), mass (kg), and resting heart rate as before. For this equation, R = 0.791, R^2 = 0.626, and SEE = 204.78.

The prediction equation is as follows:
RMR (kcal/day) = 14.129 x height (cm) + 11.01 x mass (kg) + 7.356 x resting heart rate − 2035.187.

The average bias for this equation was small at 0.09 (upper 95% CI = 42.7, lower 95% CI = −42.5) kcal/day (see Figure 1a in supplementary materials). The upper limit of agreement was 394.48 (upper 95% CI = 467.6, lower 95% CI = 321.3), and the lower limit of agreement was −394.31 (upper 95% CI = −321.2, lower 95% CI = −467.4).

Finally, because a larger proportion of younger individuals identify as gender diverse (25.3% of people who are transgender are 13-17 years of age, and 28.9% are between 18-24 years of age)[26] our current sample of 6.4% gender diverse individuals may underrepresent the overall population. Because of this, we created a new data set, keeping all gender-diverse individuals and randomly drawing and equal number of cisgender females (n = 15) and cisgender males (n = 15). For model 1 with the randomized dataset, R = 0.769, R^2 = 0.592, and standard error of the estimate (SEE) = 229.05 (see table 4a in supplementary materials). Mass, waist-to-hip ratio, waist girth, and hip girth were found to violate the multicollinearity assumption, and waist-to-hip ratio was removed from the model as in the initial procedure (see model 2 for this dataset and table 5a in supplementary materials), R = 0.767, R^2 = 0.588, and standard error of the estimate (SEE) = 226.06. Finally, in model 3 all nonsignificant variables were removed (see Table 6a in supplementary materials) including only height (cm), and mass (kg). For this equation, R = 0.715, R^2 = 0.511, and SEE = 230.95.

The prediction equation is as follows:
RMR (kcal/day) = 14.476 x height (cm) + 10.966 x mass (kg) – 1632.349.

The average bias for this equation was small at 0.02 (upper 95% CI = 75.9, lower 95% CI = −75.9) kcal/day (see Figure 2a in supplementary materials). The upper limit of agreement was 439.556 (upper 95% CI = 570.4, lower 95% CI = 308.7), and the lower limit of agreement was −439.525 (upper 95% CI = −308.6, lower 95% CI = −570.4).

Like we did with the larger data set, we removed data from gender-diverse individuals from the randomized sample to observe their influence on the model. For model 1 with gender-diverse individuals removed from the randomized dataset, R = 0.751, R^2 = 0.564, and standard error of the estimate (SEE) = 243.57 (see table 7a in supplementary materials). Mass, waist-to-hip ratio, waist girth, and hip girth were found to violate the multicollinearity assumption, and waist-to-hip ratio was removed from the model as in all other iterations (see model 2 for this dataset and table 8a in supplementary materials), R = 0.748, R^2 = 0.56, and standard error of the estimate (SEE) = 239.29. Finally, in model 3 the same variables were removed (see Table 9a in supplementary materials) including only height (cm), and mass (kg). For this equation, R = 0.691, R^2 = 0.477, and SEE = 240.77.

The prediction equation is as follows:
RMR (kcal/day) = 12.523 x height (cm) + 10.885 x mass (kg) – 1284.185.

The average bias for this equation was 9.14 (upper 95% CI = 96.2, lower 95% CI = −77.9) kcal/day (see Figure 3a in supplementary materials). The upper limit of agreement was 465.9 (upper 95% CI = 616.3, lower 95% CI = 315.5), and the lower limit of agreement was −447.62 (upper 95% CI = −297.2, lower 95% CI = −598.0).

Discussion

The purpose of this study was to derive an inclusive, gender-agnostic equation for RMR estimation. The result of the multiple linear regression process yielded significant variables including participant height, body mass, and resting heart rate in the prediction equations reinforcing stability and generalizability. To the best of our knowledge, this is the first study providing a RMR prediction equation to include participants who do not identify as exclusively cisgender female or cisgender male.

The oldest and arguably most well-known equations for predicting metabolism are from Harris and Benedict, which utilized 103 females and 136 males.[6] The resultant equations were split according to sex and may have influenced successive authors to take a similar tact.[8,9] In 1990, the Mifflin-St Joer equations represented an update to what was derived by Harris and Benedict, utilizing healthy females (n = 247) and males (n = 251).[7] While several iterations were presented, including equations that did not require the input of sex, the final equations, commonly known as the Mifflin-St Joer equations, were partitioned by sex.[7] We utilized the second equation from the Mifflin et al paper[7] because it relied on body mass and was gender-agnostic; however the equation significantly underestimated RMR in our sample, likely because the average age of our population was younger (mean = 25 years) than Mifflin et al (mean = 45 years). More recent RMR prediction equations also take a gender-agnostic approach including De Lorenzo et al (N = 51 males),[12] Tinsley et al (n = 10 females, n = 17 males),[15] and Marra (N = 126 males).[14] Each of these equations significantly overestimated RMR in the current sample, likely because the population tested in those studies were composed of exclusively male participants[12,14] or physique athletes who can be expected to have greater muscle mass than the general population.[15]

This study fills a need to provide an easy to use, gender-inclusive prediction equation for RMR that can be used until population-specific equations for gender diverse individuals can be derived. The measure of RMR is used to estimate caloric needs for a number of applications, including daily energy balance and dietary prescription,[37] determining the effect of health and chronic conditions,[38] and the progression of disease risk.[39] An inclusive prediction of RMR is important because people who identify as gender-expansive generally experience poorer health outcomes than those who identify as cisgender.[24,40-42] Specifically, people who identify as transgender report more frequent poor physical health days per month than cisgender people (7.9 vs. 4.4)[40] and poorer overall physical health than cisgender individuals.[41] Approximately 34% of the transgender adult population self-report that they are in fair or poor health compared to 18% of the general population.[42] Furthermore, the population of individuals who identify as gender expansive in the U.S. has been estimated from 1%[24] to 5%,[25] but reporting may grow[26] as a greater proportion of younger individuals express a desire to not be constrained into the female/male binary.[25] Thus, there is a growing need for a gender-inclusive prediction equation for RMR as piloted in the current investigation.

We acknowledge this study is not without limitations. While we followed best practices as outlined by Compher et al,[32] a 15-min RMR period is a relatively short timeframe, and it is unknown whether greater lengths of time (i.e., 30-min) would yield differing results. Another potential methodological limitation is that we did not account for individual chronotype with respect to time of testing, which is known to affect metabolic processes,[43] All participants were required to report to the laboratory in the morning between 0700 and 0830, and it is possible that disruption of circadian rhythm in individuals who are considered "night owls" may have affected the RMR reading, which warrants further investigation. Further, participants were required to report to the laboratory, which may have similar effects as white coat hypertension, in that participants might have registered higher RMR readings than in locations in which they are comfortable. This possibility warrants further investigation as well. Another limitation is that we experienced data loss of some individuals (n = 6) which may have ultimately affected the prediction equation. Finally, while we recruited and tested gender-expansive participants at a slightly greater percentage than reported in the literature,[25] the sample size in relation to cisgender individuals was small. When data from the gender-diverse individuals were removed, the outcome suggests they had minimal impact on the ensuing prediction equation despite gender affirming hormonal and surgical health care interventions. The same conclusions were reached when the gender-diverse individuals made up a larger percent of a randomly drawn sample (~17%) and then data removed (i.e. the same factors were significant predictors in both iterations). As with RMR equations derived specifically for athletic populations,[12,14,15] it may be beneficial for the gender-expansive community to have prediction equations specific to the population.

In conclusion, we present a prediction equation for RMR that is gender-agnostic so that it may be used in an inclusive manner. In order to use the prediction equation, an individual would need to have accurate measurements of their height, body mass, and resting heart rate. The equation represents an improvement in comparison to other prediction models that do not require sex input,[7,12,14,15] with a small bias (0.03 kcal/day) and average difference (−8 kcal/day) when compared to measured RMR.

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During the preparation of this work the author(s) used Google Gemini in order to guide the statistical approach in SPSS. After using this tool/service, the author(s) reviewed and edited the content as needed and take full responsibility for the content of the publication.

Data described in the manuscript will be made publicly and freely available without restriction at https://doi.org/10.7910/DVN/MIOESN

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Supplementary Materials

Table 1a. Model 1 (full dataset with gender diverse individuals removed): RMR multiple linear regression prediction with all variables included.

Model		*B*	Std. Error	*t*	Sig.
1	(Constant)	-1595.943	3295.749	-.484	.630
	Age	-2.156	3.178	-.678	.499
	Height	11.040	3.942	2.801	.006
	Mass	18.438	5.789	3.185	.002
	Waist girth	-11.845	41.282	-.287	.775
	Hip girth	-.879	31.326	-.028	.978
	W-H ratio	827.321	4214.776	.196	.845
	Resting heart rate	7.037	2.393	2.941	.004

Table 2a. Model 2 (full dataset with gender diverse individuals removed): RMR multiple linear regression prediction with multicollinear variable (waist-to-hip ratio) removed.

Model		*B*	Std. Error	*t*	Sig.
2	(Constant)	-971.655	859.042	-1.131	.261
	Age	-2.006	3.067	-.654	.515
	Height	11.122	3.897	2.854	.005
	Mass	18.303	5.714	3.203	.002
	Waist girth	-3.816	5.556	-.687	.494
	Hip girth	-6.945	5.100	-1.362	.177
	Resting heart rate	6.932	2.318	2.990	.004

Table 3a. Model 3 (full dataset with gender diverse individuals removed): RMR multiple linear regression prediction including only significant variables.

Model		*B*	Std. Error	*t*	Sig.
3	(Constant)	-2035.187	453.550	-4.487	<.001
	Height	14.129	2.751	5.137	<.001
	Mass	11.010	1.960	5.618	<.001
	Resting heart rate	7.356	2.184	3.368	.001

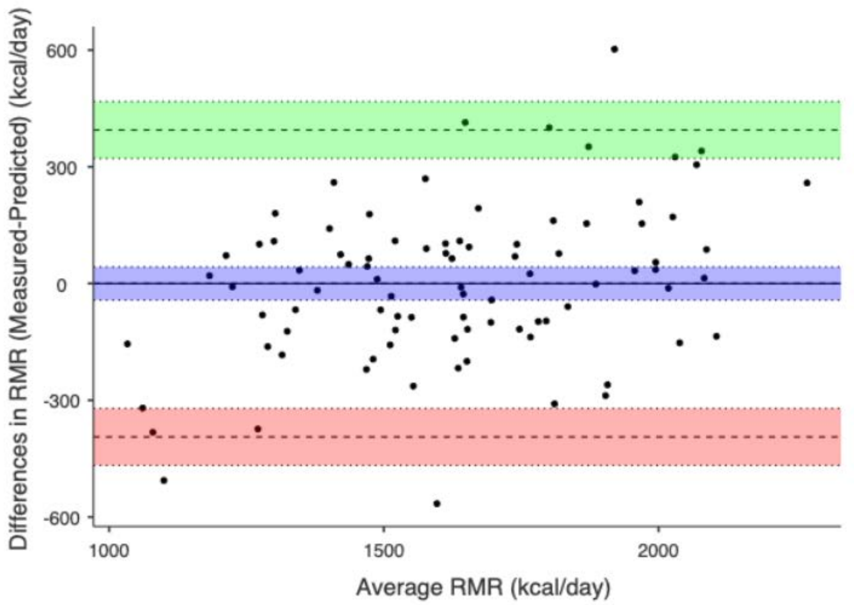

Figure 1a. Differences between RMR measured via indirect calorimetry and estimated using the derived prediction equation with gender diverse individuals removed (N = 88). RMR = resting metabolic rate

Table 4a. Model 1 (randomized dataset with *n* = 6 gender diverse, *n* = 15 cisgender female, *n* = 15 cisgender male): RMR multiple linear regression prediction with all variables included.

Model		*B*	Std. Error	*t*	Sig.
1	(Constant)	3952.004	6166.861	.641	.527
	Age	4.663	4.857	.960	.345
	Height	5.727	6.950	.824	.417
	Mass	30.865	9.614	3.210	.003
	Waist girth	19.243	77.720	.248	.806
	Hip girth	-41.183	59.703	-.690	.496
	W-H ratio	-4052.646	8156.473	-.497	.623
	Resting heart rate	2.082	4.523	.460	.649

Table 5a. Model 2 (randomized dataset with *n* = 6 gender diverse, *n* = 15 cisgender female, *n* = 15 cisgender male): RMR multiple linear regression prediction with multicollinear variable (waist-to-hip ratio) removed.

Model		*B*	Std. Error	*t*	Sig.
2	(Constant)	989.764	1556.114	.636	.530
	Age	3.562	4.265	.835	.410
	Height	4.888	6.654	.735	.468
	Mass	31.263	9.456	3.306	.003
	Waist girth	-18.997	10.687	-1.778	.086
	Hip girth	-11.810	8.242	-1.433	.163
	Resting heart rate	1.950	4.456	.438	.665

Table 6a. Model 3 (randomized dataset with *n* = 6 gender diverse, *n* = 15 cisgender female, *n* = 15 cisgender male): RMR multiple linear regression prediction including only significant variables.

Model		*B*	Std. Error	*t*	Sig.
3	(Constant)	-1632.349	740.549	-2.204	.035
	Height	14.476	4.635	3.123	.004
	Mass	10.966	3.108	3.528	.001

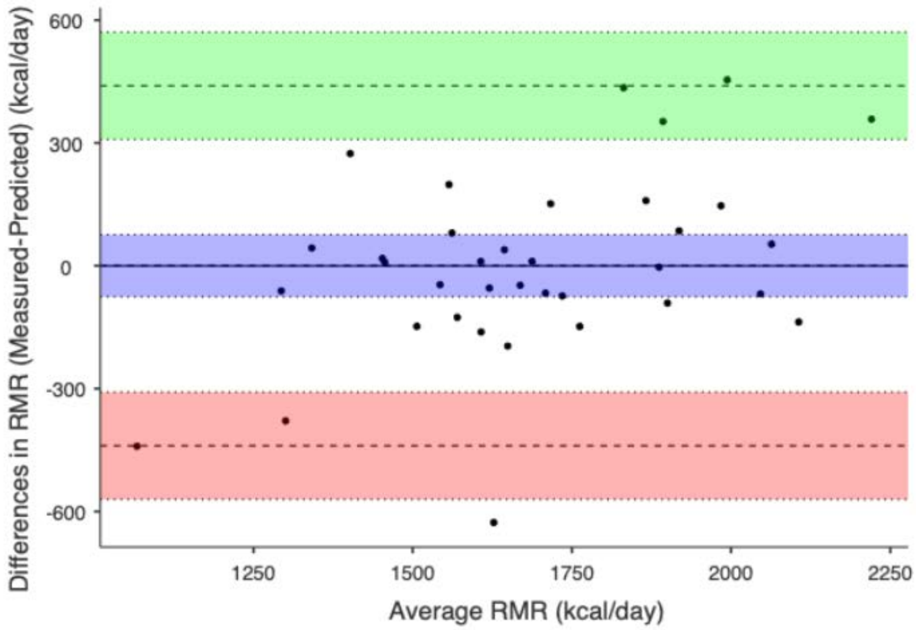

Figure 2a. Differences between RMR measured via indirect calorimetry and estimated using the derived prediction equation with gender diverse individuals and a random sampling of cisgender females and cisgender males (N = 36). RMR = resting metabolic rate

Table 7a. Model 1 (randomized dataset with gender-diverse removed, *n* = 15 cisgender female, *n* = 15 cisgender male): RMR multiple linear regression prediction with all variables included.

Model		*B*	Std. Error	*t*	Sig.
1	(Constant)	3663.349	7299.100	.502	.621
	Age	5.442	6.756	.806	.429
	Height	6.443	8.087	.797	.434
	Mass	28.581	11.385	2.510	.020
	Waist girth	29.219	91.268	.320	.752
	Hip girth	-46.599	70.993	-.656	.518
	W-H ratio	-4266.949	9552.151	-.447	.659
	Resting heart rate	6.003	5.932	1.012	.323

Table 8a. Model 2 (randomized dataset with gender-diverse removed, *n* = 15 cisgender female, *n* = 15 cisgender male): RMR multiple linear regression prediction with multicollinear variable (waist-to-hip ratio) removed.

Model		*B*	Std. Error	*t*	Sig.
2	(Constant)	509.877	1822.327	.280	.782
	Age	3.752	5.499	.682	.502
	Height	5.766	7.804	.739	.467
	Mass	28.680	11.183	2.565	.017
	Waist girth	-11.132	12.805	-.869	.394
	Hip girth	-15.208	9.912	-1.534	.139
	Resting heart rate	5.802	5.811	.998	.328

Table 9a. Model 3 (randomized dataset with gender-diverse removed, *n* = 15 cisgender female, *n* = 15 cisgender male): RMR multiple linear regression prediction including only significant variables.

Model		*B*	Std. Error	*t*	Sig.
3	(Constant)	-1284.185	835.565	-1.537	.136
	Height	12.523	5.200	2.408	.023
	Mass	10.885	3.336	3.262	.003

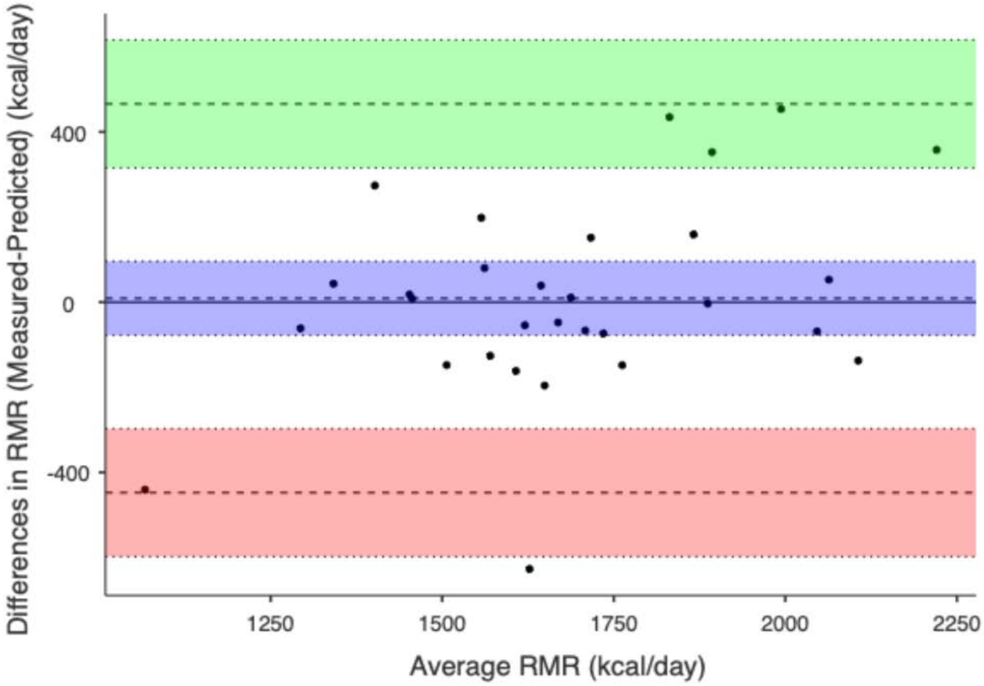

Figure 3a. Differences between RMR measured via indirect calorimetry and estimated using the derived prediction equation with data from gender-diverse individuals removed from a random sampling of cisgender females and cisgender males (N = 30). RMR = resting metabolic rate