Predicting basal metabolic rate in men with motor complete spinal cord injury

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Abstract

Purpose: To assess the accuracy of existing basal metabolic rate (BMR) prediction equations in men with chronic (> 1 year) spinal cord injury (SCI). The primary aim is to develop new SCI population-specific BMR prediction models, based on anthropometric, body composition and/or demographic variables that are strongly associated with BMR.

Methods: Thirty men with chronic SCI (Paraplegic; n = 21, Tetraplegic; n = 9), aged 35 ± 11 years (mean ± SD) participated in this cross-sectional study. Criterion BMR values were measured by indirect calorimetry. Body composition (dual energy X-ray absorptiometry; DXA) and anthropometric measurements (circumferences and diameters) were also taken. Multiple linear regression analysis was performed to develop new SCI-specific BMR prediction models. Criterion BMR values were compared to values estimated from six existing and four developed prediction equations

Results: Existing equations that use information on stature, weight and/or age, significantly ($P < 0.001$) over-predicted measured BMR by a mean of 14–17% (187–234 kcal/day). Equations that utilised fat-free mass (FFM) accurately predicted BMR. The development of new SCI-specific prediction models demonstrated that the addition of anthropometric variables (weight, height and calf circumference) to FFM (Model 3; $r^2 = 0.77$), explained 8% more of the variance in BMR than FFM alone (Model 1; $r^2 = 0.69$). Using anthropometric variables, without FFM, explained less of the variance in BMR (Model 4; $r^2 = 0.57$). However, all the developed prediction models demonstrated acceptable mean absolute error ≤ 6%.

Conclusion: BMR can be more accurately estimated when DXA derived FFM is incorporated into prediction equations. Utilising anthropometric measurements

provides a promising alternative to improve the prediction of BMR, beyond that achieved by existing equations in persons with SCI.

Key Words: Basal Metabolism, Anthropometry, Body Composition, Spinal Cord Injuries, Indirect Calorimetry.

Introduction

A critical determinant of body weight fluctuations over time is the imbalance between energy intake and expenditure (kcal). Energy intake reflects the ingestion of macronutrient food groups (carbohydrate, protein, fat and alcohol), whereas energy expenditure can be partitioned into three components; basal metabolic rate (BMR), dietary induced thermogenesis (DIT) and activity energy expenditure (AEE). BMR represents the energy required to maintain homeostasis and the metabolic activities of cells at rest. It is the largest component of total daily energy expenditure (TDEE), approximately 70% for inactive persons with chronic spinal cord injury (SCI) (1). In comparison to non-disabled controls, BMR is significantly reduced by 14 – 27% in persons with SCI, although, values were comparable between groups when adjusted for fat free mass (FFM) (2). Reductions in BMR after SCI are primarily driven by skeletal muscle disuse atrophy below the level of the injury (3, 4). The adoption of a more sedentary lifestyle after SCI reduces AEE (1, 5), further eroding TDEE, which can lead to a sustained positive energy balance and thus the accumulation of excess adiposity. Obesity, and its associated negative metabolic sequelae (i.e. impaired glucose tolerance, insulin resistance and dyslipidaemia), commonly occurs at a heightened frequency in persons with SCI (6-8).

Considering BMR accounts for the greatest proportion of TDEE in inactive populations, its accurate measurement is of utmost importance. Multiples of BMR can be used to derive an individual's daily energy needs and inform energy intake adjustments in a clinical setting. From a public health perspective, the prescription of a calorie-restricted diet is integral for obesity management, through the creation of a sustainable energy deficit. The gold standard method for assessing BMR is indirect calorimetry. However, this approach requires expensive, specialised equipment (i.e. metabolic cart) which typically restricts its use to research settings. Accurate BMR measurements should be performed upon waking in a quiet, darkened, thermal neutral room, following an overnight fast, with participants in a complete resting posture. To achieve these appropriate conditions, BMR is usually measured following an overnight in-patient stay, which may be impractical. Consequently, in clinical practice, BMR is often predicted using equations which feature variables that are easily measured; body weight, stature and/or age (9-11). However, a recent review reported that such equations, derived from able-bodied populations, over-predicted BMR by 4 – 92% in persons with SCI (12). Variations in the prediction error across studies likely reflect both error intrinsic to the equations themselves and variance between study populations. For example, when using the equation from the seminal work of Harris and Benedict (9), Aquilani *et al*, (13) observed only a 4% overestimation compared to criterion BMR. Not only did these participants have sub-acute injuries (~2 months post traumatic SCI) but they were also hypermetabolic due to the presence of urinary tract infections and pressure injuries, which may explain the reduced overestimation. Therefore, the accuracy of commonly used BMR prediction equations remains to be assessed in a cohort representative of men with chronic (>1 year) SCI.

A major disadvantage of equations that utilise body weight to predict BMR is that this variable is unable to distinguish between FFM and fat mass (FM). FFM has been shown to explain most of the variance in BMR (14-16), with other studies demonstrating an independent, secondary contribution of FM (17). In persons with SCI, recent evidence would suggest incorporating FFM measured via dual energy X-ray absorptiometry (DXA) more accurately predicts BMR than using height and weight measurements (16). However, it is possible that prediction models utilising FFM alone might not be sensitive enough to estimate individual BMR, and perhaps other sources of variation (i.e. age and injury characteristics) should also be considered (18, 19). Moreover, equations incorporating FFM also require the acquisition of body composition data using expensive equipment (i.e. DXA), which might not be available in a clinical setting, or inaccurate techniques (i.e. bioelectrical impedance). Therefore, anthropometric measurements (i.e. circumferences and/or diameters) might improve BMR prediction accuracy, with a trivial increase in clinician/nutritionist workload to attain desirable predictor variables.

It remains to be seen whether the incorporation of injury characteristics could act as surrogates for FFM or anthropometric measurements in the prediction of BMR. Both level of injury and time since injury (TSI) influence body composition parameters (3, 20). Significant differences have been reported in BMR measured via indirect calorimetry between paraplegic and tetraplegic participants (21). Utilising such easily attainable injury characteristics to predict BMR in persons with SCI would further reduce the burden on clinicians/nutritionists. The primary aim was to develop new SCI population-specific BMR prediction models, based on injury characteristics or anthropometric variables that are strongly associated with BMR. The secondary aim of this study was to assess the accuracy of existing BMR predictive equations in men with chronic (> 1 year) SCI.

Methods

Participants

Thirty men with chronic (> 1 year) motor complete (American Spinal Injury Association Impairment Scale classification; A or B) SCI participated in this study. All participants had lesion levels below C5 and were aged between 18 – 65 years old with a BMI less than 32 kg/m^2. Exclusion criteria included; cardiovascular disease, hypertension, type II diabetes, pressure ulcers greater than grade II and urinary tract infection or symptoms. This experimental protocol was approved by the McGuire Veteran Affairs Investigational Research Board and the Virginia Commonwealth University (VCU) Office of Research and Innovation. All participants provided written informed consent and procedures were conducted in accordance with the principles of the Declaration of Helsinki.

Basal metabolic rate

Participants were woken up ~6.30 am, following a 12 hour overnight fast. All BMR measurements were completed in a darkened, thermoneutral environment (ambient temperature between 20-25°C). Participants abstained from caffeine, nicotine and alcohol ≥ 12 hours, in accordance with minimal criteria for best practice BMR guidelines (22). A portable metabolic system (COSMED K4b^2, Rome, Italy) was used to measure BMR. The unit was calibrated prior to use according to manufacturer's instructions and has been demonstrated to be valid (23). Following calibration, a canopy was placed over the participant's head as they lay in a supine position, with continuous breath-by-breath measurements made over a 20-minute period. Gas exchange values for the first 5 minutes were discarded, with BMR (kcal/day) averaged over the last 15 minutes. Energy expenditure was determined using the Weir equation (24). If respiratory exchange ratio (carbon dioxide production / oxygen used) values were < 0.70 or > 1.00 participants were excluded from the analysis, as these values are deemed indicative of protocol violations or inaccurate gas measurements (22).

Anthropometric measurements

Prior to performing anthropometric measurements, participants were instructed to void their bladder. Body mass (kg) was obtained using a digital wheelchair scale (Tanita PW-630U, IL, USA), with the weight of the wheelchair subtracted from the combined weight of participant and wheelchair to derive the participants mass. Participants' height was measured in a supine position following transfer onto a mat. The distance between two wooden boards, one at the apex of the head and the other positioned at the sole of the foot, was measured using a Holtain height caliper to the nearest 0.1 cm. For participants with knee flexion contracture, segmental measures were taken from the greater trochanter to the lateral knee joint and from the lateral knee to the lateral aspect of the sole of the foot.

Circumference measurements were taken using a standard inflexible measuring tape (MFG, Lufkin, Executive Diameter Pocket Tape measure). The mean of three values (within 0.5 cm of each other) was recorded to the nearest 0.1 cm. Abdominal circumference was measured at the level of the umbilicus. Waist circumference was measured at the midpoint between the crest of the illium and the inferior margin of the last rib. Hip circumference was measured around the widest part of the trochanters. These measurements were taken after exhalation of a preceding deep breath. Thigh and calf circumferences were also measured on the right leg. Thigh circumference was measured at the midpoint between the anterior superior iliac spine and the superior border of the patellar. Calf circumference was taken at the widest point. All circumference measurements were taken in a supine position, except for the calf, which was taken with participants sitting in their wheelchair. Sagittal and transverse abdominal diameters (SAD and TAD) were also measured at the level of the umbilicus in a supine position, using a Holtain-Kahn abdominal caliper.

Dual energy X-ray absorptiometry

A trained operator measured body composition using a dual energy X-ray absorptiometry (DXA) scanner (Lunar Prodigy Advance DXA scanner, WI, USA). Whole-body lean mass, FM and bone mineral content (BMC) were extracted from DXA computer software. FFM was calculated by adding BMC and lean mass. Whole-body FFM was also predicted from body weight using the following equation, Gorgey *et al*, (25): 0.288 × body weight (kg) + 26.3. This was to assess whether, in the absence of a direct DXA FFM measurement, predicted FFM could be used to accurately predict BMR in persons with chronic SCI.

Basal metabolic rate prediction equations

BMR (kcal/day) was estimated using three established equations, which incorporated weight, height and age (9-11). For male adults, the Schofield equation utilised three separate equations to predict BMR from weight, depending on the participants' age group (age 18-30, 30-60, >60 years). This equation was previously used by the Food and Agricultural Organization, World Health Organisation and United Nations University (FAO/WHO/UNU) technical report series (26). BMR was also estimated using body composition parameters (FFM and FM) (14, 16, 17). These equations are described in full in Table 1.

[PLEASE INSERT TABLE 1 ABOUT HERE]

Statistical Analysis

Data modelling

To explore the associations between criterion BMR and potential predictive traits, simple univariate linear regressions were performed to derive Pearson correlation values (r). A multivariate regression analysis, with both forward inclusion and backward deletion, was then performed to develop SCI-specific BMR prediction Models, incorporating the best combination of predictor variables (demographic characteristics, anthropometric measurements and body composition parameters) that explain the greatest variance in criterion BMR. Standard error of the estimate (SEE) was also calculated to determine the accuracy of these prediction models. A 95% Limits of Agreement (LoA) analysis was performed (mean difference ± 1.96 SD) comparing criterion and predicted BMR, with data displayed using Bland-Altman plots.

Error statistics

Predicted BMR from each of the six established equations and generated prediction models was compared to corresponding criterion BMR for each participant. Comparison statistics included mean signed error (MSE) and mean absolute error (MAE). Error of estimate data is presented as a percentage [*Eq*. Percentage error = (Estimated BMR – criterion BMR) / criterion BMR × 100]. Differences between predicted and criterion BMR were also compared by paired *t*-tests, with a Bonferroni stepwise correction applied to correct for multiple comparisons. Statistical significance was set at a priori of $\alpha < 0.05$ and all analyses were performed using SPSS Statistics 25 for Windows (IBM, NY, USA).

Results

Participant demographics are presented in Table 2. Mean ± SD measured BMR and respiratory exchange ratio (RER) was 1499 ± 162 kcal/day and 0.83 ± 0.04, respectively.

[PLEASE INSERT TABLE 2 ABOUT HERE]

[PLEASE INSERT FIGURE 1 ABOUT HERE]

Associations between predictive traits and basal metabolic rate

FFM measured by DXA explained most of the variance (69%) in BMR ($r = 0.83$; P < 0.01). Predicted FFM using Gorgey *et al.* (17) did not explain anymore of the variance in BMR than weight, however, both were strongly associated with criterion BMR ($r = 0.56$, P < 0.01). The predicted FFM equation significantly under-estimated

FFM by 3.6 kg ($P < 0.001$). Height and other anthropometric measurements (supine waist and abdominal circumference, sitting calf circumference) were moderately associated with BMR (Table 3). None of the demographic or injury characteristics were associated with BMR.

[PLEASE INSERT TABLE 3 ABOUT HERE]

Accuracy of developed prediction models

The addition of circumferences and diameters to FFM (Model 2) slightly improved the prediction of BMR in comparison to just FFM alone (Model 1) (Table 4). However, the best prediction algorithm generated was Model 3 (incorporating FFM, weight, height and calf circumference as predictor variables), which explained 77% of the variance in BMR. For researchers/clinicians without access to expensive scanning equipment (DXA), a final prediction algorithm was generated (Model 4), with the FFM predictor variable removed. This explained the least variance in criterion BMR ($r^2 = 0.57$). Relative to criterion BMR, mean bias for all the generated prediction models was zero. The 95% limits of agreement (indicative of random error) were greatest for Model 4 (anthropometrics alone: ± 207 kcal/day) and the smallest for Model 3 (FFM plus anthropometrics: ± 152 kcal/day) (Figure 1). Entering predicted FFM into Model 1 resulted in a mean bias ± 95% LoA of –84 ± 262 kcal/day.

[PLEASE INSERT TABLE 4 ABOUT HERE]

[PLEASE INSERT FIGURE 1 ABOUT HERE]

Accuracy of established and developed prediction models of basal metabolic rate

The variability in error of established and newly developed BMR prediction equations are displayed in Figure 2. Established equations, which feature variables that are easily measured (body weight, stature and/or age), significantly ($P < 0.001$) over-predicted measured BMR by a mean of 14 – 17% (187 – 234 kcal/day). Established equations that utilised FFM (highlighted in grey) more accurately predicted measured BMR in persons with SCI. The Nelson *et al*, (17) equation, which also incorporated FM, significantly ($P < 0.001$) under-predicted BMR by 5 ± 6% (82 ± 95 kcal/day). The remaining two established equations were not significantly different from the criterion BMR and displayed negligible mean bias ± SD; -1 ± 6% (-20 ± 92 kcal/day) and 1 ± 6% (3 ± 91 kcal/day) using the Cunningham, (14) and SCI-specific (16) equations, respectively. Mean absolute percentage error for the generated Models were small (≤ 6%) and comparable to the Cunningham (14) and Chun *et al*, (16) prediction equations. There was a trend ($P = 0.065$) for significantly elevated absolute percentage error using predicted FFM in Model 1 (8 ± 6%) (not shown on Figure), as opposed to DXA measured FFM (5 ± 4%).

[PLEASE INSERT FIGURE 2 ABOUT HERE]

Discussion

Existing equations developed for non-disabled individuals, which incorporate stature, weight and/or age, significantly over-predicted BMR and are not fit for purpose in person with SCI. Equations that utilise FFM, the Cunningham (14) and newly-developed SCI-specific model (16), were not significantly different to criterion BMR. In this sample of participants with chronic SCI, FFM as a single predictor variable explained the greatest variance in BMR ($r^2 = 0.69$), which is in accordance with previous studies ($r^2 = 0.63 – 0.79$) (2, 15, 27). However, the addition of volumetric (circumferences and diameters) and anthropometric (height and weight) measurements to FFM explained an additional 8% of the variance in BMR. Removal of FFM from generated prediction models increased the prediction error, but offered a useful alternative methodology in the absence of FFM measurement and improved the prediction of BMR relative to existing equations validated for use in non-disabled individuals.

We hypothesised that it might be possible to use certain demographic and injury characteristics, such as age, level of injury and TSI, which are easily attainable and thus reduce the burden on clinicians/nutritionists to predict BMR. We found no significant differences in BMR between paraplegic (1497 ± 148 kcal/day) and tetraplegic (1467 ± 178 kcal/day) participants. Previous studies have demonstrated increased BMR in paraplegic compared to tetraplegic participants of 224 and 370 kcal/day (21, 28), whereas other researchers have shown there to be no difference (16, 29). One possible reason for similar BMR's between the subgroups in this current study could be due to race. BMR has been shown to be higher in White than in African-American individuals (30) and in this study, there was a greater percentage of White participants with tetraplegia than paraplegia, 82% and 57%, respectively. Due to the relatively small sample size and the requirement to develop models with external validity to the wider male SCI population, it was not possible to develop race-specific equations. As FFM is strongly associated with BMR, it is surprising that age or TSI are not also associated with BMR, given the loss of skeletal muscle mass with aging (31) and post SCI (3). It appears that these variables cannot be used as surrogates for FFM in BMR prediction models for persons with SCI.

Besides skeletal muscle, bone mineral content (which contributes to FFM) is significantly correlated to BMR (r = 0.48). Yilmaz *et al,* (28) demonstrated that hip bone mineral density was significantly associated with BMR (R_s = 0.41) in persons with SCI. These results indicate that bone metabolism is a major component of BMR and might explain why height as an anthropometric variable explains 18% of the variance in BMR. To date, no studies in persons with SCI have sought to assess the improvement in the prediction of BMR with the addition of simple anthropometric measurements that can be easily obtained. In non-disabled individuals, the addition of FFM to a regression equation using the predictors of mass, height and age increased the associations between predicted and criterion BMR from r^2 = 0.71, (SEE = 125 kcal/day) to r^2 = 0.80 (SEE = 103 kcal/day) (32). Similarly, the results of this current study demonstrate the addition of anthropometric measurements to FFM (Model 3) explains an additional 8% of the variance in BMR.

Whilst our generated multiple linear regression models demonstrate a negligible mean bias (Figures 1 & 2), this can be somewhat misleading as under and over-estimations for each participant likely cancel each other out. Using a limits of agreement analysis (exploring the distribution of individual differences) and mean absolute percentage error (ignoring the sign/direction of difference) are alternative approaches that offer greater insight into the accuracy of developed models. The 95% LoA for all the generated models ranged between ± 152 kcal (Model 3) to ± 207 (Model 4), which are less than the values reported previously for the Cunningham (14) and SCI-specific (16) equations, 236 and 231 kcal, respectively. Moreover, the mean absolute percentage error was small, even for Model 4, which utilised only anthropometric measurements (MAE = 6 ± 4%), and were comparable to existing equations that incorporate FFM. Therefore, in the absence of direct analyses of body composition, we posit that the use of anthropometric measurements in models derived specifically for males with chronic SCI can be used to improve the prediction of BMR. This is in accordance with data from non-disabled individuals, which suggests utilizing anthropometric data (height, weight, mid-upper arm and waist and hip circumferences) provides a useful alternative methodology to better predict BMR when detailed information on body composition is not available (33).

A recent systematic review highlighted the problems in predicting BMR in persons with SCI from existing equations developed for non-disabled individuals (12). The Harris Benedict (9) and Schofield *et al*, (11) equations have previously been shown to over-predict BMR by 15-32% and 6% respectively (2, 34, 35). In conjunction with findings herein, it is therefore not advisable to utilise equations developed for non-disabled individuals that incorporate stature, weight and/or age to predict BMR in persons with SCI. This study cross-validated, for the first time, the SCI-specific BMR prediction equation developed by Chun *et al*, (16). This SCI-specific equation was generated with criterion indirect calorimetry measurements taken between 8:00 and 10:00 am, rather than upon waking (~ 6:30am) in a darkened room following an overnight stay. Occasionally in the wider literature, resting metabolic rate (RMR; often measured under less restricted conditions) and BMR (as measured in this current study) are often used interchangeably, but it is important to distinguish the differences in terminology as this can help to reflect differences in prediction error between studies. Moreover, the Chun *et al*, (16) equation was developed in East Asian participants, with a considerably lower mean FFM than participants in this current study (42.1 vs. 51.3 kg). Nevertheless, this equation showed the lowest mean ± SD bias of the pre-existing equations tested, 1 ± 6% (3 ± 91 kcal/day) and further highlights the importance of incorporating a measurement of FFM into BMR prediction models.

An alternative approach could be to utilise estimates of FFM, although whole-body FFM was significantly under-predicted (3.6 kg) using the Gorgey *et al,* (25) equation in this study. Consequently, using estimates of FFM in Model 1 significantly ($P < 0.001$) under-predicted BMR (mean bias ± 95% LoA; -84 ± 262 kcal/day), with increased mean absolute percentage error (8 ± 6%). This equation estimates FFM from weight, and weight itself explains the same amount of variance in criterion BMR. Therefore, in the absence of expensive scanning equipment it is perhaps advisable to use Model 4 (including height, weight and transverse abdominal diameter) to predict BMR in persons with SCI. It is worth noting, that any error in the estimation of BMR will be amplified if these data are used to derive an individual's total daily energy expenditure (TDEE). For context, multiplying BMR by an activity factor of 1.2 [as has been used previously in inactive persons with SCI (36)] would equate to a TDEE of 1799 kcal/day in our sample. Extrapolating the mean absolute error percentage for Model 3 & 4 indicates there is the potential to under or over-predict TDEE by 72 and 108 kcal/day, respectively. Despite our generated equations showing acceptable error (< 5%), it is important for practitioners to be aware of the implications of using predicted BMR to estimate TDEE, when looking to prescribe a suitable energy intake in persons with SCI.

Limitations

The accuracy of the generated prediction models was assessed using the same sample of participants that developed the model. In these circumstances evaluation statistics (i.e. mean bias) can be somewhat biased (37). These equations were only tested in men with motor-complete SCI to ensure a more homogenous sample. The performance of these generated Models therefore remains to be assessed in women with SCI, who represent 25% of the entire SCI population. It is possible the development of future sex-specific Models are necessary to accurately predict BMR in women with SCI. Spasticity, whereby motor control of skeletal muscles is disturbed, occurs in more than 80% of persons with SCI (38). If episodes of spastic hypertonia were to occur during the assessment of criterion BMR, this can lead to increased energy expenditure due to excessive co-contraction (39). Therefore, future studies should consider multiple measurements of BMR by indirect calorimetry to accurately evaluate BMR in persons with severe spasticity (15). Although the use of anthropometric measurements can improve the accuracy of BMR prediction and potentially negate the requirement to use expensive scanning equipment (i.e. DXA), it should be noted that transferring participants into the supine position could be difficult. This is especially relevant when assessing persons with higher-level injuries where access to lifting apparatus is not available.

Conclusion

Existing equations incorporating age, stature and weight that have been validated in non-disabled individuals show considerable prediction error when used in persons with SCI and are not fit for purpose. When direct measurements of FFM are available, utilising FFM-based prediction equations offers a more accurate estimation of BMR, which can be further improved with the incorporation of anthropometric measurements. Moreover, in the absence of detailed body composition information, utilising anthropometric measurements (height, weight and transverse abdominal diameter) offers a useful alternative methodology to predict BMR in persons with chronic SCI. However, these generated Models should be cross-validated with an independent, larger sample of male and female participants, with a range of body composition characteristics to demonstrate external validity to the wider SCI population.

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Conflict of Interest

The authors have no conflict of interest to declare. The results of the study are presented clearly, honestly, and without fabrication, falsification, or inappropriate data manipulation. The results of the present study do not constitute an endorsement by the American College of Sports Medicine.

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Figure Legend

Figure 1: Bland-Altman plots depicting mean bias (solid line) and 95% limits of agreement (dashed lines) of estimated relative to criterion basal metabolic rate measured by indirect calorimetry for prediction Model 1 (FFM alone; **A**), 2 (FFM plus anthropometrics and circumferences; **B**), 3 (FFM plus anthropometrics; **C**) and 4 (anthropometrics alone; **D**). Bias represents predicted-criterion BMR. Abbreviations: BMR, basal metabolic rate.

Figure 2: Scatterplot displaying BMR prediction error for each of the pre-existing equations (absolute, **A**; percentage, **C**) and generated Models (absolute, **B**; percentage, **D**). Mean error for each equation is displayed as a thick black bar, with individual data points also shown (open circles). The highlighted areas (grey) are for equations that utilize fat free mass (FFM) to predict BMR, with the dashed line representing zero prediction error. Absolute error (accounting for under and over-prediction) mean ± SD is displayed for each equation above the Figures. ♯ Significant difference between predicted and criterion BMR ($P < 0.001$). Abbreviations: BMR, basal metabolic rate.

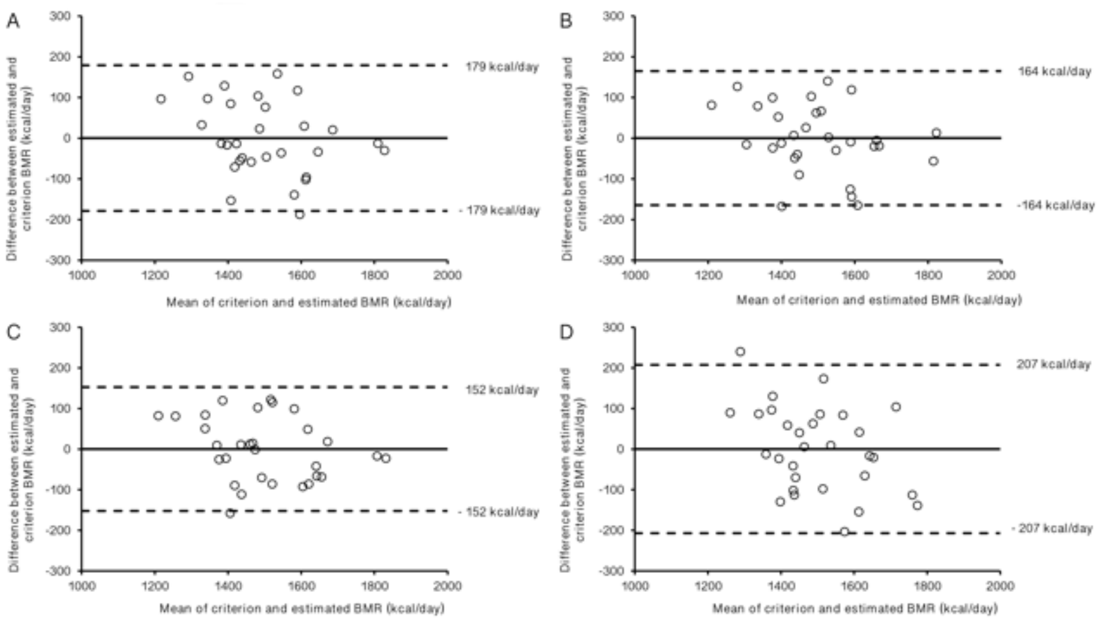
A
B
C
D
Difference between estimated and criterion BMR (kcal/day)
Mean of criterion and estimated BMR (kcal/day)
179 kcal/day
- 179 kcal/day
164 kcal/day
-164 kcal/day
152 kcal/day
- 152 kcal/day
207 kcal/day
- 207 kcal/day
300
200
100
0
-100
-200
-300
1000
1200
1400
1600
1800
2000

Figure 1

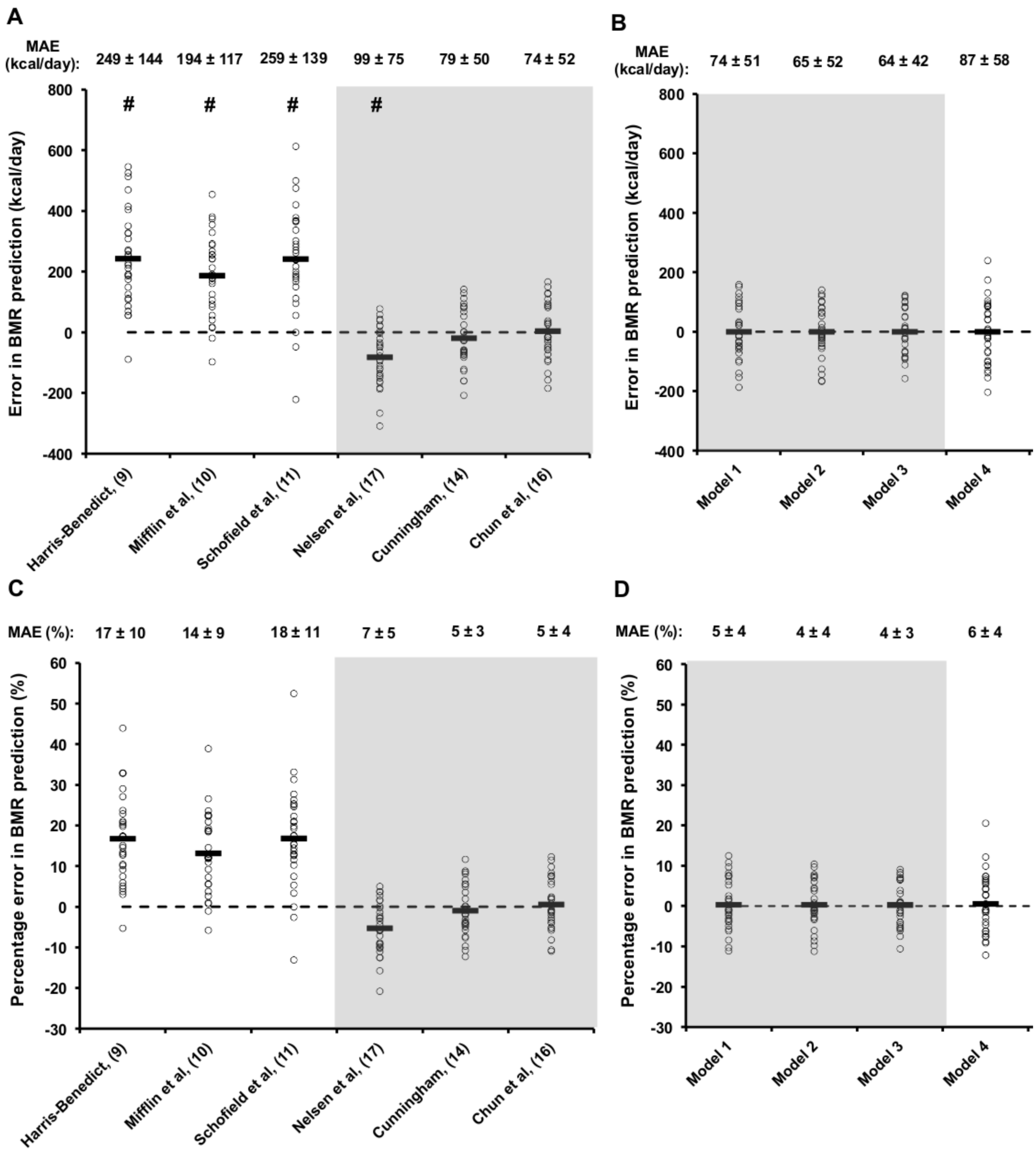
A
MAE (kcal/day):
249 ± 144
194 ± 117
259 ± 139
99 ± 75
79 ± 50
74 ± 52
#
#
#
#
Error in BMR prediction (kcal/day)
800
600
400
200
0
-200
-400
Harris-Benedict, (9)
Mifflin et al, (10)
Schofield et al, (11)
Nelsen et al, (17)
Cunningham, (14)
Chun et al, (16)
B
MAE (kcal/day):
74 ± 51
65 ± 52
64 ± 42
87 ± 58
Error in BMR prediction (kcal/day)
800
600
400
200
0
-200
-400
Model 1
Model 2
Model 3
Model 4
C
MAE (%):
17 ± 10
14 ± 9
18 ± 11
7 ± 5
5 ± 3
5 ± 4
Percentage error in BMR prediction (%)
60
50
40
30
20
10
0
-10
-20
-30
Harris-Benedict, (9)
Mifflin et al, (10)
Schofield et al, (11)
Nelsen et al, (17)
Cunningham, (14)
Chun et al, (16)
D
MAE (%):
5 ± 4
4 ± 4
4 ± 3
6 ± 4
Percentage error in BMR prediction (%)
60
50
40
30
20
10
0
-10
-20
-30
Model 1
Model 2
Model 3
Model 4

Figure 2

Table 1: Basal metabolic rate prediction equations

Equation author	BMR prediction equation
Weight, height and age	
Harris-Benedict (9)	= 66.4730 + (13.7516 × weight) + (5.0033 × height) – (6.7550 × age)
Mifflin-St. Jeor (10)	= 10 × weight + 6.25 × height – 5 × age + 5
Schofield (11)	= 15.057 × weight + 692.2 (age, 18 – 30 years)
	= 11.472 × weight + 873.1 (age, 30 – 60 years)
	= 11.711 × weight + 587.7 (age, > 60 years)
FFM and FM	
Nelson *et al,* (17)	= 25.80 × FFM + 4.04 × FM
Cunningham (14)	= 370 + 21.6 × FFM
Chun *et al,* (16) *SCI-specific*	= (24.5 × FFM + 244.4)

Abbreviations: **BMR, basal metabolic rate; FFM, fat free mass; FM, fat mass.**

Table 2: Participant characteristics

Characteristic	Mean ± SD	Range (minimum – maximum)
Age (years)	35 ± 11	19 - 61
Body mass (kg)	74.5 ± 14.1	52.3 – 106.3
Height (m)	1.78 ± 0.05	1.69 – 1.87
Race	11 African American (37%) 19 white (63%)	
Body fat (%)	30.6 ± 10.2	14.8 – 48.2
Fat mass (kg)	22.9 ± 11.3	8.7 – 47.5
Bone mineral content (kg)	2.95 ± 0.39	2.09 – 3.66
Fat free mass (kg)	51.3 ± 5.7	41.4 – 64.7
Level of injury	9 Tetraplegic (30%) 21 Paraplegic (70%)	C5 – C7 T4 – L1
TSI (years)	9 ± 9	1 - 34
AIS	20 A (67%) 8 B (27%) 2 C (6%)	
BMR (Kcal/day)	1499 ± 162	1169 - 1843
RER	0.83 ± 0.04	0.74 – 0.90

Abbreviations: **AIS, American Spinal Injury Association Impairment Scale; BMR, basal metabolic rate; RER, respiratory exchange ratio; TSI, time since injury.**

Table 3: The association (*r*) between independent predictive traits (injury and demographic characteristics, body composition components and anthropometric measurements) and criterion basal metabolic rate

Demographic and injury characteristics		Body composition		Anthropometric measurements	
Age (yrs)	0.04	DXA-FFM (kg)	**0.83†**	Body mass (kg)	**0.56†**
LOI	0.22	DXA- FM (kg)	0.30	Height (cm)	**0.42***
TSI (yrs)	0.06	DXA-BMC (kg)	**0.48†**	Supine waist circumference (cm)	**0.41***
		Predicted FFM (kg)	**0.56†**	Supine abdominal circumference (cm)	**0.37***
				Supine hip circumference (cm)	0.32
				Supine thigh circumference (cm)	0.27
				Sitting calf circumference (cm)	**0.47†**
				Supine SAD (cm)	0.30
				Supine TAD (cm)	0.29

Abbreviations: **BMC, bone mineral content; DXA, dual-energy x-ray absorptiometry; FFM, fat free mass; LM, lean mass; LOI, level of injury; SAD, sagittal abdominal diameter TAD, transverse abdominal diameter; TSI, time since injury.**

*** P < 0.05, † P < 0.01**

Table 4: Generated basal metabolic rate prediction models using fat free mass and anthropometric measurements

Model name	BMR (kcal/day) prediction algorithm	R^2	SEE (kcal/day)
1. FFM alone	= 23.469 × FFM (kg) + 294.330	0.69	93
2. FFM plus circumferences and diameters	= 23.995 × FFM (kg) + 6.189 × SAD (cm) + 6.384 × TAD (cm) – 6.948 × THIGH CIRC (cm) + 275.211	0.73	90
3. FFM plus anthropometrics	= 19.789 × FFM (kg) + 5.156 × weight + 8.090 × height – 15.301 × calf (cm) – 860.546	0.77	84
4. Anthropometrics alone	= 13.202 × height (cm) + 11.329 × weight (kg) – 16.729 × TAD (cm) – 1185.445	0.57	112

Abbreviations: **BMR, basal metabolic rate; FFM, fat free mass; SAD, sagittal abdominal diameter; SEE, standard error of the estimate; TAD, transverse abdominal diameter; THIGH CIRC, thigh circumference.**