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Recovering data from basal metabolic rate and body-mass index

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Abstract
Many clinically significant parameters are estimated from height (*h*), weight (*w*) and age (*y*). Two important examples are body mass index (BMI) and basal metabolic rate (BMR). There are circumstances when it might be desirable to estimate *h*, *w* and *y* for a particular subject from BMI and BMR (or other similar combinations). While there is only one mathematical expression for BMI, there are many competing expressions for BMR which complicates this process. Here we describe methods for solving this problem for three different classes of BMR equation when the coefficients are known. We also provide means of identifying the coefficients of an unidentified BMR equation. We apply these technique to our own data, data published by others and in computer simulations, from which we conclude that in the most challenging case our method yields the correct result in more than 99% of cases and identifies the likelihood of error in about 0.96% of cases, leaving only about 0.03% of cases of unidentified error. Application of these techniques to data obtained using an Omron HBF-362 demonstrate some of the difficulties that can arise.

Keywords: anthropometry, body mass index, metabolic rate.

1. Introduction

Many parameters of biomedical significance, including body surface area [1], blood volume [2] and blood pressure [3], are routinely estimated from the height (*h*), weight (*w*) and, sometimes, age (*y*) of an individual. Basal metabolic rate (BMR) is also estimated from *h*, *w* and *y*, although the formulae may involve all, two or just one of these variables (some commonly used equations are summarised in Table 1). A general expression for BMR is

$$BMR = aw^{\beta} + bh + cy + d\,, \qquad (1)$$

where the coefficients (*a*, *b*, *c*, *d*) depend on gender (Table 1) and, in some cases, different equations are specified for different age ranges. Usually, $\beta = 1$, as is the case for the examples shown in Table 1, but in a few cases $\beta < 1$ [4]. Other equations may appear to have other variables, but these are often also calculated from *h* and *w*, as is the case for body surface area [1]. A few BMR equations have been developed that use the fat-free mass (FFM), body fat (BF) and, sometimes other body composition parameters [5-8]. However, there is an enormous literature comparing the suitability of various equations to individuals varying, for example, in age, gender, ethnicity, BMI or disease state [9-13]. Consequently there are very many slightly different expressions for BMR.

Recently, we acquired data including estimates of the basal metabolic rate (BMR) and body-mass index (BMI), *h*, *w* and *y*, among other variables. There was a strong, but not perfect, correlation between BMI and BMR (Figure 1), which prompted us to examine our data more closely. The data were estimated using an Omron HBF-362 KaradaScan body composition monitor which measures *w*, is given *h* and reports BMR, BMI, body fat (BF) and skeletal muscle (SM), among other parameters. This instrument is fairly commonly used [14, 15] and other models made by the same manufacturer are also in use [16-24]. There are some reports of comparative tests that indicate that these are reasonably reliable instruments [16, 23, 25-28]. Despite all this work, it appears that the equation used by these instruments to calculate BMR or BF have not been released by the manufacturer [17], certainly none of the user manuals we have examined give any indication.

This prompted us to develop methods to (a) recover *h* and *w* from the BMR-BMI data and (b) identify the most likely BMR equation from BMR-BMI data alone.

2. Subjects and methods

The subjects were 112 students (68% female, 32% male) in the first year of the medicine, pharmacy and diploma courses at the Royal College of Medicine Perak, Universiti Kuala Lumpur (Table 2). The BMR (kcal d^{-1}) and BMI (kg m^{-2}) data we consider here were obtained

using an HBF-362 KaradaScan body composition monitor (Omron, Japan). The HBF-362 is provided with h (cm), y (years) and gender (G), and reports w (kg), body fat (%, BF), visceral fat (VF), the subcutaneous fat (%, SF) and skeletal muscle (%, SM) of the whole body (SFb and SMb, respectively), trunk (SFt and SMt, respectively), arms (SFa and SMa, respectively) and legs (SFl and SMl, respectively), and BMR, body age (A) and BMI. The equation used by this instrument to calculate BMR is not known. We used the body fat estimate (BF) and w to calculate the fat free mass

$$FFM = (1 - 0.01BF)w. \quad (2)$$

For testing purposes, other data were obtained from the literature [29-31].

All statistical analyses were performed in R [32] and dimension reduction was carried out using the package `dr` [33]. We assessed the relative success of the regressions using analysis of variance [34], log likelihood (log L) and two forms of penalised log L, the Akaike information criterion (AIC) [35] and the Bayesian information criterion (BIC) [36].

3. Theory

The general expression for BMR (1) and the body mass index

$$BMI = \frac{w}{h^2} \quad (3)$$

can be used to recover h, w and y. The approach used depends on (i) whether or not the coefficients (a, b, c, d) of (1) are known and (ii) the number of non-zero coefficients in (1).

3.1. Known coefficients (a, b, c, d)

Case 1. One parameter equations ($b = c = 0$)

Where $b = c = 0$, such as those of Owen *et al.* [5, 6] or

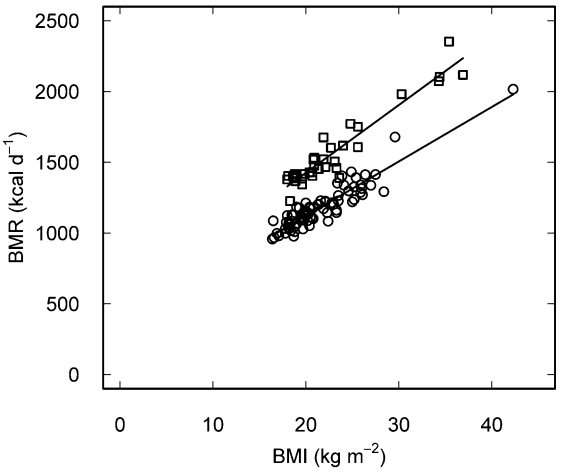

Figure 1. Correlation between BMR and BMI for males (□) and females (○). The least squares regressions are $BMR = (38.5 \pm 1.8)\ BMI + (351.3 \pm 40.4)$ ($R^2_{adj} = 0.853$, $n = 76$) and $BMR = (47.9 \pm 2.7)\ BMI + (467.6 \pm 63.1)$ ($R^2_{adj} = 0.903$, $n = 36$) for females and males, respectively.

Schofield [37] (Table 1), then (1) and (3) can be rearranged to obtain explicit estimates of

$$h = \sqrt{\frac{BMR - d}{aBMI}} \quad (4)$$

and

Table 1. Equations of the form of (1) often used to estimate BMR (kcal d^{-1}) from height (cm), weight (kg) and age (y). In each case $\beta = 1$.

Source	Gender	Coefficients			
		a	*b*	*c*	*d*
Owen *et al.* [5]	F	7.18	0	0	795
Owen *et al.* [6]	M	10.2	0	0	879
Schofield [37]	F[a]	14.818	0	0	486.6
Schofield [37]	M[a]	15.057	0	0	692.2
FAO/WHO/UNU [38]	F[a]	13.3	3.34	0	35
FAO/WHO/UNU [38]	M[a]	15.4	-0.27	0	717
Mifflin *et al.* [7]	F	9.99	6.25	-4.92	-161
Mifflin *et al.* [7]	M	9.99	6.25	-4.92	5
Harris and Benedict [43]	F	9.56	1.84	-4.67	665.09
Harris and Benedict [43]	M	13.75	5.0	-6.75	66.47

[a] Age range 18-30 years.

Table 2. Details (mean ± SD) of the measurements obtained from the subjects.

	Female (n = 76)	Male (n = 36)
Height (h) (cm)	157.7 ± 5.3	169.8 ± 5.7
Weight (w) (kg)	53.4 ± 11.5	66.5 ± 18.0
Age (y) (y)	19.6 ± 0.7	19.6 ± 0.9
Body age (A) (y)	24.9 ± 8.0	32 ± 38
Body mass index (BMI) (kg m^{-2})	21.4 ± 3.9	22.9 ± 5.2
Basal metabolic rate (BMR) (kcal d^{-1})	1178 ± 164	1565 ± 262
Body fat (BF) (%)	27.7 ± 4.7	17.8 ± 7.0
Skeletal muscle (%)		
body (SMb)	26.7 ± 1.7	35.0 ± 2.9
trunk (SMt)	22.0 ± 2.2	28.9 ± 4.1
arms (SMa)	30.1 ± 4.0	40.5 ± 2.8
legs (SMl)	38.8 ± 1.6	53.0 ± 6.1
Subcutaneous fat (%)		
body (SFb)	23.6 ± 4.6	12.7 ± 5.1
trunk (SFt)	19.7 ± 4.8	11.1 ± 5.1
arms (SFa)	40.2 ± 5.6	19.5 ± 6.3
legs (SFl)	36.2 ± 6.0	18.7 ± 6.8
Visceral fat (VF) (%)	3.1 ± 3.0	6.2 ± 5.3
Fat-free mass (FFM) (kg)	38.2 ± 5.9	53.5 ± 9.1

$$w = \frac{BMR - d}{a}, \quad (5)$$

but no estimate of y can be obtained directly.

Case 2. Two parameter equations ($c = 0$)

Where $c = 0$, such as those of WHO/FAO/UNU [38] (Table 1), (1) and (3) give explicit estimates of

$$h = \frac{-b + \sqrt{b^2 + 4aBMI(BMR - d)}}{2aBMI}, \quad (6)$$

if $d < BMR$, and

$$w = \frac{BMR - d}{a} + \frac{b}{2a}\frac{b - \sqrt{b^2 + 4aBMI(BMR - d)}}{aBMI}, \quad (7)$$

but no estimate of y can be obtained directly. Equations (6) and (7) reduce to (4) and (5), respectively, if $b = 0$.

Case 3. Three parameter equations

For the three parameter equations, more information is required to recover *y* as well as *h* and *w*. It is clear from Table 1 that the contribution of *y* to the estimated BMR is smaller (for $y = 30$, $cy \approx -150$ kcal d^{-1}) than those of *w* and *h* ($aw \approx 900$ kcal d^{-1} and $bh \approx 1100$ kcal d^{-1}, respectively). Moreover, *y* is reported as an integer and, even if a range is not known, the range is constrained. Therefore a small number of calculations using a range of *y* can provide relatively reliable estimates of *y* or, at least, an indication that the estimate is not reliable.

As *h* and *w* are usually reported to the nearest n_h and n_w decimal places, respectively, the estimates calculated from BMI and BMR tend to reflect this. For example, *h* is usually reported to 1 mm or 0.001 m ($n_h = 3$) and *w* is generally reported to 0.1 kg ($n_w = 1$). Estimates of *h* and *w* derived from BMI and BMR should be identical (or at least close) to the original values and should retain the same number of significant figures (generally 4 and 3 for *h* and *w*, respectively, for the examples given). Any decimal places in excess of n_h or n_w indicate error in the estimate. They can be recovered (neglecting their order of magnitude for reasons that will become apparent) from estimates of *h* or *w* (denoted by *x*) using

$$f(x;n_x) = 10^{n_x} x - \lfloor 10^{n_x} x \rfloor, \qquad (8)$$

where $\lfloor s \rfloor$ denotes the largest integer smaller than *s*. Ideally, for a correct estimate $f(x;n_x) = 0$, but allowing for some small error (ε), a value of *x* for which $f(x;n_x) < \varepsilon$ may be correct and the value of *x* for which $f(x;n_x)$ is closest to zero is most likely to be correct.

For a given value of *y*, estimates of *h* and *w* can be obtained from (6) and (7) rewritten as

$$h(y) = \frac{-b + \sqrt{b^2 + 4aBMI\,(BMR - cy - d)}}{2aBMI}, \qquad (9)$$

if $cy + d < BMR$, and

$$w(y) = \frac{BMR - cy - d}{a} + \frac{b}{2a}\frac{b - \sqrt{b^2 + 4aBMI\,(BMR - cy - d)}}{aBMI} \qquad (10)$$

to make the contribution of *y* explicit. Based on the argument surrounding (8), an empirical strategy for estimating *y* in the absence of any other information is to calculate *h* (9) and *w* (10) for a range of *y* determined by the anticipated age range of the subjects and selecting the 'best' *y* on the basis of (8). The age (*y*) of a particular subject is estimated using

$$y = \{\, i : \min(f(h(i);n_h) < \varepsilon,\ f(w(i);n_w) < \varepsilon) \} \qquad (11)$$

where $i = y_{\min}, y_{\min} + 1, \ldots, y_{\max}$. In practice there are four possible outcomes:

(i) the minima of $f(h;n_h) < \varepsilon$ and $f(w;n_w) < \varepsilon$ occur at the same value of *y* in which case there is no ambiguity concerning the identification of *y*;

(ii) the minima of $f(h;n_h) < \varepsilon$ and $f(w;n_w) < \varepsilon$ occur at different values of *y* in which case the *y* giving the smallest minimum is selected;

(iii) the minimum of either $f(h;n_h)$ or $f(w;n_w)$ is less than ε, but the other $f(\cdot) > \varepsilon$, whether or not the minima occur at the same *y*, the *y* giving the former minimum is selected; and

(iv) the minima of $f(h;n_h)$ and $f(w;n_w)$ are each greater than ε, which indicates that it is not possible to estimate *y*.

Based on simulations (1 million combinations of *h*, *w* and *y*) carried out in R [32], the wrong age is estimated from (11) in about 0.7% of cases, similar to the error rate observed using the real data of Retzlaff *et al.* [30] and Harris and Benedict [31]. However, taking $\varepsilon = 10^{-5}$ in (11), it is possible to identify more than 96% of those errors. Based on these simulations, the rate of undetected errors in the estimation of *y* is about 0.03%. In summary, (11) yields a correct estimate of *y* in about 99% of cases, and, a failure of (11) to yield the correct *y* is detected in about 96% of cases of error. While (11) is just an empirical numerical approach to the problem of estimating *y*, it is satisfactory.

3.2. Unknown coefficients

In the case where the coefficients (*a*, *b*, *c*, *d*) are unknown, *h*, *w* and *y* may or may not be available. If *w*, *h* and *y* are not known, it is not possible to recover the coefficients. If *h*, *w* and *y* are known, then it is a simple matter to determine the coefficients (*a*, *b*, *c*, *d*) from the data. In principle, the data for four subjects ($i = 1, 2, 3, 4$) of the same gender and, ideally, in a single standard age range in case the coefficients are defined for different age ranges, can be used to write

$$\mathbf{B} = \begin{pmatrix} BMI_1 \\ BMI_2 \\ BMI_3 \\ BMI_4 \end{pmatrix} = \begin{pmatrix} w_1 & h_1 & y_1 & 1 \\ w_2 & h_2 & y_2 & 1 \\ w_3 & h_3 & y_3 & 1 \\ w_4 & h_4 & y_4 & 1 \end{pmatrix} \begin{pmatrix} a \\ b \\ c \\ d \end{pmatrix} = \mathbf{PC}, \qquad (12)$$

which is just the equivalent of (1) with $\beta = 1$. The coefficient vector (**C**) is just

$$\mathbf{C} = \mathbf{P}^{-1}\mathbf{B} = \mathbf{P}^{-1}\mathbf{PC}, \qquad (13)$$

which might have to be determined for each age range and both genders. However, if there are errors in data reporting or recording then different sets of four subjects may yield different estimates of **C.** The least squares solution to this problem is to use all of the data for a particular gender and age range ($i = 1, 2, \ldots, n$), replacing $\mathbf{P}_{4\times 4}$ written above with $\mathbf{P}_{n\times 4}$ in which case the least squares estimate of **C** becomes

$$\mathbf{C} = (\mathbf{P}^T\mathbf{P})^{-1}\mathbf{P}^T\mathbf{B}, \qquad (14)$$

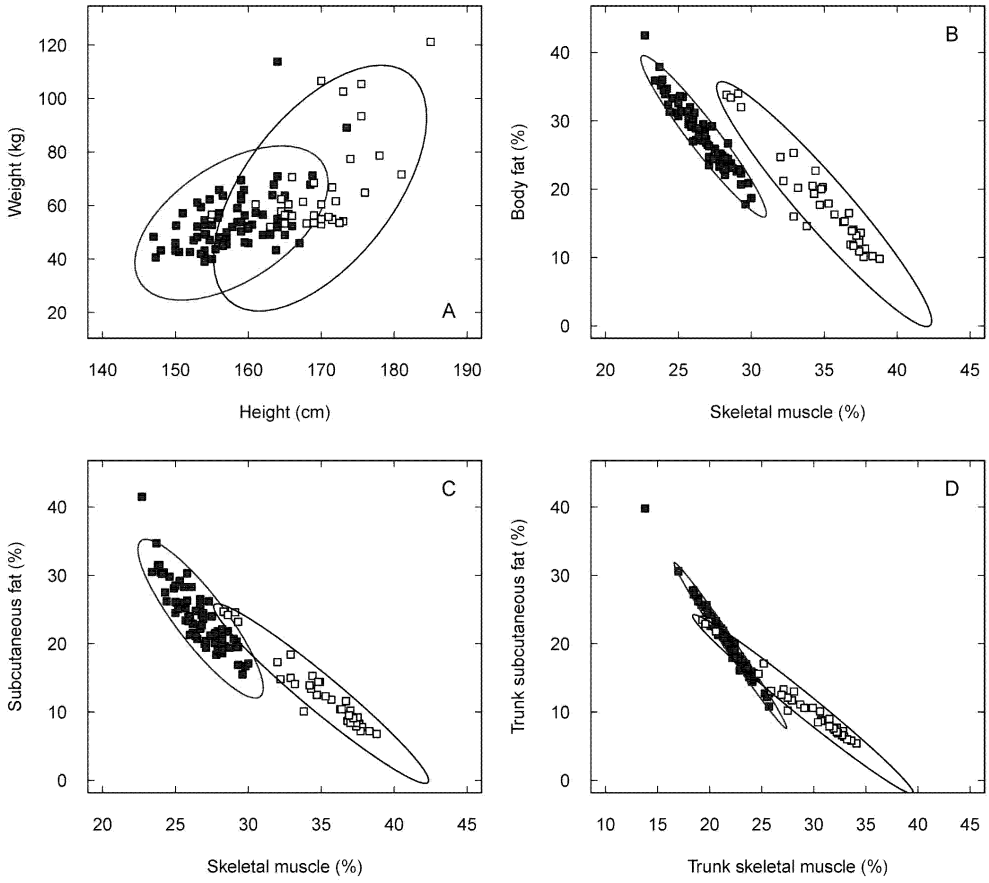

Figure 2. Correlations between and 95% confidence ellipses of the data reported by the HBF-362 for the males (□) and females (■) detailed in Table 2.

which is complicated slightly because the inverse of **P** in (13) is replaced with its pseudo-inverse. This is conveniently implemented in the multiple regression routines of standard statistical packages.

4. Application

4.1. Possible BMR equations used in the Omron HBF-362

While the foregoing has been framed in terms of *h*, *w*, and *y*, other parameters could be used in the estimation of BMR. For example, one of the common results of impedance measurements is an estimate of body fat, from which (with *w*) the fat-free mass (FFM) can be calculated (2), although FFM is often estimated using the resistance obtained from impedance measurements as well as *h* and *w*, for example [39-41]. As we have pointed out, the BMR expression used by the HBF-362 is unknown, but it does estimate body composition by impedance and it is possible that these data may be used. The approach described here can be used to obtain some indication of those expressions that are most likely.

Recall that the HBF-362 is provided with *h*, *y* and gender (*G*), and reports *w*, *BF*, visceral fat (*VF*), the subcutaneous fat (*SF*) and skeletal muscle of the whole body (*SFb* and *SMb*, respectively), trunk (*SFt* and *SMt*, respectively), arms (*SFa* and *SMa*, respectively) and legs (*SFl* and *SMl*, respectively), and *BMR*, body age (*A*) and *BMI*. Given all of these variables, it is possible (if unlikely) that the statistical model could be written [42]

$$BMR \sim \begin{pmatrix} w + BF + VF + SFb + SMb + SFt + \\ SMt + SFa + SMa + SFl + SMl + \\ A + BMI + FFM + h + y + G \end{pmatrix}, \quad (15)$$

in which case **P** would be a 17 × 17 matrix, even without considering possible interactions. Of course, such a problem exhibits multi-collinearity because some variables are estimated from others (such as BMI (3) and FFM (2)), some are likely to be based on common sets of (unreported) impedance measurements and some correlations are inevitable (Figure 2). An objective means of dimension reduction is required.

Dimension reduction was carried out in R [32] using the implementation of the sliced average variance estimation (SAVE) algorithm in the package `dr` [33]. For comparison we also applied the sliced inverse regression (SIR) algorithm from which similar results were obtained. The dimension tests indicated that $d = 4$ ($p = 4.2 \times 10^{-5}$) or maybe 5 ($p = 0.1012$) and the conservative application of the algorithms resulted in the identification for females of two possible constrained statistical models

$$BMR \sim w + BF + SFb + SMt + BMI + FFM \quad (16)$$

and

$$BMR \sim BF + SFb + SFl + BMI \quad (17)$$

($p < 0.0471$ and $p < 0.0412$, respectively) and one unconstrained possibility

$$BMR \sim BF + SFb + SFl \quad (18)$$

($p < 0.0492$). These models are significantly simpler than (15) and have some common factors, so they were examined in more detail and, for comparison, we also considered models of the form of (1) taking $\beta = 1$ (Table 3). Deletion of *BMI* and *SMt* from (16) did not appreciably reduce the quality of the regression (Table 3). and, obviously, the contribution of *FFM* to (16) is mathematically equivalent to a *w*BF* term (2) . This prompted consideration of the more general model

$$BMR \sim w * BF * SFb - w : BF : SFb\,, \quad (19)$$

which is a significant improvement on the other models (Table 3), but is much more complex and less amenable to the recovery of the variables.

Despite the values of R^2_{adj} it is clear from Tables 4 and 5 that expressions of the forms of (1) or (16-19) are not those used by the HBF-362. Had the correct combination of variables been identified, and assuming no significant error in recording the data, then the error estimates of each of the regression coefficients would have been much smaller than they are. In simulations using published data [29-31] and specific expressions for BMR the error estimates were of the order of 10^{-14} when the correct combination of variables was employed. Given that we started with 17 variables (15), it seems likely that it is the underlying impedance data, to which we have no direct access, that are missing.

4.2. Limitations

We have shown that it is possible to recover data from measurements of BMI and BMR. However, this is much more reliable if the coefficients of the BMR model are known. Irrespective of this, it is not possible if all of the data are not available. Consequently, the main limitation of instruments such as the HBF-362 is that some of the data stored in the microprocessor are not available to the user. Not only does that impede efforts to recover the data, but it makes it difficult to detect some errors in the instrument. No matter how much reliability testing is done [16, 23, 25-28], manufacturers should be encouraged to provide researchers (and other users) with better access to the data stored in the microprocessor and explicit information about the calculations performed by the instrument.

5. Conclusions

It is possible to recover data from measurements of BMI and BMR without difficulty, even if the coefficients are not known, provided that (i) sufficient data are available that include the relevant variables and (ii) the BMR model does not rely on too many variables. If the coefficients are known, the underlying data can be recovered.

Table 3. Some possible approximations of the expression for BMR used by the Omron HBF-362 assessed using the data obtained from 76 females (Table 2). For each model, except $BMR \sim 1$, $p < 2.2 \times 10^{-16}$.

BMR ~	RSS	AIC	BIC	log *L*	F
w + BF + SFb + FFM + SMt + BMI	72.0	227.6	246.3	-105.8	3.2×10^5
w + BF + SFb + FFM + SMt	77.8	231.5	247.8	-108.7	3.6×10^5
*w + BF + SFb + FFM ≡ w*BF + SFb*	84.4	235.7	249.7	-111.8	4.2×10^5
*w*BF*SFb – w:BF:SFb*	55.7	208.0	226.7	-96.0	4.2×10^3
BF + SFb + SFl + BMI	238559	839.6	853.6	-413.8	1.3×10^2
BF + SFb + SFl	277380	849.1	860.7	-419.5	1.5×10^2
w + h + y	8364	582.9	594.6	-286.5	8.6×10^3
w + h	8550	582.6	591.9	-287.3	7.4×10^3
w	13680	616.3	623.3	-305.2	1.1×10^4
1	2023967	994.1	998.8	-495.0	

Table 4. Details of the regressions based on (16), (17), (18) and (19).

BMR ~	Female (n = 76)	Male (n = 35)	Female and male (n = 111)
w + BF + SFb + FFM			
intercept	323 ± 3	401 ± 10	389 ± 23
β_w	10.6 ± 0.1	11.1 ± 0.4	10.1 ± 0.8
β_{BF}	1.0 ± 0.2	20.6 ± 0.7	4.1 ± 0.9
β_{SFb}	-1.6 ± 0.2	-31.0 ± 0.8	-5.6 ± 0.9
β_{FFM}	7.8 ± 0.2	8.4 ± 0.5	9 ± 1
β_{Gender}	—	—	-91 ± 7
R^2_{adj}	0.9999	0.9998	0.9983
BF + SFb + SFl			
intercept	600 ± 66	1273 ± 53	1269 ± 40
β_{BF}	-53 ± 7	-11 ± 16	7 ± 6
β_{SFb}	53 ± 11	229 ± 35	120 ± 13
β_{SFl}	22 ± 12	-129 ± 16	-73 ± 12
β_{Gender}	—	—	-500 ± 56
R^2_{adj}	0.8572	0.8944	0.8710
*w*BF*SFb – w:BF:SFb*			
intercept	305 ± 4	375 ± 6	366 ± 24
β_w	19.0 ± 0.2	20.2 ± 0.2	20.0 ± 0.4
β_{BF}	3.8 ± 0.5	49 ± 4	7 ± 2
β_{SFb}	-4.7 ± 0.7	-70 ± 6	-12 ± 2
$\beta_{w:BF}$	-0.14 ± 0.01	-0.62 ± 0.08	-0.15 ± 0.03
$\beta_{w:SFb}$	0.050 ± 0.009	0.7 ± 0.1	0.03 ± 0.03
$\beta_{BF:SFb}$	0.02 ± 0.01	0.10 ± 0.03	0.09 ± 0.03
β_{Gender}	—	—	-71 ± 8
R^2_{adj}	1.0	0.9999	0.9986

Table 5. Details of the regressions based on (1), with $\beta = 1$, and its derivatives.

BMR ~	Female (n = 76)	Male (n = 35)	Female and male (n = 111)
w + h + y			
intercept	191 ± 49	325 ± 242	362 ± 78
β_w	13.7 ± 0.1	14.1 ± 0.4	13.9 ± 0.2
β_h	1.9 ± 0.3	2 ± 1	1.8 ± 0.4
β_y	-2 ± 2	0 ± 6	-2 ± 2
β_{Gender}	—	—	-184 ± 6
R^2_{adj}	0.9957	0.9856	0.9948
w + h			
intercept	156 ± 40	302 ± 180	332 ± 64
β_w	13.7 ± 0.1	14.1 ± 0.4	13.9 ± 0.1
β_h	1.8 ± 0.3	2 ± 1	1.8 ± 0.4
β_{Gender}	—	—	-183 ± 6
R^2_{adj}	0.9956	0.9861	0.9948
w			
intercept	420 ± 7	602 ± 21	612 ± 10
β_w	14.2 ± 0.1	14.5 ± 0.3	14.3 ± 0.1
β_{Gender}	—	—	-200 ± 5
R^2_{adj}	0.9931	0.9853	0.9939

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