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Predicting the Basal Metabolic Rate in Adolescents: A Correlated (Re)-Analysis

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Abstract A basal metabolic rate(BMR) that is too low is an indicator of a poor physical condition, and could be one of the reasons for overweight. Measuring BMR though, is a time-consuming exercise, and there has long been interest in developing statistical models to predict BMR from demographic and anthropometric measurements. Poh *et al.* [1] developed ordinary linear regression models on a cohort of 139 Malaysian children measured three years bi-annually. However, since each child contributed six times to the total data set, these models ignore the correlated nature of the data. We re-analyzed these data using correlated linear models. We show that our approach taking correlation into account is important to establish important covariates, but does not improve prediction.

Keywords Basal metabolic rate; correlated data linear model; linear mixed model

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1 Introduction

Basal metabolic rate (BMR) refers to the minimum amount of energy required to sustain vital functions such as breathing, digestion and circulation when completely at rest. BMR usually accounts for 50 to 80 per cent of the total energy use and can thus be used to estimate the energy requirements of a subject. BMR is highly variable between individuals. Having an accurate picture of a subject's BMR could be useful in a dietary program to see amount of calories involved to loose or gain weight. During the early part of the 20th century, BMR measurements were used as metabolic reference in clinical nutrition, notably in the diagnosis of hypo- and hyperthyroidism, diabetes and leukaemia [2].

Measuring BMR is, however, time consuming and requires special equipment [3]. As early as 1915, Benedict [4] initiated research on factors affecting basal metabolism and in 1918, after a monumental effort, Harris and Benedict [5] developed the first linear model predicting BMR measurements from healthy subjects (136 men and 103 women) and based on height, weight and age. In 1985, Schofield [6] reviewed 114 published studies of BMR involving of 7173 data points and developed linear models to predict BMR from weight in twelve strata (age groups 0-3, 3-10, 10-18, 18-30, 30-60, >60 years for males and females). These models have been adopted in the FAO/WHO/UNU[1] [7] report for general use in predicting BMR. However most of the BMR values were obtained from European and North American subjects. Later, Henry [8] developed new predictive equations for estimating BMR among tropical people.

Although, Harris-Benedict formula and Schofield's equation are commonly used to calculate BMR, they have been criticized in that they ignore important factors such as lean body mass [9], fat mass or fat-free mass [10–12]. Hence, the classical equations do not take into account that lean bodies need less calories than others. These equations therefore underestimate caloric needs for the more muscular bodies and will overestimate caloric needs for the overweight subjects [13,14]. In 2005, Henry [15] re-assessed FAO/WHO/UNU equations and developed a database for BMR known as Oxford database and computed new BMR equations (Oxford equations). Prediction models have also been developed for specific target groups, such as children and adolescents [16–18], obese children [11,14,19,20], adults [9,21–25] and obese adults [11]. For Malaysian children, Poh *et al.* [1] developed various linear regression models which include lean body mass as predictor based on a cohort of 139 children measured three years bi-annually.

Poh *et al.* [1], however, ignored the clustered nature of the longitudinal measurements within each subject. In this paper, we show the impact of ignoring this correlation and develop prediction models that explicitly take the correlated nature of the data into account. To this end we make use of correlated linear models. We show in this paper that taking this correlation into account is important to establish important covariates, but does not improve prediction. More specifically, we show that the model of Poh *et al.* [1] underestimates the standard error of the regression coefficients. To support our findings we performed a limited simulation study wherein we assessed the impact of ignoring correlation on the predictive ability of a model.

2 Methodology

2.1 Subjects and Measurements

A cohort of 139 Malaysian children aging between 10 and 13 years was enrolled into a study designed to determine the relationship of basal metabolic rate and growth. These children were pupils of a primary school in Bandar Baru Bangi, Selangor. Only healthy children (without chronic disease at recruitment) were included in the study with a body weight and height that was in the normal range according to the National Center for Health Statistics (NCHS) growth standards [26]. In total, 295 boys and 282 girls were screened but parental approval was obtained for only 70 boys and 69 girls. Informed consent was obtained for all these children from their parents. All children were measured longitudinally at 6 months-intervals for 3 years.

The BMR of the children was measured using a canopy ventilated system with the

[1]Abbreviation: FAO/WHO/UNU-Food & Agriculture Organization, World Health Organization and United Nations University

children in a post-absorptive state, lying still and relaxed, and rested for minimum of 30 minutes. BMR was expressed as kilojoule per 24 hours. The body weight was measured using a standard weighing scale in kilograms whereas height was measured in a standing position in centimeters. The lean body mass was measured as the difference between the weight and the body fat in kilograms. More details on the procedures measuring BMR, body weight, height and lean body mass can be found elsewhere [27]. It then becomes clear that determining BMR is laborious and that it would pay off to have a substitute for physically establishing BMR.

2.2 Statistical Analysis

Descriptive statistics were computed to describe the characteristics of the children at each observation time, i.e. means and standard deviation for measurements that follow (approximately) a Gaussian distribution and median and interquartile range (25%-ile, 75%-ile) for measurements with a skewed distribution. At each observation time a Student's T-test or a Wilcoxon test compares the boys and girls for Gaussian and skewed distributed measurements, respectively. Graphical output further illustrates the findings.

To predict BMR from gender, age, weight, height and lean body mass, two approaches were considered. The first approach consists of multiple linear regression models at each observation time. Hence the following models were considered:

$$Y_{ij} = \beta_{0j} + \beta_{1j}x_{i1j} + \cdots + \beta_{pj}x_{ipj} + \varepsilon_{ij}, \tag{1}$$

whereby x_{ikj} represents the kth predictor value ($k = 1, \ldots, p$) of the ith child ($i = 1, \ldots, 139$) at the jth ($j = 1, \ldots, 6$) observation time, β_{kj} ($k = 0, \ldots, p$) represents the intercept and the genuine regression coefficients, Y_{ij} represents the observed value of BMR and ε_{ij} is the measurement error of the ith child at the jth observation time. It is assumed here that $\varepsilon_{ij} \sim N(0, \sigma^2)$. Estimation of the regression coefficients is done using the ordinary least-squares (OLS) approach with the SAS® procedure REG.

The above approach, however, does not exploit the link between the six BMR measurements of a same subject. Poh *et al.* [1] regressed all BMR measurements (of the six observation times) on the above indicated regressors into one multiple linear regression, but ignored the correlated nature of measurements taken from the same child. To illustrate the correlation between repeated BMR measurements we computed the intraclass correlation (ICC) as in [28] by calculating the proportion of between-children variance (the sum of between and within children variance of BMR) to the total variance i.e ICC=$\sigma^2_{between}/\sigma^2_{total}$. We also computed the ICC for boys and girls data, separately.

In this paper, we took the correlation into account by fitting the multivariate multiple linear regression model:

$$Y_{ij} = \beta_0 + \beta_1 x_{i1j} + \ldots + \beta_p x_{ipj} + \varepsilon_{ij}, \quad j = 1, \ldots, 6, \tag{2}$$

where the index i runs over the children. Model (2) assumes that the regression coefficients β_k are the same for the six observation times. The multivariate model arises by assuming that $\boldsymbol{\varepsilon}_i = (\varepsilon_{i1}, \ldots, \varepsilon_{i6})^T$ has a multivariate normal distribution with mean zero and covariance matrix Σ. Estimation was done using a maximum likelihood (ML) or restricted maximum likelihood (REML) approach, whichever was appropriate, each time with the SAS® procedure MIXED. Note that, since estimation is done via (RE)ML, this approach allows for missing BMR measurements. Various models (2) were fitted to the data, checking the difference between boys and girls and the impact of age. In addition, we tested the appropriate expression of the covariance matrix Σ by dedicated likelihood ratio tests [29].

For all regression procedures, SAS/STAT® version 9.2 was used. The predictive ability of the models was validated using a 10^{th} fold cross validation [30]. That is, we split the dataset into 10 sets. Then, we built the model based on 90% of the data and tested the predictive ability of the model on the remaining 10% of the data. This process was repeated for ten times.

2.3 Simulation Study

In the simulation study, we considered five scenarios. In first scenario (A) we set the sample size to 30, and used the estimated parameters from the actual data set as the fixed value for the regression coefficients and covariance matrix. For scenarios B and C, we increased the sample size to 100 and 2000, respectively. For scenarios D and E, the sample size was taken equal to 100 but we varied the correlations. For each scenario, we generated 100 simulations. These scenarios were applied to boys and girls separately.

3 Results

3.1 Descriptive Analysis

Children were measured at baseline and at five 6 month-intervals afterwards. Table 1 shows the number of children at each observation time by gender. As can be seen from the table, 34 children dropped from the study at the end of the examination period. The reasons for dropping out have no relationship to the BMR measurements. Indeed, the primary reason for discontinuation was either that the child moved to a new school as the family migrated to another state or the children were enrolled in a secondary boarding school in a different state. Thus the missing data mechanism can be safely assumed to be missing completely at random ([31]). This justifies the use of OLS and (RE)ML estimation techniques.

Table 1: Number of the children at each observation time

	Boys	**Girls**
Baseline	70	69
Time 1	63	66
Time 2	60	56
Time 3	57	54
Time 4	56	55
Time 5	54	53

Table 2 shows the descriptive statistics of BMR, and the regressors to be used in the regression models. Statistical comparisons between the gender classes show significant differences for age, basal metabolic rate and lean body mass at each observation time.

The distribution of BMR follows approximately a Gaussian distribution at each of the observation times. Further, the BMR measurements correlated highly within children, see Figure 1. The correlations and standard deviations are also given in Figure 1. Pooled over the observation times, Figure 2 illustrates that BMR increases with age for boys and girls, but also that the slopes differ between the two gender classes. BMR also increases with weight, height and lean body mass for boys and girls.

Although the intraclass correlation (ICC) coefficient of 0.63 shows that the data are moderately correlated within each children, it suggests also that ignoring the correlated structure will underestimate the standard error of the parameters. The girls' data have a higher ICC (0.66) compared to the boys' data (0.52) and hence the girls' BMR measurements are more closely related in time than those of the boys.

Table 2: Characteristics of the Children at Each Observation Time

		Boys	**Girls**	**P-value**
Basal metabolic rate (kJ/day)*	**Baseline**	4971.04(649.17)	4610.29(563.40)	0.001
	Time 1	5140.84(715.72)	4751.62(617.54)	0.001
	Time 2	5452.33(684.01)	5108.27(561.29)	0.004
	Time 3	5592.98(660.26)	4965.94(590.24)	< 0.001
	Time 4	5786.34(627.16)	5014.13(493.43)	< 0.001
	Time 5	5918.11(734.47)	4947.40(529.29)	< 0.001
Age (years)*	**Baseline**	11.73(0.39)	10.93(0.34)	< 0.001
	Time 1	12.05(0.39)	11.25(0.34)	< 0.001
	Time 2	12.68(0.42)	11.90(0.33)	< 0.001
	Time 3	13.36(0.43)	12.55(0.36)	< 0.001
	Time 4	13.74(0.42)	12.93(0.36)	< 0.001
	Time 5	14.32(0.43)	13.50(0.37)	< 0.001
Weight (kg)*	**Baseline**	33.18(5.42)	32.51(5.56)	0.477
	Time 1	35.14(6.33)	34.44(6.06)	0.523
	Time 2	37.79(6.44)	38.49(6.53)	0.563
	Time 3	40.78(6.84)	41.24(6.88)	0.722
	Time 4	43.28(6.87)	43.43(6.73)	0.911
	Time 5	45.65(7.31)	44.27(6.75)	0.312
Height (cm)*	**Baseline**	140.75(5.90)	139.96(5.19)	0.406
	Time 1	143.39(6.46)	142.48(5.11)	0.375
	Time 2	148.00(6.56)	147.15(5.21)	0.444
	Time 3	153.45(6.65)	150.68(4.91)	0.014
	Time 4	156.24(6.25)	152.35(4.89)	< 0.001
	Time 5	159.81(6.21)	153.58(4.74)	< 0.001
Lean body mass (kg)‡	**Baseline**	26.27(5.22)	24.63(5.22)	0.004
	Time 1	27.69(5.62)	26.16(5.52)	0.006
	Time 2	29.86(5.77)	29.09(6.35)	0.050
	Time 3	33.11(6.61)	31.16(5.32)	0.002
	Time 4	35.16(6.74)	31.77(4.81)	< 0.001
	Time 5	37.29(7.01)	32.35(4.10)	< 0.001

*:Values are given as means and standard deviations
Student's T-test used for comparing boys and girls.
‡: Values are given as median and inter-quartile range.
Wilcoxon test used for comparing boys and girls.

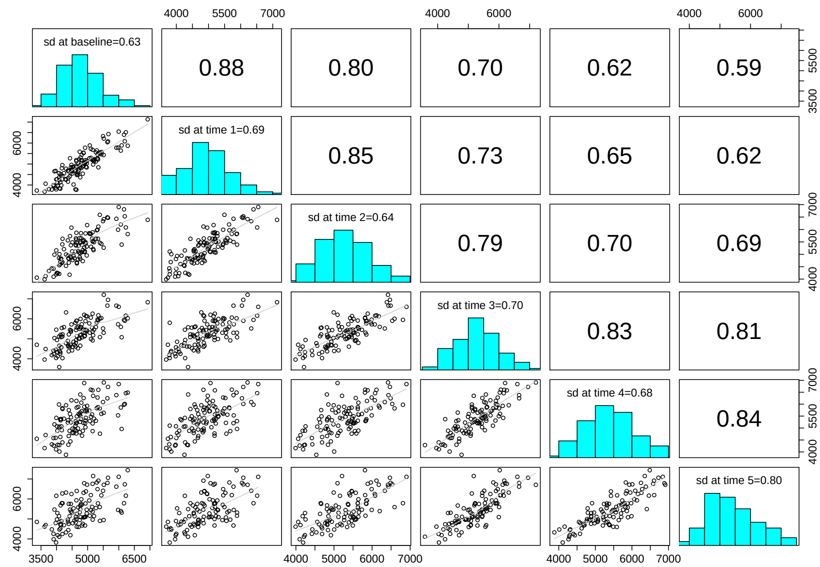

Figure 1: Distribution and Relationship of Basal Metabolic Rates as Per 1000 Kilojoule Per Day at Each Observation Time (Note: SD = Standard Deviation)

3.2 Multiple Linear Regression Models at Each Observation Time

The effect of gender (boys), age, weight, height and lean body mass on BMR obtained from a multiple linear regression model at each observation time is shown in Table 3. The explained variation for the regression models varies around 0.70, as indicated by the cross-validated R^2, suggesting that these models have high predictive power in explaining the basal metabolic rate from the considered regressors. However, the impact of the different regressors appears to vary considerably over the observation times. Note the negative regression coefficient of age which could be interpreted as 'when the child grows older the BMR decreases on average'. However, with increasing age also weight and height increase and with positive regression coefficients such that there is an average increase of BMR with increasing age.

3.3 Correlated Linear Models

We evaluated the performance of various models predicting BMR from the above indicated regressors from all measurements based on model (2). The following models were considered:

- Model A: basic model with regressors gender (boys), age, weight, height and lean body mass;
- Model B: model A augmented with interaction terms with gender, with the interaction terms selected by significance testing;

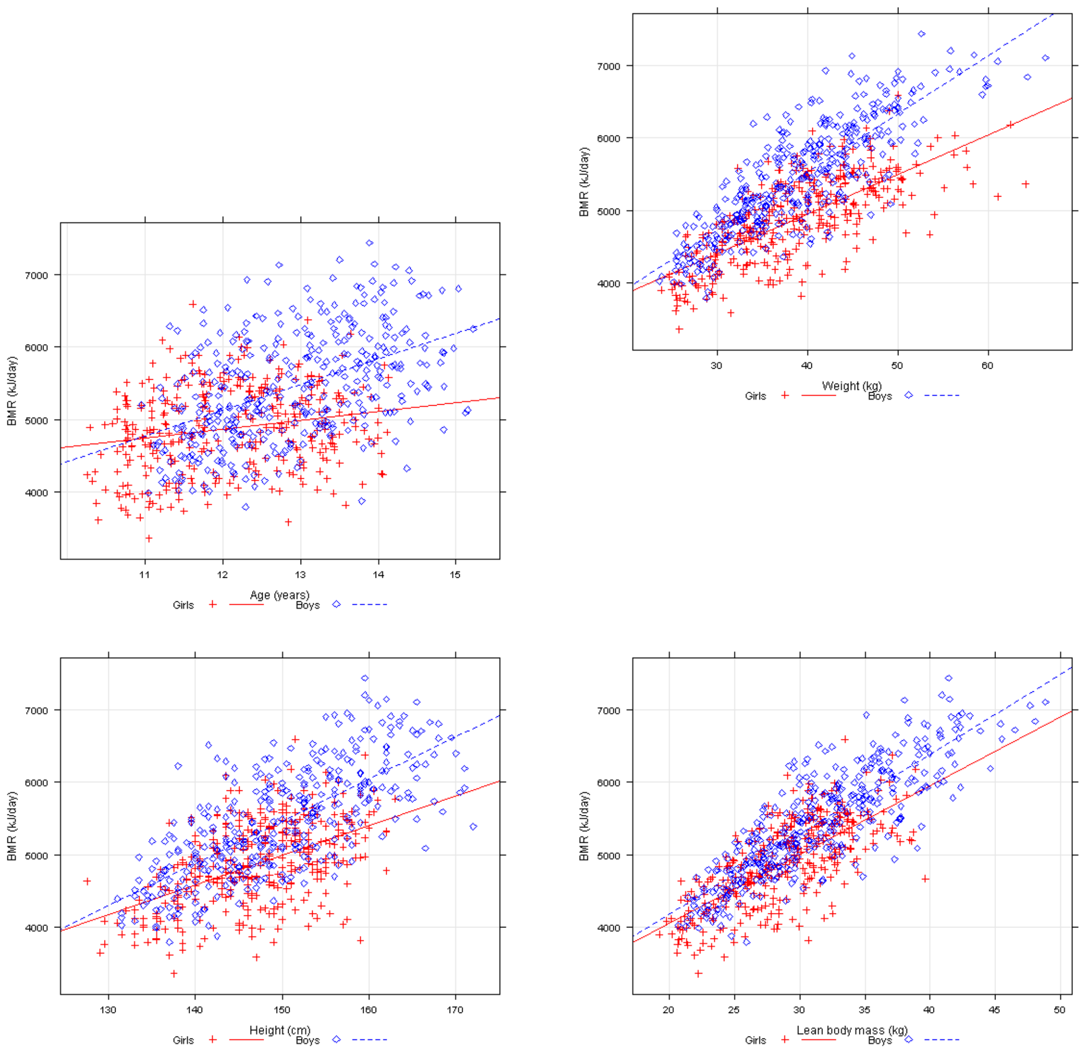

Figure 2: Basal Metabolic Rate (BMR, kJ/day) as a Function of Age (Years), Weight(kg), height(cm) and Lean Body Mass(kg) in Boys and Girls

Table 3: Multiple Linear Regression of Basal Metabolic Rate at Each Observation Time

Model		Intercept β_0	Gender(Boys) β_1	Age β_2	Weight β_3	Height β_4	Lean body mass β_5	R^2
Baseline	Estimates	0.501	-0.081	0.039	0.015	-0.0004	0.135^{**}	0.71
	SE	1.142	0.092	0.078	0.015	0.008	0.029	
Time=1	Estimates	-0.211	-0.074	0.071	0.021	0.004	0.113^{**}	0.74
	SE	1.396	0.109	0.092	0.015	0.009	0.031	
Time=2	Estimates	0.250	-0.205	-0.016	0.023	0.014	0.082^{*}	0.72
	SE	1.355	0.106	0.086	0.014	0.009	0.027	
Time=3	Estimates	2.193	-0.508^{**}	-0.060	0.037^{*}	0.004	0.063^{*}	0.73
	SE	1.478	0.113	0.088	0.013	0.009	0.026	
Time=4	Estimates	1.560	-0.601^{**}	0.033	0.037^{*}	0.006	0.036	0.65
	SE	1.730	0.127	0.097	0.014	0.009	0.026	
Time=5	Estimates	4.249	-0.609^{**}	-0.214^{*}	0.012	0.004	0.095^{**}	0.73
	SE	1.943	0.149	0.103	0.014	0.010	0.027	

SE: estimated standard error
$*$: significant at 0.05
$**$: significant at 0.001
Note: BMR expressed as per 1000 kilojoule per day

- Model C: model A but with a non-linear effect of age in the model;
- Final model.

Model A and a specific type of model C was also considered by [1], but fitted using OLS. For all models, we checked whether a structured (in other words simplified) covariance matrix Σ could be assumed, but in all cases a simplication of the covariance matrix was not supported by the data.

Model A

Table 4 shows the estimated regression coefficients for predicting BMR. Residual diagnostics indicate no major deviation of the assumed model. The model shows again a high predictive ability, i.e. R^2=0.702 (10-fold cross-validation).

Model B

The effect of gender was tested on the model (2). A likelihood ratio test showed that there was significant interaction term of gender with weight. the estimated model is shown in Table 5. This model has 10-fold cross-validation R^2 of 0.704.

Model C

Inspired by the analysis done in [1], we included age on a categorical scale (into five age classes). The aim of this analysis is to see if age has a non linear effect on BMR. Now the model has a 10-fold cross-validated R^2 equal to 0.699. However, since the effect of age on BMR appear to be linear, we discarded model C.

Table 4: BMR as a Function of Age on a Continuous Scale Together with the Impact of Gender, Weight, Height and Lean Body Mass

Effect	Parameter	Estimates	SE
Intercept	β_0	1.856	0.500
Age (years)	β_1	-0.202	0.028
Gender(Boys)	β_2	0.461	0.056
Weight (kg)	β_3	0.030	0.008
Height (cm)	β_4	0.016	0.005
Lean body mass (kg)	β_5	0.067	0.015

SE: estimated standard error

All regression coefficients are significant at 0.001

Table 5: BMR as a Function of Age on a Continuous Scale Together with the Impact of Gender, Weight, Height, Lean Body Mass and Interaction with Gender

Effect	Parameter	Estimates	SE
Intercept	β_0	2.118^{**}	0.499
Age (years)	β_1	-0.191^{**}	0.027
Gender(Boys)	β_2	-0.104	0.194
Weight (kg)	β_3	0.032^{**}	0.008
Height (cm)	β_4	0.017^{*}	0.005
Lean body mass (kg)	β_5	0.050^{*}	0.016
Weight*gender	β_6	0.016^{*}	0.005

$*$: significant at 0.05

$**$: significant at 0.001

Final Model

Model B has a better predictive ability than model A and the effect of gender in the interaction term with weight was significant. In addition, significance tests revealed that no other regressors should be transformed or interaction term should be added. Therefore, we chose model B as our final model.

3.4 Comparing Our Analysis to Those of Poh *et al.* [1]

In Table 6, we evaluated the performance of the regression models predicting BMR for boys and girls separately, which were obtained by Poh et al. [1] using OLS. However, we recomputed the regression model and evaluated its predictive ability with a 10-fold cross-validated R^2. We compared these fitted models to the corresponding ones allowing for correlated responses. The following conclusions can be made:

- the correlation among the responses cannot be ignored, as shown by significantly higher maximized likelihoods with the correlation models;
- R^2 is slightly greater when correlation is taken into account, but the difference is not important;
- the regression coefficients for both analysis are similar;
- the standard errors for the correlation models are greater than those obtained under independence, indicating that they are underestimated under independence.

We compared Poh *et al.*'s model in Table 6 with our final model.

Table 6: BMR Predictive Models Estimated using OLS Ignoring Correlation and with the Correlated Linear Model

Model		**Intercept** β_0	**Age** β_1	**Weight** β_2	**Height** β_3	R^2	**-2LL**
Boys							
Independent	Estimates	**1.168**	**-0.120**	**0.070**	**0.021**	0.702	399.1
(Poh et al., 1999)	SE	0.446	0.033	0.005	0.005		
Correlated	Estimates	0.570	**-0.130**	**0.067**	**0.026**	0.703	288.6
	SE	0.544	0.043	0.006	0.006		
Girls							
Independent	Estimates	**2.353**	**-0.199**	**0.056**	**0.019**	0.573	342.9
(Poh et al., 1999)	SE	0.472	0.028	0.003	0.004		
Correlated	Estimates	**1.531**	**-0.235**	**0.056**	**0.028**	0.574	191.2
	SE	0.634	0.037	0.005	0.006		

SE: estimated standard error

Bold: significant at 0.001

3.5 Simulation Study

We have conducted a simulation study to investigate the impact of ignoring the correlated structure of the data on estimation and prediction. The same configurations as those in section 3.4 were used. In Table 7, we report the results of the average of estimated R^2. Most of those R^2 are slightly greater when correlation is taken into account in all scenarios. However, the difference is not significant.

Table 7: Simulations Results

Scenario	Gender	Model	$\bar{R}^2$
A	Boys	Independent	0.7168
		Correlated	0.7178
	Girls	Independent	0.7039
		Correlated	0.7046
B	Boys	Independent	0.7149
		Correlated	0.7152
	Girls	Independent	0.6283
		Correlated	0.6285
C	Boys	Independent	0.6804
		Correlated	0.6804
	Girls	Independent	0.6631
		Correlated	0.6631
D	Boys	Independent	0.6924
		Correlated	0.6930
	Girls	Independent	0.6550
		Correlated	0.6551
E	Boys	Independent	0.7005
		Correlated	0.7022
	Girls	Independent	0.6847
		Correlated	0.6857

4 Conclusion

In this paper we fitted a variety of regression models predicting BMR from gender, age, weight, height and lean body mass based on the data collected and analyzed by [1]. However, in contrast to their analyses we took the correlated nature of the data into account. We showed that our approach taking correlation into account is appropriate to establish important covariates. Hence, this will has an impact over important predictors need to be selected. However, it did not improve prediction. This conclusion was confirmed by our limited simulation study.

We have taken one particular approach to model BMR to its regressors. In addition, our aim was to see how the regression model changes with the age of the child. In this respect, one could opt also for another approach. That is, one could model the evolution of BMR, weight, height and lean body mass (and possibly other anthropometric measurements) jointly and in a longitudinal manner as a function of age and then employ this model to predict BMR at each chosen age. This involves a multivariate linear mixed model using the approach of Fieuws and Verbeke [32,33]. We are currently exploring this approach and will report the results in a subsequent paper.

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