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New Mathematical Modelling on BMR and Weight Prediction for Ghanaians

Ian Yaw Asare[1,2*], Ezer Osei Yeboah-Boateng[1]

[1]Faculty of Computing & Information Systems, Ghana Communication Technology University, Accra, Ghana
[2]Department of Computer Science & Technology, Knutsford University College, Accra, Ghana
Email: *ian.was.asare3@gmail.com

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Abstract

Background: Basal Metabolic Rate (BMR) is the quantum of calories needed for optimum body function when at rest. This has long been an indicator of one's health and the basis for determining the metabolic age of individuals. Many scholastic projects have led to the establishment of mathematical models and inventions that measure the BMR and other body composition parameters. However, existing computations have limitations as they do not offer accurate results for Ghanaians. Aim: The purpose of the study was to model BMR metrics that are most suitable for Ghanaians and to investigate the effect of caloric difference on weight, Lean Body Mass (LBM) and % fat composition that can be implemented with Information Technology. Research Methods and Procedures: This was an experimental study that adopted a quantitative approach. BMR and body composition were measured in a sample of 242 Ghanaian adults (141 males and 101 females) from 19 to 30 years of age. Body composition was measured using bioelectrical impendence analysis (BIA) in all participants. Each participant was under study for 7 days. A simple linear regression model was used to examine associations between BMR/calorie intake and total body weight and LBM. Results: There was a significant statistical relation between BMR and LBM and between BMR and weight of both men and women. Equations for BMR and weight were established for males and females. Furthermore, caloric intake differences affected changes in total weight as well as differences in % fat composition. Caloric intake however did not affect the difference in LBM. Conclusion: Caloric difference had an impact on total body weight and Lean Body Mass. The model derived from the study predicts weight change and BMR of Ghanaians from 19 to 30 years of age. It is termed the Health and Age Monitoring System (HAMS).

Keywords

Basal Metabolic Rate (BMR), Lean Body Mass (LBM), Weight, Calories

1. Introduction

Many health-related mobile applications and online calculators based on Atwater-specific factors help individuals manage and track their weight for health reasons. Heart disease and stroke remain the leading cause of death [1] [2]. These morbidities are often attributed to diet [3] and lifestyle [4] [5]; hence, it is no surprise to see apps and online calculators providing solutions in the area of weight management and Basal Metabolic Rate (BMR) [6]. BMR calculations are crucial in the regulation of one's health and weight management. Although these attempts are plausible, these solutions require concrete scientific formulae with high degrees of accuracy [7].

Several studies have been done in this area as scientists and nutritionists seek to develop applications and gadgets that accurately measure Metabolic Rate and Metabolic Age (M.A) [8]. However, for a health-related mobile application to work efficiently, it needs to be based on a concrete scientific formula. Several formulae developed have taken into consideration the age, height, gender, and weight of the individual [9] [10] [11]. Each equation has its degree of accuracy and is the basis for several online BMR calculators, however, it is critical. Some inventors have innovatively invented gadgets that measure body weight and other body composition factors, such as fat and water. Nevertheless, there remains the necessity to develop a more accurate formula for online usage for Ghanaians.

Furthermore, most of these formulae derive from research on non-African racial groups. The Harris-Benedict equation is one of such popular equations currently being used [7]. In addition, there have been studies to improve the precision of these formulas however, the emphasis has not been on African groups. It will be advantageous to have similar studies on Africans, particularly Ghanaians. A medical case in point is where race has played a crucial role in generating several formulae to determine renal output, which is critically related to chronic kidney diseases.

$$\text{GFR} = 141 \times \min\left(S_{cr}/\kappa, 1\right) - 1.209 \times 0.993\ \text{Age} \times 1.018\left[\text{if female}\right] \times 1.159\left[\text{if Black}\right]$$

In this equation, race is considered an important factor in determining GFR. GFR refers to the Glomerular Filtration Rate [12].

This study, therefore, sought to develop a more accurate formula for online usage that will apply to people of Ghanaian descent since climate conditions significantly influence the BMR [13]. Also, this research was crucial since the existing BMR equations were founded on data collected from non-Africans groups and would yield less accurate results when used by Ghanaians. Furthermore, the research aimed to develop an appropriate Ghanaian adaptable model of a health monitoring system to assess how the change in calorie intake can affect an individual's BMR using data from students of the University of Ghana, Legon, and Korle Bu Campuses.

2. Methods

2.1. Study Sites and Participants

Research participants were recruited from several halls of residence and hostels of the University of Ghana, Korle bu. The study involved male and female Ghanaians, aged 19 to 30 years but excluded heavy-weight athletes, pregnant women, females during their menstrual period, individuals who were mentally stressed and individuals on medication. They were excluded to prevent the distortion of anthropometric and body composition measurements [14] [15]. This age bracket was selected because participants less than age 35 are less likely to have health conditions such as high blood pressure [16]. A questionnaire was provided with the sole purpose of recruiting suitable research participants based on the above exclusion criteria. A questionnaire was sent to 620 potential research participants, and 435 responded to the questionnaire. 86 respondents were excluded from the study due to their incompatibility with the predefined inclusion criteria. The study therefore recruited a total of 349 research participants; however, 242 individuals participated in the study as a result of considerations about data validity, research protocol, and integrity. The study covered 230 days, with each cohort under examination for seven days. Due to the limited number of pocket-weighing scales and body composition analyzers (19 pocket-weighing scales and 2 body composition analyzers), 16 participants were examined in a week. Figure 1 shows the recruitment and data collection process of the study.

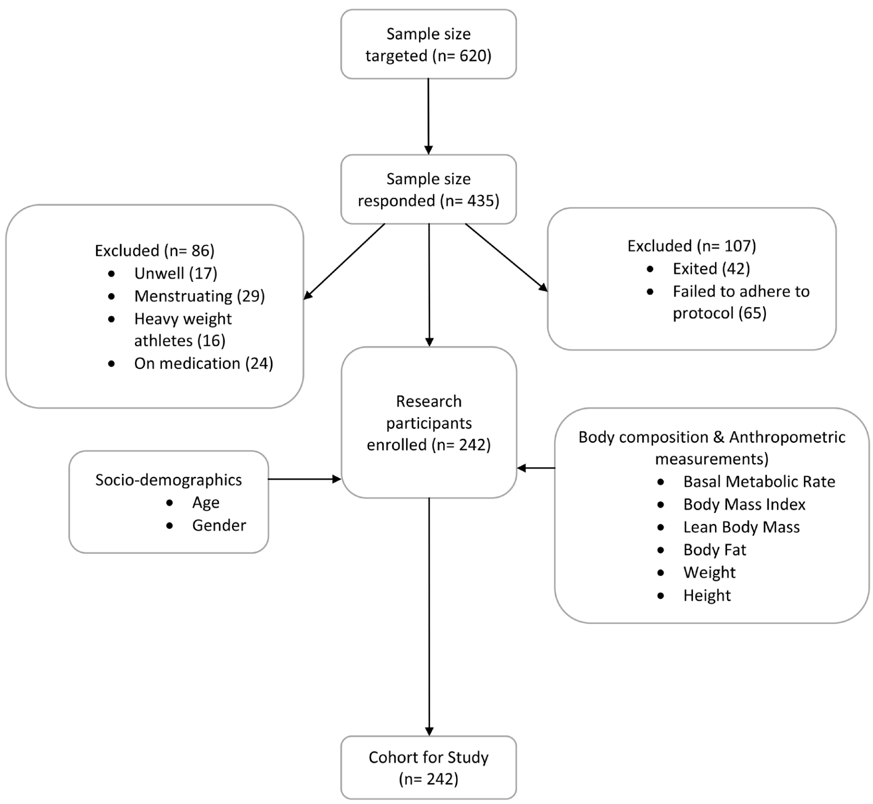

Figure 1. A simple diagram representing the process of data collection.

Figure 1 describes the stages leading to the development of the HAMS formula. Participants were targeted, and selected after the screening process, and body composition and dietary measurements were taken during the study period; however, participants who failed to adhere to the prescribed protocols were evicted from the study.

2.2. Basal Metabolic Rate

It is important to note that BMR is a function of the biological system. As with all living organisms, there is a tendency to maintain a homeostatic condition to keep the organisms fit. Any condition or situation that creates a departure from the homeostatic condition triggers a metabolic reaction to reverse the system back to normal. This explains why several factors influence the BMR of the individual. For this reason, scientists have laid down some protocols that need to be followed to ensure the BMR obtained reflects the actual BMR and not the synergic result of metabolic and homeostatic activities [14]. These protocols were strictly adhered to in the choice of candidates and also were relied on to justify whether the data of the individual was valid for analysis or not. For instance, all participants were made to sit calmly under the sample atmospheric condition for 30 minutes to 1 hour before being allowed to take their parameter reading. Also, those who got sick or started menstruating during the study period were automatically evicted from the research. Finally, measurements were appropriate for the focus group of the study because climate, temperature, diets and genetic makeup, which are said to influence BMR, were peculiar to the Ghanaian environment, unlike the existing equations with non-African subjects [17] [18] [19].

BMR and other body composition parameters of research participants were measured using bioelectrical impendence analysis (BIA). The principles underpinning the BIA method have been well described and validated in other studies [20].

2.3. Body Composition and Anthropometrics

Research instruments used in this research included questionnaires, anthropometric assessments, and dietary measurements. On week 0, and day 0, anthropometric assays were performed on the research participants to obtain their respective heights. Each participant stood barefoot with heels and knees together in such a way that the Frankfurt plane and the floor were parallel. A Seca stadiometer (Hamburg, Germany) to the nearest 0.1 cm was used in measuring the heights of the research participants. The heights, dates of birth, and genders of research participants were computed on the OkOk international health mobile application (Google Play Store). All participants' body composition data were then obtained by standing barefoot on the Smart Bioelectric Body analyser (TiZhong 267, China) with light clothing. With Bluetooth and Wi-Fi connectivity function between the Smart Bioelectric Impendence analyser and the researcher's LG v30+ smartphone, measurements of each participant's body composition data were immediately transferred to the researcher's phone. On day 1, body composition assays were performed on each participant. This served as the pre-feeding data, and on the 7th day, which was the completion day, this was referred to as the post-feeding data. Thus, each participant in the test group was their respective control on day 1. Thus, between 6 am and 8 am (daily before meals), each participant had to stand upright and barefoot with light clothing after 12 hours of fasting to have their Weight, BMI, Fat, Muscle, Water, Visceral Fat, Bone Mass, BMR, MA, and LBM estimated by the Smart Bioelectric Impendence analyser. Body composition parameters of research participants were transferred from the Smart Bioelectric Impendence to the researcher's phone and computer through Bluetooth and Wi-Fi connectivity. The Smart Bioelectric Impendence analyser was validated before the commencement of experiments by comparing the data of 40 participants obtained to that of the OMRON HBF-516B Body Composition Monitor and Scale (Lake Forest, IL, USA). Data was found comparable and acceptable.

2.4. Dietary Measurement

Food was measured in kilograms (kg) and reported in 0.01 kg using a Delphin digital pocket scale (Revuca, Slovakia), with the food placed in a light polythene bag and hooked to the digital pocket scale. Participants had to stand upright, lift the digital pocket scale with the food hooked to the waist level, and stay still for about 5 seconds to have the reading of the food measured. The weight of the food was recorded and transmitted electronically. This measurement had to be repeated for every meal consumed throughout the 7 days. The nutritional facts of snacks eaten, such as biscuits, were recorded and sent electronically. Using the Atwater-specific factors, the calories in the diet were calculated.

The weight of meals was measured in kilograms (kg) and reported in 0.01 kg using a Delphin digital pocket scale (Revuca, Slovakia), with the food placed in a light polythene bag and hooked to the digital pocket scale. To have the reading of foods measured, participants stood upright, lifted the pocket scale with the food hooked, to the waist level, and remained still for about 5 seconds. The weight of the food was recorded and transmitted electronically. This measurement had to be repeated for every meal consumed throughout the 7 days of each participant study. The nutritional facts of snacks eaten, such as biscuits, were recorded and sent electronically. Using Atwater-Specific Factors, calories in diet consumed were calculated for the study.

2.5. Statistical Methods

Excel and R programming were used in the statistical analysis to ascertain the impact of calories on the weight and the LBM of the individuals and how this translates into the wider population of the focus group. Data were expressed as continuous variables, with the equations being derived from the lines of best fit and regression statistics. A simple linear regression model was used to examine associations between calorie intake and total body weight in addition to the examination of associations between calorie intake and LBM. One-way ANOVA was used for between-group comparisons, with a post hoc test conducted using Fisher's Least Significant Difference (LSD) test. In all the analyses, the level of significance p was < 0.01. This means that relationships established were highly statistically significant and the study would be taking a risk as low as 1% in rejecting the null hypothesis.

2.6. Ethics

Participants gave individual consent and Ethics approval was sought from the Ethics Committee of the Ghana Communication Technology University. Reference number obtained: BMT-/1001/GH522/2021. Participants were informed of the possible discomfort in their initial 12-hour fast. Participants were also informed of their choice to withdraw from the study at any time and also assured of their confidentiality by the usage of unique identification codes. They were also assured that results obtained from the study would remain confidential and used only for research purposes.

3. Results

A total of 242 participants had their data analyzed after having gone through the research. These individuals were from the ages of 20 to 30 years. BMI was characterized as "underweight (BMI < 18.50 kg/m^2), normal weight (BMI: 18.50 - 24.99 kg/m^2), overweight (BMI: 25.00 - 29.99 kg/m^2) and obese (BMI ≥ 30 kg/m^2)". Body fat was characterized as low (Fat < 11%), healthy (Fat: 11% - 16.99%), High (Fat: 17% - 26.99 %) and obese (Fat ≥ 27%). Muscle was characterized as insufficient (Muscle < 49.4 kg/m^2), healthy (Muscle: 49.5 - 59.4 kg/m^2) and excellent (Muscle ≥ 59.5 kg/m^2). BMR was characterized as low (BMR < 1425.0), healthy (BMR: 1425.0 - 1574.9) and High (Fat ≥ 1575.0).

Table 1 gives a summary of statistics of research participants under the parameters: of age, weight, BMI and LBM. Weight and LBM were measured in kilograms (kg).

From the study, it was discovered that there is a very strong Pearson correlation between BMR and the LBM and between the BMR and the weight of the individuals of both sexes (Figures 2-5). Given the values obtained for the R^2 in the males, Figure 2 & Figure 4 (0.9817 and 0.9313 respectively), it was evident that more than 98% of the variability in the LBM could be explained by the BMR of the individual and more than 93% of the variations in the weight change (DIFF.WEIGHT) were attributable to the BMR. Also, for their female counterparts, Figure 3 & Figure 5, the R^2 values indicated that 95% of the variations in LBM and more than 86% of the variations in weight were explained by the BMR. There was a significant statistical relation between BMR and LBM ($p < 0.0001$ & $p < 0.0001$) and between BMR and weight ($p < 0.0001$ & $p < 0.0001$) of both sexes. Also, the 99% confidence interval tells the range in which we can find the true mean, and the lower and upper boundaries are the limits of such range.

Table 1. Summary statistics of all participants.

N = 242	Mean ± SD	Median
Age	23.11 ± 2.55	23 (20 -30)
Weight	64.58 ± 13.32	62.93 (41.1 - 106.2)
BMI	22.89 ± 3.69	22.15 (16.6 - 33.1)
LBM	46.52 ± 10.02	44.5 (26.5 - 71.19)

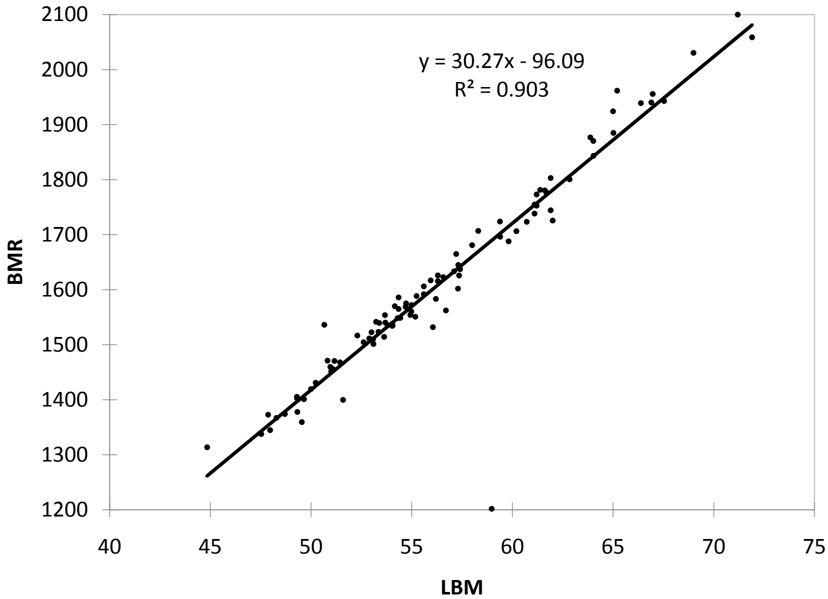

Figure 2. A graph of BMR and LBM of males.

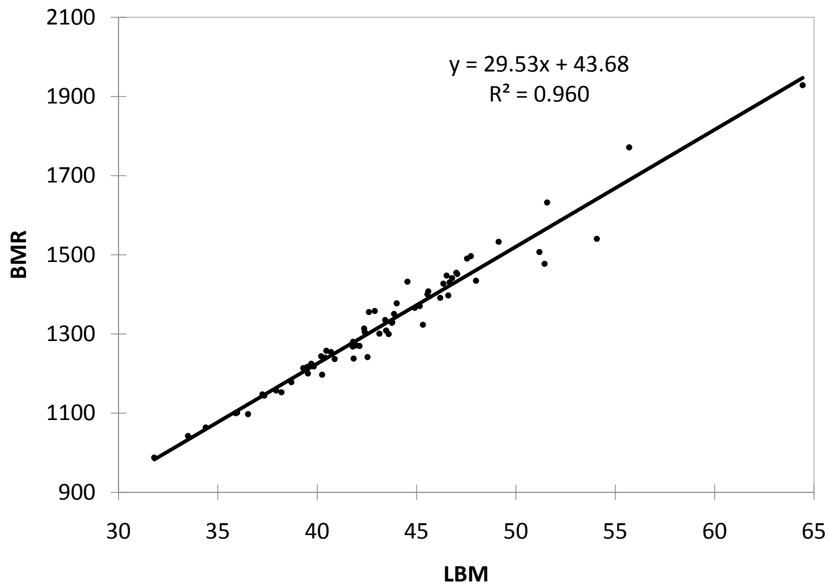

Figure 3. A graph of BMR and LBM of females.

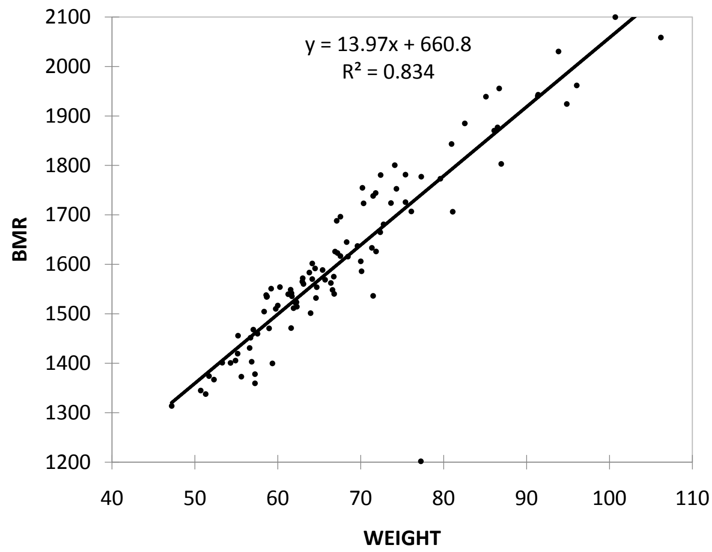

Figure 4. A graph of BMR and Total Body Weight of males.

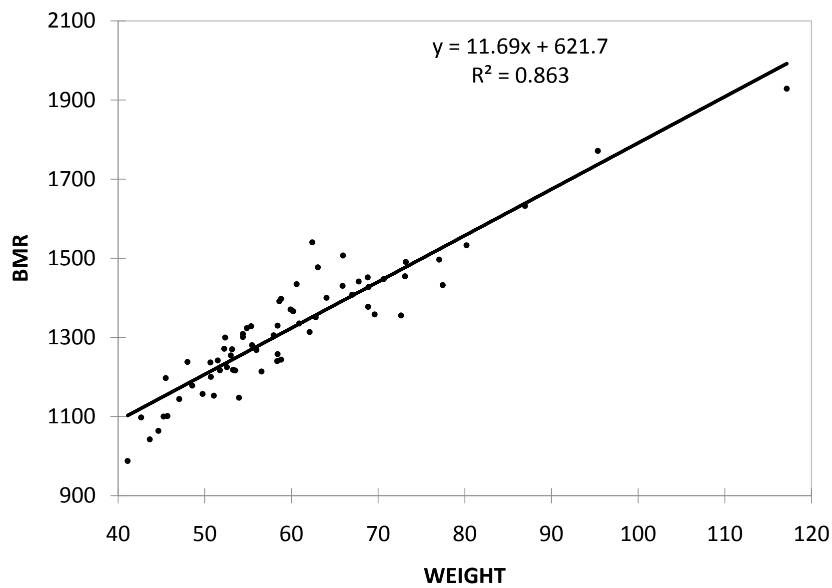

Figure 5. A graph of BMR and Total Body Weight of females.

The summary of dependent variables Weight, LBM and % difference in Fat composition of research participants are described in Table 2 and Table 3. From the R^2 values obtained by the regression of dependent variables by the independent variable (Table 2), it could be said that per the study, 22%, 3% and 12.5% of the variability in DIFF. WEIGHT, DIFF. LBM and % DIFF. IN FAT COMPOSITION can be explained by Caloric difference (Excess/Deficit in calories consumed) by males. Whereas 22%, 0% and 14.2% of the variability in DIFF. WEIGHT, DIFF. LBM and % DIFF. IN FAT COMPOSITION can be explained by Caloric difference by females (Table 3). Although results of the study also show that there was significant statistical relation between Caloric difference consumed and weight change ($p < 0.0001$) and between Caloric difference and %

DIFF. IN FAT COMPOSITION ($p < 0.0001$), there was no such significant relation between Caloric difference and change in LBM/DIFF. LBM ($p = 0.028$) for males (Table 2). The same trend was observed in females, as indicated by the records in Table 3. This showed that eating did not affect the LBM of an individual. However, eating influences one's total body weight and %fat composition. The study shows with confidence that the change in calorie intake affected the weight change which leads to a new BMR estimation after eating. Given the significant statistical relationship between Caloric difference and change in weight ($p < 0.0001$, Table 2 & Table 3) and that of BMR and Weight ($p < 0.0001$, Table 2 & Table 3). Mobile applications could be developed based on these mathematical relations.

$$\Delta w_{\text{Male}} = 0.083(e_1 - e_0) + 20.71 \tag{1}$$

and

$$\text{BMR}_{\text{Male}} = 13.79(w_i + \Delta w) + 660.84 \tag{2}$$

for Males, whiles

$$\Delta w_{\text{Female}} = 0.07(e_1 - e_0) + 45.56 \tag{3}$$

and

$$\text{BMR}_{\text{Female}} = 11.68(w_i + \Delta w) + 43.69 \tag{4}$$

for Females, were derived from the calorific analysis where Δw = Difference In Weight, w_i = Initial Weight, e_1 = Metabolizable Energy in Diet and e_0 = Basal Metabolic Rate.

Table 2. Summary for all dependent variables versus Caloric difference for males.

	DIFF. WEIGHT	DIFF. LBM	% DIFF. IN FAT COMPOSITION
R^2	0.22	0.034	0.125
F	39.227	4.926	19.865
Pr > F	<0.0001	0.028	<0.0001
Caloric difference	39.227	4.926	19.865
	<0.0001	0.028	<0.0001

Table 3. Summary for all dependent variables versus Caloric difference for females.

	DIFF. WEIGHT	DIFF. LBM	% DIFF. IN FAT COMPOSITION
R^2	0.22	0	0.142
F	28.033	0	16.412
Pr > F	<0.0001	0.982	<0.0001
Caloric difference	28.033	0	16.412
	<0.0001	0.982	<0.0001

4. Discussion

From the study, it was evident that the BMR of individuals is a product of the LBM and weight. However, the LBM has a greater influence on BMR than weight has, as indicated by the coefficient of correlation, the R of both genders in **Figure 2** and **Figure 3**. The study confirms the fact that LBM is the main determining factor of the metabolic rate (BMR) of an individual, similar to the study of Menon, Mishra and Rathore in 2016 [21]. LBM forms the major component of the body's weight and is metabolically more active than the fat muscle, which explains why the correlation between BMR and LBM was higher than that between BMR and weight.

Equations derived from this study are therefore a Ghanaian adaptable model for predicting the effects of caloric intake on weight and BMR. A mobile application could be developed using HAM's operational equations for each gender to predict BMR and weight change of individuals. The application could also contain local Ghanaian dishes and their caloric value based on the grams measured by the user. This, therefore, means that an individual could select their food, input the amount in grams and be able to predict the difference in their weight. BMR could also be predicted based on an individual's initial and current weight.

A limitation of the study is its extent of generalization. Considering the sample size of the study, potential variation in racial genome and the age bracket of the study, BMR and weight prediction equations of the study are not to be generalized but recommended specifically to Ghanaians within the age bracket of 19 to 30.

It is worth noting that equations 2 and 4 give similar BMR values as the Katch Mcardle formula; $\text{BMR} = 370 + (21.6 \times \text{LBM})$ [22] and Harris-Benedict equation [7]. The possible explanations for the difference in the BMR values obtained from the two equations include the following; Firstly, possible variations in the racial genome of the participants of the two studies may be a contributing factor. Secondly, the body composition machines used for the two studies were different and responsible for a possible percentage error. Lastly, Katch Mcardle's formula involved data for both sexes, whereas the HAM's BMR formulae were on gender-specific data.

Also, Luke *et al.* formula; $\text{REE} = 355 + (21.4 \times \text{LBM})$ [23], although a formula derived from studies done on Africans, it is not gender specific or applicable to a particular age group. The HAMS model is gender specific and tailored to Ghanaians from 19 to 30 years of age.

5. Conclusion

In conclusion, there was a significant statistical relation between Caloric Difference and Weight Difference, and also between Caloric Difference and % DIFF. IN FAT COMPOSITION. The mathematical equations and model derived from the study predict weight change and BMR of Ghanaians between the ages of 19 to 30.

The study generated an appropriate Ghanaian adaptable equation for predicting the effects of caloric intake on the weight, BMR and LBM of Ghanaians of the selected age bracket.

Declarations

Author Contribution Statement

Ian Asare and Ezer Osei Yeboah-Boateng: Conceived and designed the experiments; Performed the experiments; Analyzed and interpreted the data; Contributed equipment, materials, analysis tools or data; Wrote the paper.

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Data availability Statement

Data is in the University's repository and could be made available upon request.

Additional Information

No additional information is available for this paper.

Conflicts of Interest

The authors declare no conflicts of interest regarding the publication of this paper.

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