International Journal of Nutritional Sciences

Open Access

Austin Publishing Group

Research Article

Statistical Evaluation of Total Energy Intake Based on the Number of Food Portions and Body Weight

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Received: May 14, 2021; **Accepted:** June 11, 2021; **Published:** June 18, 2021

Abstract

The evaluation of food intake based on various assessment methods is critical and underreporting is frequent. The aim of the study was to develop an indirect statistical method of the total energy intake estimation based on gender, weight and the number of portions. Energy intake prediction was developed and evaluated for validity using energy expenditure measurements given by the WellBeNet app. A total of 190 volunteers with various BMIs were recruited and assigned either in the train or the test sample. The mean energy provided by a portion was evaluated by linear regression models from the train sample. The absolute values of the error between the energy intake estimation and the energy expenditure measurement were calculated for each volunteer, by subgroup and for the whole group. The performance of the models was determined using the validation dataset. As the number of portions is the only variable used in the model, the error was 30.7% and 26.5% in the train and test sample. After adding body weight in the model, the error in absolute value decreased to 8.8% and 10.8% for the normal-weight women and men, and 11.7% and 12.8% for the overweight female and male volunteers, respectively. The findings of this study indicate that a statistical approach and knowledge of the usual number of portions and body weight is effective and sufficient to obtain a precise evaluation of energy intake (about 10% of error) after a simple and brief enquiry.

Keywords: Prediction of energy intake; Total number of food portions; Body mass index; Energy expenditure; Dietary apps

Abbreviations

DLW: Doubly Labelled Water; TEE: Total Energy Expenditure; BMI: Body Mass Index; ICT: Information and Communication Technology; NW: Normal Weight; OW: Overweight; EI: Energy Intake; GLM: General Linear Model; LSMeans: Least Squares Means; M: Men; W: Women; SD: Standard Deviation; P_i: Number of Portion for an Individual i; W_i: Body Weight for an Individual i; E_i: Error for an Individual i

Introduction

The evaluation of dietary intake is commonly performed using the 24-hour dietary recall or frequency questionnaire, or 3- to 7-day reported food intake [1,2]. Doubly Labelled Water (DLW) is used as a reference method to measure Total Energy Intake (TEE) in free-living conditions and to validate reported energy intake in many studies [3,4]. This reference methodology is based on the fundamental principle of the energy balance, meaning that Total Energy Expenditure (TEE) is equal to energy intake when the body weight is stable (in the absence of a significant weight change) [5]. Many authors found a positive correlation between TEE measured by DLW and body weight, but a flat slope between TEE and reported energy intake [6-8]. According to these authors, the underestimation of energy intake concurrent with increasing weight may be due to the imitation error of the food reported by the general population. That means that food intake is reported in the same way, regardless of the body weight range. This is confirmed by Novotny et al. (2003), who found an overall underreporting of 294kcal/d energy intake [9]. This underestimation of energy intake was higher in women than in men: 85% of women underreported their food intake by 621kcal/d, whereas 61% of men underreported theirs by 581kcal/d. In contrast, 15% of women over reported their energy intake by 304kcal/d and 39% of men by 683kcal/d. The poor food intake estimation was mainly related to body fat mass and body dissatisfaction. The higher the body fat percentage was, the higher the underreporting of energy intake was [9]. Gender also played an important part in the correct estimation of food intake, and men were better estimators than women. Many other studies have proved that both underreporting and overreporting occur, regardless of the methods used for food intake assessments [3,10].

Since the cost of the DLW method is a liming factor for large-scale studies such as epidemiological ones, it would be advantageous to replace DLW by another less costly technique or procedure able to estimate energy intake with a high level of accuracy. The development of the new information and communication technologies and the widespread use of smartphones open new application prospects in nutrition and dietary assessment. For example, the use of dietary mobile applications led to a decrease in weight, waist circumference and energy intake compared to control in adults with chronic diseases [11]. Researchers also expect that technology could improve diary reporting by reducing memory and representation bias and errors from data processing [12]. In several studies, volunteers were told to take photographs with their smartphones in order to improve reporting and avoid food omission. However, there were many problems with the quality, the angle and the lack of pictures

Citation: Rousset S, Médard S, Fleury G, Fardet A, Goutet O and Lacomme P. Statistical Evaluation of Total Energy Intake Based on the Number of Food Portions and Body Weight. Int J Nutr Sci. 2021; 6(2): 1054.

or descriptive comments associated with the picture [13]. Pendergast et al. (2017) used the smartphone meal diary app (FoodNow) to measure food intake and compare the energy intake estimation with the total energy expenditure provided by an accurate physical activity research monitor (SenseWear Armband) in a population of young people with a healthy BMI range [14]. The authors demonstrated that there is a high correlation coefficient between the estimated energy intake and the measured energy expenditure. The mean difference between the estimation and the measurement was 197 kcal/d for a mean energy expenditure of 2395kcal/d, i.e., an underestimation of energy intake by about 8%. However, they showed wide levels of agreement between the two methods (Armband and FoodNow app) at the individual level (-886kcal to +491kcal). The authors concluded that the app is a more suitable tool for estimating the mean energy intake of a group rather than that of an individual. A recent review of food evaluation provided by smartphone showed that smartphone applications provided similar but not better validity or reliability when their results were compared with classical dietary assessments [14].

Further work is necessary to improve Information and Communication Technology (ICT) tools used for in-depth evaluation. Improvement of food intake evaluation should focus on data collection but, instead, on data treatment. In this study, we propose a simple model of energy intake estimation with a satisfactory level of accuracy.

Methods

Volunteers

This observational study was conducted on 190 volunteers. They were recruited anonymously for the open-door event of an INRAE center and through social networks. The volunteers must be adult (older than 18 years), have an Android smartphone and consent free to participate to the study during four days. Moreover we asked them to fill in personal and diet information honestly in the App.

116 women and 74 men, either normal weight (NW, n = 123), or overweight (OW, n = 67), were studied in free-living conditions (Table 1). A total of 131 were used for model development (train sample) and 59 volunteers (test sample) were used to evaluate the validity of energy intake estimation.

Data collection and energy balance principle

The volunteers downloaded the WellBeNet app at the Play Store and informed the researcher about age and gender. They filled in height and weight in the app. They were then asked to use the eMouve and NutriQuantic parts of the WellBeNet application for four consecutive days (three weekdays and one day during the weekend). They were told to wear the smartphone in a pant pocket to collect accelerometry data for the waking period. eMouve provides an accurate estimation of Total Energy Expenditure (TEE) in normal-weight and overweight volunteers, i.e., approximately 5% of error in absolute value [15,16].

Table 1: Characteristics of both train and test samples (Mean values and standard deviations, n=131, n=59).

Sample	Train		Test	
Variables	Mean	SD	Mean	SD
Gender (% Women)	60		64	
Wt status (% NW)	65		63	
Age (years)	37.5	12.2	37.4	14
Height (cm)	169.8	10.1	168.8	9.4
Weight (kg)	71.1	16.9	71.6	19.6
BMI (kg/m^2)	24.6	5.7	25.1	6.6

NW: Normal Weight.

NutriQuantic was used to collect the number of portions consumed, regardless of the food category, during the same period. A guide for the estimation of a portion was sent to each volunteer. A nutritional score was assigned to each of the 11 food categories based on the number of portions and according to French and international nutritional guidelines [17]. The score varies between 0 and 1. The nutritional balance score of the diet is the result of a confidential calculation over the 11 food categories [18].

Energy balance is based on the fundamental principle that Energy Intake (EI) is equal to energy expenditure during a stable body weight period [5].

Ethical approval

This observational study was conducted according to the guidelines laid down in the Declaration of Helsinki and the French legislation for the collection of anonymous human data. Written or verbal informed consent was obtained from all volunteers for the aggregated treatment of their data. Verbal consent was witnessed and formally recorded.

Statistical models

A Chi-2 test (χ^2) was used to compare the distribution of men/women, and normal-weight/overweight individuals in the two populations (train and test groups). Statistical significance was set at $p < 0.05$.

For each gender, a one-way analysis of variance model (GLM) was carried out to determine the effects of BMI status (normal weight *vs.* overweight) on age, height, weight, number of portions per day, nutritional balance score and daily TEE. A mean comparison test (LSMeans) was carried out when $p < 0.05$. SAS software, version 9.4, was used to carry out the frequency test and analysis of variance.

In the first step, two types of linear regression models were tested for all the volunteers of the population. The first one used only one variable, the total mean number of portions per day, to explain the energy expenditure. The second one used the total mean number of portions and the body weight of the volunteer. In the second step, four models (2*2) were performed by gender and BMI group on a train sample and validated on a test sample different from the train sample. The regression models were implemented in Python to compute the model errors in absolute value in both train and test samples and to assess the energy intake of each volunteer. Two constraints were added to the solutions given by the regression models: their values have to be positive (for the number of portions and weight) or null (weight). The value of the coefficient for the number of portions has to be positive because each food portion provides energy. The constraint on body weight is assumed to be lower: if the number of portions could completely account for the energy intake, then weight could have a negligible effect on energy intake. In this case, the value of the coefficient will take the null value, if not a positive value. The values

Table 2: Effect of BMI status on behavioral data in men and women (Mean values and standard deviations, n=116, n=74).

Variables	Women				Men			
	NW-W		OW-W		NW-M		OW-M	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Number of portions/d	11.9	3.9	11.1	4.1	12.7	5.3	11.4	3.9
Nutritional balance score	6.1	1.1	5.6 **	1.1	5.5	1.4	5.7	1.2
Total energy expenditure (kcal/d)	2080	319	2435 ***	505	2610	502	2983**	486

NW-W: Normal-Weight Women; OW-W: Overweight Women; NW-M: Normal-Weight Men; OW-M: Overweight Men. *, **, *** Mean value was significantly different from that of the overweight group (P<0.05, P<0.01, P<0.001).

Table 3: Mean energy contribution estimated from weight and the number of food portions (Mean weight and number of portion and values of regression coefficients for body weight and portion according to gender and weight status).

Volunteer	Wt (kg)	Portions (Nb)	Regression coefficient associated with		Energy part (kcal) explained by		Added contribution (%) in OW imputable to	
			Wt	Portion	Wt	Portion	Wt	Portion
NW-M	69.3	11.8	33.7	22.1	2334	260.4		
OW-M	95.6	11.4	27.1	36.7	2586.9	418.3	10.8	60.6
NW-W	57.4	12.7	30.3	22.3	1737.5	282.7		
OW-W	84.9	11.2	23.8	32.3	2016.4	361.8	16.1	28

NW-M: Normal-Weight Men; OW-M: Overweight Men; NW-W: Normal-Weight Women; OW-W: Overweight Women.

of coefficients were determined from the data collected by the train sample: normal-weight and overweight men and normal-weight and overweight women. These values were then applied to the data of the test sample for validation.

Agreement between the Energy Intake (EI) and TEE was evaluated by Bland-Altman plots [18]. The plots were drawn up showing the mean difference between estimated EI values and TEE values provided by eMouve against the mean of the two methods. The bias is estimated by the mean difference (M) and the standard deviation (s). Statistically, 95% of the differences will range between M ± 2s (agreement limits). The validity of EI was evaluated in each regression model by comparing the agreement level between the EI and TEE.

Results

Differences between BMI statuses

The train and test samples were similar in gender and BMI status distribution ($\chi^2 = 0.40$, p = 0.52; $\chi^2 = 0.69$, p = 0.81, respectively). There was no difference in the BMI status distribution between men and women ($\chi^2 = 0.35$, p = 0.55).

The one-way analysis of variance showed that age, body weight, nutritional balance score and total energy expenditure differ between normal-weight and overweight women (Table 2). Overweight women were older (43 *vs.* 37 y), their body weight (85 *vs.* 57 kg, p <0.0001) and energy expenditure were higher (Table 2). They took a number of food portions similar to that of normal-weight women, but their nutritional score was lower than that of normal-weight women (Table 2). There was no significant difference in age for men (38 vs. 34 years), or in the number of portions between the two weight statuses (11.2 *vs.* 12.7 portions/d). The significant differences observed were that body weight (94 *vs.* 69 kg, p <0.0001) and energy expenditure were higher in overweight subjects (Table 2).

Errors of regression models and agreement with total energy expenditure

The first model included only one variable: the total number of portions/d.

$EI_{1i} = 174.8 \times P_i + E_i$ (First model for all the volunteers).

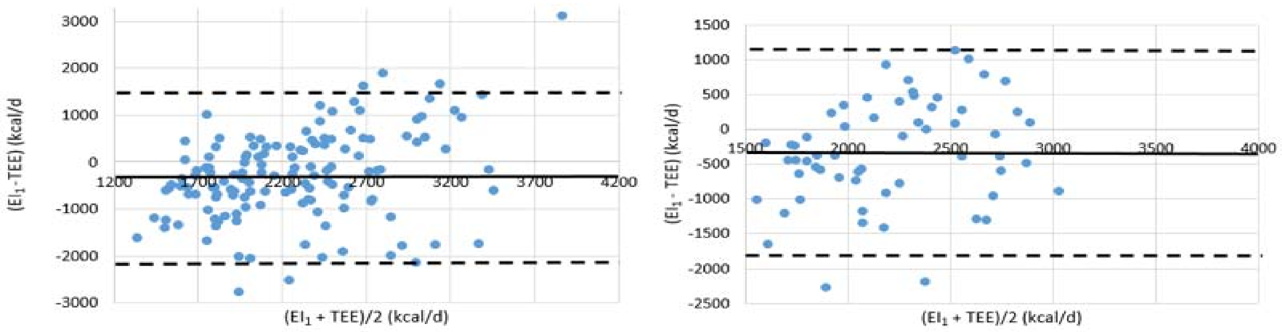
P_i: Number of portions (mean number/d); and E_i: Error for an individual i.

The estimated energy intake of a portion was 174.8kcal. The error in absolute value was 30.7% and 26.5% in the train and test populations, respectively. The Bland and Altman plots show that all the points except six (in the train sample) and two (in the test sample) are included between the lower and upper limits of agreement (Mean + 2 SD; Mean - 2 SD; Figure 1).

The bias, equal to -287 and -324 kcal/d in the two volunteer samples, indicated that the estimated EI_1 was underestimated by about 10%, but the 95% limits of agreement were wide (-2199 to 1611 kcal/d and -1825 to 1176 kcal/d). This first model did not provide satisfactory results on individual energy intakes because of large gaps between estimated energy intake and energy expenditure.

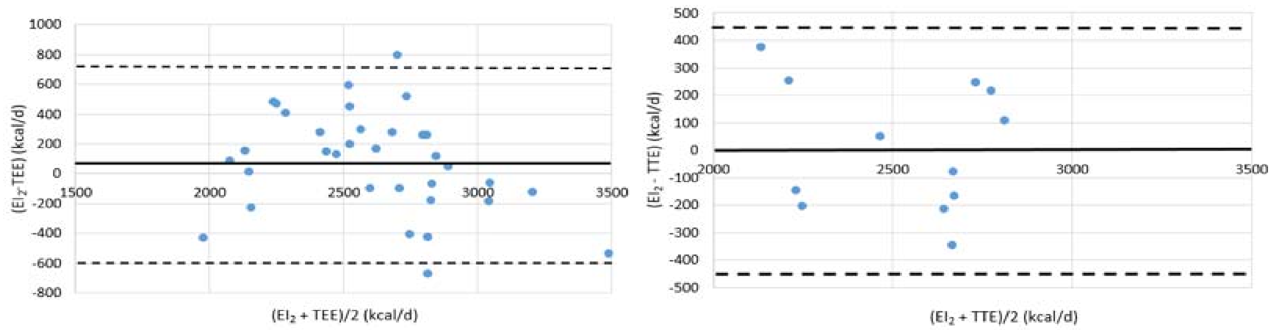
Since the energy intake of women and normal-weight subjects is lower than that of men and overweight subjects, and because underreporting is frequent as body mass index increases, we performed four status regression models (for each gender and weight status) with two explanatory energy intake variables: number of portions and body weight.

The values of regression coefficients for the number of portions and the body weight determined in the train sample are shown in Table 3. All the coefficients for weight are positive. Energy intake of normal-weight (69kg) and overweight men (95kg) is explained by weight contribution (33.7 × 69 = 2334 and 27.1 × 95 = 2570) and by the food portions (22.1 × 12 = 265kcal and 36.7 × 11 = 404kcal). Energy intake of normal-weight and overweight women (57kg and 85kg on average) is explained by weight (1737kcal and 2019kcal) and food portions (289kcal and 335kcal). These results showed that body weight explained 90% and 86% of energy intake in normal-weight men and women, and 87% and 85% in overweight volunteers.



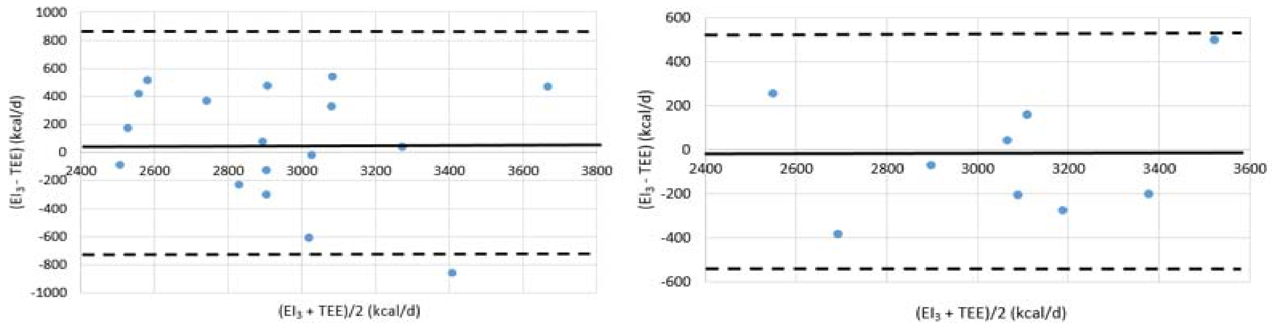
A **B**

Figure 1: Bland and Altman plots of the agreement level between Total Energy Expenditure (TEE) measured by eMouve, and Energy Intake (EI1) estimated by NutriQuantic in (A) The train and (B) The test sample. Bias is represented as mean difference (2 standard deviations).



A **B**

Figure 2: Bland and Altman plots of the agreement level between Total Energy Expenditure (TEE) measured by eMouve, and Energy Intake (EI2) estimated by NutriQuantic in normal-weight men (A) In the train sample and (B) In the test sample. Bias is represented as mean difference (2 standard deviations).



A **B**

Figure 3: Bland and Altman plots of the agreement level between Total Energy Expenditure (TEE) measured by eMouve, and Energy Intake (EI3) estimated by NutriQuantic in overweight-weight men (A) In the train sample and (B) In the test sample. Bias is represented as mean difference (2 standard deviations).

These results also showed that the higher energy intake observed in overweight compared to normal-weight volunteers can be explained by a higher number of food portions and body weight contributions. Thus, the energy intake estimated from both food portions and body weight increased in both overweight men and women (Table 3).

$EI_{2i} = 33.7 \times W_i + 22.1 \times Pi + Ei$ (Second model for normal-weight men).

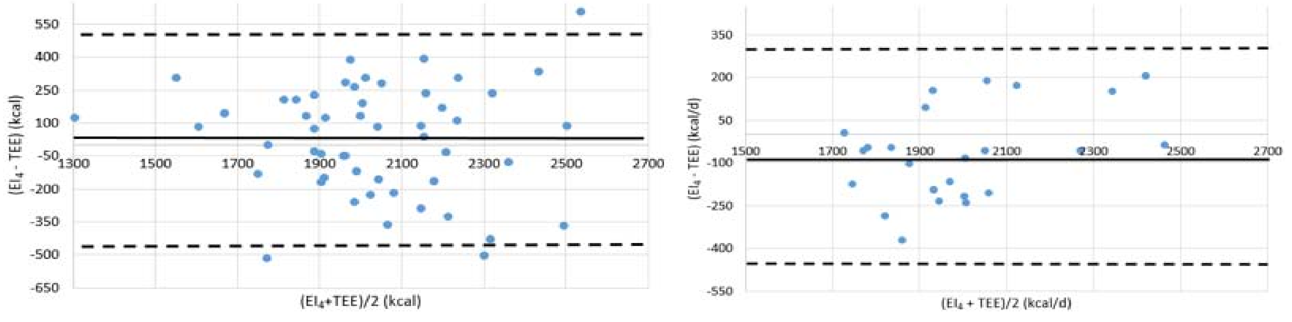
$EI_{3i} = 27.1 \times W_i + 36.7 \times P_i + E_i$ (Third model for overweight men).

$EI_{4i} = 30.3 \times W_i + 22.3 \times P_i + E_i$ (Fourth model for normal-weight women).

$EI_{5i} = 23.8 \times W_i + 32.3 \times P_i + E_i$ (Fifth model for overweight women).

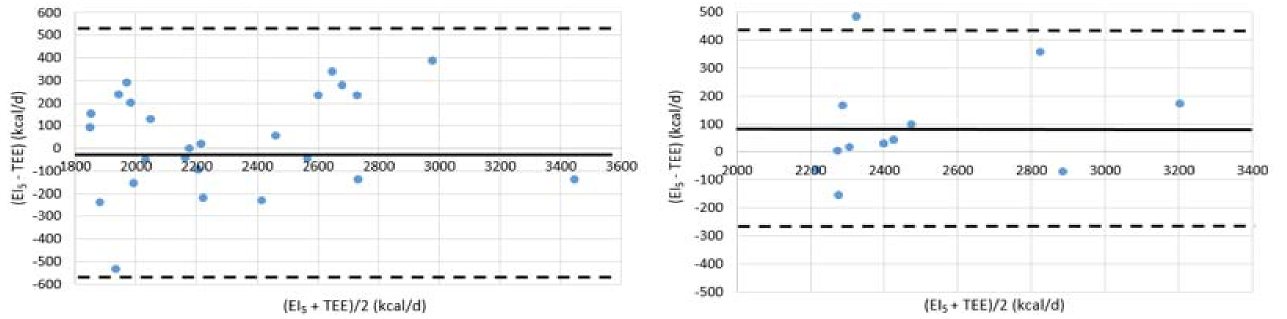
W_i: Weight (kg); P_i: Number of portions (mean number/d); and E_i: Error for an individual i.

For normal-weight men, the errors in absolute value fell to 11.5%



A B

Figure 4: Bland and Altman plots of the agreement level between Total Energy Expenditure (TEE) measured by eMouve, and Energy Intake (EI4) estimated by NutriQuantic in normal-weight women (A) In the train sample and (B) In the test sample. Bias is represented as mean difference (2 standard deviations).



A B

Figure 5: Bland and Altman plots of the agreement level between Total Energy Expenditure (TEE) measured by eMouve, and Energy Intake (EI5) estimated by NutriQuantic in normal-weight women (A) In the train sample and (B) In the test sample. Bias is represented as mean difference (2 standard deviations).

and 8.2%, respectively, in the train and test samples. The bias is close to zero (78 and 9 kcal/d; Figure 2) with 95% agreement limits, which is half the size of the full sample bias. Only two individuals are located outside the agreement limits in the train sample and none in the test sample. The two outliers reported 30 portions/d and 5.5 portions/d. The gap between energy intake (EI_2) and TEE is lower than 400kcal/d in most of the volunteers in the train sample and in all of the volunteers in the test sample (Figure 2).

The errors in absolute value are 11.5% and 7.6%, respectively, in the train and test samples with overweight men. The bias is close to zero (55 and -20 kcal/d; Figure 3). The 95% agreement limits are slightly higher than for the normal-weight men but only one individual is located outside the agreement limits in the train sample and none in the test sample. As for the normal-weight men, the (EI_3 - TEE) gap is frequently lower than 400kcal/d.

The gaps between EI_4 and TEE are 10.3% and 8.1% in absolute value for the normal-weight women. The bias is close to zero (29kcal/d and -95kcal/d for the train and test samples, respectively; Figure 4). Only three volunteers in the train sample are outside the agreement limits. One of them reported a very low number of portions: 4.75 portions/d. All the women belonging to the test sample had an energy intake close to TEE (±300kcal/d).

For the overweight women, the difference between estimated EI_5 and TEE was 9.1% and 5.8% in the train and test samples. The bias is close to zero (-17 and 91 kcal/d; Figure 5). None of the volunteers are outside the agreement limits and only one is in the test sample. This woman reported a higher number of portions than the average (17.7 *vs.* 11.1 portions). Most of the overweight women had an estimated intake equal to TEE ± 300kcal/d.

Discussion

The aim of this study was to assess energy intake on the basis of simple variables. Our work showed that two variables were essential to reach this objective: body weight and the reported number of food portions. This study proves that the number of portions was not significantly different between gender or BMI status: the mean number of standardized portions reported for the general population was between 10 and 13 portions/d [6]. Since energy requirements are known to be higher in men than in women, and higher in overweight than in normal-weight people, the size and/or the energy content of the portion could differ between them [20]. Models of regression were performed, taking account of the number of portions in the 11 food categories (results not shown), but the estimations of energy intake were not better than those of the total number of food portions. The findings of Kelly et al. (2008) may explain our results: they observed that the increased risk of obesity may not be associated with specific foods/food groups but rather with an overall increase in the range of foods and food groups being consumed [21].

The difference in portion size is probably an explanatory factor for the lack of association between the number of portions, size and BMI status. Even if we gave the volunteers a guide to evaluate the portion size, the volunteers used their own references to determine the portion unit. Ledikwe et al. (2005) and Bhupathiraju and Hue (2016) found that large food portion size was associated with obesity in America (22, 23). Overall energy intake increased by 35% when food portion size doubled [22]. In contrast, regular food portion size contributes to adequate energy intake and, consequently, weight maintenance.

Another explanatory factor is the underreporting of the number of portions or of the energy intake. Rippin et al. (2019) found that 32% and 44% of overweight adults were under-reporters of energy intake in the French INCA2 and UK NDNS studies (24). The percentages of normal-weight under-reporters were much lower: 18% and 23%, respectively [24]. Other studies found few associations between food portion size and adiposity. The authors reported that the under-reporting of food intake could mask this association [20,21]. Moreover, Rippin et al. (2019) compared the consumption of energy-dense food by normal-weight and overweight volunteers and observed that consumption frequency of cake and chocolate was negatively associated with increasing BMI [24]. Because this result was unexpected, the authors supposed that there were high under-reporting levels, especially in the overweight and obese volunteers.

The first model of estimated EI (EI_1) for all the volunteers that included only the number of food portions gave poor results. The estimation of an energy intake by portion led to an error of 30%. This estimation led to an overestimation or an underestimation of total energy intake up to 1000kcal/d compared to energy expenditure. It is not surprising considering the potential of both under-reporting and the large variation of portion size among volunteers. For this reason, we did not try to improve the accuracy of data collection because it is impossible to know the real values concerning the number and size of the portion. Thus, if a volunteer feels ashamed to report the consumption of energy-dense food, he/she forgets it consciously or unconsciously. We preferred to assess energy intake by a statistical data treatment, taking account of body weight, BMI status and gender in food intake requirements and reports.

By adding body weight in the regression models and separating volunteers into four groups (normal-weight men and women, overweight men and women), we found that both body weight and the number of food portions played an essential role in the explanation of energy intake. The differences between estimated EI and TEE varied between 5 and 12% according to the volunteer group. In other studies, energy intake was underestimated up to 100% in a widely varied range [6,25]. Since the values of the regression coefficients and of body weight were high, body weight made a significant contribution in the evaluation of energy intake compared to the number of food portions, regardless of weight status and gender. In overweight volunteers, the coefficients for the number of portions were higher than those in normal-weight volunteers, meaning that a portion provided more energy in overweight than in normal-weight people. In other words, the size of the portion could be bigger or more energy-dense with increasing BMI. According to BMI, O'Brien et al. (2015) found various results: in the NSIFCS 2001 study, the portion size of milk and butter was evaluated to be greater in obese volunteers than in normal-weight volunteers and vice versa in the NANS 2011 [20]. Pearcey & de Castro (2002) examined meal patterns and food intake of weight-stable and weight-gaining people, and reported that the greater EI in the weight-gaining group was attributed to significantly larger meal consumption [26]. They also suggested that the dysregulation of food intake might be an integral component of weight gain. Similarly, Rolls et al. (2002) reported that the size of the food portion served at a lunch could significantly influence EI [27]. Burger et al. (2007) found that an individual's BMI accounted for 28-51% of the variance in choice of food portion size [28].

In the four regression models, one for each gender and BMI status, we improved not only the bias but also the agreement limits between the evaluation of EI and TEE. The bias was lower than 100 kcal, whereas it was close to -300kcal in the first model. The best agreement limits of energy intake (460, 430 and 350 kcal/d) were observed for the subgroups of NW-M, NW-W and OW-W of the test samples. The agreement limits for overweight men were larger: 570kcal/d.

Very few studies compared the energy intake estimated by mobile applications with the TEE estimated by reference methods or research devices. In the work of Pendergast et al. (2017), the estimation of energy intake of a sample of young, normal-weight and educated volunteers was made by the FoodNow app on the basis of picture capture and a vocal message recording describing the food and beverages consumed [14]. The analyses of pictures and vocal messages was made in duplicate by trained nutritionists (double checking of each food code and amount). The energy intake estimated by this process was compared with TEE given by a very accurate research device (Armband). The bias was -197kcal and the agreement limit between Armband TEE and EI was 425kcal. The bias is lower and the limits of agreement are similar or slightly higher in the present study. Our statistical approach to energy intake is competitive with those much more cumbersome and time-consuming analyses of food pictures. Contrary to many studies, we did not exclude the volunteers who recorded a low number of portions (3 to 8 portions/d) nor a high number of portions (20 to 30 portions/d). These small and big reporters represented 15.8% and 3.1% of the volunteers, respectively. This way of reporting food consumption could be volunteer-dependent: it might be due to either infrequent reports with large-size portions or underreporting, or very frequent reports with small-size food portions. We adopted this point of view because we wanted our models to take account of both under- and over reporting, and for the various sizes of the portions. Obviously, our models are less suited to these small and big food reporters.

Study Strengths and Limitations

The strength of this study is to provide a high estimation of energy intake from four easily collectable variables: body weight, the total number of portions consumed by day, gender and BMI group. Most of these variables are well known to the individuals. The calculation is very quick and does not require nutritional knowledge. Moreover, this algorithm could be implemented in a new smartphone application dedicated to the general public. It could be made available to health professionals like dieticians in order to make a first estimation of a patient's energy intake. This procedure is much simpler and cheaper, less time-consuming and intrusive for both patients/volunteers and health professionals/researchers than the conventional methods.

The limitations of this study are the large agreement limits, but which are no larger than those obtained by standard methods (food frequency, dietary report). Moreover, this algorithm is not food category-dependent and does not provide the energy intake estimation by food category. Furthermore, this study does not provide information about the food category that must be modified to improve weight status. If body weight does not change, the estimation of energy intake cannot vary to a large extent. It can only be used during a period of stable body weight and food consumption.

Conclusion

All four of the regression models based on body weight and the number of food portions were effective in estimating total energy intake in four subgroups of the population aged between 18-60 years. Knowing the individual body weight of the volunteers made it possible to avoid the issue of food underreporting. Body weight is a major contributor in the four groups of volunteers, and the number of portions provided a better explanation for more energy intake in the overweight volunteers. These models may serve as an innovative and practical tool to estimate the total energy intake of the adult population.

Acknowledgements

The authors thank the volunteers who participated in this study. They also thank Gail Wagman for proofreading this paper.

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