

# Comparison between Human and Bite-Based Methods of Estimating Caloric Intake



James N. Salley, MS; Adam W. Hoover, PhD; Michael L. Wilson, MS; Eric R. Muth, PhD

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## ABSTRACT

**Background** Current methods of self-monitoring kilocalorie intake outside of laboratory/clinical settings suffer from a systematic underreporting bias. Recent efforts to make kilocalorie information available have improved these methods somewhat, but it may be possible to derive an objective and more accurate measure of kilocalorie intake from bite count.

**Objective** This study sought to develop and examine the accuracy of an individualized bite-based measure of kilocalorie intake and to compare that measure to participant estimates of kilocalorie intake. It was hypothesized that kilocalorie information would improve human estimates of kilocalorie intake over those with no information, but a bite-based estimate of kilocalorie intake would still outperform human estimates.

**Participants/settings** Two-hundred eighty participants were allowed to eat ad libitum in a cafeteria setting. Their bite count and kilocalorie intake were measured. After completion of the meal, participants estimated how many kilocalories they consumed, some with the aid of a menu containing kilocalorie information and some without. Using a train and test method for predictive model development, participants were randomly divided into one of two groups: one for model development (training group) and one for model validation (test group).

**Statistical analysis** Multiple regression was used to determine whether height, weight, age, sex, and waist-to-hip ratio could predict an individual's mean kilocalories per bite for the training sample. The model was then validated with the test group, and the model-predicted kilocalorie intake was compared with human-estimated kilocalorie intake.

**Results** Only age and sex significantly predicted mean kilocalories per bite, but all variables were retained for the test group. The bite-based measure of kilocalorie intake outperformed human estimates with and without kilocalorie information.

**Conclusions** Bite count might serve as an easily measured, objective proxy for kilocalorie intake. A tool that can monitor bite count may be a powerful assistant to self-monitoring.

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**H**UMANS ARE NOTORIOUSLY POOR AT ESTIMATING kilocalorie consumption, typically underestimating the kilocalorie content of meals and underreporting kilocalorie intake in food diaries over time. For example, Carels and colleagues<sup>1</sup> found that, on average, participants tended to overestimate the kilocalorie content of unhealthy foods by 17% and underestimate the kilocalorie content of healthy foods by 16%. Also, Stanton and Tips<sup>2</sup> found that only 28% of participants were able to estimate within 100 kcal of actual kilocalorie content. While the use of food diaries can improve kilocalorie estimates, Krall and Dwyer<sup>3</sup> found that, on average, participants omitted about 9% of food items, resulting in an underreporting bias. Errors in kilocalorie estimation have been shown to be associated with many of the same factors associated with inaccurate self-reporting.<sup>2,4,5</sup> These factors include body mass index (BMI; calculated as kg/m<sup>2</sup>), portion size, portion-size

estimation abilities, perceived healthiness of food items, and diet history.<sup>2,4,6-8</sup>

One factor that seems to contribute to accurate kilocalorie counting, and subsequently accurate self-monitoring, is the presence or absence of kilocalorie information. Nutrition labeling is the most readily available source of kilocalorie information for most food items, and is one of the most critical factors in determining kilocalorie intake outside of structured behavioral interventions. The Affordable Care Act included menu-labeling provisions that require restaurants that operate in 20 or more locations to provide kilocalorie information for their food items and notifications of daily recommended kilocalorie intake levels. This builds on prior local regulations and provides kilocalorie information in environments where that information has traditionally been difficult to obtain.<sup>9,10</sup> These requirements have opened new avenues of study on the effects of kilocalorie labeling on

food and portion choices, and although the epidemiological impact of these laws have not been investigated, several studies have offered insights into their effects. Indeed, several studies have provided evidence that this information leads to an increase in kilocalorie-estimation abilities and a decrease in kilocalorie consumption.<sup>11-13</sup> However, the findings of these studies have been inconsistent, and further research on the efficacy of restaurant nutrition information is necessary.<sup>14,15</sup> In addition, many restaurants do not meet the 20-store minimum, and subsequently are not likely to provide kilocalorie information for their menu items unless required to by their local jurisdiction. Consequently, there is an opportunity for the development and use of tools that can help the individual measure kilocalorie intake in free-living conditions.

Wearable monitors are tools that attempt to automatically and objectively monitor eating behavior. For example, Lopez-Meyer and colleagues<sup>16</sup> have described a method that can determine food intake with an accuracy of 94% by using a device that detects chewing and swallowing. This device was recently used to predict kilocalorie intake and was found to outperform self-reports.<sup>17</sup> Another tool that offers the potential of objectively and automatically calculating kilocalorie intake through monitoring ingestive behavior is the Bite Counter.<sup>18</sup>

The Bite Counter tracks bites of food taken, where a bite is defined as putting food in the mouth, and has been demonstrated to accurately count bites across a wide range of food items and eating utensils.<sup>18</sup> The function of the device is to provide an automated method of tracking wrist motion to estimate kilocalorie intake. There are two versions of the Bite Counter that have been used for research purposes. The first is a “free-living” version that provides feedback to the user, but only stores bite counts on the device instead of raw sensor data because of limited memory capacity. The second is a “tethered” version, which is used in laboratory studies, that does not provide the users with feedback, but captures the raw sensor data so that the bite-counting algorithm can be further refined.

Bite count has been shown to predict kilocalorie intake without the need for information about the specific kilocalorie content of the food being consumed.<sup>19</sup> It is possible that the prediction can be improved by calibrating the device to an individual's bite size or the kilocalories per bite that they typically ingest. For example, Lawless and colleagues<sup>20</sup> found height to strongly correlate ( $r=.75$ ) with sip size. In addition, Scisco and colleagues<sup>19</sup> found that men typically consumed 19 kcal/bite, whereas women consumed 11 kcal/bite, indicating that sex is a significant contributor to kilocalories per bite. However, studies by Scisco and colleagues and others<sup>21,22</sup> did not replicate findings of previous work that found a relationship between bite size and BMI, they found no significant difference in kilocalories per bite between participants in different BMI categories. This indicates the need for further replication and investigation into the relationship between inter-individual differences and kilocalories per bite. Furthermore, a regression equation for predicting kilocalories per bite from individual variables, which could be beneficial to other researchers hoping to derive kilocalorie intake from bite count, has not been published.

The present study developed a kilocalories per bite equation that allows kilocalorie intake to be derived from

bite count and easily obtained body dimension and demographic variables. Notably, this model does not require information about the kilocalorie content of food items consumed. Performance of this equation was compared with participants' estimates of kilocalories, with and without the presence of a menu containing kilocalorie information. There were three primary hypotheses of this study: 1) physical and demographic variables, including height, weight, waist-to-hip ratio (WHR), sex, and age would independently predict kilocalories per bite; 2) participant estimates of kilocalorie intake would be better in the presence of kilocalorie information than in its absence; and 3) an estimate of kilocalorie intake derived from bite count would be more accurate than participant estimates of kilocalorie intake.

## METHODS

### Participants

Two hundred eighty participants (132 male) were recruited from the faculty, staff, and student population of Clemson University and the surrounding area via fliers, e-mails, and word of mouth. Participants were offered \$10 and a free meal for participating in the study. Those with a self-reported history of eating disorders were excluded from the study. Participants were selectively sampled to obtain a variance in age, sex, and ethnicity that was representative of the local population. The study was approved by the Clemson University Institutional Review Board. After filling out an online screening questionnaire, all participants provided informed consent before participating in the study.

### Procedure

Upon recruitment, participants completed an online demographics and screening questionnaire. Participants were scheduled to complete the eating session for either a lunch (11:00 AM or 1:00 PM) or dinner (5:00 PM or 7:00 PM) eating session in groups of 2 to 4. Before arrival, participants were randomly assigned to either the “kilocalorie information given” or the “no kilocalorie information given” condition, using an online randomization tool. Participant condition placement was fully randomized, without consideration of demographic characteristics or physical differences. Upon arrival, their height and weight were measured. The WHR of each participant was measured using a MyoTape (Accu-Measure) tape measure. Waist circumference was measured by wrapping the tape measure around the smallest circumference section of the abdomen. Hip circumference was measured by wrapping the measure around the widest circumference section of the buttocks. The measure was adjusted snugly, but not enough to cause compressions on the skin. Measurements were taken to the nearest half-inch. Participants were then led to an on-campus dining hall.

At the dining hall, the participants were instructed by a pair of undergraduate assistants to eat as much as they liked. To allow portion size and food selection to vary, participants were allowed to choose any of the food items in the dining hall available that day, and to go back for as many courses as they wished. The dining hall had a wide variety of foods to choose from, including items that were available daily, such as a salad bar, a pizza and pasta bar, and a

sandwich station, and many other items that varied day to day. Participants' food choices were not restricted in any way, other than by what was available in the cafeteria. Participants were allowed to select kilocalorie beverages (such as sweet tea and soda). Participants consumed their meal at an instrumented table (Figure 1). Video cameras were mounted in the ceiling above each participant, which recorded the eating session. A course was defined as the time between the participant sitting down with food, prompting the experimenters to begin the recording process, and the participant getting up from the table, either to get another course or to end the session. Video recording was stopped between courses and restarted once the participant had been reseated for the next course. Upon sitting at the table with food, the tethered Bite Counter was placed on the participants' dominant wrist, which was determined by self-report. Participants were instructed to eat and interact as naturally as possible, and to facilitate this, their eating behavior was not restricted in any way to accommodate for the Bite Counter; they were allowed to use napkins and eat with whichever hand they preferred, regardless of Bite Counter position.

After each participant had made their food selections, an undergraduate assistant wrote down each food item, the portion size, and any customization made to the item (eg, adding condiments). Assistants used a menu provided by the dining hall that contained each food item that was supposed to be served in the cafeteria that day, along with a reference portion size for each item and kilocalorie content for that portion (eg, 1 cup of seasoned corn contains 103 kcal) to cross-check the participants' selections.

Upon completion of the meal, participants were given a custom post-meal questionnaire that asked questions seeking to gather data on how the cafeteria setting and the Bite Counter influenced their eating patterns. These data are not reported in this article. However, pertinent to this study, this questionnaire also asked participants to estimate their overall meal kilocalorie intake with the following sentence: "Please estimate the number of calories you just consumed." Participants in the kilocalorie information given condition were given the daily menu



**Figure 1.** The instrumented table. Each station has a tethered bite counter and a camera mounted in the ceiling to record the meal.

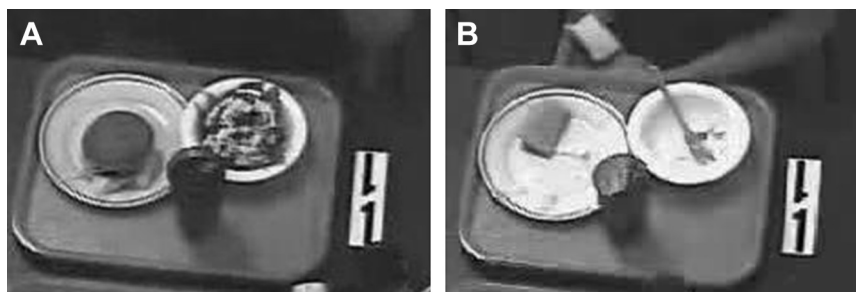
with kilocalorie information for their session to assist them in their estimations. The no kilocalorie information condition did not receive this information. After completing the questionnaire, the participants were debriefed, which involved telling the participants that the purpose of the study was to compare their kilocalorie estimates to estimates derived from the Bite Counter and to improve the accuracy of the device. In addition, any questions they had were answered, and they were free to leave.

## Measures

**Measured Kilocalorie Intake.** Kilocalorie intake was determined using an adaptation of the digital photography method described by Williamson and colleagues.<sup>23</sup> Their study found the accuracy of visual estimations of portion consumption based on photographs to be strongly correlated with visual estimations based on direct observation, estimating most plate food waste to within a mean of 6 g. Three raters were trained to use the digital photography method to estimate plate waste. The training process was led by the lead author of this article, and involved studying the methods used in the 2003 study by Williamson and colleagues.<sup>23</sup> To practice the method, the raters were shown each of the dishes that were used in the study, along with a standard portion of select food items (eg, 1 cup of water in a glass, 1 cup of rice on a large plate). They then participated in several joint practice sessions comparing starting portions with completed meals and estimating plate waste in the form of percentage of selected portion consumed, using the cafeteria dishes as a reference.

After training, the raters estimated the participant's selected portion of each food item in comparison with a standard reference portion obtained from daily menus provided by the dining hall using still frames from video recordings of the food on each participant's plate (Figure 2A). For example, if the raters estimated that a participant had selected twice the standard portion of a serving of mashed potatoes, they would record this as 200% of the standard portion. Standard dishes were used for all meals, so the selected portion could be reliably compared with the reference portion. The raters then compared the initial video still frame to a still frame taken at the end of the course, after the participant had finished eating (Figure 2B). Each rater then estimated the percentage of the selected portion that was actually consumed. Continuing with the previous example, if the participant only consumed half of their selected portion of mashed potatoes, then the raters would estimate that they consumed 50% of the selected portion. Percentage of the reference portion consumed was then calculated by multiplying percent of reference selected by percent of reference consumed.

Each food item was examined by all three raters. To examine inter-rater reliability, an intra-class correlation was calculated on the percent of reference consumed ratings found by each of the three raters. The analysis was conducted using a 2-way, random effects model with an absolute agreement definition and found to be very strong at 0.86.<sup>24</sup> Subsequently, the percentage of the reference portion consumed for each food item was determined by averaging the three ratings.



**Figure 2.** Before (A) and after (B) screenshots used to visually estimate starting portions and portions consumed.

Once food selection, portion selection, and portion consumption had all been verified, total kilocalorie intake for a specific food item was calculated as follows: total kilocalorie intake = kilocalories of reference portion  $\times$  % of reference portion selected  $\times$  % of portion consumed.

For example, for a participant who selected buttermilk mashed potatoes, the menu lists this item as 1 cup having 124 kcal. The participant selected half of the standard serving of the item. The mean rating for portion consumed was 80%. Total kilocalorie intake for that item would be determined by: 124 (kilocalories of reference)  $\times$  0.5 (% of reference)  $\times$  0.8 (% of portion consumed) = 49.6 kcal.

Due to the high levels of customization found for some of the selected food items, the kilocalorie information provided by the dining hall could not be used for these items. These items consisted primarily of sandwiches, which the participants made themselves at the sandwich station, and salads made from the salad bar. Kilocalorie intake for these items was determined using the Automated Self-Administered 24-Hour Recall developed by the National Cancer Institute.<sup>25</sup> A single trained experimenter entered each of these items using the graphical tools provided by the Automated Self-Administered 24-Hour Recall and the portion consumption information obtained as described previously. The Automated Self-Administered 24-Hour Recall utilizes an extensive food database and provides kilocalorie information for each item entered. Once kilocalorie intake of each food item had been determined, total kilocalorie intake for a participant was calculated by summing that participant's kilocalorie intake for all selected items.

**Bite-Based Model of Kilocalorie Intake.** Bites were detected using the tethered version (Figure 3) of the Bite Counter and the bite-detection algorithm described by Dong and colleagues.<sup>18</sup> The Bite Counter is worn on the wrist and identifies a movement pattern that is characteristic of moving food from a dish to the mouth, as measured by a gyroscope. It has been shown to detect 86% of bites in settings where food items and utensil use are unrestricted (such as the one in the present study), with about 20% recorded bites being a false positive. While true bite count was measured via the video recordings, the automatically detected bite counts were used for the present study, as we wanted to develop a model that could be used in uncontrolled settings where true bite count would not be known.

Estimated kilocalories per bite were derived using the predictive equation described in the Results section. In short, kilocalories per bite were predicted by individual

demographic and physical characteristics, and specific foods were not taken into consideration. Estimated kilocalories per bite were then multiplied by bite count to obtain the bite-based estimate of kilocalorie intake. Bite-based error was then calculated for the test group by subtracting each participant's true kilocalorie intake from their bite-based estimate of kilocalorie intake.

**Participant Estimates of Kilocalorie Intake.** Participant kilocalorie estimations were provided by each participant at the end of their experimental session. Participants in the kilocalorie information given condition were allowed to use the menus provided by the cafeteria to aid in their estimations. Participant error was calculated by subtracting each participant's true kilocalorie intake from their estimations. For example, if a participant ate 750 kcal and their estimate was 1,000 kcal, their error would be 250, showing an overestimate of 250 kcal.

### Study Design

The first part of the present study used multiple regression to develop a model of kilocalories per bite based on height, weight, WHR, sex, and age. In order to develop and validate this model from the same sample, a train and test paradigm was used. After data collection, participants were randomly assigned to either the training group or the test group using a



**Figure 3.** Tethered version of the Bite Counter.

50/50 split, but balanced for kilocalorie information condition (ie, an equal number of participants in both kilocalorie information conditions were assigned to the training and test groups). The model was developed on the training group, and the intercept and slopes for the predictors resulting from the analysis were used with the test group to determine the bite-based estimate of kilocalorie intake and its respective error for that group.

The second part used two *t* tests, with estimation method (participant vs bite-based) as a paired samples variable and kilocalorie information presence (or absence) as an independent-samples variable. This analysis was performed within the test group in order to validate the equation generated from the training group and to compare the model of bite-based kilocalorie intake to human estimates.

### Data Analyses

All analyses were performed using SPSS version 17 (2008, SPSS Inc). The hypothesis that height, weight, sex, WHR, and age would predict kilocalories per bite was tested within the training group using multiple regression. The hypothesis that participant estimates of kilocalorie intake would improve with kilocalorie information was tested using a between-subjects *t* test comparing estimates of kilocalorie intake made with the presence of kilocalorie information to those made without it. This test was performed with the train and test samples combined to increase power. The hypothesis that an estimate of kilocalorie intake obtained from a bite-based model would outperform participant estimates was tested using a within-subjects *t* test comparing human estimates of kilocalorie intake in the presence of kilocalorie information to the bite-based estimate of kilocalorie intake, derived using the equation generated from the training group. This analysis was performed within the test group only. All tests were performed with a type I error rate of 0.05.

## RESULTS

### Sample Statistics

Of the 280 participants recruited for this study, there were data recording errors for 11. These errors resulted from missing or corrupted video files, which made determining true kilocalorie intake or bite count impossible. These 11 were excluded from further analyses. Outlier analyses were conducted for the remaining 269 participants by regressing the hypothesized predictors on the whole dataset and calculating Cook's Distance, Mahalanobis Distance, and Studentized Deleted Residuals. Six participants were identified as outliers based on their leverage statistics, indicating that they had an exceedingly higher impact on the model than would be expected from a single data point. Further inspection showed that these participants had unusually high kilocalorie intake, or had unusually high or low bite counts. These six participants were excluded from further analysis, leaving a final sample size of 263 participants.

Demographic characteristics for the remaining participants are shown in Table 1. Participants had a mean age of 29.73 years (standard deviation=11.70 years, range=18 to 75 years). Twenty-five participants identified themselves as African American, 2 as American Indian, 28 as Asian or

Pacific Islander, 184 as white, 11 as Hispanic, and 13 as other. Participants had a mean BMI of 25.36 (standard deviation=5.18, range=17.4 to 46.2), with 4 being underweight (BMI <18.5), 156 were normal weight (BMI 18.5 to 25), 64 were overweight (BMI 25 to 30), and 39 were obese (BMI >30) according to the National Heart, Lung, and Blood Institute classifications.<sup>26</sup> Thirty participants responded "yes" to the question, "Do you follow a special diet?" Of these, 16 explicitly stated that they followed a diet for the purposes of improving diet quality, weight loss, or weight maintenance. Participants were not asked whether they had experience with kilocalorie counting or self-monitoring.

### Meal Statistics

Five-hundred fifteen unique food items were available for participants to choose from. A few of these food items were available in the cafeteria every day, and subsequently show a larger representation in the dataset than other items, which were only available once or twice in most cases during the course of data collection. Participants consumed multiple food items each. A total of 1,844 food items were consumed for the sample. Of these, 221 were identified as having a high level of customization, requiring the use of the Automated Self-Administered 24-Hour Recall to determine kilocalorie content, as described here. The 10 most commonly selected food items, along with the number of times they were chosen, are shown in Table 2.

### Regression on the Training Group

Participant data were randomly assigned to either the training or the test group, with both groups balanced for kilocalorie information condition. Descriptive statistics for all predictors and dependent variables are shown for both groups in Table 1, with independent samples *t* tests used to ensure no significant differences between the two groups. Correlations between the independent and dependent variables within the training group are presented in Table 3. Of note, kilocalories per bite shared a significant but weak positive correlation with height and weight and a weak negative correlation with age. There was also a moderate positive correlation between kilocalories per bite and sex (females=0 and males=1). A multiple regression analysis was run on the 131 participants assigned to the training group, regressing kilocalories per bite on age, sex, height, weight, and WHR. Results from the regression are shown in Table 4. Only age ( $B=-.128$ ,  $t(125)=-2.197$ ;  $P<0.05$ ) and sex ( $B=6.167$ ,  $t(125)=2.779$ ;  $P<0.05$ ) significantly predicted kilocalories per bite. The model explained a significant amount of variance in kilocalories per bite (adjusted  $R^2=0.154$ ,  $F(5, 119)=5.498$ ;  $P<0.001$ ).

Despite being nonsignificant, height, weight, and WHR were retained in the prediction equation because prior research suggests that they may actually be significant contributors to kilocalories per bite.<sup>19-21</sup> This leaves the regression equation used on the test group as follows: estimated kilocalories per bite =  $-.128$  age +  $6.167$  sex (females=0) +  $.034$  height +  $.035$  weight -  $12.012$  WHR +  $22.294$ .

In a train and test paradigm, the reliability of a regression model (ie, the likelihood of finding different coefficients in

**Table 1.** Descriptive statistics and *t* tests for all demographic characteristics, predictors, and dependent variables for participants in a study to develop and test a model of kilocalorie intake based on bite count, with data shown for the total sample, the group used to develop the model (training group), and the group used to test the model (test group)

Variable	Total sample (n=263)	Training group (n=131)	Test group (n=132)	<i>t</i> (df <sup>a</sup> =261) <sup>b</sup>	<i>P</i> value
	← <i>n</i> (%) →				
<b>Ethnicity</b>					
African American	25 (9.5)	10 (7.6)	15 (11.4)	—	—
American Indian	2 (0.8)	1 (0.8)	1 (0.8)	—	—
Asian or Pacific Islander	28 (10.7)	13 (9.9)	15 (11.4)	—	—
White	184 (70)	98 (74.8)	86 (65.2)	—	—
Hispanic	11 (4.2)	3 (2.3)	8 (6.1)	—	—
Other	13 (4.9)	6 (4.6)	7 (5.3)	—	—
<b>BMI<sup>c</sup> category</b>					
Underweight (BMI <18.5) <sup>d</sup>	4 (1.5)	2 (1.5)	2 (1.5)	—	—
Normal Weight (BMI 18.5-24.9) <sup>d</sup>	156 (59.3)	78 (59.5)	78 (59)	—	—
Overweight (BMI 25.0-29.9) <sup>d</sup>	64 (24.3)	30 (22.9)	34 (25.8)	—	—
Obese (BMI >30.0) <sup>d</sup>	39 (14.8)	21 (16)	18 (13.6)	—	—
<b>Following a special diet</b>	30 (11.3)	15 (11.5)	15 (11.4)	—	—
Dieting to lose weight	16 (6.1)	6 (4.6)	10 (7.6)	—	—
<b>Sex</b>					
Male	127 (48.3)	57 (43.5)	70 (53)	—	—
Female	136 (51.7)	74 (56.5)	62 (47)	—	—
	← <i>mean</i> ± <i>SD</i> <sup>e</sup> →				
<b>BMI<sup>f</sup></b>	25.36±5.18	25.67±5.42	25.06±4.93	0.95	0.341
<b>Age (y)</b>	29.73±11.70	30.68±13.33	28.8±9.78	1.31	0.192
<b>Height (in)</b>	67.76±3.83	67.6±3.99	67.9±3.68	-0.66	0.513
<b>Weight (lb)</b>	166.25±36.70	167.8±40.07	164.71±33.09	0.68	0.496
<b>Waist-to-hip ratio</b>	0.855±0.087	0.847±0.086	0.864±0.086	-1.59	0.113
<b>Bites</b>	72.73±24.66	71.63±23.66	72.94±26.33	-0.43	0.667
<b>Kilocalories per bite</b>	19.16±8.76	18.68±8.88	19.63±8.65	-0.88	0.38
				<b><i>t</i> (df)</b>	
<b>Kilocalories per bite (normal weight)</b>	19.13±8.31	18.92±8.07	19.34±8.58	0.320 (154)	0.75
<b>Kilocalories per bite (overweight)</b>	19.28±9.79	18.11±11.26	20.31±8.33	0.895 (62)	0.374
<b>Kilocalories per bite (obese)</b>	19.92±8.96	19.20±8.53	20.77±9.62	0.540 (37)	0.592

<sup>a</sup>df=degrees of freedom.

<sup>b</sup>The *t* test is checking for significant differences between the training and test groups, to ensure that a regression equation derived from the training group could appropriately be applied to the test group.

<sup>c</sup>BMI=body mass index; calculated as kg/m<sup>2</sup>.

<sup>d</sup>According to National Heart, Lung, and Blood Institute classifications.

<sup>e</sup>SD=standard deviation.

<sup>f</sup>Not included as a predictor.

similar samples) is assessed by comparing the *R*<sup>2</sup> value of the training group to the squared correlation of the predicted values and the observed values within the test group (referred to as shrinkage). The predicted values shared a

Pearson correlation with the observed values of 0.374, providing a shrinkage value of 0.014 (1.4%, calculated by subtracting the squared correlation from the adjusted *R*<sup>2</sup> of the regression).

**Table 2.** The 10 most commonly selected food items in a cafeteria setting and how many times they were selected

Food item	No. of times selected
Water	145
Salad	141
Sweet tea	79
French fries	75
Pepperoni pizza	35
Pasta	34
Diet cola	33
Cheese pizza	25
Ice cream	25
Bread side	24

### Effects of Estimation Method and Kilocalorie Information on Estimation Error

An independent samples *t* test was used to compare participant estimation error between the kilocalorie information conditions using the whole sample (training and test groups combined). Mean estimation error for the group provided with kilocalorie information was  $-184.96 \pm 501.54$  kcal, whereas mean estimation error for the no information provided group was  $-349.04 \pm 748.20$  kcal, a significant difference ( $t[220.358] = -2.078$ ;  $P < 0.05$ ). Figure 4 displays boxplots of the estimation error for these two groups, showing a wide range of error and a tendency toward underestimation for both groups.

A paired samples *t* test was used to compare the bite-based method to the best human-based estimation (the kilocalorie information given condition). Mean estimation error was  $-257.36 \pm 790.22$  kcal for participant estimates and  $71.21 \pm 562.14$  kcal for the bite-based method. There was a significant difference between participant and bite-based error in the kilocalorie information given condition ( $t[67] = -3.683$ ;  $P < 0.001$ ), such that estimation error was lower for the

bite-based method. Boxplots of participant error and model prediction error are shown in Figure 5, indicating a smaller range of error for the bite-based method and no apparent bias toward over- or underestimation. To check for differences in the bite-based model's accuracy related to BMI, a one-way analysis of variance was performed on bite-based estimation error for normal weight ( $n=82$ ), overweight ( $n=28$ ), and obese ( $n=22$ ) individuals in the test group. The analysis revealed no main effect for BMI category ( $F[2, 129] = .436$ ;  $P = 0.648$ ). Furthermore, a Pearson correlation showed no relationship between BMI and bite-based estimation error ( $r = -.115$ ;  $P = 0.186$ ).

### DISCUSSION

This study demonstrated that an estimate of an individual's kilocalorie intake using bite count and mean kilocalories per bite determined by a formula based on demographic and physical characteristics can potentially predict kilocalorie intake more accurately than individual estimations, even with the aid of kilocalorie information. This is consistent with previous research that has shown that individuals are poor at accurately estimating the kilocalorie content of meals, tending to err toward underestimation.<sup>2</sup> This study also replicated previous work showing that kilocalorie information can increase an individual's ability to estimate kilocalorie intake.<sup>11,12</sup> Policies that encourage providing diners at restaurants with kilocalorie information for food options show promise for allowing individuals to better estimate their kilocalorie intake and possibly even alter their food choices. However, these estimations are still biased and largely inaccurate, and an accurate objective measure of kilocalorie intake could significantly help individuals self-monitor.

Several researchers are currently working on the development of objective and automatic measures of free-living kilocalorie intake. One research group has developed a device that can automatically detect chewing and swallowing, and have published a study that derived individualized estimates of kilocalorie intake from chews and swallows, which outperformed diet diaries.<sup>17,27</sup> Other researchers are working on developing pattern recognition software that can automatically identify food items and portion sizes from digital photography.<sup>28,29</sup> Using data obtained from the CALERIE (Comprehensive Assessment of

**Table 3.** Pearson correlations for the predictors and kilocalories per bite for a group of participants used to develop a model of kilocalorie intake based on age, sex, height, weight, and waist-to-hip ratio

Predictors	Age (y)	Sex (females = 0)	Height (in)	Weight (lb)	Waist-to-hip ratio	Kilocalories per bite
Age (y)	1					
Sex (females = 0)	-.128	1				
Height (in)	-.091	.642 <sup>a</sup>	1			
Weight (lb)	.247 <sup>a</sup>	.359 <sup>a</sup>	.450 <sup>a</sup>	1		
Waist-to-hip ratio	.058	.594 <sup>a</sup>	.371 <sup>a</sup>	.434 <sup>a</sup>	1	
Kilocalories per bite	-.209 <sup>b</sup>	.372 <sup>a</sup>	.285 <sup>a</sup>	.191 <sup>b</sup>	.152	1

<sup>a</sup>Correlation is significant at the 0.01 level (two-tailed).

<sup>b</sup>Correlation is significant at the 0.05 level (two-tailed).

**Table 4.** Regression results for a model of kilocalorie intake based on age, sex, height, weight, and waist-to-hip ratio<sup>a</sup>

Predictors	<i>B</i> <sup>b</sup>	Standard error	$\beta$ <sup>c</sup>	<i>t</i>	<i>P</i> value
(Constant)	22.294	18.265	—	1.221	0.225
Age (y)	-0.128	0.058	-.195	-2.197	0.030
Sex (females=0)	6.167	2.219	.350	2.779	0.006
Height (in)	0.034	0.249	.016	0.138	0.890
Weight (lb)	0.035	0.022	.159	1.543	0.126
Waist-to-hip ratio	-12.012	10.900	-.120	-1.102	0.273

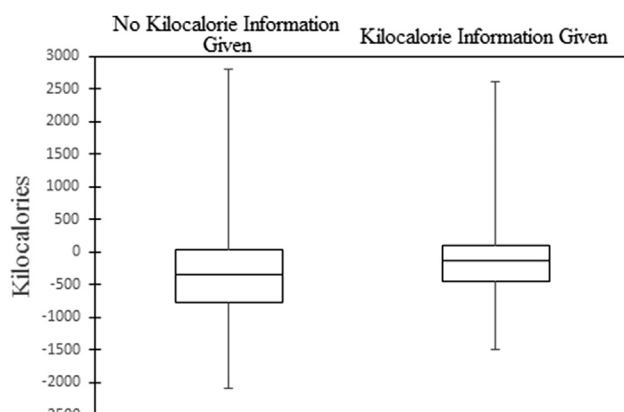
<sup>a</sup>Adjusted  $R^2=0.154$ ; standard error of the estimate=8.10;  $F(5, 119)=5.498$ ;  $P<0.001$ .

<sup>b</sup>Unstandardized coefficient.

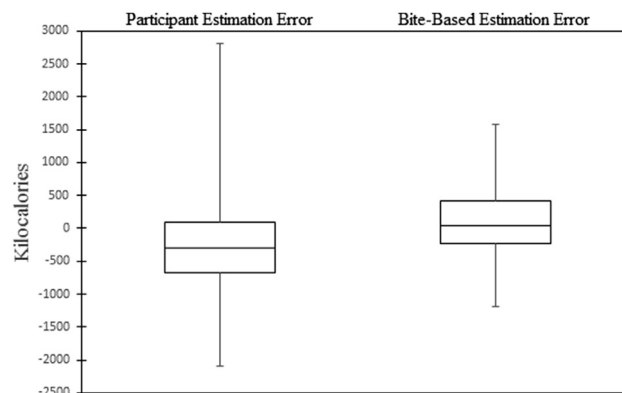
<sup>c</sup>Standardized coefficient.

Long-Term Effects of Reducing Intake of Energy) study, Sanghvi and colleagues<sup>30</sup> describe a method of estimating long-term kilocalorie intake using only demographic variables and changes in weight that is accurate to within 132 kcal/day for most participants. These new methods offer promising avenues for individuals to track their kilocalorie intake.

Accurate kilocalorie counting hinges on accurate estimates of portion size and accurate estimates of the relative energy density, or kilocalories per gram of food items. However, weighing individual foods and looking up their energy densities is cumbersome and, even for the most dedicated dieters, not very practical for daily kilocalorie counting when meals are eaten both in and out of the home and prepared by both oneself and others. Most people make estimations of the kilocalorie content of meals by comparing portion sizes relative to assumed standard serving sizes, or by simply



**Figure 4.** Boxplot of kilocalorie estimation error for two groups of participants estimating their kilocalorie intake. Participants in the kilocalorie information given group were provided a menu containing kilocalorie information for the food items they consumed to assist in their estimations, and participants in the no kilocalorie information given group were not. Estimation error describes the difference between the participants' estimates and their actual intake. Negative values indicate underestimation and positive values indicate overestimation.



**Figure 5.** Boxplot of estimation error for two methods of estimating kilocalorie intake. Participation estimation error describes the difference between the participants' estimated kilocalorie intake and their actual kilocalorie intake. Bite-based estimation error describes the difference between participants' model-estimated kilocalorie intake and actual kilocalorie intake. Negative values indicate underestimation, and positive values indicate overestimation.

relying on their own knowledge and simple heuristics.<sup>1</sup> However, the goal of the bite-based measure is to provide individuals with a kilocalorie intake measure when portion size and energy-density information are either unavailable or difficult to obtain. Also, it could offer the user a convenient and automated alternative to manually calculating the kilocalorie content of a meal, encouraging their adherence to dietary changes.

An objective estimate of kilocalorie intake could also prove to be a valuable tool for researchers. As mentioned previously, most methods used to calculate meal-level variables affecting kilocalorie intake depend on self-reports, which should not be relied upon for scientific conclusions regarding kilocalorie intake or for predictive models, due to their underreporting.<sup>31</sup> While the doubly-labeled water method can accurately measure kilocalorie intake over a period of a few days, it does not provide kilocalorie intake information at the meal level, which reduces its applicability for explaining free-living eating behavior differences between individual meals. Of course, for the Bite Counter to be useful as an objective tool for monitoring eating behavior for individual meals, the relationship between bites and kilocalorie intake should be further explored and refined.

### Limitations and Future Directions

One of the primary limitations of this study was the method used to measure true kilocalorie intake. While the digital photography method has been shown to accurately determine the kilocalorie content of foods to a degree, a study design that incorporated premeasured portions with known kilocalorie content would have yielded a more accurate measure of kilocalorie intake.<sup>23</sup> However, a bite-based measure of kilocalorie intake is better suited to free-living conditions in which food and portion choices vary significantly and, to that end, this study was designed to capture a wide variety of food items and portion sizes. A related limitation was the decision to include highly customized items (which were therefore variable in kilocalorie content),



such as salads and sandwiches, in the analysis. This decision introduced two problems. First, it required the experimenters to use an alternative method (the Automated Self-Administered 24-Hour Recall) to determine their kilocalorie content with an acceptable level of accuracy, and it would be expected that the degree of accuracy obtained would vary more than for those items that could be reliably measured using the digital photography method. Second, because the kilocalorie information provided to the participants only gave an estimate of the mean kilocalorie content of those items, participant estimation accuracy may naturally be worse for these items than for other, less variable items.

Another limitation of this study is the simple model used to predict kilocalories per bite, and the decision to retain nonsignificant variables for the test group. The model does not include any aspects of the food items or the meal itself that could reasonably be assumed to predict kilocalories per bite, such as food item energy density, item consistency (ie, was it a solid item, an amorphous item, or a beverage), and item shape, which limits the model's predictive capabilities. The variables chosen to predict kilocalories per bite were selected based on their availability to the average user; one could calibrate the Bite Counter to their individual physical and demographic variables and have a reasonable proxy for kilocalorie intake. Nonsignificant variables were retained because they have been shown to be related to bite size in previous studies; it is unclear why there was no significant relationship in the present study. Future studies should examine more complex models and test for interactions between variables, perhaps taking a multi-level model approach, examining bite-, food item-, meal-, day-, and individual-level variables, which could potentially refine the accuracy of the estimated kilocalories per bite. It would also be preferable to measure individuals across several meals, but within a context that the participant's kilocalorie intake can be accurately measured.

This study could be viewed as having limited external validity, as food choices were necessarily constrained, and there is evidence that participants display different eating patterns between free-living and laboratory meals. For example, Petty and colleagues showed that participants varied their eating rates between free-living and laboratory-controlled meals.<sup>32</sup> However, it should be noted that the cafeteria environment does represent a step between the laboratory and free living with a wide variety of food choices in a social eating environment. Nonetheless, future studies should examine the differences between free-living and controlled environments and their effect on bite size and kilocalories per bite to determine the generalizability of laboratory-derived kilocalories per bite equations.

No data were collected on the participants' background and familiarity with self-monitoring. It is possible that dietetics students and registered dietitian nutritionists, and those with a significant amount of experience with self-monitoring, could have performed better at estimating their kilocalorie intake, particularly in the no kilocalorie information given condition. This could have reduced external validity. However, participants were recruited from throughout the university, with no particular emphasis on any specific major or

department, so there is no reason to believe that individuals with a strong background in nutrition or dietetics would have been overrepresented.

Finally, while bite count may foreseeably be used to track kilocalorie intake, it is strictly a tool for monitoring and controlling portion size and alone cannot encourage users to improve their diet quality. However, future versions of the Bite Counter may incorporate food selection either by adjusting the kilocalories per bite based on the energy density of the food items selected or by incorporating a "point" system, similar to other weight-loss programs, in which users would be given points as feedback instead of kilocalories, and the points would be adjusted based on bite count, energy density, and the quality of the food item.

## CONCLUSIONS

A bite-based measure of kilocalorie intake shows promise as a tool for both individual use for self-monitoring and for researchers to use to monitor free-living kilocalorie intake. It is an easily collected and objective physiological signal based on wrist motion that could be refined to more accurately estimate kilocalorie intake with the inclusion of a measure of energy density and individual variables that are indicative of kilocalories per bite. With further development, a measure of bite count could be valuable to individuals trying to lose weight and researchers attempting to monitor free-living eating behavior.

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## AUTHOR INFORMATION

J. N. Salley is a graduate research assistant and doctoral degree candidate, M. L. Wilson is a graduate research assistant and doctoral degree candidate, and E. R. Muth is a professor, Department of Psychology, and A. W. Hoover is a professor, Department of Electrical and Computer Engineering, all at Clemson University, Clemson, SC.

Address correspondence to: Eric R. Muth, PhD, Department of Psychology, Clemson University, 410J Brackett Hall, Clemson, SC 29634-1355. E-mail: [muth@clemson.edu](mailto:muth@clemson.edu)

## STATEMENT OF POTENTIAL CONFLICT OF INTEREST

E. R. Muth and A. W. Hoover have formed a company, Bite Technologies, to market and sell a bite counting device. Clemson University owns a US patent for intellectual property known as "The Weight Watch," US Patent No. 8310368, filed January 2009, granted November 13, 2012. Bite Technologies has licensed the method from Clemson University. E. R. Muth and A. W. Hoover receive royalty payments from bite counting device sales. No potential conflict of interest was reported by the other authors.

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