RESEARCH
Original Research

Between- and Within-Subjects Predictors of the Kilocalorie Content of Bites of Food

James N. Salley, PhD; Adam W. Hoover, PhD; Eric R. Muth, PhD

ARTICLE INFORMATION

Article history:
Submitted 3 May 2018
Accepted 14 December 2018

Keywords:
Energy intake
Microstructural analysis
Self-monitoring
Free-living
Bite count

https://doi.org/10.1016/j.jand.2018.12.009

ABSTRACT

Background This study builds on previous research that seeks to estimate kilocalorie intake through microstructural analysis of eating behaviors. As opposed to previous methods, which used a static, individual-based measure of kilocalories per bite, the new method incorporates time- and food-varying predictors. A measure of kilocalories per bite (KPB) was estimated using between- and within-subjects variables.

Objective The purpose of this study was to examine the relationship between within-subjects and between-subjects predictors and KPB, and to develop a model of KPB that improves over previous models of KPB. Within-subjects predictors included time since last bite, food item enjoyment, premeal satiety, and time in meal. Between-subjects predictors included body mass index, mouth volume, and sex.

Participants/setting Seventy-two participants (39 female) consumed two random meals out of five possible meal options with known weights and energy densities. There were 4,051 usable bites measured.

Main outcome measures The outcome measure of the first analysis was KPB. The outcome measure of the second analysis was meal-level kilocalorie intake, with true intake compared to three estimation methods.

Statistical analyses performed Multilevel modeling was used to analyze the influence of the seven predictors of KPB. The accuracy of the model was compared to previous methods of estimating KPB using a repeated-measured analysis of variance.

Results All hypothesized relationships were significant, with slopes in the expected direction, except for body mass index and time in meal. In addition, the new model (with nonsignificant predictors removed) improved over earlier models of KPB.

Conclusions This model offers a new direction for methods of inexpensive, accurate, and objective estimates of kilocalorie intake from bite-based measures.
J Acad Nutr Diet. 2019;■:■-■.

RATES OF OVERWEIGHT AND OBESITY WITHIN THE United States remain at an all-time high, with prevalence continuing to increase among some demographics.[1] Considering the health risks associated with these conditions, there is a continuing need for new tools to monitor free-living eating behavior, both for researchers investigating eating behaviors and weight management techniques, and for individuals attempting to lose or maintain weight. Traditional tools are either too costly for widespread use, or over-rely on self-reporting, leading to systematic inaccuracies in measurement.[2,3] Several new tools have been developed that offer the potential to objectively and accurately monitor eating behavior, and to examine microstructural eating behaviors that were previously only measurable in laboratory environments.[4-6]

Within the context of eating behavior research, microstructural analysis refers to the examination of eating behaviors that are dynamic over the course of a single meal, such as bite size and eating rate.[7] Measuring these behaviors has merit, as patterns in these behaviors have been related to measures of obesity. For example, early research found that normal-weight participants tended to show more rapid decreases in eating rate over time, whereas overweight and obese individuals maintained a steadier eating rate throughout the course of a meal.[8,9] The eating behaviors measured with microstructural analysis have the potential to serve as indicators of energy intake indirectly through their association with the kilocalorie content of specific bites of food, or kilocalories per bite (KPB).

KPB is a function of bite size and the energy density of the food item consumed. When coupled with bite count, accurate estimates of KPB can lead to accurate estimates of meal energy intake. Several microstructural eating behaviors have been related to bite size and energy density. Food-item energy density has been shown to influence food palatability, such that individuals tend to enjoy items with higher energy densities.[10] Bite rate and meal duration have been shown to be negatively associated with bite size.[11] Hill and McCutcheon[11] also found that higher starting hunger levels lead to larger initial bite sizes. In addition, larger mouth volumes are associated with larger bites of food.[12] Some studies have suggested that individuals with higher body mass index (BMI; calculated as kg/m^2) show higher starting eating rates (measured as grams per unit of time) than individuals with lower BMIs, and they maintain those eating rates for longer, which might be due to larger bite sizes.[9] In addition, men have been shown to have higher KPB than women.[4,13]

With advances in mobile and wearable technology, the analysis of microstructural eating behaviors outside the laboratory is becoming more accurate and cost-effective. For example, Fontana and colleagues[14] describe an "automatic ingestion monitor" that utilizes a jaw sensor, a gesture sensor, and an accelerometer to accurately detect eating. A watch-like device, the Bite Counter, tracks wrist motion through the use of a gyroscope and identifies bites of food through a wrist-roll motion that is characteristic of eating behavior.[15] Devices such as these offer the potential to perform microstructural analysis of eating behavior in free-living environments at a low cost.

Recently, a few studies have attempted to utilize the Bite Counter to measure total kilocalorie intake based on bite count and simple demographic variables. Scisco and colleagues[13] examined differences in KPB between men and women, finding that men, in general, had a higher KPB than women, though they did not test the accuracy of a sex-based KPB estimate relative to other methods. In addition, Salley and colleagues[4] examined the relationship between several between-subjects variables and KPB, finding that even a simple model based on bite count, height, weight, age, sex, and waist-to-hip ratio outperformed human estimates of kilocalorie intake. Incorporating additional within-subjects, microstructural eating behaviors as predictors would likely improve the accuracy of these earlier models.

The present study sought to develop a model of KPB using within- and between-subjects variables that can be measured using self-report measures and the bite counter. In analysis 1, it was hypothesized that among the within-subjects predictors, time since last bite (TSLB) and food item enjoyment would have a positive influence on KPB, and premeal satiety and time in meal would have a negative influence. Among the between-subjects predictors, it was hypothesized that BMI and mouth volume would have a positive influence on KPB. In addition, it was hypothesized that men would have a higher KPB than women. In the second analysis, it was hypothesized that the new model would more accurately predict KPB than the between-subjects models described by Salley and colleagues[4] and Scisco and colleagues.[13]

METHODS

Participants

Seventy-two participants (39 female) were recruited via fliers and mass e-mails from the Clemson University student body, faculty, and staff. Participant mean age was 36.96 (standard deviation [SD]=12.71) years and ranged from 19 to 66 years. Ethnicity and BMI information are presented in Table 1. Only those without a self-reported history of eating disorder, who were willing to consume the potential food items, and who did not have any prohibitive dietary restrictions were allowed to participate in the study. Participants were given $5 for attending their first session, and $15 for attending their second. This study was approved by the Clemson University Institutional Review Board, and all participants provided written informed consent.

RESEARCH SNAPSHOT

Research Question: Can individual characteristics and meal-level eating behaviors be used to estimate the kilocalorie content of individual bites of food, and does the inclusion of meal-level behavioral predictors improve estimates over earlier methods?

Key Findings: Across 72 participants consuming two meals consisting of three food items each, time between bites, food item enjoyment, premeal satiety, sex, and mouth volume significantly predicted bite kilocalorie content. In addition, this model estimated bite kilocalorie content more accurately than models based on individual characteristics and sex alone.

Materials and Measures

Food Items. There were five possible meal options, two breakfasts and three dinners (see Table 2). Food items in each meal were selected in an attempt to obtain a wide sampling of food enjoyment and food energy density, while also being easy to prepare given the time, equipment, and personnel constraints of the study. Participants in 7:00 AM or 9:00 AM sessions were given breakfast items, while participants in 1:00 PM, 5:00 PM, and 7:00 PM sessions were given dinner items. Because the 11:00 AM time slot could be either a late breakfast or early lunch time, participants in 11:00 AM sessions were randomly provided with either breakfast or dinner items based on the distribution of assigned meals in order to get a relatively equal distribution of food items consumed (ie, to keep breakfast meals from being overrepresented, some participants were randomly assigned dinner meals for the 11:00 AM sessions). Energy densities for

Table 1. Body mass index and ethnicity distributions from a sample of 72 participants in a study examining microstructural eating behaviors

Characteristic	n	% of Total sample
BMI[a] category[b]		
Underweight (BMI <18.5)	2	3
Normal weight (BMI 18.5 to 24.9)	23	32
Overweight (BMI 25 to 29.9)	24	33
Obese (BMI ≥30)	23	32
Ethnicity		
White	53	74
African American	11	15
Asian or Pacific Islander	3	4
Hispanic	3	4
American Indian or Alaskan Native	1	1.5
Mixed (African American and white)	1	1.5

[a]BMI=body mass index.
[b]BMI categories based on National Heart, Lung, and Blood Institute classifications.[16]

Table 2. Weight and kilocalorie information for a group of five meals presented to participants in a study of microstructural eating behavior

Food item	Weight (g)	kcal	Energy density (kcal/g)
Breakfast meals			
Meal 1			
Quaker maple and brown sugar oatmeal[a]	163	160	1.02
Banana	118	105	0.95
Hostess powdered mini donut[b]	60	240	4.66
Meal 2			
Quaker butter instant grits[a]	148	100	0.61
Yoplait strawberry low-fat yogurt[c]	170	90	0.42
Entenmann's Little Bites mini blueberry muffins[d]	47	180	4.15
Dinner meals			
Meal 3			
Stouffer's chicken Alfredo[e]	200	231	1.5
Birds Eye ranch broccoli[f]	72	44	0.78
Edwards cookies and crème pie[g]	123	470	4
Meal 4			
Stouffer's lasagna with meat sauce[e]	215	270	1.52
Birds Eye Steamfresh mixed vegetables[f]	68	38	0.55
Great Value vanilla ice cream[h]	132	280	2.36
Meal 5			
Stouffer's meatloaf[e]	234	315	2.16
Birds Eye Steamfresh asparagus spears[f]	60	15	0.79
Sara Lee Original cream cheesecake[i]	121	340	2.79

[a]Quaker Oats Company (PepsiCo).
[b]Hostess Brands.
[c]General Mills/Sodiaal.
[d]Bimbo Bakeries USA.
[e]Nestlé S.A.
[f]Pinnacle Foods (USA).
[g]Edwards Baking.
[h]Walmart Inc.
[i]Sara Lee Corporation.

each food item were measured using a bomb calorimeter. A full list of meals with macronutrient information is provided in Table 2.

Instrumented Table. Participants consumed their meals in groups of up to four at an instrumented table. The table had recessed scales that continuously measured plate weight at a rate of 15 Hz. In addition, cameras were mounted above the table to record participants as they ate. The recessed scales and cameras are shown in the Figure, panels A and B. Potential bites were identified through patterns in the scale data using the method described by Mattfeld and colleagues.[17] These weight changes were used to suggest potential bites, but to ensure accuracy, bites were manually tallied using the video recordings. Bite weight was measured as the change in plate weight between each bite of food. KPB were determined by multiplying the weight of each bite of food by its corresponding food item's energy density. TSLB was measured as the amount of time (in seconds) that had elapsed since the previous bite of food. Time in meal was measured as the amount of time (in seconds) that had passed since the first bite of food, the first bite occurring at time 0.

BMI, Mouth Volume, and Subjective Measures. BMI was calculated according to the National Heart, Lung, and Blood Institute's definitions using weight and height measurements, which were obtained from a scale and stadiometer.[16] Mouth volume was obtained using the voluntary mouth fill method described by Lawless and colleagues.[12] Briefly, participants were asked to fill their mouths with water to their maximum capacity, then spit the water into a cup. The weight of the cup was then measured to determine how much water had been placed in the participant's mouth.

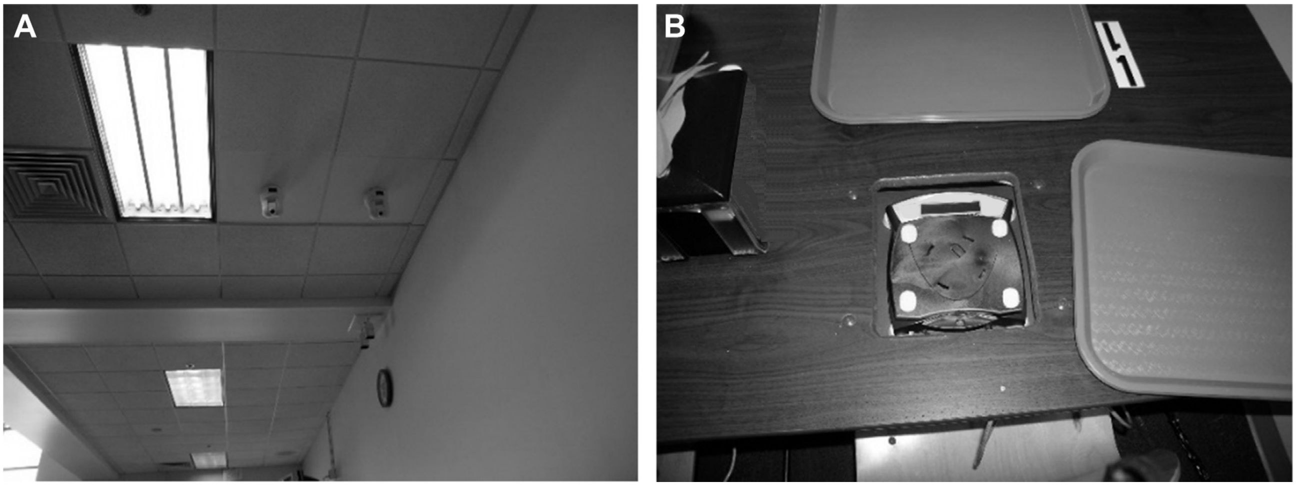

Figure. An instrumented eating station designed to conduct microstructural analysis of eating behavior, including ceiling mounted cameras (A) and the recessed scales for measuring changes in food weight over time (B).

Premeal satiety was measured using the Satiety Labeled Intensity Magnitude (SLIM) scale.[18] The SLIM scale is a 100-mm visual analogue scale anchored on each end with "greatest imaginable hunger/fullness." Food item enjoyment was measured for each consumed food item using the Labeled Affective Magnitude (LAM) scale.[19] Similar to the SLIM scale, the LAM scale is a 100-mm visual analogue scale anchored by "greatest imaginable like/dislike." Participants put a mark on the line where they subjectively experience their hunger/food enjoyment. The distance of the mark (in millimeters) from the low anchor was used to quantify the response.

Procedure

After initial screening, participants were scheduled for two sessions from possibilities occurring Monday through Saturday at 7:00 AM, 9:00 AM, 11:00 AM, 1:00 PM, 5:00 PM, and 7:00 PM. They were assigned to two of the five different meal conditions based on their availability, with participants in the 7:00 AM and 9:00 AM sessions being given one of the two breakfast meals and participants in the 1:00 PM, 5:00 PM, and 7:00 PM sessions being given one of the three dinner meals. Participants in the 11:00 AM sessions were semi-randomly assigned to breakfast or dinner meals to ensure that each meal was equally represented, based on the distribution of assigned meals. Participants were scheduled to eat in groups of 2 to 4 participants. Meals were prepared before participant arrival with an effort to time the completion of preparation with when the participants would begin eating. Meals were prepared and plated in a room separate from the participants.

Study Sessions. Upon arrival in the laboratory, participants' height, weight, mouth volume, and pre-meal satiety were measured. Participants were then instructed on how to eat the meal. They were asked to be mindful of the scale under their place settings, and to avoid putting any extra weight on their plates. For items that they ate with their hands (ie, without utensils), such as the doughnuts and muffins, they were asked to return the item to the plate after each bite. The doughnuts and muffin food items were served in small, individual units, which might have had an influence on average bite size for those items (eg, the last bite of a doughnut was limited by the amount remaining). Bite sizes for all other items were allowed to vary according to participant preference and utensil capacity. Participants were instructed that they did not have to finish each item they were served, but they did need to take at least one bite of each item so that they could provide ratings on their food enjoyment for each item and so that their decisions to continue or discontinue eating the item were based on actual food enjoyment rather than a preconception of how the item would taste. They were asked to avoid using their phones or other distracting items, but were encouraged to converse with each other throughout the meal in order to adequately represent the influence of communal eating on eating rate and meal duration.

Each food item was served in equal portions to each participant. Each different food item was placed on a separate dish to allow for easier measuring of food weights and to prevent food item mixing. Participants were instructed to eat each food item one at a time, with each item being placed on the scale individually to ensure accurate weight measurement. During the meal, an experimenter monitored the participants to ensure that they were following the instructions and not placing any additional weight on the scales.

Upon completion of the meal, participants completed one LAM scale for each food item consumed and paid $5 for their time. In between sessions, participants completed a demographics questionnaire online. The procedure for the second session was identical to the first, except the height, weight, and mouth volume were not measured again. After their second session, participants were paid $15 and debriefed on the purpose of the study.

Statistical Methods

All hypotheses for the first analysis were tested using multilevel modeling (MLM) for repeated measures analysis, a form of maximum likelihood regression that allows for analysis of both within- and between-subjects predictors.[20] The within-subjects predictors of the present study were TSLB and time in meal (one measurement for each bite of food), post-meal LAM ratings (one measurement for each food item consumed), and pre-meal SLIM ratings (one measurement for

Table 3. Descriptive statistics for within- and between-subjects predictors measured across 72 participants in a study examining microstructural eating behaviors and used to develop a model of bite kilocalories

Variable	n	Mean	SD[a]	ICC[b]
KPB[c]	4,032	15.08	11.44	0.18
Within-subjects				
TSLB[d]	3,620	2.74	0.54	0.21
Time in meal	4,032	333.85	226.39	0.15
LAM[e] score	415	66.82	15.57	0.27
SLIM[f] score	139	39.06	16.02	0.63
Between-subjects				
BMI[g]	72	27.65	5.69	—
Sex	72	0.54	0.5	—
Mouth volume	72	75.55	17.33	—

[a]SD=standard deviation.
[b]ICC=Intra-class correlation, a measure of the proportion of within- and between-subject variance.
[c]KPB=kilocalories per bite.
[d]TSLB=time since last bite.
[e]LAM=Labeled Affective Magnitude score, a measure of food item enjoyment.
[f]SLIM=Satiety Labeled Intensity Magnitude score, a measure of premeal satiety.
[g]BMI=body mass index; calculated as kg/m^2.

each meal session). The between-subjects predictors of this study were BMI, mouth volume, and sex. For the second analysis, the model was re-fitted with a limited training sample and its accuracy was examined on a test sample. Finally, KPB as measured by the new model was compared to KPB derived by two previous models using a repeated-measures analysis of variance. All analyses were performed using IBM SPSS Statistics for Windows, version 23.[21]

RESULTS

Data Cleaning and Descriptive Statistics

Across the 72 participants in this study, there were a total of 139 meals consisting of 4,051 usable bites. Two participants did not return for their second meals, and three participants had meals with unusable data due to scale or video errors. All variables were examined for normal distributions. Time in meal and TSLB showed excessive positive skew across several participants. A natural log transformation was applied to these variables for subsequent analyses. However, the transformation for time in meal did not significantly improve its relationship to KPB, so statistics for the non-transformed time in meal are shown here. Because TSLB would be artificially inflated for the first bite of each food item (due to a time delay from switching between food items), the first bite of each food item was excluded from the analysis. However, unequal measurement occasions between predictors do not present a problem for MLM.[20]

Table 3 shows means and standard deviations for all predictors and KPB. Means for within-subjects variables represent grand means. In addition, an intraclass correlation is shown for all within-subjects variables and the dependent variable, which provides a proportion of how much variance in the variable is between subjects and how much is within. Values closer to 1 indicate that a higher proportion of variance is associated with between-subjects differences. All

Table 4. Results from a multilevel model of bite kilocalories across a sample of 72 participants in a study examining microstructural eating behaviors

	Model 1[a]				Model 2[b]			
Variable	Coefficient	SE[c]	t	P value	Coefficient	SE	t	P value
Intercept	14.55	2.76×10^{-1}	52.75	<0.001	−12.15	4.77	−2.55	<0.05
Within-subjects								
lnTSLB[d]	4.81	5.87×10^{-1}	8.19	<0.001	5.03	8.31×10^{-1}	6.06	<0.001
Time in meal	2.98×10^{-3}	2.84×10^{-3}	1.41	0.17	—	—	—	—
LAM[e] score	2.97×10^{-1}	5.11×10^{-2}	5.81	<0.001	2.58×10^{-1}	3.77×10^{-2}	6.85	<0.001
SLIM[f] score	-1.80×10^{-1}	6.30×10^{-2}	−2.85	<0.01	-1.28×10^{-1}	4.87×10^{-2}	−2.62	<0.05
Between-subjects								
Sex[g]	−2.88	6.86×10^{-1}	−4.19	<0.001	−3.5	1.68	−2.08	<0.05
Mouth volume	8.76×10^{-2}	1.91×10^{-2}	4.58	<0.001	2.71×10^{-2}	4.49×10^{-2}	0.6	0.55
BMI[h]	5.14×10^{-2}	4.49×10^{-2}	1.14	0.25	—	—	—	—

[a]Model 1 represents the parameters derived from the full data set.
[b]Model 2 represents the parameters derived from a smaller, training sample with the nonsignificant predictors from Model 1 removed.
[c]SE=standard error.
[d]lnTSLP=natural log of time since last bite.
[e]LAM=Labeled Affective Magnitude score, a measure of food item enjoyment.
[f]SLIM=Satiety Labeled Intensity Magnitude score, a measure of pre-meal satiety.
[g]Females coded as 1, males coded as 0.
[h]BMI=body mass index; calculated as kg/m^2.

values show that variance is split between and within subjects, justifying the use of MLM for this analysis.[20]

Analysis 1: Study Model

Before the regression, all predictors were grand-mean centered.[22] Predictors were not normalized before the regression to facilitate the interpretability of the model. As there was no anticipated pattern of covariance between the predictors and KPB, all covariance parameters were estimated.[20] Table 4 shows the outcome of the regression. Of the hypothesized predictors, the natural log of TSLB, LAM scores, and mouth volume all positively and significantly predicted KPB ($P<0.001$). Pre-meal satiety (SLIM scores) negatively and significantly predicted KPB ($P<0.01$). Neither time in meal ($P<0.17$) nor BMI ($P=0.25$) significantly predicted KPB.

Model Fit. Model fit for MLM is assessed for within- and between-subjects variables independently.[20] The fit for between-subjects variables is assessed as the percentage of variance in mean KPB (intercept variance) explained by the between-subjects predictors. The model in analysis 1 explained 59.81% of the variance in mean participant KPB. The fit for within-subjects variables is assessed as the amount of individual residual variance explained by the within-subjects predictors. The model in analysis 1 accounted for 58.44% of the within-subjects residual variance.

Analysis 2: Comparison to Earlier Models

For the train-and-test analysis, one of each participant's two meals was assigned to a "train" condition, and one to a "test" condition. Only participants with two usable meal sessions were included in this analysis, meaning that 67 participants were included in analysis 2. Whether the first or second meal would be used in the train or test condition was randomly assigned to participants with an even split. That is, the first meal was used as the "training" meal for 34 participants, whereas the second meal was used as the training meal for 33 participants.

Model Training. The MLM regression from analysis 1 was applied again to the meals in the train condition. Only those predictors that were significant in analysis 1 were included in analysis 2, meaning that BMI and time were not included as predictors. Because only one meal was included in this analysis for each participant, SLIM score was treated as a between-subjects predictor, having only one measurement occasion per participant. To facilitate equation interpretation, variables were not mean-centered, and all covariance parameters were estimated. The results from this analysis are presented in Table 4. With the exception of mouth volume, all variables that were significant in analysis 1 remained significant for the training data set. The equation used to predict KPB within the test condition is as follows:

$$\begin{aligned} KPB = & -12.15 - 5.03 lnTSLB + 0.258 LAM - 0.128 SLIM \\ & - 3.50 sex\ (females = 1) + 0.0271 mouth\ volume\ (mL) \end{aligned}$$

Comparison to Earlier Models. The coefficients obtained from the analysis of the training data set were used to predict KPB within the test condition. Estimated KPB was calculated for each bite using these coefficients. In addition, estimated KPB was calculated using the coefficients provided by Salley and colleagues,[4] the equation being:

$$\begin{aligned} KPB = & \ 22.29 - 0.13 age\ (years) + 6.17 sex\ (female = 0) \\ & + 0.03 height\ (inches) + 0.04 weight\ (lbs) \\ & - 12.01 WHR \end{aligned}$$

Finally, estimated KPB was calculated using the sex-based estimates provided by Scisco and colleagues,[13] with men having an estimated KPB of 17 and women having an estimated KPB of 11.

Because the previous two models did not consider within-meal predictors of KPB, a bite-to-bite comparison of the models was not possible. To compare estimated total kilocalorie intake across the three models, KPB was calculated for each bite using the current model and summed across the meal for a meal-level kilocalorie intake estimate. Estimations for the two earlier models were calculated by multiplying the number of bites by estimated KPB, calculated using the coefficients described here. The three estimations of KPB and actual KPB were examined for normality and sphericity. Q-Q plots showed mild positive skew for all four levels and the sphericity assumption was violated ($\chi^2[3]=0.67$; $P<0.05$). Therefore, a Greenhouse-Geisser correction was applied to the degrees of freedom for the analysis ($\varepsilon=0.67$). An omnibus repeated-measures analysis of variance comparing KPB intake with the three estimates revealed a significant main effect for estimation method ($F[2.02, 43.87]=51.45$; $P<0.001$). Post hoc least significant difference comparisons revealed no significant difference between actual mean intake (mean [SD]=394.59 [203.12] kcal) and estimations based on the current model (mean [SD]=399.51 [192.35] kcal; $P=0.71$). However, the estimation by Salley and colleagues[4] (mean [SD]=483.24 [239.18] kcal) was significantly higher than both actual intake and the estimation based on the current model ($P<0.001$). In addition, the sex-based estimate (mean [SD]= 356.57 [169.06] kcal) was significantly lower than both actual intake ($P<0.05$), and the estimation based on the current model ($P<0.001$).

DISCUSSION

The purpose of this study was to develop a new model of KPB that improves on previous models and identifies new predictors of KPB. It was hypothesized that a longer time between bites would be associated with a higher KPB. This hypothesis was supported—a longer time between bites led to a higher KPB. While this would seem to contradict other studies showing a negative relationship between time between bites and bite size, it is important to note differences in the literature in the ways eating rate is defined and measured, which can explain some of these contradictory findings.[23,24] Eating rate can be measured in terms of bites per unit time, kilocalories per unit time, or grams per unit time, with the last being the most frequently used by researchers. Hill and McCutcheon[11] found that longer bite durations (which the authors defined as the amount of time spent chewing food) were associated with larger bites and a slower bite rate.

It was hypothesized that food item enjoyment would share a positive relationship with KPB. This hypothesis was also supported. This is in line with earlier studies that showed positive relationships between eating rate and food enjoyment and between food energy density and food enjoyment.[7,10] In addition, higher premeal satiety was associated with lower KPB, matching Hill and McCutcheon's[11] findings that lower starting hunger levels lead to lower initial eating rates and bite sizes.

The analysis showed that men had a higher KPB than women. While this corroborates earlier findings from our laboratory, it was suggested that this might be due to differences in mouth volume.[4,13] The present study showed that mouth volume and sex both had an independent effect on KPB, indicating that the influence of sex on KPB cannot be entirely explained by differences in mouth volume. BMI, however, did not predict KPB. While there is disagreement in the literature on the relationship between BMI and eating rate, this finding is in line with previous studies that have found no relationship between BMI and KPB or bite size, yet is in disagreement with others that have demonstrated this relationship.[4,13,23,25] This relationship merits further investigation.

Time in meal did not significantly predict KPB. While several studies have shown a decrease in eating rate over time, it is unclear whether this is due to a reduced bite size over time or a reduced bite rate over time.[26,27] The findings of the current study would imply that these changes in eating rate might not be due to changes in bite size. However, it should be noted that presentation order may have confounded the effect of time-in-meal on KPB due to the fact that participants consumed the high energy dense item last for each meal. Further examination of the influence of time in meal on bite size might reveal an effect.

Finally, it was hypothesized that the model developed in the current study would outperform the measures of KPB described by Scisco and colleagues[13] and Salley and colleagues.[4] This hypothesis was supported; estimations of KPB based on the current model did not differ significantly from actual intake, whereas the model by Salley and colleagues significantly overestimated intake and the sex-based model significantly underestimated intake. The current study improves over these previous efforts in that food weight, energy density, and within-subjects variables were measured in a more controlled environment, allowing for greater accuracy. These findings offer hope that further refined models of KPB will continue to improve on estimates of kilocalorie intake.

Limitations

While the present study offers several improvements over prior efforts to predict kilocalorie consumption, there are a few limitations to the use of this model in future studies. While an effort was made to include a variety of food items, the limited number of items selected may not be representative of items that are normally consumed. The easy-to-prepare, yet low-quality nature of the food items served may have resulted in eating patterns that would not translate to meals normally consumed by the participants. Future studies should examine a wider range of food items and examine participant behaviors across multiple meals. In addition, as with all laboratory studies, it is possible that the laboratory environment may have altered subject eating behaviors in a way that limits the validity of the findings. Specific decisions to ensure the accuracy of measurement, such as the requirement that participants eat each item individually and the limited selection of food items, may affect the applicability of the new model to naturalistic settings.

Time since last meal and previous meal composition were not assessed. These two variables might have influenced several of the predictors used to estimate KPB, thus indirectly affecting KPB. Future studies should examine the impact of time spent fasting and previous meal composition for direct and indirect impacts on KPB. In addition, true bite count was only assessed by one reviewer, making a measure of inter-rater reliability impossible and possibly leading to some inaccuracy in bite counts.

This study only examined linear relationships and did not look specifically at any interactions. It is possible that more complicated relationships between KPB and the predictors described here may develop a more accurate and more descriptive model. In addition, the current study did not examine detailed mediation effects (eg, meal duration likely influenced TSLB, causing it to have an indirect effect on KPB through TSLB). Future studies should evaluate both direct and indirect effects of these predictors on KPB.

It should be noted that KPB only measures the kilocalorie content of food items; a more robust measurement of food item macro- and micronutrient content would be necessary for in-depth evaluations of the impacts of food quality on health. Finally, our estimate of KPB assumes a homogenous energy density for each bite of food for a given item. Because the specific content of any given bite of food may vary, estimates of KPB for a single bite may be less accurate for bites that do not contain a homogenous mixture of an item (eg, taking a bite of cheese off the top of lasagna).

Future Directions

While the model derived in this study may provide a relatively accurate model of energy intake, the ideal model of KPB would be tailored to the individual. This would involve monitoring an individual over several meals and could be costly and cumbersome, but would likely result in individualized models with higher accuracy. In addition, while this study describes a model that can be applied to other studies, it does not differentiate between the relationship of the predictors with bite size and food item energy density, the two components of KPB. An understanding of the correlations between the predictors and each of these components would offer further information about microstructural eating behaviors.

While the current study demonstrated some evidence of improvement over prior efforts to model KPB, the accuracy of the model may be due to it being tested against data collected from the same study that was used to train the model. Future studies should compare these estimation methods across a variety of food items and scenarios. Both free-living and laboratory studies should be considered.

Finally, the current study served a dual purpose: to explain the relationship between the hypothesized predictors and KPB, and to incrementally improve over previous models of KPB. This decision limits the predictive validity of the model. While future studies should continue to investigate likely predictors of KPB, more robust methods of generating predictive models that assess non-linearities and interactions between predictors using large data sets will need to be applied to create a model with high predictive ability.

Implications

The current study offers several new predictors of KPB that can be used to refine earlier approximations of KPB, resulting in more accurate measures of kilocalorie intake. In addition, the current study adds to the body of KPB-related data available for developing models of KPB and identifies new behaviors that can be used to estimate KPB. The time between bites is an eating behavior that can be objectively and easily measured using the Bite Counter. In addition, mouth volume and sex can be measured and offered as inputs by individuals in free-living environments. While premeal satiety and food-item enjoyment are measured subjectively, they can be quickly assessed and input at meal time (presumably through an accompanying software, eg, a smartphone application). With the demonstrated improvement over previous methods of estimating KPB, the new model offers researchers the potential to objectively measure kilocalorie intake in free-living studies.

References

1. Flegal KM, Kruszon-Moran D, Carroll MD, Fryar CD, Ogden CL. Trends in obesity among adults in the United States, 2005 to 2014. *JAMA*. 2016;315(21):2284.
2. Dhurandhar NV, Schoeller D, Brown AW, et al. Energy balance measurement: When something is not better than nothing. *Int J Obes*. 2015;39(7):1109-1113.
3. Schoeller DA, Thomas D, Archer E, et al. Self-report-based estimates of energy intake offer an inadequate basis for scientific conclusions. *Am J Clin Nutr*. 2013;97(6):1413-1415.
4. Salley JN, Hoover AW, Wilson ML, Muth ER. Comparison between human and bite-based methods of estimating caloric intake. *J Acad Nutr Diet*. 2016;116(10):1568-1577.
5. Fontana JM, Higgins JA, Schuckers SC, et al. Energy intake estimation from counts of chews and swallows. *Appetite*. 2015;85:14-21.
6. Kalantarian H, Sarrafzadeh M. Audio-based detection and evaluation of eating behavior using the smartwatch platform. *Comput Biol Med*. 2015;65:1-9.
7. Guss JL, Kissileff HR. Microstructural analyses of human ingestive patterns: From description to mechanistic hypotheses. *Neurosci Biobehav Rev*. 2000;24(2):261-268.
8. Westerterp-Plantenga M. Eating behavior in humans, characterized by cumulative food intake curves—a review. *Neurosci Biobehav Rev*. 2000;24(2):239-248.
9. Ohkuma T, Hirakawa Y, Nakamura U, Kiyohara Y, Kitazono T, Ninomiya T. Association between eating rate and obesity: A systematic review and meta-analysis. *Int J Obes*. 2015;39(11):1589-1596.
10. Yao M, Roberts SB. Dietary energy density and weight regulation. *Nutr Rev*. 2001;59(8 Pt 1):247-258.
11. Hill SW, McCutcheon NB. Contributions of obesity, gender, hunger, food preference, and body size to bite size, bite speed, and rate of eating. *Appetite*. 1984;5(2):73-83.
12. Lawless HT, Bender S, Oman C, Pelletier C. Gender, age, vessel size, cup vs. straw sipping, and sequence effects on sip volume. *Dysphagia*. 2003;18(3):196-202.
13. Scisco JL, Muth ER, Hoover AW. Examining the utility of a bite-count-based measure of eating activity in free-living human beings. *J Acad Nutr Diet*. 2014;114(3):464-469.
14. Fontana JM, Farooq M, Sazonov E. Automatic Ingestion Monitor: A Novel Wearable Device for Monitoring of Ingestive Behavior. *IEEE Trans Biomed Eng*. 2014;61(6):1772-1779.
15. Scisco JL, Muth ER, Dong Y, Hoover AW. Slowing bite-rate reduces energy intake: an application of the bite counter device. *J Am Diet Assoc*. 2011;111(8):1231-1235.
16. NHLBI Obesity Education Initiative. *Clinical Guidelines on the Identification, Evaluation, and Treatment of Overweight and Obesity in Adults*. Bethesda, MD: National Heart, Lung, and Blood Institute; 1998. https://www.ncbi.nlm.nih.gov/books/NBK2003/. Accessed February 11, 2019.
17. Mattfeld RS, Muth ER, Hoover A. Measuring the consumption of individual solid and liquid bites using a table-embedded scale during unrestricted eating. *IEEE J Biomed Heal Informatics*. 2017;21(6):1711-1718.
18. Cardello AV, Schutz HG, Lesher LL, Merrill E. Development and testing of a labeled magnitude scale of perceived satiety. *Appetite*. 2005;44(1):1-13.
19. Schutz HG, Cardello AV. A labeled affective magnitude (LAM) scale for assessing food liking/disliking. *J Sens Stud*. 2001;16(2):117-159.
20. Tabachnick BG, Fidell LS. *Using Multivariate Statistics*. 6th ed. Boston, MA: Allyn & Bacon/Pearson; 2014.
21. *IBM SPSS Statistics for Windows [computer program]. Version 22.0*. Armonk, NY: IBM Corp; 2013.
22. Hofmann DA, Gavin MB. Centering decisions in hierarchical linear models: Implications for research in organizations. *J Manage*. 1998;24(5):623-641.
23. Spiegel TA, Kaplan JM, Tomassini A, Stellar E. Bite size, ingestion rate, and meal size in lean and obese women. *Appetite*. 1993;21(2):131-145.
24. Zijlstra N, De Wijk RA, Mars M, Stafleu A, De Graaf C. Effect of bite size and oral processing time of a semisolid food on satiation. *Am J Clin Nutr*. 2009;90(2):269-275.
25. Mattfeld RS, Muth ER, Hoover A. A comparison of bite size and BMI in a cafeteria setting. *Physiol Behav*. 2017;181:38-42.
26. Dovey TM, Clark-Carter D, Boyland EJ, Halford JCG. A guide to analysing Universal Eating Monitor data: Assessing the impact of different analysis techniques. *Physiol Behav*. 2009;96(1):78-84.
27. Laessle RG, Lehrke S, Dückers S. Laboratory eating behavior in obesity. *Appetite*. 2007;49(2):399-404.

AUTHOR INFORMATION

J. N. Salley is a cognitive systems engineer, Resilient Cognitive Solutions, LLC, Pittsburgh, PA; at the time of the study, he was a graduate student and PhD candidate, Department of Psychology, Clemson University, Clemson, SC. A. W. Hoover is a professor, Department of Electrical and Computer Engineering, and E. R. Muth is a professor, Department of Psychology, both 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

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,” USA, 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 J. N. Salley.

FUNDING/SUPPORT

This work was partially funded by a grant from the National Institute of Diabetes and Digestive and Kidney Diseases, grant number 2R42DK091141-02, titled “Assessing the Bite Counter as a Tool for Food Intake Monitoring: Phase II.”

AUTHOR CONTRIBUTIONS

J. N. Salley collected the data and wrote the first draft of the manuscript. A. W. Hoover provided the tools and algorithms for detecting bite counts and bite weights. E. R. Muth assisted with study design manuscript drafting. All authors reviewed and commented on subsequent drafts.