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BETWEEN- AND WITHIN-SUBJECTS PREDICTORS OF THE KILOCALORIE CONTENT OF BITES OF FOOD

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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 (KPB), the new method incorporates time- and food-varying predictors. A measure 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, pre-meal satiety, and time in meal. Between-subjects predictors included body-mass index, mouth volume, and gender.

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

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JNS collected the data and wrote the first draft of the manuscript. AWH provided the tools and algorithms for detecting bite counts and bite weights. ERM assisted with study design manuscript drafting. All authors reviewed and commented on subsequent drafts.

Statement of Potential Conflict of Interest

Authors ERM and AWH 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. ERM and AWH receive royalty payments from bite counting device sales.

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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 ANOVA.

Results—All hypothesized relationships were significant, with slopes in the expected direction, except for BMI and time in meal. Additionally, the new model (with non-significant 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.

Keywords

Energy intake; microstructural analysis; self-monitoring; free-living; bite count

Background

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 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 (Kilocalories-per-bite, or 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 & McCutcheon also found that higher starting hunger levels lead to higher initial bite sizes. Additionally, larger mouth volumes are associated with larger bites of food.¹² Some studies have suggested that individuals with higher BMI's show higher starting eating rates (measured as

grams per unit of time) than individuals with lower BMI's and maintain those eating rates for longer, which might be due to larger bite sizes.⁹ Additionally, men have been shown to have higher KPB's 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, Farooq, & Sazonov, describe an "automatic ingestion monitor" that utilizes a jaw sensor, a gesture sensor, and an accelerometer to accurately detect eating.¹⁴ 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 in order to measure total kilocalorie intake based on bite count and simple demographic variables. Scisco et al. 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 gender-based KPB estimate relative to other methods.¹³ Additionally, Salley et al. examined the relationship between several between-subjects variables and KPB, finding that even a simple model based on bite count, height, weight, age, gender, and waist-to-hip ratio outperformed human estimates of kilocalorie intake.⁴ Incorporating additional within-subjects, microstructural eating behaviors as predictors would likely improve the accuracy of these earlier models.

Current Study

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 pre-meal 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. Additionally, 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 et al. and Scisco et al..^{4,13}

Method

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 (in years) was 36.96 ($SD = 12.71$) and ranged from 19 to 66. 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.

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 7:00am or 9:00am sessions were given breakfast items, while participants in 1:00pm, 5:00pm, and 7:00pm sessions were given dinner items. Since the 11:00am time slot could be either a late breakfast or early lunch time, participants in 11:00am 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 (i.e., to keep breakfast meals from being overrepresented, some participants were randomly assigned dinner meals for the 11am sessions). Energy densities for 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 15hz. Additionally, cameras were mounted above the table to record participants as they ate. The recessed scales and cameras are shown in Figures 1a and 1b. Potential bites were identified through patterns in the scale data using the method described by Mattfeld, Muth, & Hoover.¹⁶ 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 was determined by multiplying the weight of each bite of food by its corresponding food item's energy density. Time since last bite 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.

Body-mass index, 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 stadiometer¹⁷. Mouth volume was obtained using the voluntary mouth fill method described by Lawless, Bender, Oman, & Pelletier. 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.

Pre-meal satiety was measured using the Satiety Labeled Intensity Magnitude (SLIM) scale¹⁸. The SLIM scale is a 100mm 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 100mm visual analogues 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 7:00am, 9:00am, 11:00am, 1:00pm, 5:00pm, and 7:00pm. They were assigned to two of the five different meal conditions based on their availability, with participants in the 7:00am and 9:00am sessions being given one of the two breakfast meals and participants in the 1:00pm, 5:00pm, and 7:00pm sessions being given one of the three dinner meals. Participants in the 11:00am 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 prior to 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 lab, 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 (i.e., without utensils), such as the doughnuts and muffins, they were asked to return the item to the plate after each bite. The donut and muffin food items were served in small, individual units which might have had an influence on average bite size for those items (e.g. the last bite of a donut 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 pre-conception 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 weren't 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. 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 each meal session). The between-subjects predictors of this study were BMI, mouth volume, and gender. 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 ANOVA. All analyses were performed using IBM SPSS version 23.

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

Analysis 1: Study Model

Prior to the regression, all predictors were grand-mean centered²¹. Predictors were not normalized prior to 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 ($p < .001$). Pre-meal satiety (SLIM scores) negatively and significantly predicted KPB ($p < .01$). Neither time in meal ($p = .17$) nor BMI ($p = .25$) 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. Since 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 dataset. The equation used to predict KPB within the test condition is as follows:

$$KPB = -12.15 - 5.03 \ln TSLB + 0.258 LAM - 0.128 SLIM - 3.50 \text{gender} (\text{females} = 1) + 0.0271 \text{mouth volume (ml)}$$

Comparison to earlier models—The coefficients obtained from the analysis of the training dataset were used to predict KPB within the test condition. Estimated KPB was calculated for each bite using these coefficients. Additionally, estimated KPB was calculated using the coefficients provided by Salley et al., the equation being:⁴

$$KPB = 22.29 - 0.13 \text{age (years)} + 6.17 \text{gender (female} = 0) + 0.03 \text{height (inches)} + 0.04 \text{weight (lbs)} - 12.01 WHR$$

Finally, estimated KPB was calculated using the gender-based estimates provided by Scisco et al., with men having an estimated KPB of 17 and women having an estimated KPB of 11.¹³

Since 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 kcal intake across the three models, KPB was calculated for each bite using the current model and summed

across the meal for a meal-level kcal intake estimate. Estimations for the two earlier models were calculated by multiplying the number of bites by estimated KPB, calculated using the coefficients described above. 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 ($\chi^2(3) = 0.67, p < .05$). Therefore, a Greenhouse-Geisser correction was applied to the degrees of freedom for the analysis ($\epsilon = 0.67$). An omnibus repeated-measures ANOVA comparing KPB intake with the three estimates revealed a significant main effect for estimation method, $F(2.02, 43.87) = 51.45, p < .001$. Post-hoc LSD comparisons revealed no significant difference between actual mean intake ($M = 394.59$ kcal, $SD = 203.12$) and estimations based on the current model ($M = 399.51$ kcal, $SD = 192.35$), $p = .71$. However, the Salley et al. estimation ($M = 483.24$ kcal, $SD = 239.18$) was significantly higher than both actual intake and the estimation based on the current model, $p < .001$.⁴ Additionally, the gender-based estimate ($M = 356.57$ kcal, $SD = 169.06$) was significantly lower than both actual intake, $p < .05$, and the estimation based on the current model, $p < .001$.

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.^{22,23} 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 & McCutcheon 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.¹¹

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. Additionally, higher pre-meal satiety was associated with lower KPB, matching Hill & McCutcheon's findings that lower starting hunger levels lead to lower initial eating rates and bite sizes.¹¹

The analysis showed that men had a higher KPB than women. While this corroborates earlier findings from our lab, it was suggested that this might be due to differences in mouth volume.^{4,13} The present study showed that mouth volume and gender both had an independent effect on KPB, indicating that the influence of gender on KPB cannot be entirely explained by differences in mouth volume. Body-mass index, 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.^{4,13,22,24} 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.^{25,26} 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 ED 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 et al. and Salley et al.^{4,13} This hypothesis was supported; estimations of KPB based on the current model did not differ significantly from actual intake, whereas the Salley et al. model significantly overestimated intake and the gender-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. Additionally, as with all laboratory studies, it is possible that the laboratory environment may have altered subject eating behaviors in a way that limit 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. Additionally, 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. Additionally, the current study did not examine detailed mediation effects (e.g. 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 micro-nutrient 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. Since 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 (e.g. 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. Additionally, 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 datasets 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. Additionally, 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. Additionally, mouth volume and gender can be measured and offered as inputs by individuals in free-living environments. While pre-meal satiety and food-item enjoyment are measured subjectively, they can be quickly assessed and input at meal time (presumably through an accompanying software, e.g. 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.

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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, pre-meal satiety, gender, and mouth volume significantly predicted bite kilocalorie content. Additionally, this model estimated bite kilocalorie content more accurately than models based on individual characteristics and gender alone.

Figure 1.
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).

Table 1

BMI and Ethnicity distributions from a sample of 72 participants in a study examining microstructural eating behaviors.

Characteristic	N	% of total sample
BMI Category ^a		
Underweight (BMI < 18.5)	2	3
Normal weight (BMI 18.5–24.9)	23	32
Overweight (BMI 25–29.9)	24	33
Obese (BMI ≥ 30)	23	32
Ethnicity		
Caucasian	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 & Caucasian)	1	1.5

^aBMI categories based on NHLBI classifications.¹⁷

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)	Kilocalories (kcal)	Energy Density (kcal/g)
Breakfast Meals			
<i>Meal 1</i>			
Quaker Maple™ & Brown Sugar			
Oatmeal	163	160	
Banana	118	105	0.95
Hostess™ Powdered Min Donut	60	240	4.66
<i>Meal 2</i>			
Quaker™ Butter Instant Grits	148	100	0.61
Yoplait™ Strawberry Low-fat Yogurt	170	90	0.42
Little Bites™ Mini Blueberry Muffins	47	180	4.15
Dinner Meals			
<i>Meal 3</i>			
Stouffers™ Chicken Alfredo	200	231	1.5
Bird's Eye™ Ranch Broccoli	72	44	0.78
Edward's™ Cookies & Crème Pie	123	470	4
<i>Meal 4</i>			
Stouffers™ Lasagna with Meat Sauce	215	270	1.52
Bird's Eye™ Steamfresh Mixed			
Vegetables	68	38	
Great Value™ Vanilla Ice Cream	132	280	2.36
<i>Meal 5</i>			
Stouffers™ Meatloaf	234	315	2.16
Bird's Eye™ Steamfresh Asparagus Spears	60	15	0.79
Sarah Lee™ Original Cream			
Cheesecake	121	340	2.79

Table 3

Descriptive statistics for within- and between-subjects predictors measured across 72 participants, used to develop a model of bite kilocalories.

Variable	<i>N</i>	<i>Mean</i>	<i>SD</i> ^f	<i>ICC</i> ^g
KPB ^a	4032	15.08	11.44	0.18
Within-Subjects				
TSLB ^b	3620	2.74	0.54	0.21
Time in Meal	4032	333.85	226.39	0.15
LAM Score ^c	415	66.82	15.57	0.27
SLIM Score ^d	139	39.06	16.02	0.63
Between-Subjects				
BMI ^e	72	27.65	5.69	-
Gender	72	0.54	0.5	-
Mouth				
Volume	71	75.55	17.33	-

^aKilocalories-per-bite

^bTime since last bite

^cLabeled Affective Magnitude score, a measure of food item enjoyment

^dSatiety Labeled Intensity Magnitude score, a measure of pre-meal satiety

^eBody-mass Index

^fStandard deviation

^gIntra-class correlation, a measure of the proportion of within- and between-subject variance.

Table 4

Results from a multilevel model of bite kilocalories across a sample of 72 participants. Model 1 represents the parameters derived from the full dataset, whereas Model 2 represents the parameters derived from a smaller, training sample with the non-significant predictors from Model 1 removed.

Variable	Model 1				Model 2			
	Coefficient	SE ^a	t-value	p-value	Coefficient	SE ^a	t-value	p-value
Intercept	14.55	2.76×10^{-1}	52.75	<.001	-12.15	4.77	-2.55	<.05
Within-Subjects								
InTSLB ^b	4.81	5.87×10^{-1}	8.19	<.001	5.03	8.31×10^{-1}	6.06	<.001
Time in Meal	2.98×10^{-3}	2.84×10^{-3}	1.41	0.17	-	-	-	-
LAM Score ^c	2.97×10^{-1}	5.11×10^{-2}	5.81	<.001	2.58×10^{-1}	3.77×10^{-2}	6.85	<.001
SLIM Score ^d	-1.80×10^{-1}	6.30×10^{-2}	-2.85	<.01	-1.28×10^{-1}	4.87×10^{-2}	-2.62	<.05
Between-Subjects								
Gender ^e	-2.88	6.86×10^{-1}	-4.19	<.001	-3.5	1.68	-2.08	<.05
Mouth Volume	8.76×10^{-2}	1.91×10^{-2}	4.58	<.001	2.71×10^{-2}	4.49×10^{-2}	0.6	0.55
BMI ^f	5.14×10^{-2}	4.49×10^{-2}	1.14	0.25	-	-	-	-

^aStandard error

^bThe natural log of time since last bite

^cLabeled Affective Magnitude score, a measure of food item enjoyment

^dSatiety Labeled Intensity Magnitude score, a measure of pre-meal satiety

^eFemales coded as 1, males coded as 0

^fBody-mass Index