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An Examination of Predictors of Variance in the Caloric Content of Specific Bites of Food

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AN EXAMINATION OF PREDICTORS OF VARIANCE IN THE CALORIC CONTENT OF SPECIFIC
BITES OF FOOD

A Dissertation
Presented to
the Graduate School of
Clemson University

In Partial Fulfillment
of the Requirements for the Degree
Doctor of Philosophy
Human Factors Psychology

by
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May 2017

Accepted by:
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ABSTRACT

Obesity continues to be a leading health risk throughout the world, and there is a need for tools to assess free-living eating behavior for both researchers attempting to study how specific eating behaviors contribute to obesity outside the lab and for individuals to use as self-monitoring aids. This study sought to examine how variance in individual traits and eating behaviors can be used to understand and predict the kilocaloric content of specific bites of food (KPB). It was hypothesized that meal duration, pre-meal satiety, food enjoyment, eating rate, age, gender, mouth volume, and body metrics would significantly predict KPB. Seventy-two participants were asked to eat two meals, consisting of three food items each. Participants were randomly assigned to two of five possible meals, never eating the same meal twice. Multi-level linear modelling was used to examine predictors of KPB: time in meal, time since last bite, food item enjoyment, pre-meal satiety, BMI, body fat percentage, waist-to-hip ratio, gender, mouth volume, and age. Additionally, the following mediation effects were hypothesized: the effect of time in meal would be mediated by time since last bite, satiety would be mediated by food item enjoyment, and the three body metrics would be mediated by food item enjoyment. Food enjoyment, pre-meal satiety, time in meal, and eating rate surfaced as the strongest predictors of KPB. The effect of time in meal on KPB appears to be partially mediated by time since last bite. However, there is no evidence that the effect of satiety is mediated by food item enjoyment. Additionally, a train-and-test analysis for model validation was performed, with one of each participant's meals being used to train the model and the other used to test the model. The resulting model was found to perform better than previously derived models of KPB. While this study offers some new insight into predictors of KPB, additional work will be necessary before an accurate and applicable model of KPB can be derived from easily measured variables.

DEDICATION

I dedicate this dissertation to my wife, Caroline Christ. I can't imagine a more patient, supportive or understanding partner in life, and I never would have made it this far without her.

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I would like to thank Dr. Eric Muth for teaching me how to think like a scientist and for his guidance and patience throughout these past seven years. Thanks, Eric, for helping me learn to communicate complicated topics to a wide audience and for your always constructive criticism. I would also like to thank Dr. Adam Hoover for his technical help throughout my graduate career, Dr. Elliot Jesch for his expertise in eating behavior and the use of his lab for my calorimetry measurements, and Dr. DeWayne Moore for his statistical expertise and guidance in class and for my dissertation.

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TABLE OF CONTENTS

	Page
TITLE PAGE.....	i
ABSTRACT	ii
DEDICATION	iii
ACKNOWLEDGMENTS	iv
CHAPTER	
I. INTRODUCTION	1
Overview	1
Monitoring Eating Behavior	1
Using Microstructural Analysis to Predict Caloric Intake	12
Present Study, Design, and Hypotheses.....	14
II. METHODS	19
Participants.....	19
Materials and Measures.....	21
Procedure	26
III. RESULTS.....	32
Analysis 1: Multi-level Model of KPB.....	32
Analysis 2: Mediation Analysis	43
Analysis 3: The Applied Model and Cross-Validation.....	47
IV. DISCUSSION	53
Multi-level Analysis of KPB	53

The Applied Model	62
Limitations.....	64
Future Directions.....	66
Conclusion	68
APPENDICES.....	69
A. Describing Obesity	70
B. Additional Variables.....	75
C. Recruitment E-mail	78
D. Recruitment Flyer	79
E. Screening Questionnaire.....	80
F. Demographic Questionnaire.....	87
G. Dieting Behaviors Scale.....	89
H. The Mindful Eating Questionnaire.....	90
I. Self-Efficacy for Dietary Control.....	93
J. The Three-Factor Eating Questionnaire R-18	94
K. Weight Efficacy Lifestyle Questionnaire	96
L. Pre-Meal Questionnaire.....	99
M. Post-Meal Questionnaire	100
N. Data Cleaning	102
O. Hierarchical Breakdown of Analysis 1.....	108
P. MLM Analysis of Bite Weight.....	115
Q. Mediation Analysis of Bite Weight	122
R. Multiple Regression of Level 2 Variables on KPB.....	124
REFERENCES	125

LIST OF TABLES

Table		Page
1.1	Each predictor, along with its level in the model and hypothesized effect on KPB	16
2.1	Sample demographic characteristics	21
2.2	Nutrition information for the selected meals.....	23
3.1	Descriptive statistics for bite (level 1) and participant (level 2) variables	36
3.2	Correlations between all variables	37
3.3	Predictor summary of MLM analysis	42
3.4	Results from mediation analysis of the effect of time in meal on KPB, mediated by InTSLB	46
3.5	Results from mediation analysis of the effect of satiety on KPB, mediated by food enjoyment	47
3.6	Summary of MLM for analysis 3	49
3.7	Descriptive statistics for KPB estimates and estimation error at the bite- and meal- levels	52
B1	Additional variables and their expected relationship to KPB	77
O1	Estimates of random effects and model fit statistics	109
O2	Estimates of fixed effects.....	110
P1	Estimates of random effects and model fit statistics	116
P2	Estimates of fixed effects.....	117
Q1	Results from mediation analysis of InTSLB, TIM, and bite weight.....	123
R1	Multiple regression of KPB using level 2 variables	124

LIST OF FIGURES

Figure		Page
1.1	The zone of biological indifference.....	4
1.2	Hypothesized model	17
2.1	The instrumented eating station	24
2.2	Software used for detecting bites and bite weights.....	29
2.3	An accurately detected bite.....	30
3.1	Scatterplots of the level 1 predictors with KPB	38
3.2	Scatterplots of the Level 2 predictors with KPB	39
3.3	Bar graph showing differences in KPB between males and females.....	40
3.4	The hypothesized effect of time in meal on KPB, mediated by time since last bite.....	44
3.5	Scatterplot of observed and predicted KPB.....	50

CHAPTER ONE: INTRODUCTION

Overview

The purposes of this study were to examine the effects of a variety of easily measured variables on kilocalories per bite (KPB) and to develop a model of KPB that could be used in future studies to estimate kilocalorie (kcal) intake. Seventy-two participants ate two meals consisting of three food items in a laboratory setting. Individual bite weights were measured using universal eating monitors (Kissileff, Klingsberg, & Van Itallie, 1980). Energy density of selected food items was assessed using a bomb calorimeter. KPB was derived by multiplying bite weight by energy density. Body fat percentage, BMI, waist-to-hip ratio, age, mouth volume, gender, food preference, satiety, time in meal, and eating rate data were used as predictors. Multi-level modelling was used to characterize variance at the bite and individual levels. The results of this study provide formulae that can be used to more accurately monitor caloric intake in free-living scenarios. These formulae may be useful for research examining differences in meal eating patterns between healthy, overweight, and obese individuals.

Monitoring Eating Behavior

Obesity continues to be one of the leading health risks worldwide (Ogden, Carroll, Kit, & Flegal, 2014). A full description of the prevalence, causes, health risks, economic costs, and treatments for obesity can be found in Appendix A. The investigation of human eating behavior is crucial to the development and refinement of behavioral treatments for obesity, as it allows researchers and clinicians to identify and target specific behaviors that are associated with food choice, excessive caloric consumption, and weight gain. While monitoring eating behavior in the lab is relatively simple, its external validity is limited as individuals are known to change their

intake levels and other eating behaviors in laboratory and clinical settings (Petty, Melanson, & Greene, 2013). However, certain behaviors may be indicative of free-living eating patterns and subsequently allow researchers to develop models of the relationship between objectively observable variables and free-living eating behaviors.

Several variables of interest have been identified in the literature that contribute to higher BMI levels and/or higher meal and long-term kcal intake. These factors affect decisions that can be classified into time-dependent categories: decisions about when (and how often) to eat, what to eat and how much to serve (food choice and portion selection), and the decision of when to stop eating. These decisions can influence each other, and are affected by overlapping and interacting physiological, behavioral, psychological, and environmental factors. While each of these decision areas have received extensive research, both to understand behaviors that lead to obesity and to investigate possible avenues of treatment, the decision to stop eating is of particular interest. Increased portion consumption is thought to be a significant contributor to the current obesity epidemic and is a direct result of meal cessations occurring after larger quantities (and therefore, more kcals) have been consumed (Nestle, 2003; Nielsen & Popkin, 2010; Lisa R Young & Nestle, 2003).

Satiation and satiety cues. Meal cessation can occur for a variety of reasons. For example, individuals may stop eating because they are intentionally attempting to control their portion intake, and have met a pre-determined portion limit. However, for most individuals in most meals the act of meal cessation comes as a result of satiation, or the loss of desire to continue eating. Whereas Tuomisto, Tuomisto, Hetherington, and Lappalainen (1998) found that hunger was described as the reason for meal commencement in 20% of obese individuals,

they found that the most commonly given reason for meal cessation was satiation. Considering that obese individuals ate more than lean individuals, this would seem to indicate that obese individuals are either insensitive to meal cessation cues that would have them stop earlier in the meal, or they do not experience subjective satiety until later in the meal than lean individuals. A satiety cue is a factor that either directly contributes to satiation or that causes an individual to evaluate their satiation level and decide to stop eating. A number of satiety cues have been identified, and they have been classified by many researchers as either internal or external (Wansink, Payne, & Chandon, 2007). This distinction can be somewhat confusing, as some cues can be difficult to classify neatly into one of the two categories. However, before this can be clarified, a discussion of the role of satiety in meal cessation is necessary.

Zone of biological indifference. Herman & Polivy (2005) describe satiation as a range of food consumption rather than an isolated state, referring to this range as the “zone of biological indifference.” Below the bottom end of the zone, an individual continues to feel a subjective experience of hunger. At the top end, a feeling of fullness develops and continued eating becomes physically uncomfortable. The authors claim that a person can stop eating anywhere between these two points. Unless a top-down or external influence is exerted on eating behavior, eating will continue until the bottom of the zone is reached; internal satiety cues influence at what point during the meal an individual reaches this point. Once the zone of indifference has been reached, eating will continue until a variety of other cues (such as an empty plate, top-down influence or mindfulness, eating companions ceasing eating activity, etc.) cause an evaluation of the physiological state and eating stops. If no salient satiety cue is presented (for example, when eating in darkness with a large quantity of food available),

individuals will eat until they reach the “full” state, where eating begins to be uncomfortable (Scheibehenne, Todd, & Wansink, 2010). Additionally, the length of the zone in terms of amount of food eaten may vary between individuals, and obese individuals may have a much wider zone of indifference along with a higher starting point (Herman & Polivy, 1983).

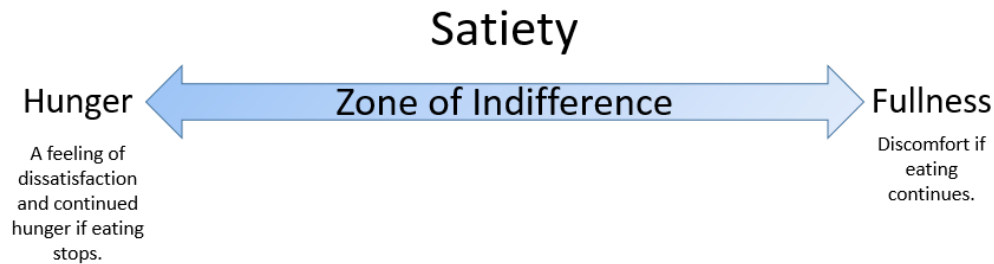


Figure 1.1. The zone of biological indifference is a range of a quantity of food consumed where an individual may stop eating and feel satisfied, but not uncomfortably full.

The reason satiety cues can be difficult to classify and neatly categorize is that while certain variables that influence meal cessation may originate internally or externally, they often interact with each other. External satiety cues may influence internal processes. Additionally, influences on meal cessation can affect the loss of hunger (at the bottom of the zone of indifference), the detection and response to satiety (where one stops eating within the zone of indifference), or both. Also, certain behaviors affect satiation, which can also be difficult to classify as internal or external. However, for the purposes of this paper, every attempt is made to divide influences on meal cessation into internal or external cues.

Internal satiety cues. The loss of physiological hunger is thought to be affected primarily by an interaction between a variety of hormones and the central nervous system. Most of the satiety cues that affect the loss of hunger must be considered within the context of hormonal influences on hunger loss, as these hormones often act as mediators between the

specific cues and the loss of hunger. Several variables that affect how quickly the zone of indifference is reached have been identified, and are discussed in detail in the following sections.

Energy density. Energy density (ED) describes the number of kcals in food per unit of weight (kcal/g). Several researchers maintain that a reduction in ED has no direct impact on satiety independent of portion consumption, and suggest ED reduction as an avenue for treatment (Ello-Martin, Ledikwe, & Rolls, 2005). For example, Bell, Castellanos, Pelkman, Thorwart, and Rolls (1998) found that ED, independent of satiety levels and food palatability, did not affect portion consumption. This resulted in participants consuming more kcals of high-ED foods for a single meal. However, other studies have suggested that ED *does* have an indirect effect on satiety through its effect on palatability, though this has not been demonstrated adequately (Yao & Roberts, 2001).

Macronutrient content. Macronutrients are the three sources from which we derive energy for metabolism: fats, proteins, and carbohydrates. The macronutrient content of food affects all aspects of eating behavior in a variety of complex ways, and its effect on satiation is no different. In a recent review of the satiation and satiety effects of different macronutrients, Bellissimo & Akhavan (2015) identify protein and medium-chain triglycerides as having strong satiating effects. Fat in general has been found to be less satiating than carbohydrates and proteins (Blundell, Burley, Cotton, & Lawton, 1993; Schutz, Flatt, & Jéquier, 1989). Bell et al. (1998) suggest that macronutrient content may influence palatability (as with energy density), but it also has an independent effect on satiation.

Palatability. Palatability describes the amount of enjoyment an individual derives from a specific food. Several studies have investigated the enjoyment of food for its impact on meal cessation. Food palatability decreases as a food is consumed, and this reduction in enjoyment is thought to contribute to the onset of satiation (M M Hetherington, 1996; B J Rolls, 1986). As described earlier, food palatability is thought to be a mediator through which energy density and macronutrient content affect the onset of satiation. Guss and Kissileff (2000) propose that the effect of palatability on satiation is at least partially due to its influence on eating rate; greater enjoyment of a specific food leads to higher initial eating rates. Wansink & Kim (2005) demonstrated that the satiating effects of palatability are influenced by the presence of environmental cues to continue eating; that is, in the presence of distraction and social facilitation, the effect of palatability on satiation disappears. Studies have shown that obese individuals may simply enjoy food more, causing them not only to eat more often, but to eat closer to the upper boundary of the zone of indifference (French, Epstein, Jeffery, Blundell, & Wardle, 2012). This would indicate that differences in the enjoyment of food may be a root cause of overeating and a significant contributor to obesity.

Starting Hunger. How hungry an individual feels at the start of the meal will have a direct effect on how much they will eat before the onset of satiation (Schlundt, Sbrocco, & Bell, 1989). Additionally, starting hunger levels can increase initial eating rate and bite size, causing an indirect effect on both the onset of satiation and meal cessation (Hill & McCutcheon, 1984). Shimizu, Payne, and Wansink, (2010) found that environmental cues had a stronger effect on meal cessation for hungrier individuals. Hunger at meal commencement is affected by the amount of time since and size of the last meal (J. M. De Castro & De Castro, 1989; John M de

Castro & Kreitzman, 1985). Since hunger can cause individuals to overeat, various treatment methods have emphasized satiety maintenance (Palmer, Capra, & Baines, 2009). However, obese individuals tend to feel hunger more often and more dramatically, further complicating the matter (Sharma & Padwal, 2010).

Eating rate, bite size, and chewing time. Though it has fallen in and out of favor with researchers over the last several decades, eating rate is one of the most heavily studied eating behavior variables thought to affect satiation. Several studies have shown a relationship between obesity and eating rate (Laessle, Lehrke, & Dückers, 2007; Otsuka, Tamakoshi, & Yatsuya, 2006a; Sasaki, Katagiri, Tsuji, Shimoda, & Amano, 2003). Guss and Kissileff (2000) took this further to show that the real difference between obese and normal weight individuals in eating rate lies in the eating rate *curve*; that is, how eating rate changes over the course of the meal. The authors describe several studies that show that obese individuals tend to maintain a more constant eating rate from start to finish, whereas normal weight individuals show a quadratic decrease in eating rate towards the end of the meal. They propose that this indicates a decreased sensitivity to satiety cues.

Despite being one of the most commonly assessed variables, eating rate is poorly defined. One of the difficulties in examining eating rate is identifying the specific measurement to be used. Meal duration is not adequate, as larger portions may lead to longer meal times, but eating rate may not be affected. Grams per second, kcals per second, and food volume (milliliters or cm^3) per second have all been used across different studies and defined as eating rate. The most commonly used metric seems to be grams per unit time. However, a weakness of eating rate as measured by grams/time is that it is made up of both bite rate (how often food

is brought to the mouth) and bite size (how much food is brought to the mouth), both of which are influenced by different factors (Hill & McCutcheon, 1984). Bite rate is affected by chewing time (also referred to as mastication cycles or oral processing), which in turn has independent effects on olfactory processing, leading to a differences in food enjoyment (Zijlstra, De Wijk, Mars, Stafleu, & De Graaf, 2009). Additionally, bite size has been shown to be influenced by hunger levels and portion size (Burger, Fisher, & Johnson, 2011; Hill & McCutcheon, 1984)

Eating rate mediates the effects of several previously described variables on the development of and response to satiety. Hill & McCutcheon (1984) examined the relationships between several variables and eating rate (measured in grams per minute) and their impact on satiety. Their findings can be summarized as follows:

- Food preference, body size, obesity, and hunger increased eating rate.
- Bite size increased and accounted for a higher eating rate for obese subjects, subjects who reported higher food enjoyment, and subjects with larger body sizes.
- Higher hunger levels decreased the amount of time participants spent chewing their food.
- Food enjoyment increased bite rate but reduced bite size (with a net increase in overall eating rate).
- Men ate faster than women.

Eating rate is thought to affect satiety through the release of the hormones cholecystokinin (CCK), glucagon-like peptide-1 (GLP-1), peptide YY, pancreatic polypeptide, and insulin, as well as triglycerides (Robinson et al., 2014). Zhu, Hsu, & Hollis (2013) found that

increasing the number of chews per bite of food (thus reducing eating rate) increased blood levels of CCK, insulin, and glucose and reduced levels of Ghrelin.

External satiety cues. There is evidence that we are trained at an early age to ignore our internal satiety cues and rely rather on external cues for when to stop eating. One study showed that 3-year-olds ate similar amounts, regardless of portion size, but 5-year-olds ate more with larger portions, showing similar levels of satiety (B J Rolls, D., & Birch, 2000). Another study showed that children who were rewarded for “cleaning their plate” ate more than children who were instructed to stop eating when they were satisfied (Birch, McPhee, Shoba, Steinberg, & Krehbiel, 1987).

Wansink et al. (2007) found that normal weight individuals are more likely than obese individuals to be influenced by internal cues, as opposed to obese individuals who were more likely to be influenced by external cues. This indicates that reinforcing external cues and the use of external signals to initiate attention to internal cues may offer a viable treatment route for the obese. All of the external cues described below are potential avenues for treatment or for the application of behavioral interventions.

Distraction. Distractions are environmental factors that draw attention away from physiological and sensory satiety cues. Distraction can come from various activities that people often perform while eating such as working, watching television, or having conversation. Brunstrom and Mitchell (2006) found that distraction reduced perceived changes in hunger or fullness and attenuated reduction in desire to eat food that had already been consumed. Hetherington, Anderson, Norton, & Newson (2006) found that eating while watching TV increased energy intake by 14% over baseline. Wansink (2004) states that distraction not only

diverts attention from internal satiety cues, but also other external cues that may provide environmental feedback that could lead to meal cessation. Distractions can also offer a cue to end an eating activity, such as the decision to stop eating once a television show has ended (Tuomisto et al., 1998).

Portion selection. Portion selection (or meal size, serving size) has been extensively studied in recent years, as it is thought to contribute to excessive intake. Increases in standard restaurant serving sizes and in portion sizes served at home have paralleled the rise in obesity in the United States (Nielsen & Popkin, 2010; L R Young & Nestle, 2002). Several studies have shown that participants who are served larger portions have greater energy intake, but show no difference in satiety compared to those served normal portions (Rolls, Roe, Kral, Meengs, & Wall, 2004; Scheibehenne et al., 2010).

There are two proposed mechanisms by which portion size might delay meal cessation. One is that a clean plate is a salient environmental cue to stop eating. Under distracted conditions, individuals eat through the zone of indifference until a salient external satiety cue (an empty dish) causes meal cessation, overcoming other influences such as food enjoyment (Wansink & Kim, 2005). Another is the idea of “completion compulsion,” where individuals feel that they are being wasteful if they don’t eat all of their served food (Siegel, 1957). There is evidence that this may be a cultural effect. While children are also shown to be susceptible to the effects of portion size, Rolls et al. (2000) found that portion size has an effect on 5-year-old, but not 3-year-old children. This implies that social factors that affect intake begin to influence children at a very young age (Birch et al., 1987; McConahy, Smiciklas-Wright, Birch, Mitchell, & Picciano, 2002).

Social facilitation. Social facilitation describes environmental satiety cues that arise while eating in the presence of others, and can operate through a few different mechanisms. Lumeng & Hillman (2007) found that children eating in large groups ate more than children eating in smaller groups. Pliner, Bell, Hirsch, and Kinchla (2006) have proposed that the effect of social facilitation may influence energy intake through meal duration. That is, eating with a large number of people increases the amount of time individuals spend eating, pushing them higher into their zones of indifference.

In some cases, social facilitation may *reduce* intake, indicating a greater response/sensitivity to satiation or some top-down influence, where individuals stop eating in order to adhere to eating behaviors that they feel are socially desirable (Koh & Pliner, 2009). Hetherington et al. (2006) showed that individuals who ate with strangers did not display different energy intake levels from those eating alone, despite being distracted, indicating that some social facilitation was cancelling out the effect of distraction. The same study showed that social facilitation is at least in part mediated by distraction. In short, while individuals eat with friends, they engage in conversation which distracts them from their physiological cues *while* relying on their companions for environmental cues to stop eating.

Dish size. The size of various dishes, including the dish onto which food is served, the utensil used to serve the food, and the size of the dish from which food is obtained has an indirect effect on meal cessation, mediated by portion size (Wansink, 2004). Wansink, van Ittersum, & Painter (2006) showed that even nutrition experts served themselves larger portions when given a larger bowl and a large serving spoon. Conversely, eating from smaller dishes can cause individuals to serve themselves less food. A reduction in dish size has been proposed as

an avenue for reducing overeating (Wansink, 2010). However, the studies that have examined the efficacy of reducing plate size to reduce energy intake have produced inconsistent results (Barbara J. Rolls, Roe, Halverson, & Meengs, 2007).

Using Microstructural Analysis to Predict Caloric Intake

The analysis of eating patterns within specific meals has been referred to as “microstructural analysis” (J. L. Guss & Kissileff, 2000). Studies that perform microstructural analysis tend to focus on how factors that vary within specific meals (such as eating rate and bite size) and their predictors (such as food palatability and initial hunger levels) differ between obese and normal individuals. While several studies have examined meal-level eating behaviors in order to find patterns that are indicative of unhealthy behaviors, very few have examined the possibility of using these behaviors to predict free-living energy intake. The Bite Counter is a tool capable of tracking meal duration, eating rate, time of day, time since last meal, and bite count (Dong, Hoover, Scisco, & Muth, 2012; Scisco, Muth, Dong, & Hoover, 2011). Essentially, it is a tool capable of performing some degree of microstructural analysis in free-living environments. Theoretically, a calibration meal could be used to obtain an estimate of bite size and bite size change over time which, coupled with bite count, could produce a reasonable estimate of kcal intake at the bite level (Scisco, Muth, & Hoover, 2014).

The kcal content of specific bites of food (kilocalories-per-bite, or KPB) is a direct function of the weight of a specific bite of food (often a measure of bite size) and the ED of the food item being eaten. Several studies have examined variables that are related to bite size and the impact of ED on variables that are often examined with microstructural analysis. As discussed previously, bite size has been shown to be related to mouth volume, hunger levels,

portion size, body composition and size, and food preference (Burger et al., 2011; Hill & McCutcheon, 1984; Lawless, Bender, Oman, & Pelletier, 2003). Food item energy density has been shown to be positively correlated with food enjoyment (Yao & Roberts, 2001). Food enjoyment, in turn, affects eating rate (Guss & Kissileff, 2000). These studies imply that several variables that are often examined in microstructural analysis might be indicative of KPB.

More recently, some studies have examined KPB directly. Scisco et al. (2014) found a significant difference in KPB between men and women, but no relationship with BMI. Specifically, the authors found that men had an average KPB of 17 ($SD = 7$) and women had an average KPB of 11 ($SD = 4$). Salley, Hoover, Wilson, & Muth (2016) sought to develop a model of KPB using demographic variables (height, weight, age, gender, and waist-to-hip ratio). The model developed was found to outperform human estimates, even when provided with nutritional information. The study found that participants provided with nutrition information underestimated kilocalorie intake by an average of 257 kilocalories ($SD = 790.22$), whereas the model overestimated by an average of 71 kilocalories ($SD = 562.14$).

One weakness of both of these studies was that they did not examine the influence of variables that changed over the course of a meal (such as time in meal and time between bites) because KPB was not measured for individual bites of food; rather, an average KPB was determined for each participant. Another weakness shared by these two studies is that their measures of kcal intake are subject to high error rates. The Scisco et al. (2014) study used 24-hour dietary recall data as the ground truth measure of intake, which is known to be inaccurate (Beaton et al., 1979). The Salley et al. (2016) study relied on nutritional information provided by the cafeteria in which the study took place, and independent testing of the energy content of

the food items used was not feasible. These issues limit the applicability of the estimates of KPB derived in these studies.

Present Study, Design, and Hypotheses

The present study sought to assess variance in KPB and develop a predictive model of KPB that can be used to measure kcal intake in laboratory and applied settings. Multilevel linear modelling (MLM) was used to determine which predictors influence within- and between-subject KPB. The primary purpose of this study was to develop an “applied” model, with the vision of an individual purchasing a calibration meal with known qualities, inputting personal characteristics into a computer program which will interface with and apply predictors to the Bite Counter. The Bite Counter would then, for subsequent meals, incorporate individual characteristics and meal microanalysis to predict KPB.

The predictors for these analyses are described in Table 1.1. MLM was used to regress the predictors on KPB at the bite level. The predictors themselves are described throughout this document as “Level 1,” indicating that they vary at the lowest level of measurement, in this case the “bite” level; or “Level 2,” indicating that they vary at the highest level of measurement, the individual level. To compare MLM for repeated measures to a Mixed ANOVA, Level 1 predictors can be thought of as within-subjects variables, and Level 2 predictors can be thought of as between-subjects variables. Note that food item enjoyment is treated as a bite level variable, even though in reality it was only measured six times per participant. Likewise, satiety is treated as a bite level variable even though it was only measured twice per participant. Additional variables for which data were collected, but were not used in the analyses of this study are described in Appendix B. Hypotheses for main effects are listed in Table 1.1. The hypothesized

model is shown in Figure 1.2. It was hypothesized that as time since last bite, food item enjoyment, mouth volume, BMI, body fat percentage and waist to hip ratio increased, KPB would increase. However, as time in meal, pre-meal satiety and age increased, KPB would decrease. There was an expected interaction between time in meal and the three body metrics such that the negative effect of time in meal would be weaker for participants with higher BMI's, body fat percentages, and waist-to-hip ratios. It was additionally hypothesized that men would have a higher KPB than women.

Table 1.1

Each predictor, along with its level in the model and hypothesized effect on KPB.

Predictor	Obtained from...	Unit	Range	Level	Effect on KPB
Time (in meal)	Scales and Videos	seconds	since meal start	1	Negative
Time since last bite	Scales and Videos	seconds	since last bite	1	Positive
Food Item Enjoyment	Self-report (LAM Scale)	millimeters	0-100	1	Positive
Satiety	Self-report (SLIM Scale)	millimeters	0-100	1	Negative
Gender	Self-report	male/female	n/a	2	Higher for Males
Mouth Volume	Water-fill method (see below)	milliliters	n/a	2	Positive
Age	Self-report	Years	n/a	2	Negative
BMI	Scale/Stadiometer	kg/m ²	n/a	2	Positive
Body Fat Percentage	Omron tm Body Fat Analyzer	percentage	n/a	2	Positive
Waist-to-Hip Ratio	Myo-tape	ratio	n/a	2	Positive

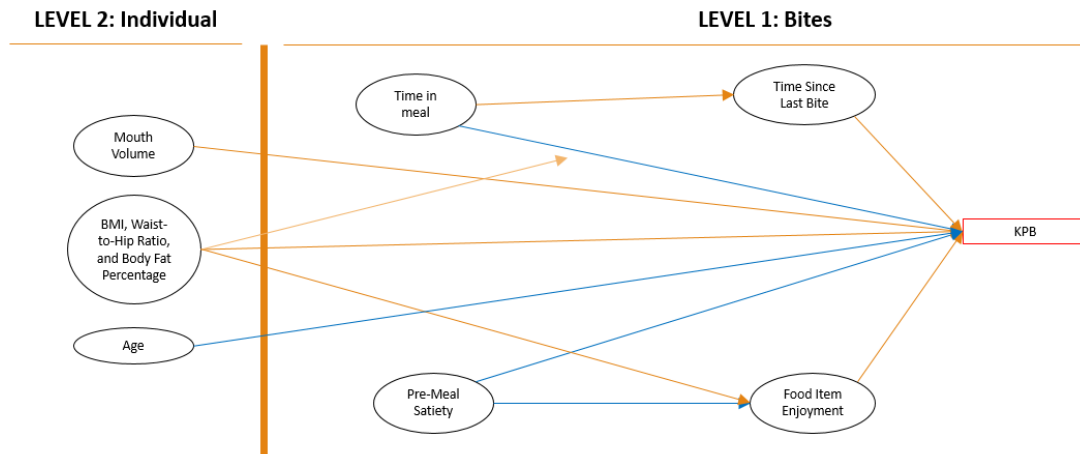


Figure 1.2. Hypothesized model. Arrows leading to predictors indicate hypothesized mediated effects, and arrows leading to arrows indicate hypothesized interactions. Orange arrows indicate positive effects; blue arrows indicate negative effects.

Regarding the hypothesized mediating relationships, it was expected that as time in meal increased, time since last bite would increase. Therefore, time in meal would have a direct negative effect on KPB and an indirect positive effect on KPB through time since last bite. Additionally, it was hypothesized that higher pre-meal satiety would lead to lower food enjoyment ratings, therefore having a direct negative effect on KPB and an indirect negative effect on KPB through food item enjoyment. Finally, it was expected that individuals with higher BMI's, body fat percentages, and waist to hip ratios would report higher food item enjoyment, therefore causing the three body metrics to have a direct positive effect on KPB and an indirect positive effect through food enjoyment.

The predictive ability of the model was tested by repeating the regression analysis, this time using one of each participant's meals (randomly selected) to train the model and the other to test it. Error distributions were examined, and the accuracy of the model was compared to models previously described by our lab. The prediction equation was generated from the

estimated slopes of the fixed effects of the MLM analysis. It was hypothesized that the newly developed model would outperform the model developed by Salley et al. (2016) and the gender-based KPB estimates described in Scisco et al. (2014). Further details are provided below.

CHAPTER TWO: METHODS

Participants

Determining power for MLM involves consideration of sample size at all levels, the number of predictors, and estimations of effect size for each predictor. Considering that this is the first application of MLM to examine the impact of various predictors on the kcal content of specific bites, estimations of effect size are difficult to ascertain. However, several researchers have proposed general guidelines for appropriate sample size with MLM. For example, Maas & Hox (2004) show that top level sample sizes (in the case of the present study, the number of participants) smaller than fifty lead to biased error estimates. Additionally, Tabachnick & Fidell (2014) state that as MLM uses maximum likelihood estimation, a sample size of sixty for five or fewer predictors is recommended. To balance power and practicality, a Level 2 sample size of seventy participants was chosen ($N = 70$). The Level 1 units in the present study were bites, and their number naturally varied between participants. (Cisco et al., 2014) showed that participants took 39 bites on average in free-living settings. However, there was a large degree of variance. Additionally, it was expected that bite counts would be different in controlled, laboratory studies compared to free-living studies, and would depend upon many of the factors discussed in the introduction. Based on unpublished data obtained from our lab, I anticipated participants would take around twenty bites per meal. At two meals per participant, this leaves a Level 1 sample size of around forty, with a large degree of expected variance ($n = 40$).

During the course of the study, four participants were unable to return for their second session, so data from both meals were available from 68 participants, with one meal available from an additional four participants. Thus, the total number of meals consumed was 140. Of

the total sample of 72, 39 were female (33 male). Mean age was 36.96 ($SD = 12.71$). Further demographic information is presented in Table 2.1. While no specific sample demographics were targeted, it was expected that demographic characteristics would be significant predictors of KPB based on prior work that has shown that individual characteristics are related to KPB (Salley et al., 2016; Scisco et al., 2014). Therefore, participants were sampled to capture a wide range of age and BMI and a relative gender balance. Participants were recruited via campus-wide e-mails to students, faculty and staff, through the use of flyers, and through a contact list obtained from a prior study. Participants were not allowed to participate if they had a history of eating disorder due to the potentially negative psychological effects that eating studies can have on this group. The potential food items were described during recruitment, so those with aversions to those items or dietary restrictions that prohibit them from consuming those items were not asked to consume those items. Participants were incentivized with staggered payments to encourage returning for the second session: \$5 for the first session and \$15 for the second.

Table 2.1

Sample demographic characteristics.

Characteristic	N	% of total sample
Gender		
Male	33	46
Female	39	54
BMI Category		
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

Materials and Measures

Meals. Each participant consumed two of five possible meals, each comprised of three foods (a main dish, a side, and a desert). Three meals were served at lunch and dinner times (11:00, 13:00, 17:00, and 19:00) and two were served at breakfast times (7:00, 9:00, and 11:00). Relevant nutrition information for each food item are presented in Table 2.2. Meals were selected in an attempt to capture a wide range of energy density and macronutrient content, and food item selection for specific meals attempted to assign one low, medium, and high energy dense food item. Food choices and portion sizes were adjusted to obtain a relative balance between total meal food weight and kcal content. The proposed breakfast meals have noticeably lower kcal and ED totals; this is because many “quick” breakfast items (including the ones used in this study), such as cereals, fruits, and shortbreads, tend to be low in ED (Cho,

Dietrich, Brown, Clark, & Block, 2003). To attempt to balance this, pastry items (also common breakfast items) were used as the high ED item for breakfast meals.

The meals were consumed at an instrumented eating station (Figure 2.1a). The eating station was equipped with four Cisco PVC300 ceiling mounted cameras, positioned to capture video of each of the four eaters (Cisco Systems, Inc., San Jose, CA; Figure 2.1b). Each place setting contained recessed scales to capture changes in weight as food is being eaten (Figure 2.1c). Wrist-motion activity was captured using magnetic angular rate and gravity sensors (MARG), although these data were not used in the present study (Figure 2.1d).

Target portions were selected relative to package sizes and recommendations in such a way that portion sizes would meet participant expectations (larger main courses, smaller sides and desserts) and food waste was minimized by attempting to use one package of each item per session with items that would need to be discarded if not consumed. All cooked food was served fresh and never reheated.

Table 2.2
Nutrition information for the selected meals.

Food Item	Target Weight (g)	Kilocalories (kcal)	Protein (g)	Fat (g)	Carbohydrate (g)	Label ED (kcal/g)	Measured ED (kcal/g)
Breakfast Meals							
<i>Meal 1</i>							
Quaker Maple & Brown Sugar Oatmeal	163	160	4	2	33	0.98	1.02
Banana	118	105	1.3	0.4	27	0.89	0.95
Hostess Powdered Min Donut	60	240	2	12	31	4.00	4.66
<i>Meal 2</i>							
Quaker Butter Instant Grits	148	100	2	1.5	21	0.68	0.61
Yoplait Strawberry Low-fat Yogurt	170	90	5	0	16	0.53	0.42
Little Bites Mini Blueberry Muffins	47	180	2	8	26	3.83	4.15
Lunch/Dinner Meals							
<i>Meal 3</i>							
Stouffers Chicken Alfredo	200	231	16	10	31	1.16	1.5
Bird's Eye Ranch Broccoli	71.75	43.75	1.75	1.75	4.38	0.61	0.78
Edward's Cookies & Crème Pie	123	470	5	28	52	3.82	4
<i>Meal 4</i>							
Stouffers Lasagna with Meat Sauce	215	270	16	9	33	1.26	1.52
Bird's Eye Steamfresh Mixed Vegetables	67.5	37.5	1.5	0	7.5	0.56	0.55
Great Value Vanilla Ice Cream	132	280	6	14	30	2.12	2.36
<i>Meal 5</i>							
Stouffers Meatloaf	234	315	27	18	12	1.35	2.16
Bird's Eye Steamfresh Asparagus Spears	60	15	1.5	0	2.25	0.25	0.79
Sarah Lee Original Cream Cheesecake	121	340	8	18	38	2.81	2.79

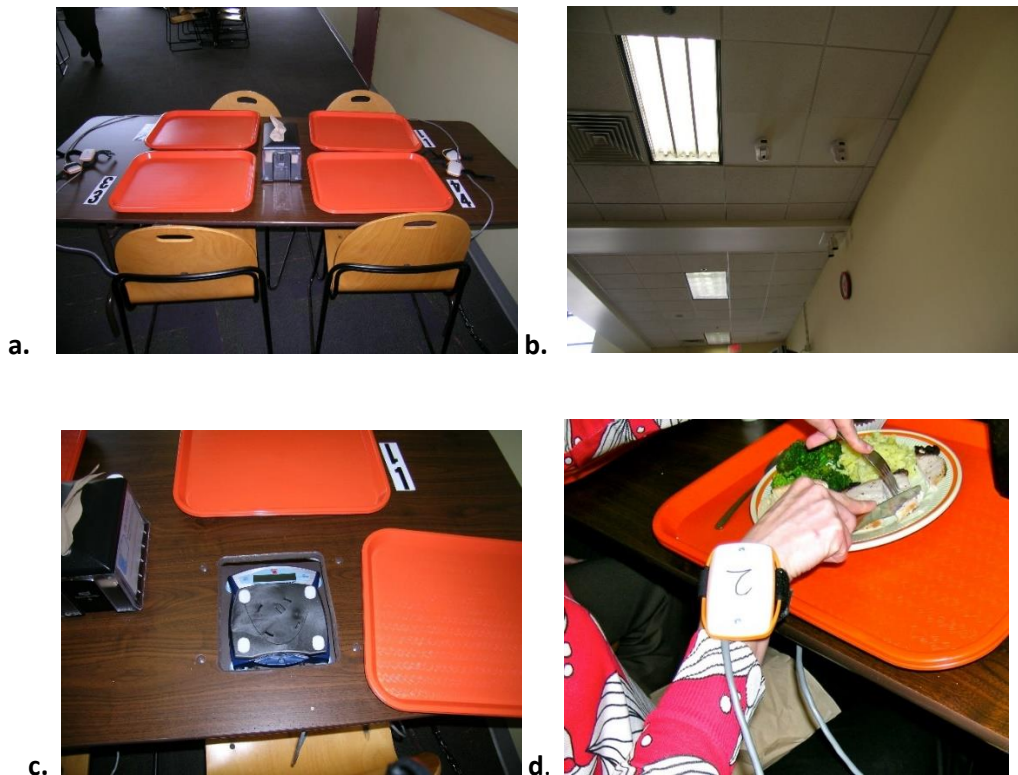


Figure 2.1. The instrumented eating station, including the table (a), the ceiling mounted cameras (b), the recessed scales (c), and the MARG (d).

Bite Time and Time since Last Bite. Bites were identified using the scale data and verified by reviewing the video recordings. An algorithm identified bites as a stable period in the scale data, followed by a disturbance, followed by another stable period of a lower weight than the initial period. The time (in seconds) between each recorded bite was used to calculate time since last bite. Additionally, time in meal was calculated as the amount of time that has passed between the first bite and a specific bite of food (a summation of all the “time since last bite” measures up to that point).

BMI, Body Fat Percentage, and Waist-to-Hip Ratio. BMI was calculated from weight and height measurements, obtained from a scale and stadiometer. Body fat percentage was

measured via electrical impedance with an Omron™ Body Fat Analyzer. Waist circumference was measured using a Myotape™ tape measure, wrapped around the waist at the navel. Hip circumference was measured in the same way, around the widest part of the hips.

KPB, Energy Density, and Food Weight. The energy density of each food item was measured by running samples of each item through a bomb calorimeter. As many samples were run of each item as was necessary to obtain three relatively consistent measurements of energy density. Food item energy density values are reported in Table 2.2 above. Discrepancies between nutrition label energy density and measured energy density could be explained in a number of ways, including intentional mislabeling or differences between expected preparation method and the methods used in this study. Considering that food preparation method was held as constant as possible throughout the study, measured energy density was used to calculate KPB. Any further references to the energy density of the food items used in this study are referring to the calorimeter measurements.

Food weight was measured in grams using the recessed scales shown in Figure 2.1c. Data from the scales were sent to two laptop PCs (one computer per two scales), recording scale weight at a rate of 15 hz. Bite weight was determined by calculating the difference in plate weight before and after a bite of food was taken. Finally, KPB was determined by multiplying the weight of each bite by the calorimeter-measured energy density of the food item that was consumed in the bite.

Food Enjoyment and Satiety. Satiety was assessed before and after each meal using the Satiety Labeled Intensity Magnitude (SLIM) scale, although only pre-meal hunger was used in this study (Cardello, Schutz, Leshner, & Merrill, 2005). Food enjoyment was assessed for each

food item after each meal using the Labelled Affective Magnitude (LAM) scale (Schutz & Cardello, 2001)

Procedure

Recruitment, Screening, and Scheduling. Participants were recruited using a campus-wide e-mail list (called Inside Clemson). This mailing list goes to all faculty and staff at Clemson University. The recruitment e-mail can be found in Appendix C. Additionally, participants were recruited via flyers (Appendix D) and through a contact list of prior participants. Upon contacting the experimenter, participants were asked to take an online screening questionnaire that assessed their diet restrictions, availability for meal times, and willingness to consume the possible food items (Appendix E). They were encouraged to invite their friends, family, and colleagues to participate in the study with them. If the participants did not have any prohibitive diet restrictions, were at least willing to consume all of the items on the food list, and show availability for at least three of the available time slots, they were invited to participate in the study and provided with their scheduled times.

Participants were scheduled for meal sessions Monday through Saturday at 7:00am, 9:00am, 11:00am, 1:00pm, 5:00pm, and 7:00pm, depending upon their availability. They were randomly assigned to two of the five different meal conditions. Participants were not allowed to choose which meals they eat. Meals occurring at 7:00am and 9:00am were assigned breakfast meals, and meals occurring at 1:00pm, 5:00pm, and 7:00pm were assigned lunch/dinner meals. Meals occurring at 11:00am were assigned either lunch or breakfast, as some flexibility was needed to achieve a relative balance in meal frequency.

Food Preparation and Presentation. Meals were prepared prior to participant arrival according to the preparation time required for each item. To control for presentation effects, meals were prepared and plated in a separate room, and were served on identical generic dishes that were identical across meals. Warm meals were kept in the roaster oven at a low temperature until they were served to the participants, so that they were warm when served.

First Study Session. Upon arrival in the lab, participants had their height, weight, waist circumference, hip circumference, and body fat percentage measured. Their mouth volume was measured according to the voluntary mouth-fill method described by Lawless, Bender, Oman, & Pelletier (2003). Briefly, participants were asked to fill their mouths with water to their maximum capacity, and then spit the water into a cup. The weight of the cup was measured to determine how much water had been placed in the participant's mouth. Participants filled out a pre-meal questionnaire (Appendix L) and a pre-meal SLIM scale. Participants were then lead to the instrumented eating station. They were asked to complete another SLIM scale, and the MARG was attached to the wrist that they ate with.

Participants were then instructed on how to eat the meal. They were told to eat as naturally as possible, including sharing conversation with each other. They were asked to be mindful of the scales beneath their place setting. This included not putting any extra weight on the plate, such as napkins and utensils. For items that were eaten 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. They were told that they did not have to finish every item that was served, but they must take at least one bite of each item. Additionally, participants were asked not to use their phones or use any other sort of distracting items.

Each participant was served roughly equal portions of each food item, with each food item being placed on a separate dish. The dishes were placed beside each participant's tray. Participants were instructed to eat each food item one at a time, adding that item's dish to their tray and removing it upon completion. Participants were asked not to begin eating until asked to by the experimenter. They were also told that if they finished eating early, they should wait until each participant had finished before getting up. However, they were told that they may continue to converse with the other participants. The experimenter then began the recording, and the participants were asked to begin eating. During the eating session, an experimenter monitored the participants and corrected them if they took any actions that may affect the scale data.

Once each participant had finished eating, the recording was stopped. The participants were given a post-meal SLIM scale. They then completed a LAM scale for each food item that was served. Finally, they were given a post-meal questionnaire and dismissed (Appendix M). Participants were then asked to complete further online surveys prior to their arrival for their second session, to minimize time spent on surveys in the lab. These included: a demographics and eating behavior questionnaire (Appendix F), the Dieting Behaviors Scale (Appendix G), the Mindful Eating Questionnaire (Appendix H), the Self-efficacy for Dietary Control scale (Appendix I), the Three-factor Eating Questionnaire R-18 (Appendix J), and the Weight-Efficacy Lifestyle Questionnaire (Appendix K). Participants were then paid \$5 for their time.

Second Study Session. Participants began their second study session no less than two days and no more than seven days after their first session. The procedure for the second session was identical to the first, with a few exceptions. Measurements of height, weight, body

fat percentage, waist circumference, hip circumference were not repeated for the second session. Prior to each participant's arrival, an experimenter confirmed that they completed the online questionnaires described previously. If they had not, they were asked to remain after the conclusion of the eating session to complete the questionnaires in the lab. Upon completion of the second session, participants were paid \$15 and debriefed on the purpose of the study.

Identifying Bites and Bite Weights. The video recordings and scale data for each meal were paired using custom software. A screenshot of this program is shown in Figure 2.2. Bites and bite weights were initially identified automatically using the following algorithm: identify a period of stability in the scale data, where the scale weight does not fluctuate by more than .1 grams (referred to as "Start Weight"), followed by another period of stability of a lower weight (referred to as "End Weight,") . Bite weight was calculated as the difference between start and end weights, with the bite itself occurring shortly after the weight change. An example of a correctly identified bite is shown in Figure 2.3.



Figure 2.2. Software used for detecting bites and bite weights.



Figure 2.3. An accurately detected bite. The scale data is shown in image a, and the same moment in the accompanying video is shown in image b.

Each meal was then manually inspected to identify and correct misses and false positives. A common error in the automatically detected bite weights included bites of foods that were picked up and then returned to the plate after a bite was taken, as the algorithm identified the end weight as occurring before the food was returned to the plate. Further screening for erroneous bite weights involved identifying discrepancies between total weight consumed as measured by plate weight before and after item consumption and as measured by the summation of individual bite weights (weight error). Some error is to be expected due to small scale fluctuations during the meal, but larger errors would indicate some recording error (missed bites or erroneously marked start and end weights). Mean weight error (the discrepancy between summed bite weights and pre-/post-meal weight) was .75 grams (SD = 7.67). Five items were identified as having error greater than three standard deviations from the mean. These were obvious outliers and were reviewed. Of these, three were found to have

incorrectly recorded bite or plate weights and were corrected. The other two had short periods of time with erratic behavior, and after further cleaning their error was reduced to within appropriate limits. Additionally, unusually large or small bite weights were reevaluated and corrected or deleted, where appropriate.

CHAPTER THREE: RESULTS

Analysis 1: Multi-level Model of KPB

After the previously described data collection, one meal of one participant was found to have unusable data. Therefore, between 72 participants, there were a total of 139 usable sessions consisting of 4,051 usable bites. To prepare the dataset for the MLM analysis, all individual meal data were merged into one file, and all Level 2 data were de-aggregated to the bite level. This was done using Microsoft Visual Basic for Applications. All subsequent analyses were performed using IBM SPSS Statistics 23. Data were cleaned according to the guidelines provided by Tabachnick & Fidell (2014) for grouped data, multiple regression, and MLM.

Data Cleaning. To identify specific unusual cases, the six Level 1 variables (KPB, time in meal (TIM), time since last bite (TSLB)) were inspected for univariate and multivariate outliers and normality within all participants individually. Additionally, since bite weight was used to calculate KPB and was a primary potential source for error in measurement or data recording, it was examined prior to examination of KPB. Starting satiety (SLIM), food item enjoyment (LAM), and the six level two predictors (Gender, age, mouth volume, body fat percentage, waist-to-hip ratio, and BMI) were examined for normality and outliers across all participants.

While the normality of the predictor variables is not an assumption of MLM, examining their distributions can help identify unusual cases and patterns. The two aspects of a distribution used to determine how closely it resembles a normal distribution are skew and kurtosis. Kurtosis describes the “peakedness” of a distribution. A distribution with more kurtosis than a normal distribution (referred to as a leptokurtic distribution) has more of the data clustered around the mean, whereas a distribution with less kurtosis than a normal

distribution (a platykurtic distribution) has more of the data clustered in the tails. Kurtosis can be assessed statistically by a ratio of a summation of the differences of each value in the distribution from the mean to the standard deviation time $n-1$, with both values raised to the fourth. The degree of kurtosis is assessed relative to the standard error of kurtosis.

Skew describes the length of the “tails” of a distribution relative to each other. Positively skewed distributions tend to have values higher than the mean that are a further absolute distance away from the mean than the values of the distribution that are lower than the mean (while the opposite is true for negatively skewed distributions). Skew can be assessed statistically by subtracting the median of a distribution from the mean and dividing it by the standard deviation. The resulting value is then compared to the standard error of skew to assess the degree of skew present.

All the level one variables that were assessed at each bite occurrence (bite weight, KPB, TIM, and TSLB) showed positive skew and kurtosis, likely because each had a hard floor at a value of 0. Only time since last bite showed extreme skew, and was thus transformed via a natural log transformation. SLIM and LAM scores showed relatively normal distributions. Of the six level two predictors, all showed relatively normal distributions except for mouth volume. Upon further examination, one participant was identified as having an exceptionally large mouth volume. This participant’s mouth volume data was excluded from further analysis, changing the distribution of mouth volume to within normal parameters.

After examining variable distributions, boxplots were created for KPB, bite weight, TSLB, and TIM within each participant and examined for obvious outliers (specified as values greater than three inter-quartile ranges outside the first and third quartiles). Several outliers were

identified as data entry or recording errors and corrected, but six bites had extreme values in one or more of the variables that couldn't be accounted for. These values were eliminated from the dataset. Boxplots were created across all participants for the remaining predictors, and no additional extreme outliers were identified.

Multivariate outliers were identified by calculating a Mahalanobis distance for each bite. Mahalanobis distance is a measure of leverage, which is the influence that a specific data point has on the overall model. Excessive values are identified based on a χ^2 significance test with a number of degrees of freedom equal to the number of predictors. If this value is significant, then the associated data point is exerting an unwarranted amount of influence on the outcome of the model. An examination of Mahalanobis distance for each data point in the full regression model identified thirteen bites that were extreme multivariate outliers, which were removed. Further details for the data cleaning procedure are provided in Appendix N.

Although three body metrics were used, these were all expected to have a high degree of multicollinearity. Additionally, it was anticipated that the effects of age and gender would be mediated by mouth volume, meaning that there would be a degree of multicollinearity among these three variables. To assess multicollinearity among the three body metric variables, Pearson's correlations were examined. BMI shared a significant moderate correlation with both WHR ($r = .611, p < .001$) and %BF ($r = .520, p < .001$). To further assess multicollinearity, tolerance statistics were assessed for each predictor within the full regression model. Tolerance is calculated statistically by regressing a predictor onto the other predictors in a model and subtracting the resulting R^2 from 1. A general rule of thumb is that tolerance values of less than .2 indicate potentially problematic levels of multicollinearity. Despite the moderate correlations,

no variable had a tolerance value of less than 0.2. For now, all three body metrics would be left in the model. To assess multicollinearity among age, MV, and gender, the same procedure was followed. MV shared a significant, albeit small correlation with age ($r = -.317, p = .006$). A two-tailed, independent samples t-test showed a significant difference in mouth volume between men and women ($t(70) = 6.091, p < .001$). Regressing these three variables on KPB revealed no tolerance values less than .2. All variables were retained for the analysis.

Analysis Prep, Descriptive Statistics, and Correlations. After outlier removal, 4,032 bites remained in the dataset, 99.5% of the original bites. Descriptive statistics for all variables are shown in Table 3.1. Table 3.2 shows correlations between all predictors and KPB, bite weight, and energy density, with all correlations with Level 2 variables aggregated to Level 2. Figures 3.1a – 3.1d show scatterplots for all Level 1 predictors with KPB. Note that in graphs 3.1c and 3.1d, data were aggregated so that each food item (3.1c) and eating session (3.1d) are represented only once. Figures 3.2a – 3.2e show scatterplots for all Level 2 predictors with KPB. Figure 3.3 shows KPB differences between men and women. An independent samples t-test revealed that men, on average, had a higher KPB than women, $t(70) = 4.58, p < .001$.

Table 3.1

Descriptive Statistics for Bite (Level 1) and Participant (Level 2) Variables.

Variable	<i>N</i>	<i>Mean</i>	<i>SD</i>	<i>ICC1</i>
Level 1				
KPB	4032	15.08	11.44	0.18
<i>Bite Weight</i>	4032	8.54	4.73	0.23
<i>ED*</i>	415	1.88	1.35	0.04
InTSLB	3620	2.74	0.54	0.21
TSLB	3620	17.95	10.57	0.19
TIM	4032	333.85	226.39	0.15
LAM*	415	66.82	15.57	0.27
SLIM**	139	39.06	16.02	0.63
Level 2				
BMI	72	27.65	5.69	-
%BF	72	28.5	8.9	-
WHR	72	0.87	0.08	-
Age	72	36.23	12.11	-
Gender	72	0.54	0.5	-
MV	71	75.55	17.33	-

**Descriptive statistics for ED and LAM were calculated with these variables aggregated to one entry per food item consumed.*

***Descriptive statistics for SLIM were calculated with this variable aggregated to one entry per meal consumed.*

Table 3.2
Correlations between all variables.

	1	2	3	4	5	6	7	8	9	10	11	12	13	14
Level 1														
1. KPB	1													
2. Bite Weight	.587**	1												
3. ED	.620**	-.151**	1											
4. InTSLB	.293**	.190**	.196**	1										
5. TSLB	.251**	.157**	.163**	.926**	1									
6. TIM	.105**	-.368**	.462**	.160**	.159**	1								
7. LAM	.196**	.086**	.197**	-.027	-.032	.124**	1							
8. SLIM	-.079**	-.067**	.000	.012	.024	-.035*	.069**	1						
Level 2														
9. BMI	.138	.073	-.060	.004	-.038	.039	-.024	.014	1					
10. BF	-.291*	-.253*	-.121	-.051	-.090	.004	.135	.121	.541**	1				
11. WHR	.228	.110	.123	.005	-.033	-.058	.138	.225	.611**	.293*	1			
12. Age	-.187	-.076	-.215	.040	.025	-.099	.108	.027	.077	.582**	.260*	1		
13. Gender	-.480**	-.363**	-.085	-.067	-.074	-.057	.162	.054	-.278*	.508**	-.368**	.319**	1	
14. MV	.484**	.466**	.010	.146	.129	-.008	-.106	-.081	.182	-.347**	.154	-.325**	-.613**	1

Gender coded as males = 0. * indicates significance at the .05 level, ** indicates significance at the .01 level.

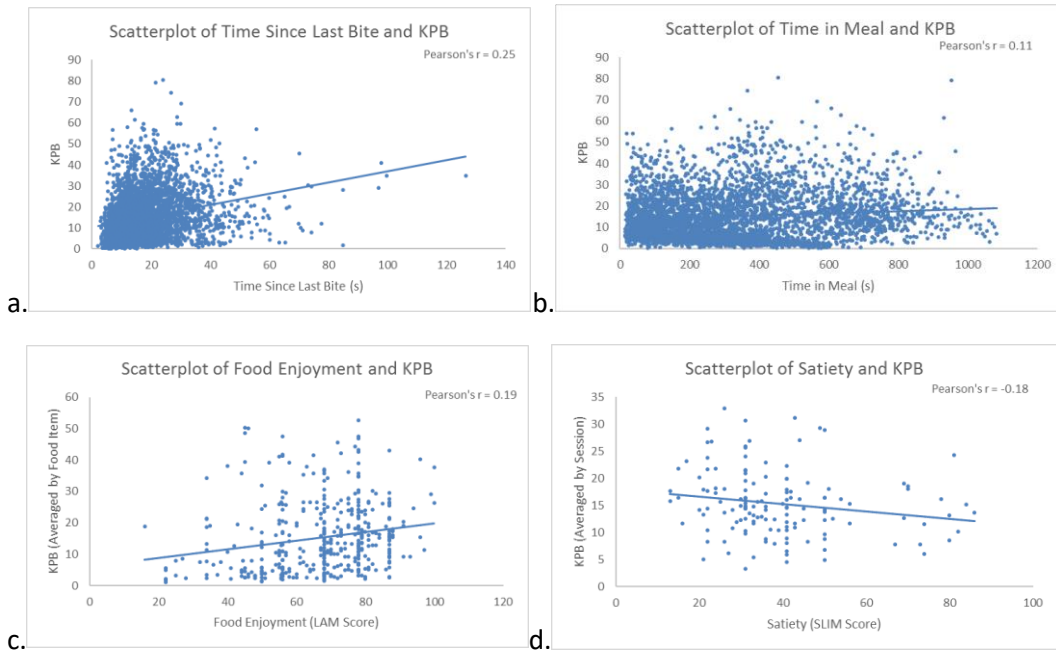


Figure 3.1. Scatterplots of the Level 1 predictors with KPB. Note that Figure c is aggregated so that each consumed food item is represented only once, and Figure d is aggregated so that each meal is represented only once.

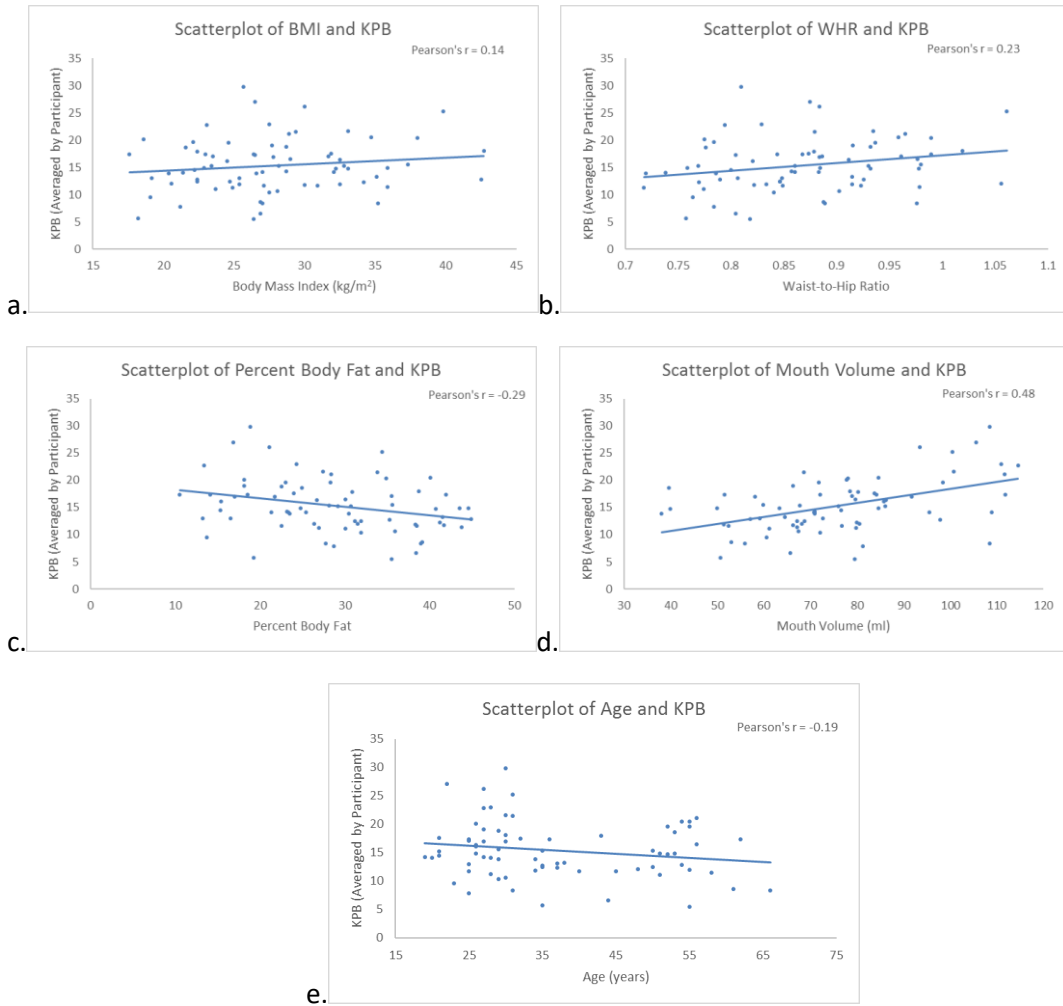


Figure 3.2. Scatterplots of the Level 2 predictors with KPB.

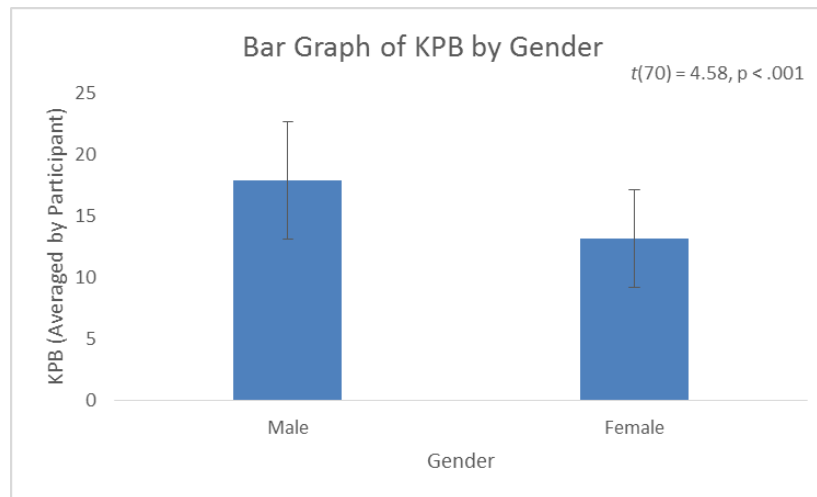


Figure 3.3. Bar graph showing differences in KPB between males and females.

To determine the amount of between and within-subjects variance for KPB, an intra-class correlation (the ICC1) was calculated for KPB. This was done by running a “null” model; the first model in the analysis, specified with no predictors. The ICC1 was found to be 0.18, meaning 18% of the variability in KPB is associated with differences between participants, supporting the decision to use MLM. MLM allows for a covariance structure to be specified if the Level 1 predictors are expected to be uncorrelated or correlated in a certain pattern. While specifying a covariance structure would increase power, the Level 1 predictors for this analysis were correlated. Therefore, the covariance structure was unspecified (unstructured). All predictor variables were grand-mean centered so that changes in within-subject intercept variance can be interpreted as changes in unexplained mean KPB variance.

Each variable was entered into the model hierarchically so that model improvement could be assessed with the addition of each predictor. If a predictor did not improve model fit or have a significant fixed effect, it was removed from the model. Fixed effects for Level 1 predictors were added first, followed by fixed effects for Level 2 predictors. Predictors were

added to the model in a decreasing order of expected effect size, so that weaker effects would not be drowned out by stronger effects. Random effects were then added hierarchically for all Level 1 predictors, followed by effects for cross-level interactions. Model fit in MLM is assessed by a measure of “deviance” from an error free model, and a reduction in deviance shows an improvement in model fit (known as a “deviance difference test”). Change in deviance for this analysis was assessed by comparing changes in the -2 log likelihood value between models, using a χ^2 difference test to assess significance. A model-by-model breakdown of this analysis is presented in Appendix O.

The results from the MLM analysis are presented in Table 3.3. While both TSLB and its log transform showed significant effects, the log transformed variable showed significantly higher improvement in model fit. Log transformed TSLB was retained through the final iteration of the model, maintaining a significant fixed effect and significant variance in within participant slopes between participants. In general, higher time between bites led to higher KPB. Time in meal was also retained through the final model, but its fixed effect lost significance once its within-participant slopes were allowed to vary, indicating that it is related to KPB but its effect is not consistent across all participants.

Table 3.3

Predictor summary of MLM analysis. Statistics reflect the final values of each variable. The analysis was performed over 16 total models.

Variable	Coefficient (SE)	t	p	Initial Model #	Final Model #	Slope Variance (SE)
*Intercept	13.73 (0.84)	16.37	0.00	0	16	-
Level 1						
Time Since Last Bite (Log Transformed)	4.79 (0.58)	8.32	0.00	1	16	15.24 (4.24)
Time in Meal	3.59 (2.64) x 10 ⁻³	1.36	0.18	3	16	4.02 (0.90) e ⁻⁴
Food Item Enjoyment	0.29 (0.06)	5.14	0.00	4	16	0.19 (0.04)
Satiety	-0.22 (0.09)	-2.45	0.02	5	16	0.47 (0.14)
Level 2						
BMI	0.11 (0.09)	1.2	0.24	6	6	-
Waist-to-Hip Ratio	9.37 (5.92)	1.58	0.12	7	9	-
Body Fat Percentage	-0.17* (0.06)	-3.01	0.00	8	8	-
Mouth Volume	5.19 (3.18) x 10 ⁻²	1.63	0.11	9	12	-
Age	-4.05 (3.97) x 10 ⁻²	-1.02	0.31	10	10	-
Gender	-2.52 (1.39)	-1.82	0.07	11	15	-

*Indicates variables that were retained through the final model.

Food item enjoyment showed significant model improvement and a significant fixed effect, with KPB increasing as participants enjoyed the food more. Within participant slopes for food item enjoyment significantly varied across participants. Satiety significantly improved model fit and had a significant fixed effect, with participants having lower KPB the more satiated they were. Within participant slopes of satiety significantly varied across participants.

The three Level 2 body metric measurements were entered independently. BMI did not have a significant fixed effect and did not improve model fit. While percent body fat did have a significant initial effect and improved model fit, its slope was not in the expected direction, and it did not improve model fit as much as waist-to-hip ratio. Waist-to-hip ratio had a significant initial fixed effect and showed improved model fit, but its effect was reduced to non-significance with the addition of mouth volume in model 9.

Mouth volume showed a significant initial fixed (between-subjects) effect in the expected direction and significant model improvement, but it lost significance when the first random (within-subjects) slopes were added to the model. Age did not show a significant fixed effect or model improvement. Gender showed an initial significant effect and model improvement, which was maintained until the random slopes of food item enjoyment were added to the model.

Analysis 2: Mediation Analysis

Mediation describes a special type of relationship between at least two predictors and the DV. In its simplest form, mediation describes a relationship in which at least part of the effect of a predictor on the DV occurs *through* its effect on another predictor. To use on the hypothesized mediation relationship in this study as an example, it was hypothesized that part

of the effect of time in meal on KPB would be *mediated* by the effect of time in meal on time since last bite; that is, time in meal affects time since last bite, which, in turn, affects KPB (Figure 3.4). In this relationship, time since last bite would be described as the *mediator*. As shown in Figure 3.4, the effect of time in meal on TSLB is referred to as the “a-path.” The effect of TSLB on KPB is the “b-path.” The combined effects of the a- and b-paths is referred to as the *indirect effect*, because the hypothesized predictor (time in meal) is operating on the DV (KPB) *indirectly* through the mediator (TSLB). The effect of time in meal on KPB *independent* of TSLB is referred to as the *c’-path*, or the *direct effect*. The combination of the a-, b-, and *c’-paths* is referred to as the *total effect*, or the *c-path*.

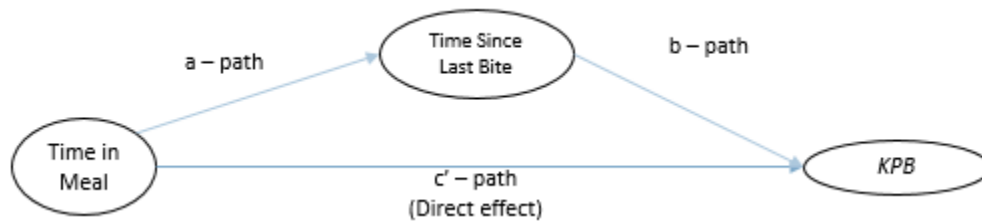


Figure 3.4. The hypothesized effect of time in meal on KPB, mediated by time since last bite.

Based on the results from analysis 1, two hypothesized mediation effects remained: the aforementioned effect of time in meal mediated by TSLB (at later time points in the meal, TSLB will increase, which will increase KPB) and the effect of satiety mediated by food item enjoyment (higher satiety will cause lower food enjoyment, causing smaller KPB). The method used to test the effect was the bootstrapping method (Preacher & Hayes, 2004a).

Bootstrapping is a non-parametric test that is ideal for testing mediation effects with small sample sizes and non-normal distributions (Preacher & Hayes, 2004b). The variables of interest are resampled thousands of times with the effects calculated with each iteration, so that a

confidence interval for the effect can be generated. Since the proposed mediation effect is simple, the INDIRECT module for SPSS developed by Preacher & Hayes (2008) was used to test for the mediation effect.

To remain consistent with analysis 1, the log-transformed TSLB (lnTSLB) was used in this analysis. All data were aggregated to Level 2 so that power was not artificially inflated (and so that the assumption of independence was not violated). The data were resampled 5000 times with bias correction. Bias correction is a means of accounting for systematic bias in resampling that can naturally occur in smaller samples, applied by comparing resampled distributions to the original, whole sample distribution (Efron, 1987). Results from the analysis of time in meal and lnTSLB can be found in Table 3.4. The effect of time in meal on lnTSLB is shown to be significant, with lnTSLB increasing as time in meal increases. Likewise, the effect of lnTSLB on KPB is shown to be significant, with KPB increasing as the time between bites increases. However, there is no significant indirect or total effect of time in meal on KPB, once its indirect effect is taken into account.

Table 3.4

Results from mediation analysis of the effect of time in meal on KPB, mediated by InTSLB.

Path	Coefficient	SE	t	p
a	0.09×10^{-2}	0.03×10^{-2}	3.06	0.00
b	7.4	2.24	3.3	0.00
c' (Direct)	-0.18×10^{-2}	0.61×10^{-2}	-0.3	0.77
c (Total)	0.51×10^{-2}	0.61×10^{-2}	0.83	0.41
ab* (Indirect)	0.70×10^{-2}	0.30×10^{-2}	-	-

* 95% confidence interval bounds: $0.25 - 1.45 \times 10^{-2}$

Adj. R2 = 0.12, F (2, 69) = 5.84, p = 0.00

The procedures for the second mediation analysis followed those of the first, this time with the effect of satiety on KPB being mediated by food enjoyment. The results from this analysis are presented in Table 3.5. While the direct effect of satiety on KPB approached significance, as did the effect of satiety on food enjoyment, there is no evidence of an indirect effect of satiety on KPB, mediated by food enjoyment.

Table 3.5

Results from mediation analysis of the effect of satiety on KPB, mediated by food enjoyment.

Path	<i>B</i>	<i>SE</i>	<i>t</i>	<i>p</i>
a	0.12	0.07	1.86	0.07
b	0.09	0.08	1.13	0.26
c' (Direct)	-0.08	0.05	-1.78	0.08
c (Total)	-0.07	0.05	-1.57	0.12
ab* (Indirect)	1.06×10^{-2}	1.37×10^{-2}	-	-

* 95% confidence interval bounds: $(-0.47 - 5.70 \times 10^{-2})$

Adj. R² = 0.02, F (2, 69) = 1.88, p = 0.16

Analysis 3: The Applied Model and Cross-Validation

The final primary analysis of the present study was to test the predictive ability of the newly developed model and compare it to the model developed by Salley et al. (2016) and a simple, gender-based bite-to-kcal conversion based on results described by Scisco et al. (2014). The general procedure for analysis 1 was repeated with a few exceptions. Random slopes were not included in the model. Predictors were not mean-centered so that the intercept value could be used in the developed equation. Additionally, the first bite of each food item was removed since it did not have a valid measure of time since last bite. Variables that were not at least initially significant in analysis 1 were not included in this analysis: age, BMI, and body fat percentage. Additionally, waist-to-hip ratio was not included as this analysis focused on variables that could be obtained outside of the laboratory.

One of each participant's meals was randomly assigned to either a "train" or a "test" group. The model was developed on the training group, and its accuracy was assessed on the test group. Since each participant was now limited to one meal for the MLM analysis, satiety

was treated as a Level 2 variable. Due to the changes applied to the dataset, data cleaning was again performed on each group. Two bites were removed from each group. This resulted in 1,747 bites remaining in the training group and 1,742 bites in the test group. A summary of the final results of the MLM analysis is provided in Table 3.6.

Table 3.6

Summary of MLM for analysis 3.

Variable	Coefficient (SE)	t	p	Initial Model #	Final Model #
*Intercept	-10.84 (2.16)	-5.91	0.00	0	8
Level 1					
*Time Since Last Bite (Log Transformed)	5.24 (0.46)	11.46	0.00	1	8
Time in Meal	1.69 (1.06) x 10 ⁻³	1.60	0.11	2	3
*Food Item Enjoyment	0.20 (0.02)	9.84	0.00	3	8
Level 2					
Satiety	-0.09 (0.05)	-1.86	0.07	4	4
Waist-to-Hip Ratio	16.57 (8.81)	1.88	0.07	5	5
Mouth Volume	0.06 (0.04)	1.40	0.17	6	7
*Gender	-4.73 (1.30)	-3.63	0.00	7	8

**Indicates variables that were retained to the final model.*

With the reduced power and absence of random slopes, satiety was no longer a significant predictor of KPB, and gender is retained to the end. Figure 3.5 shows a scatterplot of observed and predicted KPB.

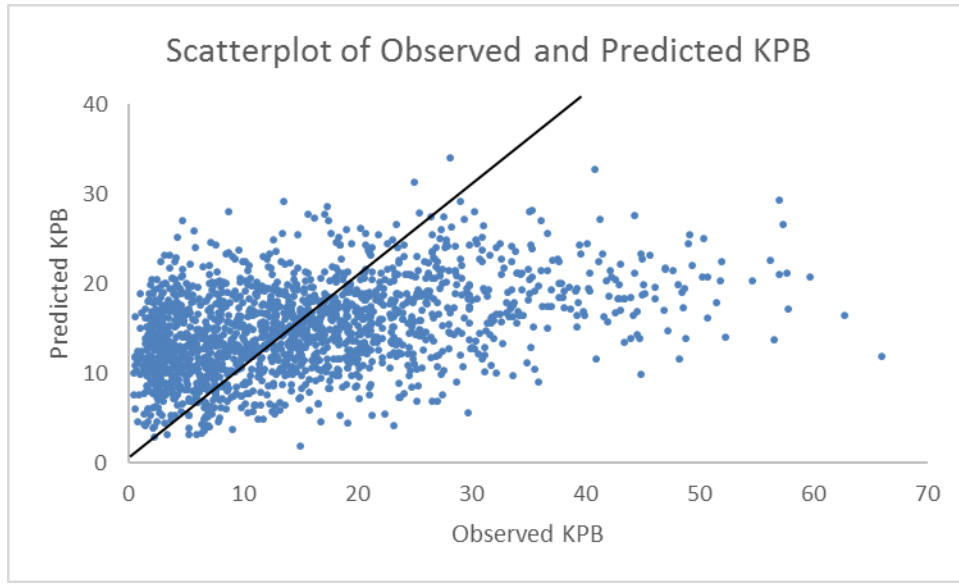


Figure 3.5. Scatterplot of observed and predicted KPB, reference line at $y = x$.

The equation resulting from the significant predictors of the analysis is as follows:

$$KPB = -10.84 + 5.24\ln TSLB + 0.2LAM - 4.73gender(male = 0)$$

The equation from (Salley et al., 2016) to which it was compared is as follows:

$$KPB = 22.29 - 0.13age + 6.17gender(female = 0) + 0.03height + 0.04weight - 12.01WHR$$

From the (Scisco et al., 2014), KPB was calculated as 17 KPB for males and 11 KPB for females.

Estimations of KPB were calculated for the test group using all 3 methods. Descriptive statistics

for each estimation of KPB and their estimation error at the bite and meal levels are shown in Table 3.7.

Table 3.7

Descriptive statistics for KPB estimates and estimation error at the bite- and meal- levels.

Variable	Mean	SD	Min	Max
Bite Level (n = 1742)				
Actual KPB	15.18	11.52	0.47	65.97
Estimated KPB (Present Study)	14.89	4.96	1.86	34.06
Estimated KPB (Salley et al., 2016)	18.59	4.58	9.55	26.28
Estimated KPB (Scisco et al., 2014)	13.71	2.99	11.00	17.00
Estimation Error (Present Study)	-0.29	10.43	-54.09	22.36
Estimation Error (Salley et al., 2016)	3.41	11.64	-50.41	24.15
Estimation Error (Scisco et al., 2014)	-1.46	11.29	-54.97	16.53
Meal Level				
Actual Kcal Consumption (n=67)	394.59	204.66	25.38	754.10
Estimated Kcal Consumption (Present Study)	387.15	176.45	55.17	767.20
Estimated Kcal Consumption (Salley et al., 2016)	483.24	240.98	83.70	1231.25
Estimated Kcal Consumption (Scisco et al., 2014)	356.57	170.33	55.00	850.00
Estimation Error (Present Study)	-7.44	105.33	-276.69	260.60
Estimation Error (Salley et al., 2016)	88.65	161.76	-294.42	585.21
Estimation Error (Scisco et al., 2014)	-38.02	130.57	-331.75	258.60

A one-way repeated measures ANOVA was performed comparing each method of estimation and actual KPB at the meal level. The omnibus test revealed a significant effect for estimation method, $F(3, 64) = 50.919$, $p < .001$. Post-hoc LSD comparisons revealed that actual meal level consumption was significantly lower than the estimated consumption using the Salley et al. (2016) method, $p < .001$, but significantly lower than the Scisco et al. (2014) method, $p < .05$. Post-hoc analysis revealed no difference between the equation developed in this study and actual kcal consumption, $p = .565$.

CHAPTER FOUR: DISCUSSION

The purpose of this study was to obtain a better understanding of the within- and between-subjects influences on the kilocalorie content of specific bites of food and to improve upon previously developed models of KPB. The following sections discuss the extent to which that goal was achieved.

Multi-level Analysis of KPB

Regarding the hypothesized effects for each predictor, only the effects of TSLB, food item enjoyment, and pre-meal satiety are fully supported by the primary analyses. However, further examination and secondary analyses provided additional support for TIM, mouth volume, and gender. Explanation of the findings of each predictor are discussed below.

Time since last bite. The original within-participant distributions of TSLB showed several distributions with heavy positive skew, likely due to lengthy pauses between bites of food so that participants could drink some water or converse with their fellow participants. TSLB was log transformed into lnTSLB to correct for this heavy skew. While both the transformed and untransformed TSLB measurements showed significant model improvement, the transformed variable showed greater improvement and was retained to the end.

In general, longer time between bites led to higher KPB. As the log of TSLB increased by one, KPB increased by 4.79 kcals. This is in line with the hypothesized effect. 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 (Hill & McCutcheon, 1984; Spiegel, Kaplan, Tomassini, & Stellar, 1993a;

Zijlstra et al., 2009). 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. All three of these measures can be found within the literature defined by the term “eating rate,” often conflating the three. This is unfortunate, as these are three different constructs and their relationship to the onset of satiety cannot be assumed to be identical (and indeed, the literature shows different relationships between these three measures and other variables that are commonly measured during eating studies). Hill and McCutcheon (1984) found that longer bite durations (defined as the amount of time spent chewing food) were associated with larger bites and a slower bite rate, but found that eating rate (defined as grams per unit time) was positively associated with bite size. This makes sense, as eating rate defined this way is a combination of bite rate and bite size.

The tendency of researchers to focus on eating rate defined as grams per unit time may be appropriate where the primary variable of interest is the onset of satiation (as it usually is) because it may be the strongest predictor of satiation (Hill & McCutcheon, 1984; Spiegel, Kaplan, Tomassini, & Stellar, 1993b). However, the goal of the present study was to assess predictors of the kilocalorie content of specific bites of food, and eating rate defined as “time since last bite” was more appropriate since, as stated previously, using grams per unit time would conflate bite rate and bite size. The present study is one of very few studies that have examined this relationship, but it is important to examine for the goal of creating an objective, sensor based estimate of kilocalorie intake.

It is important to note that when examining the relationship between KPB and time since last bite, the relationship cannot be assumed to be due entirely to the influence of bite

rate on bite size. Some studies have found a relationship between energy density (an aspect of KPB) and bite rate (Karl, Young, Rood, & Montain, 2013). In the secondary analysis of bite weight described in Appendix P, the positive relationship between TSLB and bite size is maintained. Additionally, a significant correlation between ED and TSLB was found, though it is unclear whether this is truly due to ED or to the fact that higher ED items were presented later in the meal.

Time since last bite offers a promising avenue for refining estimates of KPB from the Bite Counter, as this variable can potentially be measured from the device directly. If calculating the kcal content of a bite of food in real time, an on-board conversion algorithm could adjust kcal estimates based on the amount of time that has passed since the last bite was taken. Calculation of KPB after the fact could also potentially be done, but it would require the device to keep a running log of each bite with time stamps, and may push the storage limits of the device.

Time in meal. Time in meal showed significant model improvement and remained significant throughout most of the model iterations, though not in the expected direction. In general, for each second of meal duration, KPB went up by .004 kcals. The effect of TIM on KPB was likely confounded by the fact that higher ED items were consumed later in the meal. However, in the secondary analysis of bite size (Appendix P), TIM had a negative effect on bite size, showing that each second of meal time leads to a .01 gram decrease in bite size.

While few studies have examined bite weight over time specifically, several studies have examined changes in eating rate over time, with eating rate defined as grams per unit time (e.g. Dovey, Clark-Carter, Boyland, & Halford, 2009; Laessle et al., 2007). These studies generally find

a decrease in grams per unit time over the course of a meal, with participants generally showing a decrease in eating rate as the meal progresses. As previously discussed, measuring eating rate in this manner conflates bite size and bite rate, so while it is unclear from these studies how much of this reduction in eating rate is due to a decrease in bite size and how much is due to a decrease in bite rate, it is likely that both are reduced over the course of the meal, as the present study demonstrates.

Like TSLB, time in meal could potentially be applied to estimates of KPB on the Bite Counter in real time, directly on the device. Otherwise, to be able to apply this variable to KPB estimates after a meal, a log of timestamped bites would be necessary. Alternately, participant KPB slopes over time could be calculated in a calibration meal, and bite Kcal content could be estimated based on these slopes.

Mediation of time in meal by time since last bite. It was hypothesized that, although the overall effect of TIM on KPB would be negative, it would have a positive indirect effect on KPB through TSLB. In other words, it was hypothesized that as time in the meal passed, this would lead to an increase in the time between bites, and this increase in time between bites would correspond to an increase in KPB. The mediation analysis partially supported this hypothesis, showing TIM had a significant positive effect on TSLB, which in turn had a significant positive effect on KPB. However, within the context of the mediation analysis, no significant direct effect for TIM on KPB was found. This is not surprising given the weak effect of TIM on KPB in the primary analysis, and as previously stated, might be due to the confounding effect of increasing energy density over the course of the meal.

To address this concern, a second mediation analysis was performed with bite weight as the dependent variable and is presented in Appendix Q. This analysis fully supported the hypothesis. Time in meal had a significant negative direct effect on bite weight and a significant positive indirect effect on bite weight through TSLB. In summary, keeping the energy density of the food being eaten constant, as a meal progresses people tend to take smaller bites leading to reduced KPB. However, eating rate tends to slow down over the course of the meal. This reduction in eating rate leads to larger bites of food than would be seen with a constant eating rate. This is in line with previous studies showing a reduction in grams per unit time consumed over the course of a meal, but longer chewing times leading to larger bites of food (Hill & McCutcheon, 1984; Laessle et al., 2007). The present study is the first to disentangle these variables and examine the mediating effect of eating rate on the relationship between meal duration and bite size.

Food item enjoyment. As hypothesized, food item enjoyment led to increased KPB, with each one-point increase on the LAM scale leading to a 0.29 increase in KPB. Food enjoyment was positively correlated with energy density, and the secondary analysis of bite weight showed an increase in bite weight of 0.08g per one point increase on LAM score, indicating that food enjoyment is related to KPB through both ED and bite size. These findings are in line with previous studies showing a positive relationship between eating rate as measured by grams per unit time and food enjoyment (J. L. Guss & Kissileff, 2000). Also, it has been demonstrated that foods that are higher in energy density are generally more palatable (Yao & Roberts, 2001).

Food enjoyment offers a promising avenue for developing an accurate estimate of KPB, but applying a measure of food item enjoyment to an algorithm for use with the Bite Counter presents some difficulty. Adding a subjective measure of food item enjoyment comparable to the LAM scale directly to the Bite Counter would probably require an interface drastically different from the interface present on the most recent generation of the device. One possibility would be to ask participants to recall their food item enjoyment at the end of the day through a desktop-based companion software package for the Bite Counter. However, this could potentially present many of the same issues that are present in other dietary self-report methods, though the amount of information necessary to recall would likely be lower and would arguably be less subject to bias than food diaries or dietary recalls (D. A. Schoeller et al., 2013).

Pre-meal satiety. The findings of this study support the hypothesized relationship between pre-meal satiety and KPB. Each one-point increase on the SLIM scale (indicating higher satiety) corresponded to a 0.22 decrease in KPB. This matches Hill & McCutcheon's (1984) findings that starting hunger increases initial eating rate and bite size at the beginning of a meal. Interestingly, pre-meal satiety was not retained through the final model in the secondary analysis of bite weight, though it did share a small but significant negative correlation with bite weight.

It is unclear why pre-meal satiety might show a significant effect for KPB but not bite weight. It would imply that the effect of pre-meal satiety on KPB is related to the ED component of KPB, although there is a very near-zero, non-significant correlation between food ED and SLIM scores. Most likely it is due to the fact that SLIM was added to the model of bite weight later than it was added to the model of KPB; that is, the model of bite weight may have been under-

powered to capture the effect of SLIM. However, if this was true, it is unclear why pre-meal satiety would remain a significant predictor of KPB even after later predictors were added.

Adding a measure of pre-meal satiety to non-laboratory studies that aim to measure KPB presents a challenge. The measure would need to be administered right before a meal occurs, meaning that it would likely not be administrable from a desktop application. One possibility would be to incorporate a feature into the Bite Counter that asks users to input a rating of 1 to 10 for their current satiety level when the Bite Counter is activated. Another would be to have a companion smartphone application where users could rate their satiety ratings before each meal. While these may present future opportunities, assessing pre-meal satiety in non-laboratory settings may be unfeasible.

Mediation of Pre-Meal Satiety by Food Item Enjoyment. It was hypothesized that the effect of pre-meal satiety on KPB would be partially mediated by food item enjoyment. Specifically, it was expected that higher pre-meal satiety would lead to lower food enjoyment, resulting in lower KPB. Therefore, pre-meal satiety would have an indirect negative effect on KPB through food enjoyment as well as a direct negative effect on KPB. This hypothesis was not supported by analysis 2. While SLIM and LAM scores were weakly correlated, it was not in the expected direction. The mediation analysis revealed a near-significant effect for SLIM on LAM scores (the “a” path), but no significant effect for LAM scores on KPB (the “b” path). The direct effect of SLIM on KPB was approaching significance in the expected direction. These results, combined with the findings for pre-meal satiety and food enjoyment in analysis 1, imply that each of these variables have a significant independent effect on KPB, but no mediation is observed.

Body metrics. The hypotheses that participants with higher BMI's, body fat percentages, and waist-to-hip ratios would have higher KPB measurements were not supported in either the primary analysis of KPB or the secondary analysis of bite weight. This is consistent with findings from our own lab and others that KPB and estimates of body fat are unrelated (Salley et al., 2016; Scisco et al., 2014; Spiegel et al., 1993a). However, it would seem to contradict other studies that found a relationship between BMI and eating rate (Laessle et al., 2007; Otsuka, Tamakoshi, & Yatsuya, 2006b). There are numerous possibilities that might explain this discrepancy. The most obvious is that differences between overweight and normal weight individuals in eating rate might be due entirely to differences in *bite rate*; that is, overweight individuals do not necessarily take larger bites of food, they just take bites of food faster.

Another possibility could be due to the nature of controlled laboratory studies. Overweight individuals could choose to eat foods higher in energy density, leading to generally higher KPB's for this group in uncontrolled environments. In the present study and others, food options were limited, which would negate this effect. However, this is not necessarily the case in all studies that have failed to find a relationship between KPB and body fat (e.g., Salley et al., 2016) Finally, it is possible that BMI moderates the effect of meal duration on KPB (such that overweight individuals would have higher KPB's toward the end of a meal compared to normal weight individuals), but the present study did not assess this possibility.

Mouth volume. The hypothesis that individuals with higher mouth volumes would have higher KPB's was not supported by the primary analysis of this study. However, mouth volume was retained as a significant predictor in the secondary analysis of bite weight. This implies that,

while mouth volume may be related to KPB, its effect was not strong enough to be detected given the power and number of predictors in the primary analysis of the present study. To examine this hypothesis, an auxiliary analysis of KPB using multiple regression is presented in Appendix R. Average KPB of each participant was used as the dependent variable, and the three body metrics, mouth volume, age, and gender were all used as predictors. This analysis revealed mouth volume to be a significant predictor of KPB, with each milliliter increase in mouth volume corresponding to a 0.08 kcal increase in average KPB.

Very few studies have examined the role of mouth volume in bite size and eating rate, the one mentioned earlier having found that larger mouth volumes correspond to larger sip sizes (Lawless et al., 2003). While the effect of mouth volume on KPB may be relatively small, its ease of measurement makes it a very convenient predictor of KPB, given a lack of data for stronger predictors. Users of the Bite Counter could be asked to perform the voluntary mouth-fill method at home and record their mouth volume in accompanying desktop software.

Previous studies have mentioned the possibility that the relationships between height and KPB and gender and KPB may be mediated by mouth volume (Salley et al., 2016; Scisco et al., 2014). While height was not a primary predictor of the present study, a Pearson's correlation revealed a moderate, significant correlation between height and mouth volume ($r = 0.59, p < .001$). Additionally, an independent-samples t-test showed that men ($M = 88.51, SD = 16.6$) had significantly greater mouth volumes than women ($M = 65.81, SD = 13.03$) ($t(69) = 6.45, p < .001$). While this does not necessarily indicate mediation, it does provide evidence that gender and height are both related to mouth volume.

Age. While there is not an established theoretical framework to explain its effect, Lawless et. al. (2003) found a positive relationship between age and sip size. Conversely, in a study similar to the present study, Salley et. al. (2016) found a negative relationship between age and KPB, and so it was hypothesized that the same effect would be found in the present study. However, this effect was not replicated in any of the analyses presented. While it is possible that age may affect KPB through various means (such as a reduction in comfortable mouth capacity or reduced sensitivity to the olfactory aspects of food flavor), the present study offers no evidence to expand upon any possible relationship.

Gender. It was hypothesized that men would have a higher KPB than women, a finding present in many previous studies of bite size, eating rate, and KPB (Lawless et al., 2003; Salley et al., 2016; Scisco et al., 2014). This hypothesis was not supported in any analysis of the present study. A paired samples t-test revealed that men ($M = 17.90, SD = 4.75$) had higher average KPB's than women ($M = 13.19, SD = 3.97$) ($t(70) = 4.58, p < .001$), indicating that the lack of significance is not a quality of the sample, but rather a quality of the model. It is possible that the effect of gender was subsumed by mouth volume, as men had higher mouth volumes than women. However, the auxiliary multiple regression of KPB presented in Appendix R revealed both gender and mouth volume as significant predictors of KPB, so it is likely that the MLM analysis was underpowered and the effect of gender was too weak, resulting in a type II error, though it cannot be said for certain.

The Applied Model

The applied purpose of this study was to develop a model that outperformed previous models of KPB developed by our lab. To that end, the third set of analyses in the present study

involved separating the participants' two meals into two groups: one for training a model of KPB, and the other for testing its accuracy. Finally, the accuracy of the model was compared to models of KPB developed by Salley et al. (2016) and Scisco et al. (2014).

Findings Compared to Analysis 1. As in analysis 1, log-transformed TSLB and food item enjoyment remained significant predictors of KPB in the training model. However, possibly due to the reduction in power, pre-meal satiety and time in meal were no longer significant predictors of KPB. Gender, however, remained significant through the final model. The reason gender would be significant in the reduced sample but not in analysis one is possibly because pre-meal satiety and TIM had been removed by the time gender was added. These variables likely shared some of the explained variance in KPB with gender, and their removal allowed the effect of gender to be significant.

Accuracy of the Model. When the model of KPB was applied to the test group, average estimation error (defined as the difference between estimated KPB and actual KPB) was very close to zero, as would be expected as the training and test samples were very similar (a marked difference from zero would have indicated some systematic difference between the training and test samples). There was a fairly large amount of error variance, however, with the standard deviation of estimation error for a single bite being 10.43 kcals and 105.33 kcals for the whole meal. However, while the model would need to be tested on a variety of other meals in other situations, this degree of error shows promise to outperform subjective self-report measures, which have tendency to underestimate caloric intake and have a high degree of error variance (Bandini, Schoeller, Cyr, & Dietz, 1990; D. A. Schoeller et al., 2013; D. a Schoeller, 1995).

Improvement Over Previous Models. The new model of KPB showed a significant improvement in accuracy over the model developed by Salley et al. (2016), which overestimated KPB by an average of 3.41 kcal ($SD = 11.64$) per bite and overestimated meal kcal consumption by an average of 88.65 kcals ($SD = 161.76$). This improvement in accuracy could be due to several factors. For one, the measurements of true kcal consumption used in the Salley et al. study were based on nutrition information provided by the cafeteria that was used to conduct the study, whereas estimates of true kcal consumption in the present study were based on measurements using bomb calorimetry. Secondly, the present study measured kcal consumption of each bite of food and used time since last bite to adjust estimates of KPB throughout the meal, whereas the Salley et al. study relied solely on individual-level predictors and average KPB.

The new model also outperformed the gender-based estimate presented by Scisco et al. (2014), which underestimated the kcal content of bites by an average of 1.46 kcals ($SD = 11.29$) and underestimated meal kcal consumption by 38.02 kcals ($SD = 130.57$). Considering the KPB estimates derived from the Scisco et al. study were based on self-reported 24-hour dietary recall data, which is known to have an underestimation bias, the underestimation shown in the present study is understandable. Additionally, the model in the present study used time between bites and food enjoyment to improve model fit.

Limitations

While the present study showed several improvements over prior efforts to predict caloric consumption based on objective data, a number of issues should be addressed if further progress in this area is to be made. First, considering a few null findings that were inconsistent

with prior research, it is possible that the sample size used in this study was insufficient given the number of predictors that were assessed. Second, while an effort was made to include a wide variety of food items, it is possible that the selected items may not be representative of items that are normally consumed. Finally, as with all laboratory studies of eating behavior, there is a threat to the generalizability of the findings due to altered participant behavior in the laboratory as compared to free living.

Insufficient Power. A primary purpose of this study was to build a model that is as accurate as possible for predicting KPB. To that end, several variables were included as predictors. Unfortunately, it is possible that the sample size was not large enough to detect significant effects for all important predictors, leading to type II errors. To examine this possibility, a multiple regression analysis was run using only level 2 variables from the primary analysis (all of which were not retained through the final model of the MLM analysis), regressing them on mean participant KPB. The results from this analysis are presented in Appendix R. Indeed, gender and mouth volume are identified as being significant predictors of KPB, whereas they were not retained in the primary analysis of this study.

Despite the potential for type 2 errors, one advantage of including each of these predictors is that it allows us to isolate those predictors that most strongly predict KPB. Most notably, time since last bite, pre-meal satiety, and food item enjoyment appear to be strong predictors of KPB which have not been included in previous studies. A simpler model using only these variables could be developed, and may best represent the ideal balance between accuracy and simplicity for predicting KPB.

Food item selection. While a relatively diverse set of food items were chosen for this study, fifteen food items do not approach the level of variety individuals encounter in their everyday lives. Furthermore, pre-selected food items cannot be representative of individual food choices and meal patterns. Given the constraints of the this study, pre-packaged and easily prepared meals were used. Therefore, other types of meals (such as homemade recipes, fast food, and restaurant prepared meals) were not represented. It is possible that using only these types of foods could have systematically biased bite size or mean energy density, which would affect the generalizability of the KPB equation.

Generalizability. Besides the specific threat to generalizability presented by the limited food options is the more general issue of eating studies that are performed in a laboratory setting. That is, the participants may have changed their eating behavior in such a way as to invalidate the use of the model for predicting energy intake outside of the lab. There are examples of noted differences in eating behavior between the lab and free-living environments. For example, Petty, Melanson, & Greene (2013) show that eating rates (measured as average kcals/minute for the meal) in laboratory settings differ from those in field settings. However, no studies have shown that laboratory environments affect bite size. If participants did not change their bite size, then this would reduce the threat to generalizability.

Future Directions

The present study is best viewed as a stepping stone to future efforts to improve the accuracy of KPB estimates based on the Bite Counter device. There are numerous areas in which future studies may build upon the findings presented here.

The Ideal Calibration Study. The ideal scenario for monitoring kilocaloric intake is one in which the best balance between data collection and ease of use is achieved. This will likely involve capturing one or more meals from an individual in an environment where the kilocaloric content of each bite of food can be measured with a reasonable degree of accuracy. One possible scenario in which this principle is extended would be a study in which participants eat one or several meals with known nutritional content in a laboratory setting. A model could be built for each participant based on patterns seen in the lab. The participants would then wear the device in a longitudinal field study, where they would eat as they normally do, and the accuracy of the model could be compared to other accurate methods of monitoring free-living energy intake (e.g. the digital photography method or doubly-labelled water).

Using Individual Slopes to Predict KPB. Future studies of KPB should focus on modelling individual KPB over group KPB. While attempting to assess relationships that hold true across large samples is informative for identifying important relationships for future study, accurate models of KPB that will be used for self-monitoring will depend upon models that are tailored to individuals. The present study identifies several target variables that can be used to build individual-specific models of KPB (e.g. time in meal, time in between bites), but there are many other candidates for inquiry that the present study did not assess, such as social interaction between individuals and level of distraction over the course of the meal.

Identifying Complex Relationships. While several potential variables were identified in this study and examined for their linear relationship to KPB, the data collected in this study could be used to examine several other relationships supported by the literature. For example, non-linear effects were not examined in the present study, yet there is evidence that the effect

of time-in-meal on bite size (and subsequently KPB) may not be linear (J. L. Guss & Kissileff, 2000). Additionally, several potential interactions discussed in the introduction were not examined due to non-significant main effects and a lack of sufficient power. Future studies could focus on these complicated relationships to further develop our understanding of how the predictors described here relate to KPB.

Conclusion

The study described in this dissertation was the first to attempt to predict the kilocaloric content of specific bites of food where the true kcal content of each bite could be measured with a relatively high degree of certainty, indicating that the effects found are likely the most representative of the true relationships between the hypothesized predictors and KPB. Additionally, it was the first to attempt to model KPB in real time using within- and between-subjects variables. While the model presented is certainly not the best model that can be applied to the Bite Counter to attempt to measure kilocalorie intake, it offers new insights into possible predictors and methods of tailoring future models to individual eating patterns. Future studies should focus on pre-meal satiety, time between bites, and food enjoyment as easily measured predictors of KPB. Considering the previous discussion on mouth volume and time in meal, these variables also warrant further investigation. Should this line of inquiry be continued, it is foreseeable that the Bite Counter may provide an avenue for self-monitoring kcal intake that outperforms all other methods in accuracy, cost, and ease of use.

APPENDICES

Appendix A: Describing Obesity

While there is evidence that the sharp increase in obesity among Americans seen over the last few decades is levelling off, roughly 35% of American adults remain obese (Flegal, Carroll, Kit, & Ogden, 2012a; Rokholm, Baker, & Sørensen, 2010). Obesity is a complex disease, with environmental, psychological, and biological contributors, and there have been decades of research attempting to explain its causal mechanisms and identify the ideal avenues of treatment.

Defining Obesity

Body-fat levels are generally classified by Body Mass Index (BMI), a ratio of weight to height (kg/m^2). The National Institutes of Health characterize BMIs less than 18.5 as underweight, 18.5 to 24.9 as normal weight, 25 to 29.9 as overweight, and above 30 as obese (with additional divisions to indicate various levels of obesity) (NIH, 2000). These cutoff points were selected based on an associated increased risk of type 2 diabetes, hypertension, and cardiovascular disease (World Health Organization, 2000). While BMI is shown to correlate with health risk and adiposity, it was designed for epidemiological studies, intended as an easily-measured proxy for body fat percentage (BFP), with which it shares a moderate-to-strong correlation (Keys, Fidanza, Karvonen, Kimura, & Taylor, 2014).

Health Risks, Economic Costs, and Prevalence

Obesity is one of the leading preventable causes of death worldwide (Lopez, Mathers, Ezzati, Jamison, & Murray, 2006). As of 2012, obesity rates among U.S. adults rests at about 35%, and has remained relatively stable since 2003 after a dramatic increase between 1980 and

1999 (Flegal, Carroll, Kit, & Ogden, 2012b; Ogden et al., 2014). While it is encouraging that obesity rates appear to no longer be increasing, current levels pose serious health risks and economic burdens for millions of people worldwide. The 2013 Global Burden of Disease, Injuries, and Risk Factor study indicates that high BMI was a risk factor associated with 4.4 million deaths worldwide in that year (Forouzanfar et al., 2015). Finkelstein, Trogdon, Cohen, & Dietz (2009) estimated that total economic costs associated with obesity in the U.S. were around \$118.5 billion in 2006, and Wang, McPherson, Marsh, Gortmaker, & Brown (2011) predict that these costs will increase by \$48-66 billion per year by 2030 in the U.S. alone, based on projected obesity trends.

Much of the cost and mortality associated with obesity is due to the occurrence and treatment of the numerous comorbidities that often accompany it. The most common comorbidity is known as metabolic syndrome: high blood pressure, high fasting blood glucose, high serum triglycerides, and low levels of high-density lipoprotein, which, in turn, increase the likelihood of heart disease and diabetes (Kaur, 2014). Obesity is associated with several other physical and psychological morbidities, including (but not limited to): high blood pressure, increased chance of stroke, an increase in the severity and occurrence of several respiratory diseases, an increase in the likelihood of breast, colon, endometrium, kidney, and esophageal cancers (accounting for a quarter to a third of these types of cancers, according to the WHO), arthritis, depression, and social stigmatization (Haslam & James, 2005). However, despite a high degree of public awareness of the causes, costs, and health risks of obesity, it has proven to be a very difficult problem to address, both at a societal and individual level.

Human Metabolism and the Biology of Obesity. The human body requires energy to perform its basic functions. We consume energy when we eat in the form of three macronutrients: fat, protein, and carbohydrate. In reasonably balanced diet, humans derive roughly 50% of our energy intake (EI) from carbohydrates, 35% from fat, and 15% from protein (Austin, Ogden, & Hill, 2011). Energy is measured in units of calories or joules, with one calorie being the amount of energy necessary to heat one gram of water one degree Celsius at a pressure of one atmosphere. Within the context of human metabolism, the most common unit of measurement is the *kilocalorie*, or one-thousand calories (not to be confused with the capitalized Calorie, which is often used in the United States as a replacement for kcal). At the simplest biological level, obesity is caused by a sustained *positive energy balance* over a long period of time. Energy balance describes the difference between energy intake and energy expenditure, so a positive energy balance indicates that more kcals are being consumed than are being expended. Excess energy is converted into adipose tissue which is used as a stored form of energy to be used during periods of negative energy balance. The body uses carbohydrates preferentially, as they are easier to break down into glucose, which can be readily used by the cells for metabolism. Excess carbohydrates are stored either as glycogen, or converted into adipose tissue, both of which act as energy stores to be used once the readily available glucose has been depleted. Once glucose stores are used up, the body enters ketosis and begins to use lipids (fats). Excess fats are converted to adipose tissue.

With regards to weight loss, it was long held within the scientific community that “a calorie is a calorie,” implying that the macronutrient content of a diet was unimportant to metabolic rate (Bray, 2003; Buchholz & Schoeller, 2004). Indeed, the laws of thermodynamics

dictate that a positive energy balance will invariably lead to weight gain, whereas a negative energy balance will invariably lead to weight loss. However, recent research has shown that different macronutrient balances and different types of specific macronutrients may have different effects on metabolism. Fine & Feinman (2004) propose the possibility that certain macronutrients may have a “metabolic advantage,” meaning that the energy requirements to break down and store certain macronutrients diminish the net energy intake of these nutrients, and short-term differential weight loss between isocaloric diets with differing levels of carbohydrate restriction has been shown in a few studies (Fine & Feinman, 2004; Hall, 2010; Westman et al., 2007). Nevertheless, the efficacy of diets with specific macronutrient balances to produce differential long-term weight loss in clinical trials has not been established (De Souza et al., 2012; Sacks et al., 2009). However, the dynamics of macronutrient balance, satiety, and metabolism are complex and merit further study (Bellissimo & Akhavan, 2015).

Energy expenditure. Energy expenditure describes the burning of calories to produce work and heat. Total energy expenditure is a result of basal metabolic rate (BMR; approximated by resting metabolic rate, RMR), the thermic effect of food (TEF; sometimes called the thermic effect of feeding, diet-induced thermogenesis, or specific dynamic action), and energy expenditure due to physical activity (PA). RMR accounts for the largest percentage of total energy expenditure, but is highly variable between individuals. RMR is a result of body composition, and the strongest influence on RMR is fat-free mass, which consists of the body’s muscle and organ tissue (Cunningham, 1991), and models that take into account lean and fat mass account for about 70% of RMR, with the other 30% thought to be due to genetic

differences in different organ mass (that is, specific organs differ in their metabolic rates, and these organs vary in mass between individuals; Hall, 2012).

TEF accounts for the smallest portion of total energy expenditure and is the result of the energy expenditure necessary to digest food. It is closely proportional to energy intake (that is, for any particular food item, the TEF associated with that item will be roughly 7% to 14% of the calories consumed of that item), although there are slight differences in TEF for different macronutrients consumed (Hall, 2010, 2012). Within the weight-loss literature, energy expenditure due to physical activity is generally given the most attention of the three forms of energy expenditure, as it is the aspect of energy expenditure most amenable to treatment through behavioral interventions. Energy expenditure due to physical activity describes the energy used to perform work, and varies between individuals with different activity levels.

Environmental facilitation of obesity. While obesity has been a known health concern throughout much of human history (formerly being a status symbol despite the associated risks), it only became a widespread problem in the 20th century (Caballero, 2007). For the first time in human history, overweight and obese individuals outnumber the malnourished (Gardner & Halweil, 2000). At a macroscopic level, this epidemiological trend is thought to be the result of an obesogenic built environment, meaning that our society has structured itself in a way that facilitates and encourages excessive energy intake and discourages or impedes PA, reducing energy expenditure.

Appendix B: Additional Variables

In addition to the variables described in the body of the present study, data were collected on several additional variables, though no analysis of these variables is presented in this dissertation. These are excluded from the applied model either because they cannot be realistically measured in a free-living environment, or because their inclusion is exploratory in nature. These variables are listed in Table B1, along with how they were measured and their expected effect on KPB.

Distraction. Distraction is often measured in microstructural analysis as it had a direct effect on portion consumption – specifically, distracted individuals tend to consume more and end their meals later, presumably because they cause individuals to ignore their internal satiety cues (Hetherington et al., 2006; Wansink, 2004). In the present study, the primary source of distraction will likely be conversation. Conversation will be recorded, and distraction by conversation will be calculated as a percentage of total meal time during which conversation was occurring.

Social facilitation. Social facilitation with regards to eating describes the effects of the eating behavior of meal companions on one's own eating behavior. It can be difficult to characterize, as it is a function of how many people an individual is eating with and whether or not they are still eating. In the present study, we will attempt to characterize it by calculating the time at which the first individual to stop eating takes their last bite of food, and how quickly afterwards other participants stop eating.

Ingestion method. Ingestion method describes exactly *how* an individual puts food in their mouths. It can be characterized based on how the method constrains bite size. For

example, utensils constrain bite size in that they have a maximum capacity, and an effort associated with putting the food on the utensil. “Finger food” are not constrained by utensil capacity, but rather mouth size and the size of the unit of food. A bite of a sandwich will possibly be as large as a participant feels comfortable taking. However, drinking a beverage directly from a glass is totally unconstrained, as an individual can hold the glass to their mouths, and even drink beyond their mouth volume’s capacity if they swallow while they simultaneously continue to fill their mouths. Ingestion method is included because its effects on bite size have not been extensively studied.

Macronutrient content. While the macronutrient content of food items has been studied for the extent to which different macronutrient maintain satiety, their effects on variables associated with microstructural analysis have received little attention. Bell et al. (1998) suggest that some macronutrients may make foods more enjoyable, which means that they would have an indirect effect on bite size, mediated by palatability. In the present study, the effects of macronutrient content, both as a percentage of total caloric content of specific items and as a raw amount by weight, will be examined for their effects on bite size and KPB and their indirect effect, mediated through palatability.

Mindfulness. Mindfulness training is a relatively new tool used by clinicians in behavioral interventions attempting to treat obesity. In general, mindful eating describes the act of paying deliberate attention to internal satiety cues, and attempting to cease eating once the zone of indifference has been entered. Individuals are known to display different levels of mindfulness, and in the present study, the Mindful Eating Questionnaire will be used to assess its impact on bite size (Framson et al., 2009).

Body composition. In the calibration meal scenario described in the body of this paper, the only measure of body composition that could reasonably be acquired is BMI, calculated from weight, height, and gender obtained from self-report. The descriptive model will assess actual BMI, body fat percentage, and waist-to-hip ratio. As these variables are known to be correlated, they will be entered separately to examine their independent effect sizes.

Table B1

Additional variables and their expected relationship to KPB.

Predictor	Obtained from...	Unit	Range	Level	Effect on KPB
Distraction	Conversation recording	% of meal time	0 – 100	1	Positive
Social Facilitation	MARG	seconds	n/a	1	Positive
Ingestion Method	Observed	n/a	utensil, hand, or drink	1	Categorical
Macronutrient Content	Food nutrition information	% fat/ carb/ protein	0 – 100	1	n/a
Mindful Eating	MES	subjective rating		2	Negative

*These variables are included because they will be aggregated to a higher level, or used in interaction terms.

Appendix C: Recruitment E-Mail

Two Free Meals and \$20 for participating in an Eating Study

Researchers in the psychology department are seeking volunteers for a study on eating behavior. Participants will receive three free meals and will be paid \$20. The study takes place over three sessions on three separate days, and each session lasts about an hour. Faculty and students alike are encouraged to participate. Contact James Salley at jnsalle@clermson.edu for more information.



Department of
Psychology study
**Earn \$30 and
three free meals!**



We are seeking men and women 18+ years old for this study. The study will require you to eat three meals with three other participants in a laboratory setting. During the meal, you will wear a wrist-worn device that can measure eating and your activity will be recorded.

We are recruiting participants during the Spring 2016 semester Contact James Salley by e-mail at jnsalle@clemson.edu or by phone at 864-656-1144 to sign up for the study.

James Salley 864-656-1144
jnsalle@clemson.edu
Cofeterna study

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jnsalle@clemson.edu
Cofeterna study

Appendix E: Screening Questionnaire

1. Have you ever been diagnosed with an eating disorder (e.g., Anorexia, Bulimia)?

Yes

No

2. Do have any dietary restrictions (due to allergy, health, religious, or ethical reasons)?

Yes

No

a. If yes, please describe: _____

Please note that if you participate in this study, you will be randomly assigned to eat many of the following food items, i.e., we select the foods for you. For each of the following food items, please rate your willingness to consume that item.

1. Chicken Alfredo

I consume this often and enjoy it.

I do not consume this often, but I enjoy it.

I neither like nor dislike this item.

I could force myself to consume this in limited quantities.

I would not consume this item.

2. Ranch Broccoli

I consume this often and enjoy it.

I do not consume this often, but I enjoy it.

I neither like nor dislike this item.

I could force myself to consume this in limited quantities.

I would not consume this item.

3. Cookies and Crème Pie

- I consume this often and enjoy it.
- I do not consume this often, but I enjoy it.
- I neither like nor dislike this item.
- I could force myself to consume this in limited quantities.
- I would not consume this item.

4. Lasagna

- I consume this often and enjoy it.
- I do not consume this often, but I enjoy it.
- I neither like nor dislike this item.
- I could force myself to consume this in limited quantities.
- I would not consume this item.

5. Mixed Vegetables

- I consume this often and enjoy it.
- I do not consume this often, but I enjoy it.
- I neither like nor dislike this item.
- I could force myself to consume this in limited quantities.
- I would not consume this item.

6. Vanilla Ice Cream

- I consume this often and enjoy it.
- I do not consume this often, but I enjoy it.
- I neither like nor dislike this item.
- I could force myself to consume this in limited quantities.
- I would not consume this item.

7. Meatloaf

- I consume this often and enjoy it.
- I do not consume this often, but I enjoy it.
- I neither like nor dislike this item.
- I could force myself to consume this in limited quantities.
- I would not consume this item.

8. Asparagus

- I consume this often and enjoy it.
- I do not consume this often, but I enjoy it.
- I neither like nor dislike this item.
- I could force myself to consume this in limited quantities.
- I would not consume this item.

9. Cheesecake

- I consume this often and enjoy it.
- I do not consume this often, but I enjoy it.
- I neither like nor dislike this item.
- I could force myself to consume this in limited quantities.
- I would not consume this item.

10. Maple & Brown Sugar Oatmeal

- I consume this often and enjoy it.
- I do not consume this often, but I enjoy it.
- I neither like nor dislike this item.
- I could force myself to consume this in limited quantities.
- I would not consume this item.

11. Bananas

- I consume this often and enjoy it.
- I do not consume this often, but I enjoy it.
- I neither like nor dislike this item.
- I could force myself to consume this in limited quantities.
- I would not consume this item.

12. Small Powdered Donuts

- I consume this often and enjoy it.
- I do not consume this often, but I enjoy it.
- I neither like nor dislike this item.
- I could force myself to consume this in limited quantities.
- I would not consume this item.

13. Grits (with butter)

- I consume this often and enjoy it.
- I do not consume this often, but I enjoy it.
- I neither like nor dislike this item.
- I could force myself to consume this in limited quantities.
- I would not consume this item.

14. Low-fat Strawberry Yogurt

- I consume this often and enjoy it.
- I do not consume this often, but I enjoy it.
- I neither like nor dislike this item.
- I could force myself to consume this in limited quantities.
- I would not consume this item.

15. Blueberry Muffins

- I consume this often and enjoy it.
- I do not consume this often, but I enjoy it.
- I neither like nor dislike this item.
- I could force myself to consume this in limited quantities.
- I would not consume this item.

This study has sessions that occur at specific times throughout the week. Please indicate times that you would be regularly available throughout the week. Each session lasts about an hour. Note: If asked to participate in the study, you will be assigned to three of the time slots that you have listed that you are available.

1. Please list the times that you would be free on most Mondays (select all that apply).

- 7:00am
- 9:00am
- 11:00am
- 1:00pm
- 5:00pm
- 7:00pm

2. Please list the times that you would be free on most Tuesdays (select all that apply).

- 7:00am
- 9:00am
- 11:00am
- 1:00pm
- 5:00pm
- 7:00pm

3. Please list the times that you would be free on most Wednesdays (select all that apply).

- 7:00am
- 9:00am
- 11:00am
- 1:00pm
- 5:00pm
- 7:00pm

4. Please list the times that you would be free on most Thursdays (select all that apply).

- 7:00am
- 9:00am
- 11:00am
- 1:00pm
- 5:00pm
- 7:00pm

5. Please list the times that you would be free on most Fridays (select all that apply).

- 7:00am
- 9:00am
- 11:00am
- 1:00pm
- 5:00pm
- 7:00pm

6. Please list the times that you would be free on most Saturdays (select all that apply).

- 7:00am
- 9:00am
- 11:00am
- 1:00pm
- 5:00pm
- 7:00pm

Appendix F: Demographics Questionnaire

1. Do you normally eat breakfast?
 - Yes
 - No
 - b. If yes, about what time: _____
2. Do you normally eat lunch?
 - Yes
 - No
 - c. If yes, about what time: _____
3. Do you normally eat dinner?
 - Yes
 - No
 - d. If yes, about what time: _____
4. Are you currently following a diet in an effort to gain, lose, or maintain weight?
 - Yes
 - No
 - e. If yes, please describe: _____

5. What is your age? _____
6. What is your gender? (circle one): Male Female
7. Are you right-handed or left-handed? (If you are ambidextrous, please list the hand that you use more often for eating.) _____

8. How much do you weigh? _____ (pounds)
9. How tall are you? _____ (feet & inches)
10. What is your ethnicity?
- American Indian or Alaska Native
 - Asian or Pacific Islander
 - African-American
 - Caucasian
 - Hispanic
 - Other (please specify): _____

Appendix G: Dieting Behaviors Scale

(Blodgett Salafia, Gondoli, Corning, McEnery, & Grundy, 2007)

Instructions. These questions ask about how you feel about eating, dieting, and how much you exercise. Please circle the answer that best fits how often you do certain things.

How often

	Never	Rarely	Sometimes	Often	Usually	Always
1. have you skipped meals to lose weight?	0	1	2	3	4	5
2. have you exercised more to lose weight?	0	1	2	3	4	5
3. have you drunk diet soda (or lots of water) instead of eating?	0	1	2	3	4	5
4. have you tried to lose weight for the sport you play?	0	1	2	3	4	5
5. have you eaten diet foods (e.g., Lean Cuisine or fat-free yogurt) and drinks (e.g., diet soda) instead of regular food?	0	1	2	3	4	5
6. have you eaten smaller portions (amounts) so you could lose weight or not gain weight?	0	1	2	3	4	5
7. have you cut out sweets or snacks so you wouldn't get fat?	0	1	2	3	4	5

Appendix H: The Mindful Eating Questionnaire

(Framson et al., 2009)

NOT RANDOMIZED

1. **I stop eating when I'm full even when eating something I love.**
0 1 2 3 4
Not applicable Definitely false Mostly false Mostly true Definitely true
2. **When a restaurant portion is too large, I stop eating when I'm full.**
0 1 2 3 4
Not applicable Definitely false Mostly false Mostly true Definitely true
3. **When I eat at "all you can eat" buffets, I tend to overeat.**
0 1 2 3 4
Not applicable Definitely false Mostly false Mostly true Definitely true
4. **If there are leftovers that I like, I take a second helping even though I'm full.**
0 1 2 3 4
Not applicable Definitely false Mostly false Mostly true Definitely true
5. **If there's good food at a party, I'll continue eating even after I'm full.**
0 1 2 3 4
Not applicable Definitely false Mostly false Mostly true Definitely true
6. **When I'm eating one of my favorite foods, I don't recognize when I've had enough.**
0 1 2 3 4
Not applicable Definitely false Mostly false Mostly true Definitely true
7. **When I'm at a restaurant, I can tell when the portion I've been served is too large for me.**
0 1 2 3 4
Not applicable Definitely false Mostly false Mostly true Definitely true
8. **If it doesn't cost much more, I get the larger size food or drink regardless of how hungry I feel.**
0 1 2 3 4
Not applicable Definitely false Mostly false Mostly true Definitely true
9. **I notice when there are subtle flavors in the foods I eat.**
0 1 2 3 4
Not applicable Definitely false Mostly false Mostly true Definitely true

10. **Before I eat I take a moment to appreciate the colors and smells of my food.**
 0 1 2 3 4
 Not applicable Definitely false Mostly false Mostly true Definitely true
11. **I appreciate the way my food looks on my plate.**
 0 1 2 3 4
 Not applicable Definitely false Mostly false Mostly true Definitely true
12. **When eating a pleasant meal, I notice if it makes me feel relaxed.**
 0 1 2 3 4
 Not applicable Definitely false Mostly false Mostly true Definitely true
13. **I taste every bite of food that I eat.**
 0 1 2 3 4
 Not applicable Definitely false Mostly false Mostly true Definitely true
14. **I notice when the food I eat affects my emotional state.**
 0 1 2 3 4
 Not applicable Definitely false Mostly false Mostly true Definitely true
15. **I notice when foods and drinks are too sweet.**
 0 1 2 3 4
 Not applicable Definitely false Mostly false Mostly true Definitely true
16. **I recognize when food advertisements make me want to eat.**
 0 1 2 3 4
 Not applicable Definitely false Mostly false Mostly true Definitely true
17. **I notice when I'm eating from a dish of candy just because it's there.**
 0 1 2 3 4
 Not applicable Definitely false Mostly false Mostly true Definitely true
18. **I recognize when I'm eating and not hungry.**
 0 1 2 3 4
 Not applicable Definitely false Mostly false Mostly true Definitely true
19. **I notice when just going into a movie theater makes me want to eat candy or popcorn.**
 0 1 2 3 4
 Not applicable Definitely false Mostly false Mostly true Definitely true

20. **When I eat a big meal, I notice if it makes me feel heavy or sluggish.**
- | | | | | |
|----------------|------------------|--------------|-------------|-----------------|
| 0 | 1 | 2 | 3 | 4 |
| Not applicable | Definitely false | Mostly false | Mostly true | Definitely true |
21. **At a party where there is a lot of good food, I notice when it makes me want to eat more food than I should.**
- | | | | | |
|----------------|------------------|--------------|-------------|-----------------|
| 0 | 1 | 2 | 3 | 4 |
| Not applicable | Definitely false | Mostly false | Mostly true | Definitely true |
22. **When I'm sad I eat to feel better.**
- | | | | | |
|----------------|------------------|--------------|-------------|-----------------|
| 0 | 1 | 2 | 3 | 4 |
| Not applicable | Definitely false | Mostly false | Mostly true | Definitely true |
23. **When I'm feeling stressed at work I'll go find something to eat.**
- | | | | | |
|----------------|------------------|--------------|-------------|-----------------|
| 0 | 1 | 2 | 3 | 4 |
| Not applicable | Definitely false | Mostly false | Mostly true | Definitely true |
24. **I have trouble not eating ice cream, cookies, or chips if they're around the house.**
- | | | | | |
|----------------|------------------|--------------|-------------|-----------------|
| 0 | 1 | 2 | 3 | 4 |
| Not applicable | Definitely false | Mostly false | Mostly true | Definitely true |
25. **I snack without noticing that I am eating.**
- | | | | | |
|----------------|------------------|--------------|-------------|-----------------|
| 0 | 1 | 2 | 3 | 4 |
| Not applicable | Definitely false | Mostly false | Mostly true | Definitely true |
26. **My thoughts tend to wander while I am eating.**
- | | | | | |
|----------------|------------------|--------------|-------------|-----------------|
| 0 | 1 | 2 | 3 | 4 |
| Not applicable | Definitely false | Mostly false | Mostly true | Definitely true |
27. **I think about things I need to do while I am eating.**
- | | | | | |
|----------------|------------------|--------------|-------------|-----------------|
| 0 | 1 | 2 | 3 | 4 |
| Not applicable | Definitely false | Mostly false | Mostly true | Definitely true |
28. **I eat so quickly that I don't taste what I'm eating.**
- | | | | | |
|----------------|------------------|--------------|-------------|-----------------|
| 0 | 1 | 2 | 3 | 4 |
| Not applicable | Definitely false | Mostly false | Mostly true | Definitely true |

Appendix I: Self-Efficacy For Dietary Control

For each of the following items, please rate how confident you are on a scale of 0 to 100 (with 0 = not confident at all, and 100 = very confident).

How confident are you in your ability to...

control what you eat? _____

avoid eating unhealthy food that you like? _____

avoid unhealthy foods every day? _____

stick to your diet, even when you are hungry? _____

avoid giving in to the temptation to break a diet if offered tempting foods? _____

Appendix J: The Three-Factor Eating Questionnaire R-18

29. **When I smell a sizzling steak or juicy piece of meat, I find it very difficult to keep from eating, even if I have just finished a meal.**
- | | | | |
|------------------|--------------|-------------|-----------------|
| 1 | 2 | 3 | 4 |
| Definitely false | Mostly false | Mostly true | Definitely true |
30. **I deliberately take small helpings as a means of controlling my weight.**
- | | | | |
|------------------|--------------|-------------|-----------------|
| 1 | 2 | 3 | 4 |
| Definitely false | Mostly false | Mostly true | Definitely true |
31. **When I feel anxious, I find myself eating.**
- | | | | |
|------------------|--------------|-------------|-----------------|
| 1 | 2 | 3 | 4 |
| Definitely false | Mostly false | Mostly true | Definitely true |
32. **Sometimes when I start eating, I just can't seem to stop.**
- | | | | |
|------------------|--------------|-------------|-----------------|
| 1 | 2 | 3 | 4 |
| Definitely false | Mostly false | Mostly true | Definitely true |
33. **Being with someone who is eating often makes me hungry enough to eat also.**
- | | | | |
|------------------|--------------|-------------|-----------------|
| 1 | 2 | 3 | 4 |
| Definitely false | Mostly false | Mostly true | Definitely true |
34. **When I feel blue, I often overeat.**
- | | | | |
|------------------|--------------|-------------|-----------------|
| 1 | 2 | 3 | 4 |
| Definitely false | Mostly false | Mostly true | Definitely true |
35. **When I see a real delicacy, I often get so hungry that I have to eat it right away.**
- | | | | |
|------------------|--------------|-------------|-----------------|
| 1 | 2 | 3 | 4 |
| Definitely false | Mostly false | Mostly true | Definitely true |
36. **I get so hungry that my stomach often seems like a bottomless pit.**
- | | | | |
|------------------|--------------|-------------|-----------------|
| 1 | 2 | 3 | 4 |
| Definitely false | Mostly false | Mostly true | Definitely true |
37. **I am always hungry so it is hard for me to stop eating before I finish the food on my plate.**
- | | | | |
|------------------|--------------|-------------|-----------------|
| 1 | 2 | 3 | 4 |
| Definitely false | Mostly false | Mostly true | Definitely true |
38. **When I feel lonely, I console myself by eating.**
- | | | | |
|------------------|--------------|-------------|-----------------|
| 1 | 2 | 3 | 4 |
| Definitely false | Mostly false | Mostly true | Definitely true |

39. **I consciously hold back at meals in order not to weight gain.**
- | | | | |
|------------------|--------------|-------------|-----------------|
| 1 | 2 | 3 | 4 |
| Definitely false | Mostly false | Mostly true | Definitely true |
40. **I do not eat some foods because they make me fat.**
- | | | | |
|------------------|--------------|-------------|-----------------|
| 1 | 2 | 3 | 4 |
| Definitely false | Mostly false | Mostly true | Definitely true |
41. **I am always hungry enough to eat at any time.**
- | | | | |
|------------------|--------------|-------------|-----------------|
| 1 | 2 | 3 | 4 |
| Definitely false | Mostly false | Mostly true | Definitely true |
42. **How often do you feel hungry?**
- | | | | |
|--------------------|-------------------------|---------------------|---------------|
| 1 | 2 | 3 | 4 |
| Only at meal times | Sometimes between meals | Often between meals | Almost always |
43. **How frequently do you avoid “stocking up” on tempting foods?**
- | | | | |
|--------------|--------|---------|---------------|
| 1 | 2 | 3 | 4 |
| Almost never | Seldom | Usually | Almost always |
44. **How likely are you to consciously eat less than you want?**
- | | | | |
|----------|-----------------|-------------------|-------------|
| 1 | 2 | 3 | 4 |
| Unlikely | Slightly likely | Moderately likely | Very likely |
45. **Do you go on eating binges though you are not hungry?**
- | | | | |
|-------|--------|---------|---------------|
| 1 | 2 | 3 | 4 |
| Never | Rarely | Usually | Almost always |
46. **On a scale of 1 to 8, where 1 means no restraint in eating (eating whatever you want, whenever you want it) and 8 means total restraint (constantly limiting food intake and never “giving in”), what number would you give yourself?**
- | | | | | | | | |
|---|---|---|---|---|---|---|---|
| 1 | 2 | 3 | 4 | 5 | 6 | 7 | 8 |
|---|---|---|---|---|---|---|---|

Appendix K: Weight Efficacy Lifestyle Questionnaire

(Clark, Abrams, Niaura, Eaton, & Rossi, 1991)

NOT RANDOMIZED

For each of the following questions, please rate how confident you are that you can perform the actions described.

How confident are you that you can...

1. I can resist eating when I am anxious (nervous).

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

2. I can resist eating when I am depressed (or down).

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

3. I can resist eating when I am angry (or irritable).

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

4. I can resist eating when I have experienced failure.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

5. I can control my eating on the weekends.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

6. I can resist eating when there are many different kinds of food available.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

7. I can resist eating when I am at a party.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

8. I can resist eating when high calorie foods are available.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

9. I can resist eating when I have to say “no” to others.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

10. I can resist eating when I feel it’s impolite to refuse a second helping.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

11. I can resist eating when others are pressuring me to eat.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

12. I can resist eating even when I think others will be upset if I don’t eat.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

13. I can resist eating when I feel physically run down.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

14. I can resist eating when I have a headache.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

15. I can resist eating when I am in pain.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

16. I can resist eating when I feel uncomfortable.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

17. I can resist eating when I am watching TV.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

18. I can resist eating when I am reading.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

19. I can resist eating just before going to bed.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

20. I can resist eating when I am happy.

0 1 2 3 4 5 6 7 8 9

Not Confident

Very Confident

Appendix L: Pre-Meal Questionnaire

When was the last time you ate a full meal? (Date and time)

Date: _____

Time: _____

Describe that meal (what foods did you eat, and how much). Please remember to include beverages.

Have you consumed anything since then?

Yes

No

To the best of your ability, describe those snacks (what did you eat/drink, how much, at what time?)

Appendix M: Post-Meal Questionnaire

(Example. Items will vary depending on meal)

For each of the following questions, please refer to the following list of food items that you just consumed:

Item 1: Chicken Alfredo

Item 2: Ranch Broccoli

Item 3: Cookies and Crème Pie.

1. How healthy would you rate item 1?

Very Unhealthy 1 2 3 4 5 6 7 Very
Healthy

2. How healthy would you rate item 2?

Very Unhealthy 1 2 3 4 5 6 7 Very
Healthy

3. How healthy would you rate item 3?

Very Unhealthy 1 2 3 4 5 6 7 Very
Healthy

4. How many calories do you think you consumed of item 1?

5. How many calories do you think you consumed of item 2?

6. How many calories do you think you consumed of item 3?

7. How likely are you to eat your next meal today earlier than you normally would because of this session?

Very Unlikely 1 2 3 4 5 6 7 Very Likely

8. How likely are you to eat your next meal today later than you normally would because of this session?

Very Unlikely 1 2 3 4 5 6 7 Very Likely

9. How distracted were you from the eating activity (because of conversation, the setting, etc.)?

Not Distracted at All 1 2 3 4 5 6 7 Very Distracted

Appendix N: Data Cleaning

Data Cleaning for Level 1 Predictors.

The following describes, in detail, the findings and outcomes of the data-cleaning process for Analysis 1. Level 1 predictors and the DV were examined on a by-participant basis, whereas level 2 predictors were measured across all participants.

Bite Weight. Across all participants, distributions in bite weight had a mean kurtosis value of .104 and a mean skewness value of .470. To determine if kurtosis or skewness is excessive, these values are examined as a ratio of relative to their standard errors, 12 participants had kurtosis values >2 times their standard errors, with 10 of those having kurtosis values >3 times their errors. Several distributions were positively skewed, with 23 participants having bite weight distributions with positive skew values that exceeded 2 times their standard errors, with 16 of these exceeding 3 times the standard error. There was some overlap between leptokurtic and positively skewed distributions, with 9 of the participants with leptokurtic distributions also having highly skewed distributions. An examination of individual participant boxplots revealed 20 outliers in bite weight, all of which belonged to participants with excessive kurtosis and/or skew. These 20 cases were examined, and three of them were found to be the result of faulty scale data and deleted. For the remaining 17, no errors could be found that might explain the large bite weight values, and so were left in the dataset. It should be noted that of these 17, 14 were bites of lasagna, indicating that something about the nature of the lasagna as a food item lends it to occasionally large bites. It was expected that bite weight distributions might be positively skewed, having a hard bottom limit of 0 but no upper bound.

Given the apparent validity of the remaining extreme values found, no further action was taken to clean bite-weight values.

Kilocalories-Per-Bite. Note that bite weight, a factor in calculating KPB, was screened before KPB, and all screening of KPB was performed after bite weight was cleaned. Across all participants, distributions in KPB had a mean kurtosis value of 0.67 and a mean skewness value of 0.80. To determine if kurtosis or skewness is excessive, these values are examined as a ratio of relative to their standard errors, 18 participants had absolute kurtosis values >2 times their standard errors, with 12 of those having kurtosis values >3 times their errors. Several distributions were positively skewed, with 35 participants having bite weight distributions with positive skew values that exceeded 2 times their standard errors, with 27 of these exceeding 3 times the standard error. There was some overlap between leptokurtic and positively skewed distributions, with 16 of the participants with leptokurtic distributions also having highly skewed distributions. Given the facts that bite weight is the only source of outliers due to faulty measurement and that bite weight was cleaned prior to analysis of KPB, no further outliers were removed. It must be assumed that KPB is not normally distributed, and it is logical that it should have positive skew, with large bites of high ED items causing large measurements of KPB. However, normality of the DV is not a necessary assumption of MLM, so no transformations were made to KPB (Tabachnick & Fidell, 2014).

Time-in-Meal. Across all participants, TIM had a mean kurtosis value of -.97 and a mean skew of .26. Fourteen participants had kurtosis values of less than -2 standard errors, but none were less than -3. Five participants showed positive skew. Their skew values were all greater than 2 times their standard error but less than 3. An examination of boxplots for each

participant revealed no obvious outliers. The platykurtic distributions are likely due to the more uniform distribution of the time variable, and the tendency towards positive skew due to a decrease in eating rate towards the end of the meal. No actions were taken to clean the data.

Time Since Last Bite. Across all participants, TSLB had a mean kurtosis value of 2.45 and a mean skewness value of 1.31. Several participants showed distributions that were highly leptokurtic. Thirty-seven participants had distributions with kurtosis values of greater than twice their standard error, with 29 having values greater than 3 times. The majority of participants showed positive skew, with 58 participants having skewness values of greater than 2 standard error and 41 having a value of greater than 3. An examination of boxplots revealed 29 extreme cases. These cases were found to be the result of pauses in eating due to conversation or beverage consumption, both common occurrences. The skewed distribution of this variable indicated that it might be a candidate for transformation. An examination of scatterplots comparing TSLB with bite weight revealed a trend of non-linear relationships and non-ovular clusters. A natural log transformation dramatically reduced kurtosis, reducing the amount of participants with kurtosis/standard error values of greater than 2 to 5, though 4 of these still had values that exceeded 3. Three participants now showed negative skew, with skew/standard error values of less than -3. Five participants were still positively skewed, but none exceeded a value of 3 skewness/standard error. The transformation was retained so that its effects on the model could be examined.

Food Item Enjoyment and Energy Density. Although LAM and ED are each being treated as a level 1 variable, each participant has a maximum of six unique values for both of these variables. Therefore, outlier analysis was performed with each value entered only once

(as opposed to entering it multiple times for each food item, corresponding to a bite of that food item). Additionally, due to the relatively small sample per participant, LAM and ED were examined across all participants combined. It was hypothesized that LAM would mediate the effect of ED on bite weight, indicating that there might be multicollinearity between these two variables. LAM and ED shared a small but significant correlation ($r = .102, p < .05$). These variables were regressed on bite weight aggregated to the food item level. Both variables had tolerances well within reason (.99 for each). Both variables were retained for the analysis.

LAM showed negative skew, with a skewness value of $-.677$ ($SE = .12$). The skew/standard error value is -5.64 , showing a relatively high amount of skew. Its kurtosis value was $.255$ ($SE = .239$), indicating negligible kurtosis. An examination of a box plot showed no extreme outliers. The negative skew is likely due to the mean response being on the upper half of the scale (at 66.82). The upper end of the distribution is limited by the maximum value of the scale. A visual examination of the QQ plot for LAM showed tolerable deviations from normal. Given the lack of apparent outliers, no action was taken to clean this variable.

ED was a continuous variable that depended on the categorical variable, food item. Frequency statistics were examined. There was some frequency discrepancy due to difficulties in scheduling to accommodate food preference, availability, and number of participants present in a session. Fifteen items were consumed, having a frequency range of 25 (6%) to 32 (7.7%), indicating small discrepancies that should not present a problem for the analysis.

Starting Hunger. Similar to LAM, SLIM scores were analyzed across all participants at the session level. SLIM scores appeared to be normally distributed, having a skewness value of

.369 (SE = .206) and a kurtosis value of -.3 (SE = .408). Examination of a boxplot for SLIM scores revealed no outliers. No action was taken to clean this variable.

Level 1 Multivariate Outliers. To check for multivariate outliers among the six level one variables, LAM, ED, SLIM, TIM and lnTSLB were regressed on KPB and Mahalanobis Distances were saved. Based on a χ^2 distribution with $df = 5$ and $p < .001$, a value of 20.515 was chosen as the cutoff for multivariate outliers. Thirteen bites exceeded the cutoff, and were found to have either very small lnTSLB values or very high TIM values. These bites were eliminated. To account for bites that were the first of a food item and subsequently did not have a Mahalanobis distance due to a missing lnTSLB value, a second regression was performed without lnTSLB as a predictor, with a χ^2 cutoff of 18.467. Only first item bites were examined. Three additional multivariate outliers were identified and eliminated.

Data Cleaning for Level 2 Predictors

Level 2 Univariate Outliers. %BF, BMI, and WHR were all normally distributed. An examination of box plots revealed no outliers. Gender was a dichotomous variable, and a balance between males and females was attempted during participant recruitment. A relative balance was achieved, with 33 males and 39 females participating. An examination of the distribution of age revealed a slight positive skew of .591 (SE = .283) and a slight negative kurtosis of -1.008 (SE = .559). An examination of a boxplot for age revealed no outliers.

The distribution of mouth volume showed heavy positive skew with a skewness of 1.157 (SE = .283) and was very leptokurtic (kurtosis = 3.524, SE = .559). A boxplot revealed one participant as an extreme outlier, having a mouth volume of 169.1ml. While no date entry or recording errors could be identified, this participant's mouth volume was excluded from further

analysis. Removing this data point dramatically reduced skew and kurtosis, putting them to within normal ranges.

Level 2 Multivariate Outliers. To check for multivariate outliers among the six level two variables, Gender, Age, MV, %BF, WHR and BMI were regressed on aggregated KPB and Mahalanobis Distances were saved. Based on a χ^2 distribution with $df = 6$ and $p < .001$, a value of 22.458 was chosen as the cutoff for multivariate outliers. To account for the participant whose mouth volume was removed, a second regression was performed without mouth volume as a predictor, with a χ^2 cutoff of 20.515. No multivariate outliers were identified.

Appendix O: Hierarchical Breakdown of Analysis 1

The following describes a model-by-model breakdown of the multilevel analysis of KPB. Covariance structures were unrestricted (unstructured) for all analyses. All predictor variables were grand-mean centered; the effects of this decision on model interpretation will be discussed with the effects of each predictor.

Each predictor was entered into the model hierarchically so that model improvement could be assessed with the addition of each predictor. If a predictor did not improve model fit or have a significant fixed effect, it was removed from the model. Fixed effects for level 1 predictors were added first, followed by fixed effects for level 2 predictors. Random effects were then added hierarchically for all level 1 predictors, followed by effects for cross-level interactions. Model fit was assessed by comparing changes in the -2 log likelihood value between models, using a χ^2 difference test to assess significance. Table O1 shows random effects, with changes in the -2 log likelihood value, residual variance, random intercept variance, and random slope variance with the implementation of each model. Table O2 shows changes in the fixed intercept and slopes with the implementation of each model.

Table O1. *Estimates of Random Effects and Model Fit Statistics*

Model #	# Par.	-2LL	Δ -2LL	Residual Var.	Intercept Var.	Random Slope Variance		
						InTSLB	TIM	LAM
0 (null)	2	26885.32		106.16* (2.54)	22.67* (4.27)			
Level 1								
1	3	26623.44	261.88^	98.84* (2.37)	18.92* (3.61)			
2	3	26710.16	-86.72^	101.09* (2.42)	19.54 (3.72)			
3	4	26609.75	13.69^	98.12* (2.35)	19.05* (3.62)			
4	5	26418.85	190.90^	92.71* (2.22)	19.65* (3.71)			
5	6	26413.66	5.19^	92.53* (2.22)	18.46* (3.52)			
Level 2								
6	7	26415.13	-1.47	92.53* (2.22)	18.32* (3.52)			
7	7	26403.98	9.68^	92.53* (2.22)	17.52* (3.39)			
8	7	26408.91	4.75^	92.52* (2.22)	16.35* (3.17)			
9	8	26391.43	12.55^	92.53* (2.22)	13.20* (2.66)			
c1	7	26399.31	-7.88^	92.53* (2.22)	13.57* (2.70)			
10	8	26402.88	-3.57	92.53* (2.22)	13.56* (2.72)			
11	8	26388.76	10.55^					
Random Ef.								
12	9	26329.01	59.75^	88.87* (2.16)	12.96* (2.64)	17.81* (4.88)		
c2	8	26326.58	2.43	88.84* (2.15)	13.44* (2.70)	18.21* (4.95)		
c3	8	26338.46	-9.45^	88.90* (2.16)	14.89* (2.96)	17.57* (4.84)		
13	9	26104.80	221.78^	79.68* (1.95)	18.56* (3.78)	17.32* (4.70)	3.94* (0.86) e-4	
14	10	25723.04	381.76^	68.13* (1.69)	23.72* (4.70)	14.61* (4.08)	3.30* (0.73) e-4	0.15* (0.03)
15	11	25609.43	113.61^	62.14* (1.59)	35.4* (8.32)	15.53* (4.31)	4.01* (0.90) e-4	0.19* (0.04)
16	10	25615.85	-6.42^	62.04* (1.58)	38.39* (8.55)	15.24* (4.24)	4.02* (0.90) e-4	0.19* (0.04)

^ Indicates significant model improvement as assessed by a X^2 difference test with $df = \#$ parameters - $\#$ parameters of previous valid model. * Indicates significance at the $p < .05$ level. -2LL = -2 Log Likelihood. Δ -2LL = Change in -2 Log Likelihood from previous valid model. Standard errors are in parentheses. Models that were dropped are italicized.

Table O2

Estimates of Fixed Effects

Model #	# Par.	New Effect	Intercept	lnTSLB	TIM	LAM	SLIM	WHR	MV	Gender
0 (null)	2	15.28* (0.60)	15.28* (0.60)							
Level 1										
1: lnTSLB	3	5.72* (0.35)	15.08* (0.55)	5.72* (0.35)						
2: TSLB	3	0.24* (0.02)	15.13* (0.56)							
3: TIM	4	4.07* (0.79) e-3	15.12* (0.55)	5.52* (0.35)	4.07* (0.79) e-3					
4: LAM	5	0.21* (0.01)	15.08* (0.55)	5.60* (0.34)	2.55* (0.78) e-3	0.21* (0.01)				
5: SLIM	6	-5.46* (1.59) e-2	15.10* (0.54)	5.62* (0.34)	2.50* (0.78) e-3	0.21* (0.01)	-5.46* (1.59) e-2			
Level 2										
6: BMI	7	0.11 (0.09)	15.09* (0.54)	5.62* (0.34)	2.50* (0.78) e-3	0.21* (0.01)	-5.47* (1.59) e-2			
7: WHR	7	13.45* (6.61)	15.06* (0.53)	5.63* (0.34)	2.52* (0.78) e-3	0.21* (0.01)	-5.73* (1.59) e-2	13.45* (6.61)		
8: %BF	7	-0.17* (0.06)	15.11* (0.51)	5.62* (0.34)	2.50* (0.78) e-3	0.21* (0.01)	-5.24* (1.58) e-2	-		
9: MV	8	0.12* (0.03)	15.00* (0.47)	5.60* (0.34)	2.53* (0.78) e-3	0.21* (0.01)	-5.61* (1.57) e-2	9.37 (5.92)	0.12* (0.03)	
c1: -WHR	7	-	15.02* (0.47)	5.60* (0.34)	2.51* (0.78) e-3	0.21* (0.01)	-5.37* (1.56) e-2	-	0.12* (0.03)	
10: Age	8	-4.05 (3.97) e-2	15.04* (0.47)	5.60* (0.34)	2.50* (0.78) e-3	0.21* (0.01)	-5.35* (1.56) e-2	-	0.11* (0.03)	
11: Gender	8	-3.36* (1.13)	15.06* (0.45)	5.61* (0.34)	2.47* (0.78) e-3	0.21* (0.01)	-5.32* (1.55) e-2	-	6.74* (3.08) e-2	-3.36* (1.13)
Random Ef.										
12: lnTSLB	9	-	15.09* (0.47)	6.35* (0.62)	2.68* (0.77) e-3	0.21* (0.01)	-4.44* (1.60) e-2	-	5.19 (3.18) e-2	-3.26* (1.15)
c2: -MV	8	-	15.13* (0.47)	6.37* (0.62)	2.66* (0.77) e-3	0.21* (0.01)	-4.49* (1.60) e-2	-	-	-4.36* (0.93)
c3: -Gender	8	-	15.07* (0.49)	6.33* (0.62)	2.74* (0.78) e-3	0.21* (0.01)	-4.37* (1.61) e-2	-	0.10 (0.03)	-
13: TIM	9	-	16.07* (0.55)	5.87* (0.61)	8.50* (2.58) e-3	0.22* (0.02)	-3.39* (1.59) e-2	-	-	-4.30* (0.99)
14: LAM	10	-	15.46* (0.62)	5.14* (0.57)	4.84* (2.41) e-3	0.27* (0.05)	-5.24* (1.66) e-2	-	-	-3.76* (1.14)
15: SLIM	11	-	13.78* (0.81)	4.80* (0.58)	3.60 (2.63) e-3	0.29* (0.06)	-0.22* (1.39)	-	-	-2.52 (1.39)
16: -Gender	10	-	13.73* (0.84)	4.79* (0.58)	3.59 (2.64) e-3	0.29* (0.06)	-0.22* (0.09)	-	-	-

* Indicates significance at the .05 level. Standard errors are in parentheses. To conserve space, effects that were dropped are only listed in the “New Effect” column. Effects that were dropped are italicized.

Model 0: The Null Model. The null model offers a description of the nested qualities of the dependent variable (BW) without any predictors. As seen in Table O1, intercept variance is an estimate of the unexplained variance in participant means for KPB. It is a measurement of variance in KPB between participants. Since there are currently no predictors in the model, unexplained intercept variance is equal to total variance in participant mean bite weights. Table O1 shows us that variance in mean participant KPB (or intercept variance) is 22.67. Fixed effects will attempt to predict mean participant KPB. As valid level 2 predictors are added, we should see a reduction in unexplained intercept variance.

If predictors are not centered, intercept variance will no longer represent variance in mean KPB across participants, but rather variance in predicted KPB when predictors equal zero. This makes it impossible to examine reduction in intercept variance as predictors are added. Centering all predictors at their mean (across all participants, or grand mean) keeps the intercept variance representative of the unexplained variance in mean KPB across participants.

Residual variance is a measure of unexplained variance in the dependent variable within participants. It is an estimate of mean unexplained residual variance across all participants. The null model is the equivalent of fitting a flat line at each participant's mean KPB, so the residual variance of the null model is roughly equal to the mean of KPB variance across all participants. To put it another way, if you calculate variance in KPB for each participant, then average all of those variances, you should get a value roughly equal to null residual variance. As level 1 fixed and random slopes are fitted, residuals, and therefore residual variance, should decrease.

Since intercept variance tells us variance in KPB between individuals and residual variance tells us variance within individuals, we can obtain a measure of the amount of variance

that is due to differences between individuals by calculating a ratio of intercept variance to total variance (residual + intercept). This is the ICC1. For the present data set, this would be: $5.31 / (5.31 + 17.54)$, or .23. This indicates that 23% of the variance in bite weight is due to differences between participants.

Models 1 and 2: Fixed Effects for Time Since Last Bite. The first fixed effects to be entered into the model were the natural log transformed TSLB (Model 1) and the untransformed TSLB (Model 2). These two effects were entered separately to examine their independent effect on model fit. Adding lnTSLB to the model reduced the -2LL by 261.88 (df = 1, $p < .05$), a significant amount. Its fixed effect was also significant ($\gamma = 5.72$, SE = 0.36, $p < .05$). Comparatively, while the untransformed TSLB significantly improved model fit and had a significant fixed effect ($\gamma = 0.24$, SE = 0.02, $p < .05$), the reduction in -2LL was 86.72 less than using the transformed variable. Therefore, lnTSLB was retained for all further models.

Model 3: Fixed Effect for Time in Meal. Model 3 examine the effect of adding TIM to the model. TIM reduced -2LL by 13.69 over model 1 (df = 1, $p < .05$). The fixed slope for TIM was 0.004. While model improvement for TIM was small, this variable was retained in future models.

Model 4: Fixed Effect for Food Enjoyment. Model 4 examines the impact of food enjoyment on average bite size. LAM scores significantly improved model fit over model 3, reducing -2LL by 190.90 (df = 1, $p < .05$). The fixed effect of LAM shows that holding lnTSLB and TIM constant, an increase of roughly 5 points on the LAM scale corresponded to a 1 kcal increase in KPB.

Model 5: Fixed effect for Pre-Meal Satiety. Adding SLIM scores to the model reduced the -2LL value by 5.19, a small but significant improvement in model fit. The fixed effect shows that, holding other predictors constant, a 20 point increase in SLIM scores corresponded to a 1 kcal decrease in KP.B.

Models 6-8: Fixed effects for BMI, Waist to Hip Ratio, and Percent Body Fat. BMI, WHR, and %BF were the first level 2 predictors to be entered into the model. Due to the fact that these three variables are closely related, all three were entered independently of each other. WHR and %BF both showed slight but significant model improvement. WHR showed the most dramatic improvement, reducing -2LL by 9.68. The fixed effect for WHR indicates that a one-point increase in WHR corresponds to a 13.45 increase in KP.B. WHR was carried over into subsequent models.

Model 9: Mouth Volume and the Removal of WHR. Model 9 added MV to the model, significantly improving model fit and reducing -2LL by 12.55. However, this caused the fixed effect for WHR to no longer be significant, and WHR was dropped from the model (model “c1” in Tables O1 and O2). The fixed effect indicates that, holding other predictors constant, an 8ml increase in MV corresponds to roughly a one kcal increase in KP.B.

Models 10 – 11: Fixed Effects for Age and Gender. Model 10 added age to the equation, but it did not significantly improve model fit or have a significant fixed effect. Model 11 added gender, which reduced -2LL by 10.55. The fixed effect for gender indicates that, holding other predictors constant, men have a mean KP.B 3.36 kcals higher than women.

Models 12 – 16: Random effects for Time Since Last Bite, Time in Meal, Food Enjoyment, and Pre-Meal Satiety. The next phase of the analysis was designed to assess

whether individual slopes for the four retained level 1 predictors varied across participants. The first random effect added (model 12) was lnTSLB. The random effect of lnTSLB significantly improved model fit over model 11, reducing -2LL by 59.75 ($df = 1, p < .05$). Its slope variance was significant at 3.94, indicating that the effect of lnTSLB on KPB did indeed vary across participants. Adding the random slope for lnTSLB caused the fixed effect for MV to lose its significance. Due to the expected relationship between MV and gender, the model was retested with both of these variables independently removed (models c2 and c3). Mouth volume was removed from subsequent analysis.

Adding the random effect for TIM likewise improved model fit, reducing -2LL by 221.78 over model 12. TIM had significant slope variance, indicating that the effect of TIM on KPB did vary across participants. Likewise, adding the random effect of LAM improved model fit over model 13, reducing -2LL by 381.76. LAM had significant slope variance, indicating that the effect of LAM on KPB varied across participants.

Finally, adding the random effect of SLIM scores also improved model fit, reducing -2LL by 113.61 over model 14. Adding this random effect removed the significant effect of Gender. A final model was run (model 16) without the fixed effect of Gender. Model 16 represents the final model of the analysis.

Appendix P: MLM Analysis of Bite Weight

To determine the amount of between and within-subjects variance for bite weight, the ICC1 was calculated. This was found to be .231, meaning 23.1% of the variability in bite weight is associated with differences between participants, supporting the decision to use MLM. Covariance structures were unrestricted (unstructured) for all analyses. All predictor variables were grand-mean centered..

Each predictor was entered into the model hierarchically so that model improvement could be assessed with the addition of each predictor. If a predictor did not improve model fit or have a significant fixed effect, it was removed from the model. Fixed effects for level 1 predictors were added first, followed by fixed effects for level 2 predictors. Random effects were then added hierarchically for all level 1 predictors, followed by effects for cross-level interactions. Model fit was assessed by comparing changes in the -2 log likelihood value between models, using a χ^2 difference test to assess significance. Table P1 shows random effects, with changes in the -2 log likelihood value, residual variance, random intercept variance, and random slope variance with the implementation of each model. Table P2 shows changes in the fixed intercept and slopes with the implementation of each model.

Table P1

Estimates of Random Effects and Model Fit Statistics

Model #	# Par.	-2LL	Δ-2LL	Residual Var.	Intercept Var.	Random Slope Variance		
						InTSLB	TIM	LAM
0 (<i>null</i>)	2	20497.25		17.54* (.420)	5.31* (.981)			
Level 1								
1	3	20427.82^	-69.43	17.22* (.412)	4.85* (.904)			
2	3	<i>20457.4</i>	<i>+29.58</i>	<i>17.32* (.415)</i>	<i>5.01* (.929)</i>			
3	4	19756.95^	-670.87	14.19* (.340)	4.18* (.774)			
4	5	19606.86^	-150.09	13.55* (.325)	4.46* (.819)			
5	6	<i>19602.61</i>	<i>-4.25</i>	<i>13.52* (.324)</i>	<i>4.45* (.817)</i>			
6	6	<i>19612.7</i>	<i>+5.84</i>	<i>13.55* (.325)</i>	<i>4.31* (.797)</i>			
Level 2								
7	6	<i>19610.75</i>	<i>+3.89</i>	<i>13.55* (.325)</i>	<i>4.5* (.831)</i>			
8	6	<i>19602.45</i>	<i>-4.41</i>	<i>13.55* (.325)</i>	<i>4.52* (.834)</i>			
9	6	<i>19604.93</i>	<i>-1.93</i>	<i>13.55* (.325)</i>	<i>4.02* (.751)</i>			
10	6	19592.98^	-13.88	13.56* (.325)	3.22* (.615)			
11	7	<i>19599.09</i>	<i>+6.11</i>	<i>13.56* (.325)</i>	<i>3.27* (.630)</i>			
12	7	<i>19589.58</i>	<i>-3.4</i>	<i>13.56* (.325)</i>	<i>3.12* (.604)</i>			
Random Eff.								
13	7	19551.03^	-41.95	13.13* (.319)	3.21* (.621)	2.19* (.677)		
14	8	19418.89^	-132.14	12.29* (.302)	3.48* (.674)	1.79* (.584)	2.69e-5* (6.65e-6)	
15	9	19250.88^	-168.01	11.29* (.280)	3.73* (.733)	1.78* (.570)	2.47e-5* (6.11e-6)	.014* (.003)
Cross-Level Int.								
16	10	<i>19255.41</i>	<i>+4.53</i>	<i>11.29* (.280)</i>	<i>3.78* (.749)</i>	<i>1.78* (.571)</i>	<i>2.49e-5* (6.14e-6)</i>	<i>.014* (.003)</i>
17	11	<i>19271.13</i>	<i>+15.72</i>	<i>11.29* (.280)</i>	<i>3.79* (.750)</i>	<i>1.76* (.567)</i>	<i>2.46e-5* (6.21e-6)</i>	<i>.014* (.003)</i>

^ Indicates significant model improvement as assessed by a X² difference test with df = # parameters - # parameters of previous valid model. * Indicates significance at the p < .05 level. -2LL = -2 Log Likelihood. Δ-2LL = Change in -2 Log Likelihood from previous valid model. Standard errors are in parentheses. Models that were dropped are italicized.

Table P2

<i>Estimates of Fixed Effects</i>								
Model #	#	New Effect	Intercept	InTSLB	TIM	LAM	MV	BMI
0 (<i>null</i>)	2	8.92* (.284)	8.92* (.284)					
Level 1								
1: InTSLB	3	1.23* (.145)	8.87* (.273)	1.23* (.145)				
2: TSLB	3	.050* (.007)	8.88* (.277)					
3: TIM	4	-8.32e-3* (3.03e-4)	8.78* (.253)	1.63* (.133)	-8.32e-3* (3.03e-4)			
4: LAM	5	.07* (5.66e-3)	8.77* (.260)	1.65* (.130)	-8.85e-3* (2.99e-4)	.07* (5.66e-3)		
5: ED	6	-.179* (.063)	8.77* (.260)	1.71* (.132)	-8.41e-3* (3.37e-4)	.07* (5.71e-3)		
6: SLIM	6	-9.88e-3 (6.22e-3)	8.77* (.256)	1.65* (.130)	-8.86e-3* (2.99e-4)	.07* (5.66e-3)		
Level 2								
7: BMI	6	.031 (.045)	8.77* (.261)	1.65* (.130)	-8.85e-3* (2.99e-4)	.07* (5.66e-3)		
8: WHR	6	1.50 (3.27)	8.77* (.262)	1.65* (.130)	-8.85e-3* (2.99e-4)	.07* (5.66e-3)		
9: %BF	6	-.08* (.03)	8.77* (.248)	1.65* (.130)	-8.85e-3* (2.99e-4)	.07* (5.65e-3)		
10: MV	6	.06* (.012)	8.73* (.224)	1.65* (.129)	-8.84e-3* (2.98e-4)	.07* (5.64e-3)	.06* (.012)	
11: Age	7	-1.31e-4 (.019)	8.73* (.226)	1.65* (.129)	-8.84e-3* (2.98e-4)	.07* (5.64e-3)	.06* (.013)	
12: Gender	7	-.926 (.558)	8.73* (.221)	1.65* (.129)	-8.85e-3* (2.98e-4)	.07* (5.64e-3)	.045* (.015)	
Random Ef.								
13: InTSLB	7	-	8.70* (.225)	1.66* (.225)	-8.82e-3* (2.99e-4)	.072* (5.66e-3)	.051* (.012)	
14: TIM	8	-	8.58* (.235)	1.66* (.210)	-.010* (7.22e-4)	.077* (5.86e-3)	.051* (.013)	
15: LAM	9	-	8.63* (.245)	1.53* (.209)	-.010* (7.08e-4)	.076* (.016)	.053* (.013)	
Cross-Level Interaction								
16: BMI	10	.005 (.041)	8.63* (.246)	1.53* (.209)	-.010* (7.09e-4)	.076* (.016)	.053* (.013)	.005 (.041)
17: BMI*TIM	11	-5.97e-6 (7.69e-6)	8.63* (.247)	1.52* (.209)	-.010* (7.07e-4)	.077* (.016)	.053* (.013)	.012 (.042)

* Indicates significance at the .05 level. Standard errors are in parentheses. To conserve space, effects that were dropped are only listed in the "New Effect" column. Effects that were dropped are italicized.

Model 0: The Null Model. Table P1 shows that variance in mean participant BW (or intercept variance) was 5.31. The ICC1 for BW was .23. This indicates that 23% of the variance in bite weight is due to differences between participants.

Models 1 and 2: Fixed Effects for Time Since Last Bite. The first fixed effects to be entered into the model were the natural log transformed TSLB (Model 1) and the untransformed TSLB (Model 2). These two effects were entered separately to examine their independent effect on model fit. Adding lnTSLB to the model reduced the -2LL by 69.43 (df = 1, $p < .05$), a significant amount. Its fixed effect was also significant ($\gamma = 1.23$, SE = .145, $p < .05$). Comparatively, while the untransformed TSLB significantly improved model fit and had a significant fixed effect ($\gamma = .05$, SE = .007, $p < .05$), the reduction in -2LL was 29.58 less than using the transformed variable. Therefore, lnTSLB was retained for all further models. The fixed effect of lnTSLB reduced residual variance by .32, explaining 1.8% of within-subject variance in BW. While the fixed effect for lnTSLB is somewhat challenging to interpret in a meaningful way, we can look at the significant fixed effect for model 2 to get an idea of how TSLB affects BW; specifically, bite weight increases by 1 gram for every 20 seconds that pass between bites.

Model 3: Fixed Effect for Time in Meal. Model 3 examine the effect of adding TIM to the model. TIM reduced -2LL by 670.87 over model 1 (df = 1, $p < .05$). Residual variance was reduced by an additional 3.03 from model 1, or 17% of null residual variance. The fixed slope for TIM is quite small at -.00832, but can be interpreted as: Holding lnTSLB constant, for every 2 minutes (120 seconds) that passed during the meal, bite size decreases by 1 gram on average.

Model 4: Fixed Effect for Food Enjoyment. Model 4 examines the impact of food enjoyment on average bite size. LAM scores significantly improved model fit over model 3,

reducing -2LL by 150.09 ($df = 1, p < .05$). Residual variance was reduced by an additional .64 over model 3, or 3.6% of null residual variance. The fixed effect of LAM shows that holding InTSLB and TIM constant, an increase of 14.3 points on the LAM scale leads to an average increase in BW of 1 gram.

Models 5 and 6: Fixed effects for Energy Density and Hunger. Neither ED nor SLIM scores improved model fit significantly over model 4. ED reduced -2LL by 4.25 from model 4, a non-significant amount, but SLIM scores worsened model fit, increasing -2LL by 5.84 over model 4. Additionally, neither variable reduced residual variance by an appreciable amount. The fixed effect for SLIM was not significant. While the fixed effect for ED was significant, neither variable was retained in the model.

Models 7 – 9: Fixed effects for BMI, Waist to Hip Ratio, and Percent Body Fat. BMI, WHR, and %BF were the first level 2 predictors to be entered into the model. Unfortunately, none of the three body metric measures significantly improved model fit over model 4 (the last valid model). Neither BMI nor WHR had significant fixed effects. The fixed effect for %BF was significant, though not in the anticipated direction. Additionally, %BF reduced intercept variance by .44 over model 4 (4.46-4.02), a reduction of 9.87% (.44/4.46). However, due to the lack of improved model fit, all three variables were dropped from the model.

Models 10 – 12: Fixed Effects for Mouth Volume, Age, and Gender. Model 10 added MV to the model, significantly improving model fit over model 4. -2 Log Likelihood was reduced by 13.88 ($df = 1, p < .05$). The effect of level 2 predictors is assessed by examining the reduction in intercept variance of the last valid model. Intercept variance was reduced by 1.24 from model 4, or a 28% reduction. The fixed effect of MV was significant, indicating that holding all

other predictors constant, a 16.7ml increase in mouth volume leads to a 1-gram increase in bite size on average. Neither age nor gender significantly improved model fit, had a noteworthy impact on intercept variance, or had a significant fixed effect. Both variables were dropped from the model.

Models 13 – 15: Random effects for Time Since Last Bite, Time in Meal, and Food

Enjoyment. The next phase of the analysis was designed to assess whether individual slopes for the three retained level 1 predictors varied across participants. The first random effect added (model 13) was lnTSLB. The random effect of lnTSLB significantly improved model fit over model 10, reducing -2LL by 41.95 (df = 1, $p < .05$). Its slope variance was significant at 2.19, indicating that the effect of lnTSLB on BW did indeed vary across participants.

Adding the random effect for TIM likewise improved model fit, reducing -2LL by 132.14 over model 13. TIM had significant slope variance at 2.69×10^{-5} , indicating that the effect of TIM on BW did vary across participants. Likewise, adding the random effect of LAM improved model fit over model 14, reducing -2LL by 168.01. LAM had significant slope variance at .014, indicating that the effect of LAM on BW varied across participants.

Models 16 and 17: Cross-Level Interaction Between BMI and Time in Meal. The final phase of the analysis was to test the hypothesized cross-level interaction between BMI and TIM. Despite being non-significant, the fixed effect of BMI was added back into the model in model 16. BMI was chosen over the other two body measures because it has been demonstrated previously to moderate the relationship between time and eating rate, offering empirical support that it might moderate the relationship between time and bite size (J. L. Guss & Kissileff,

2000). As expected, adding BMI back to the model in model 17 did not improve model fit, and BMI did not have a significant fixed effect.

The cross-level interaction term was added in model 17, but only further weakened model fit, increasing -2LL by 15.72 over model 16. Additionally, the fixed effect for the interaction term was non-significant. Both BMI and the BMI x TIM interaction were dropped from the model, leaving model 15 as the final valid model for the analysis.

Appendix Q: Mediation Analysis of Bite Weight

Based on the results from the analysis of bite weight (Appendix P), the only hypothesized mediation effect that remained was the effect of TIM on BW, mediated by TSLB. The method used to test the effect was the bootstrapping method (Preacher & Hayes, 2004b). Bootstrapping is a non-parametric test that is ideal for testing mediation effects with small sample sizes and non-normal distributions (Preacher & Hayes, 2004b). The variables of interest are resampled thousands of times (usually with the leave-one-out method) with the effects (in this case, the direct and indirect effect of TIM on BW, mediated by TSLB) calculated with each iteration, so that a confidence interval for the effect can be generated. Since the proposed mediation effect is simple, the INDIRECT module for SPSS developed by Preacher & Hayes (2008) was used to test for the mediation effect.

To remain consistent with the previous analysis, the log-transformed TSLB (lnTSLB) was used in this analysis. All data were aggregated to level 2 so that power was not artificially inflated (and so that the assumption of independence was not validated). The data were resampled 5000 times with bias correction (Efron, 1987). Results from the analysis can be found in Table Q1.

Table Q1

Results from Mediation Analysis of lnTSLB, TIM, and Bite Weight

Path	IV	DV	<i>B</i>	<i>SE</i>	<i>t</i>	<i>p</i>
a	TIM	lnTSLB	0.001	0.003	3.06	< 0.01
b	lnTSLB	BW	4.4	0.99	4.40	< 0.01
c	TIM	BW	-0.008	0.003	-2.61	< 0.01
c'	TIM	BW	-0.01	0.003	-4.27	< 0.01
ab*	TIM	BW	0.004	0.003	-	-

*The indirect effect of TIM on BW, through lnTSLB. 95% confidence interval bounds: Lower = .0015, Upper = .008

Adj. R2 = 0.27, F (2, 69) = 14.01, p < .001

Appendix R: Multiple Regression of Level 2 Variables on KPB

To assess the degree to which power may have caused type 2 errors in the detection of significant effects for level 2 predictors in analysis 1, a multiple regression analysis was performed. KPB was averaged for each participant, and the level 2 predictors (BMI, body fat percentage, waist to hip ratio, mouth volume, and gender) were regressed on average KPB. This analysis was performed hierarchically, with each predictor being added one at a time and only the significant predictors retained. The results from this analysis are presented in Table R1.

Table R1

Multiple Regression of KPB using Level 2 Variables

Variable	<i>B</i>	<i>SE</i>	<i>t</i>	<i>p</i>	Initial Model #	Final Model #
Intercept	10.57	3.15	3.36	< 0.01	1	6
<i>Body Fat Percentage</i>	<i>-0.16</i>	<i>0.06</i>	<i>-2.55</i>	<i>0.01</i>	<i>1</i>	<i>1</i>
<i>Waist-to-Hip Ratio</i>	<i>13.97</i>	<i>7.13</i>	<i>1.96</i>	<i>0.05</i>	<i>2</i>	<i>2</i>
<i>BMI</i>	<i>0.12</i>	<i>0.1</i>	<i>1.17</i>	<i>0.25</i>	<i>3</i>	<i>3</i>
<i>Age</i>	<i>-0.07</i>	<i>0.05</i>	<i>-1.6</i>	<i>0.12</i>	<i>4</i>	<i>4</i>
Mouth Volume	0.08	0.04	2.39	0.02	6	6
Gender	-2.81	1.28	-2.19	0.03	6	6

Adj. R² for final model = 0.26. Italicized variables were not retained for the final model.

While body fat percentage was initially significant, it was not in the hypothesized directions. BMI, waist-to-hip ratio, and age were non-significant when first added to the model. Both mouth volume and gender remained significant.

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