SOURCES OF VARIANCE IN BITE COUNT

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ABSTRACT

The obesity epidemic affects millions of individuals worldwide. New tools that simplify efforts to self-monitor energy intake may enable successful weight loss and weight maintenance. The purpose of this study was to examine predictors of the number of bites recorded by the bite counter device during daily meals in natural, real world settings. Participants (*N* = 83) used bite counters to record daily meals for two weeks. Participants also recorded their daily dietary intake using automated, computer-based 24-hour recalls. Predictors of bite count were explored at the meal-level and individual-level using multilevel linear modeling. A positive relationship between kilocalories and bites was moderated by energy density such that participants took more bites to consume greater kilocalorie meals when energy density was low than when energy density was high. The positive relationship between kilocalories and bites was also moderated by participants' average bite size during a laboratory meal such that participants with smaller bite sizes took more bites to consume greater kilocalorie meals than participants with larger bites sizes. Participants also took more bites when they ate meals with others and when they ate meals outside of the home, although this meal location effect was not reliably produced across models. Practical implications of these results for future bite counter development and research are discussed.

DEDICATION

I dedicate this dissertation to my husband, Gary Giumetti. His love and endless support kept me moving forward during the most difficult stages of my PhD journey.

I also dedicate this dissertation to my family. My parents, Peter Scisco and Lori Scisco, provided me with constant love and encouragement throughout my 20+ years of formal education. Thank you for teaching me that I could do anything I put my mind to, and for always being there for me. I would also like to congratulate and thank my sister, Dr. Leigh Scisco, DPT, for sharing the journey to "doctor" with me.

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CHAPTER ONE

INTRODUCTION

Purpose

The purpose of this study was to examine predictors of number of bites taken during a meal by humans in their natural environments. Participants wore bite counters and recorded bite count during daily meals. Participants also recorded their daily dietary intake using 24-hour recalls. Predictors of bite count were explored at the meal-level and person-level using multilevel linear modeling. This was one of the first studies to provide long-term bite count data, an essential first step for determining sources of variance in bite count.

Obesity

Obesity has been identified as a major public health problem worldwide. The World Health Organization (WHO) has declared obesity a “global epidemic” with an estimated 1.6 billion overweight adults and 400 million obese adults in 2005 (WHO, 2011). The WHO predicts that by 2015, 2.3 billion adults will be overweight and 700 million adults will be obese (WHO, 2011). In the United States, the National Health and Nutrition Examination Survey (NHANES) data collected in 2007-2008 indicated that 33.9% of Americans were obese and 68.3% of Americans were overweight (Flegal, Carroll, Ogden, & Curtin, 2010). Throughout the continuous NHANES data collection from 1999 to 2008, obesity rates have remained fairly steady at about one third of the US population. These WHO and NHANES population estimates are based on the current standards for measuring obesity and overweight. A body mass index (BMI = kg/m^2) of 30 or greater defines obesity, and a BMI of 25 or greater defines overweight.

Obesity is associated with increased rates of type 2 diabetes mellitus, hypertension, dyslipidaemia, heart disease, cerebrovascular disease, respiratory disease, osteoarthritis, kidney disease, and cancer (Malnic & Knobler, 2006). Obesity is also associated with greater mortality from cardiovascular disease, some cancers, diabetes, and kidney disease (Flegal, Graubard, Williamson, & Gail, 2007). The increased prevalence of health problems in the obese population naturally leads to increased health care costs. In the United States, the medical costs of obesity were estimated to be $147 billion per year in 2008, doubling from $78.5 billion in 1998 (Finkelstein, Trogdon, Cohen, & Dietz, 2009). Additionally, obese and overweight employees are estimated to cost their employers $641 and $201 respectively more per employee per year due to increased doctor visits, emergency room visits, and productivity losses (Goetzel et al., 2010). It is imperative that obesity rates be reduced to improve the health of these individuals and to decrease associated health care costs.

Stated simply, obesity is the result of an energy imbalance in the body (Sharma & Padwal, 2010). The energy consumed in the form of food and drink is greater than the amount of energy expended through physical activity and basal metabolism, and this tipping of the energy scales toward excess intake results in weight gain (Dulloo, 2010). While some individuals are more susceptible to becoming obese due to genetic characteristics, the obesity epidemic is “undoubtedly attributable to dietary and behavioural causes” (Müller, Bosy-Westphal, & Krawczak, 2010, p. 612). The sources of this energy imbalance are numerous and varied (French, Story, & Jeffery, 2001). Broadly, obesity can be attributed to an “obesogenic environment” that promotes energy overconsumption and under-expenditure (Kirk, Penney, & McHugh, 2010). For example, at the national level, excess energy intake can be traced to government-subsidized commodity crops (e.g., corn), a policy that has resulted in inexpensive, widely available, and calorie-dense food products and a shortage of fresh fruits and vegetables (Wallinga, 2010). Within communities, reduced access to grocery stores is related to higher obesity rates (Lovasi, Hutson, Guerra, & Neckerman, 2009). Environmental factors can also impact rates of physical activity. Poor neighborhood walkability, limited access to facilities, and greater perceived safety hazards in a community are related to higher rates of obesity (Black & Macinko, 2008).

Although it is clear that changes are needed at a societal level in order to reduce obesogenic factors in our environment, these changes are likely to take a large amount of time, money, and effort. Before these large-scale changes are made, people can try to manage their weight by changing their eating and exercise behaviors. Additionally, some researchers can choose to address the obesity problem from an individual, behavior modification perspective. These researchers can work to provide individuals with “strategies and tools to resist the many forces in the environment that promote weight gain” (Hill, Wyatt, Reed, & Peters, 2003, p. 854).

Many lifestyle change programs have been developed to help people increase their physical activity, reduce their energy intake, and ultimately lose weight. Often, this behavioral modification results in modest weight loss success. For example, Goodpaster et al. (2010) reported that a one-year lifestyle modification program for the severely obese that included reducing energy intake with a prescribed diet and increasing activity to 60 minutes of walking 5 days per week resulted in 30% of participants achieving at least a 10% weight loss. As another example, Rock et al. (2010) examined the effectiveness of a commercial weight loss program for overweight and obese women. Results indicated that a low-fat, reduced-energy diet and 30 minutes of exercise on at least 5 days per week led to a one-year weight loss of about 10% and a 2-year weight loss of about 7%. In general, these lifestyle modification programs are typically preferred over bariatric surgery and pharmacotherapy due to their fairly promising success rates, much lower financial expense, relative safety, and wide availability to the general public (Rössner, Hammarstrand, Hemmingsson, Neovius, & Johansson, 2008).

Weight maintenance is another challenge presently facing behavioral modification programs. A recent review of the weight maintenance literature for lifestyle modifications indicated that only half of the individuals who lost weight using this approach maintained the weight loss a year or more after supervision ceased (Barte et al., 2010). In order to improve weight maintenance success and reduce obesity rates over the long term, the behaviors of individuals who have successfully lost weight and maintained the weight loss ("weight maintenance experts") can be studied and described. Effective behaviors that are common across these weight maintenance experts can be extended to the development of weight loss and maintenance programs.

Successful Weight Loss and Weight Maintenance

Successful weight loss and weight maintenance do not have standard definitions in the literature. Generally, weight loss is defined as losing a percentage of one's body weight, and weight maintenance is defined as maintaining that weight loss for a period of time. Specific definitions from the literature are provided in Table 1.1. Obesity research focuses on intentional weight loss, as opposed to unintentional weight loss resulting from disease or negative health behaviors (McGuire, Wing, Klem, & Hill, 1999). Individuals may experience periods of weight fluctuation, with repeated attempts to lose weight followed by weight gain (Elfhag & Rössner, 2010). Varying definitions of weight fluctuation from the literature are provided in Table 1.1

Table 1.1

Definitions of successful weight loss, weight maintenance, and weight fluctuation

Successful weight loss	Weight Maintenance	Weight fluctuation
5-10% weight loss: significantly improved obesity-related metabolic risk factors (Goldstein, 1992)	10% weight loss maintained for 1 year (National Weight Control Registry (NWCR); Wing & Hill, 2001)	"Repeated gains and losses of weight over time" (Diaz, Mainous, & Everett, 2005, p. 153)
5% weight loss (Crawford, Jeffery, & French, 2000)	5% weight loss maintained for 2 years (Crawford, Jeffery, & French, 2000)	Losing and regaining between 5 and 20 pounds at least once (Bishop, 2002)
Losing more than 2 BMI points (Cuntz, Leibbrand, Ehrig, Shaw, & Fichter, 2001)	Maintaining weight loss for at least 6 months (Elfhag & Rössner, 2010)	The number of times a diet has resulted in a weight loss of 10 kg or more (Strychar et al., 2009)

Successful weight loss maintainers provide important insights into behaviors that promote successful weight loss maintenance. In a qualitative study, Haeffele (2008) identified a four-stage process of weight loss maintenance, shown in Figure 1.1. First, an individual has an "ahah" or epiphany moment when they decide that they are going to lose weight. These moments have been described as triggering events that can be medical (e.g., a heart attack, death of a spouse) or emotional (e.g., a hurtful comment about one's weight) (Klem et al., 1997). Second, an individual forms goals and engages in self-regulation that involves an eating plan, regular exercise, and regular self-weighing. Third, the weight loss goal has been achieved, and an individual actively maintains weight loss through self-regulation and cognitions about food and weight maintenance strategies. Fourth, an individual reaches "transcendence", or an integration of weight maintenance into one's lifestyle. In theory, behaviors that once took much effort are now automatic and easier for the weight maintainer.

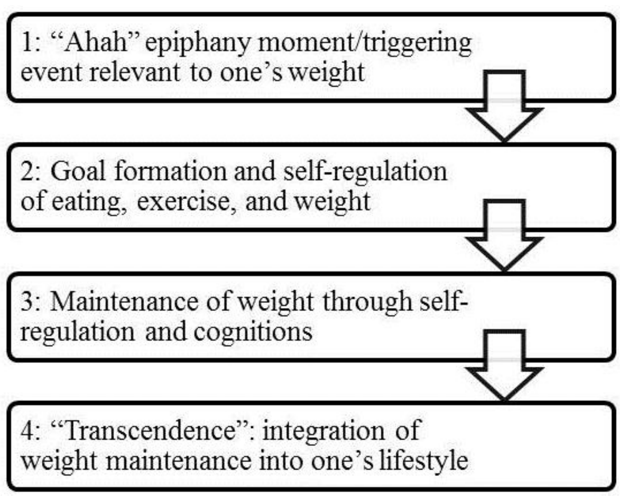


Figure 1.1. The four stage process of weight maintenance described by Haeffele (2008).

Continuous efforts to describe successful weight loss maintenance are led by the National Weight Control Registry (NWCR). The NWCR, established in 1994, is the largest ongoing study of successful weight loss maintenance with over 5,000 contributing individuals (NWCR, 2011). This registry tracks people who have entered at least the third stage in the weight loss maintenance process: they have lost weight and have been successful at maintaining that weight loss. In their first report from the NWCR, Klem, Wing, McGuire, Seagle, and Hill (1997) surveyed 629 women and 155 men who had lost at least 30 kg and kept it off for at least one year. They found that a wide variety of weight loss strategies were used, including restricting intake of certain types or classes of food (87.6% of the sample), eating all types of food but limiting the quantity (44.2%), counting calories (43.7%), and limiting the percentage of daily intake from fat (33.1%). Once the weight had been lost, weight loss was successfully maintained by limiting intake of certain foods (92%), limiting quantities of foods eaten (49.2%), limiting the percentage of daily energy from fat (38.1%), counting calories (35.5%), and counting fat grams (30%). Almost all of the registry members also exercised and weighed themselves regularly.

The NWCR researchers also investigated if losing weight using different strategies and approaches resulted in different weight maintenance behaviors. McGuire, Wing, Klem, Seagle, and Hill (1998) examined three groups in the registry: those who had lost weight on their own, those who had lost weight using a program (e.g., Weight Watchers or Jenny Craig), and those who had lost weight using liquid formulas (e.g., Slim-Fast). Despite using different methods to lose weight, all groups maintained their weight loss by consuming low-calorie, low-fat diets and performing high levels of physical activity.

The NWCR researchers have also addressed how changes in popular diets over time have affected successful weight loss maintenance. Phelan, Wyatt, Hill, and Wing (2006) tracked dietary intake of registry members from 1995-2003. Dietary trends were found to reflect popular diets. As dieters transitioned from low-fat diets to low-carbohydrate diets, registry members obtained a greater percentage of their calories from fat, consumed more saturated fat, and obtained a lower percentage of their calories from carbohydrates. However, over 75% of the registry members were still at or below recommended levels of fat intake. Vegetable consumption and dietary fiber from vegetables/fruits and beans also increased during this time period. The researchers concluded that individuals can lose and maintain weight loss on a variety of diets.

Overall, the NWCR has identified common behaviors that result in successful weight loss maintenance: a low-calorie, low-fat diet, consuming breakfast regularly, engaging in high levels of physical activity (about 1 hour per day -- walking is the most common activity), regular self-weighing, and being mindful of one's diet and physical activity (Hill, Wyatt, Phelan, & Wing, 2005; Wing & Phelan, 2005). Maintaining weight loss is associated with maintaining these behavioral changes long-term and consistently across weeks, weekends, holidays, and non-holidays (Hill, et al., 2005; Wing & Phelan, 2005). The NWCR has examined a primarily female, Caucasian, and married sample (Wing & Hill, 2001). Therefore, it is possible that successful weight loss maintenance strategies may differ in other populations. In a review of 42 randomized clinical trials of weight maintenance conducted from 1984 through 2007, a number of behaviors associated with successful weight loss maintenance were identified, including medications (e.g. orlistat), consuming a lower fat diet, adherence to physical activity, continued contact with individuals, problem-solving therapy, increased protein intake, increased caffeine intake, and acupressure (Turk et al., 2009).

Some researchers have also addressed behavioral differences between individuals who have successfully maintained weight loss and those who have regained weight. Kayman, Bruvold, and Stern (1990) interviewed and surveyed weight loss maintainers and relapsers and discovered that although both groups used similar strategies to lose weight, maintainers more frequently adapted these weight loss strategies to their own lifestyle. That is, maintainers more often devised their own personal eating and exercise plan, whereas relapsers were more likely to use a specific program like Weight Watchers. Relapsers used more restrictive diets, and negative life events caused them to relapse back to their old behaviors. Maintainers also distinguished themselves by self-monitoring their eating and weight. In another study, Kruger, Blanck, and Gillespie (2006) surveyed 1,958 people who had tried to lose weight and reported that 30% maintained a weight loss whereas 70% failed to maintain a weight loss. They found that regular exercise differentiated the two groups, with successful weight maintainers exercising more often. Interestingly, successful weight maintainers also reported more self-monitoring, including planning meals, tracking calories, tracking fat, and measuring the food on their plate on most days of the week.

When reviewing the literature on successful weight loss and weight maintenance, it becomes clear that self-monitoring is an essential part of the weight loss and weight maintenance process. Accurate and reliable tools may help individuals self-monitor consistently. Relatively new technologies, including the Internet, "lightweight data loggers" such as pedometers and accelerometers, and short message service (SMS) via cellular phones, have the potential to improve self-monitoring efforts (Svensson & Lagerros, 2010). Our research group has developed a new self-monitoring tool, the bite counter device, which has the potential to change the way individuals self-monitor their food intake (Hoover, Muth, & Dong, 2009). In order for the bite counter to be an effective self-monitoring tool, we must understand how an individual should use the device. We can begin to develop this understanding with a thorough review of the self-monitoring literature and existing self-monitoring tools.

Self-Monitoring

Self-monitoring can be defined as "observing oneself and one's behavior" (Elfhag & Rössner, 2010, p. 356). In the weight loss literature, self-monitoring refers to the process of observing one's body weight, physical activity, and/or food intake over time. Self-monitoring has been described as "the single most important ingredient to successful dietary change efforts" (McCann & Bovbjerg, 2009), the "cornerstone of the behavioral treatment of obesity" (Wadden & Letizia, 1992, p. 395), and "the single most important component of behavioral treatment for obesity" (Clark, Pamnani, & Wadden, 2010, p. 301).

Theoretical Support for Self-Monitoring

Self-monitoring emanates from self-regulation theory. Self-regulation is defined as "the many processes by which the human psyche exercises control over its functions, states, and inner processes" (Vohs & Baumeister, 2004, p. 1), "any effort by a human being to alter its own responses" (Baumeister, Heatherton, & Tice, 1994, p. 7), and "the exercise of control over oneself, especially with regard to bringing the self into line with preferred (thus, regular) standards" (Vohs & Baumeister, 2004, p. 2). Self-regulation theory emanates from systems theory and the concept of feedback loops (Baumeister et al., 1994). Basic systems theory feedback loops are called TOTE loops, an acronym for Test, Operation, Test, and Exit (Carver, 1979). An example of a TOTE loop for weight loss is presented in Figure 1.2. First, an individual compares their goal weight to their current weight. In the first Test, if there is a discrepancy between the two weights (e.g., the individual weighs more than their goal weight), an Operation takes place and the individual eats less and/or exercises more. Then the individual engages in another Test to determine if their current weight matches their goal weight. If there is no longer a discrepancy, the individual Exits the loop. If there is a discrepancy, the loop continues with another Operation.

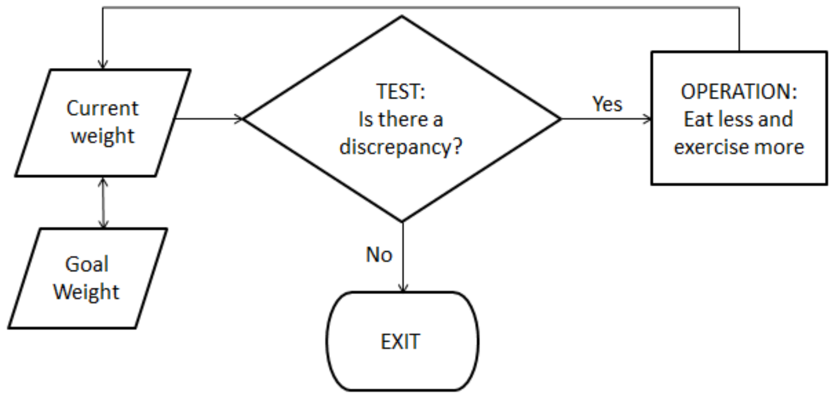


Figure 1.2. A basic TOTE feedback loop example for weight loss.

The TOTE feedback loop was restated by Carver and Scheier (1990) as a cycle of outside impacts from the environment, input functions (or perceptions), a comparator making use of reference values, and output functions (or behaviors). In this self-regulatory process, an individual compares their perception to a standard, and if a discrepancy exists the individual will adjust their behavior to reduce or eliminate the discrepancy. The self-regulation feedback loop requires three things to function: (1) standards for a clear comparison point, (2) monitoring in order to track the state of the current system, and (3) a way to change behavior in the case of a discrepancy (Baumeister et al., 1994). Therefore, self-monitoring is an essential part of self-regulation, but self-regulation will only be successful if an individual also has clear and reasonable comparison standards as well as a way to enact a behavioral change.

Kanfer (1971) has also described a model of self-regulation with three sequential stages: (1) self-monitoring, (2) self-evaluation, and (3) self-reinforcement. In this model, an individual begins the self-regulation process by self-monitoring one's behavior and attending to response feedback which can be proprioceptive, sensory, or affective. Then an individual engages in self-evaluation and compares the feedback to the performance criteria used to judge the feedback. The performance criteria originates from the individual's history, including task standards, social norms, prior reinforcements, and motivation for success. The outcome of this comparison is judged as less than the standard, at the standard, or greater than the standard, and the individual self-reinforces positively or negatively based on the outcome. The individual may decide to engage in a new behavior, continue with the current behavior, or end the behavior based on their evaluation. Once again, it is clear that self-monitoring is an important component of self-regulation, but it should be used in combination with self-evaluation and self-reinforcement to ensure that behavior change is successful (Kanfer, 1970; Kanfer & Gaelick, 1986).

Bandura (1998) has also described the process of behavioral self-regulation in similar terms. Self-regulation begins with self-observation that can vary in its informativeness, regularity, temporal proximity, and accuracy. Then, a judgment process allows the individual to compare what he or she has learned from self-monitoring to his or her own standards, standard norms, and social standards. The individual will also judge the monitored activity as important to them, not important, or relatively neutral, and determine if their performance is the result of their own actions or the actions or assistance of others. Finally, during a self-reaction phase, an individual evaluates performance positively or negatively and provides a tangible reward or punishment. According to Bandura (1998), successful self-regulation depends on successful self-monitoring because it is the self-monitoring process that provides the information necessary for an individual to set goals and to evaluate his or her progress toward those goals. Baumeister et al. (1994) applied this idea to the self-regulation of eating behavior when they stated that "the first key to successful self-regulation of eating is to self-monitor food intake" (p. 180).

Self-monitoring can also be described from the perspective of behavior therapy (Clark et al., 2010). The goal of behavior therapy in weight loss is to develop healthy eating and exercise habits that will allow individuals to reach their weight goals. Classical and operant conditioning form the basis for behavior therapy (Clark et al., 2010). Associations among activities, locations, mental states, eating behaviors, and physical activity behaviors are identified (i.e., behaviors that are classically conditioned are identified), and behaviors are rewarded or punished based on how they affect these weight loss goals (operant conditioning). Self-monitoring allows the individual to examine his or her own behaviors, identify where changes can be made, and then monitor the results of those behavioral changes. Recording food intake, activity, weight, types of food, amounts of foods, caloric values of foods, times, places, and feelings can all provide insight into associations that may be contributing to an individual's obesity (Clark et al., 2010). For example, an individual tracking her food intake may realize that she always eats ice cream when watching TV even when she is not hungry. This individual can then set a goal of no longer eating ice cream when watching TV, and only eating ice cream at a table when feeling hungry. If the individual engages in behaviors that help her to reach this goal, then the individual may see a positive result, such as a weight loss of one pound over a week. This positive reinforcement leads to the continuation of this new eating behavior pattern.

The theoretical basis for self-regulation theory and behavioral therapy both describe self-monitoring as an essential part of the individual behavior change process. Self-monitoring has been used to successfully help individuals manage their health behaviors. For example, self-monitoring of blood glucose (SMBG) helps individuals to manage type 2 diabetes (Hirsch et al., 2008; Poolsup, Suksomboon, & Rattanasookchit, 2009). Self-monitoring has also been linked to successful smoking cessation (Fisher, Lichtenstein, Haire-Joshu, Morgan, & Rehberg, 1993). A substantial body of literature has focused on examining the features of self-monitoring that are associated with successful weight loss and weight maintenance. Specifically, self-monitoring of body weight, physical activity, and food intake have been primary topics of investigation.

Self-Monitoring of Body Weight

Self-monitoring of body weight, or self-weighing, is associated with weight loss and weight maintenance success. In a review of 12 studies that examined the relationship between self-weighing and body weight, 11 studies demonstrated that self-weighing weekly or daily was associated with greater weight loss or more successful weight maintenance when compared to less frequent or no self-weighing (VanWormer, French, Pereira, & Welsh, 2008). In some of these studies, self-weighing frequency was self-reported and retrospective (Butryn, Phelan, Hill, & Wing, 2007; Linde, Jeffery, French, Pronk, & Boyle, 2005; Welsh, Sherwood, VanWormer, Hotop, & Jeffery, 2009; Wing, Tate, Gorin, Raynor, & Fava, 2006) or observational (VanWormer et al., 2009). Thus, it is possible that increased frequency of self-weighing leads to weight loss *or* successful weight loss encourages an individual to self-weigh more frequently. A series of experimental studies have partially addressed this issue of causality by manipulating self-weighing behavior, with results indicating that more frequent self-weighing is related to weight loss (Gokee-Larose, Gorin, & Wing, 2009; Levitsky, Garay, Nausbaum, Neighbors, & DellaValle, 2006; Strimas & Dionne, 2010). Interestingly, Strimas and Dionne (2010) concluded that individual differences may moderate the relationship between self-weighing frequency and weight loss. Also, interactions between self-weighing and other parts of a weight loss program are important future directions for investigation (VanWormer et al., 2008).

Self-monitoring of body weight allows an individual to compare his or her weight to a goal weight. However, a limitation of this approach is that weight alone does not provide information about how to change the behaviors that impact weight change. Weight can fluctuate one to two pounds per day which is similar to weight loss recommendations of one to two pounds per week, which provides a challenge to an individual trying to assess the source of weight loss on a weekly basis. Additionally, the mechanisms behind weight change in self-weighing studies are difficult to isolate because self-weighing is often correlated with tracking food intake and physical activity (VanWormer et al., 2008). It is possible that self-monitoring of physical activity and food intake has unique utility for an individual trying to lose weight or maintain a weight loss. By tracking the specific behaviors that impact weight changes, the individual may begin to understand the patterns of physical activity and food intake that result in weight loss or weight maintenance.

Self-Monitoring of Food Intake and/or Physical Activity

Early studies of self-monitoring of food intake and physical activity revealed that tracking eating behaviors, keeping a paper-and-pencil food diary, and entering food intake and exercise into a computer are related to weight loss (Burnett, Taylor, & Agras, 1985; Fujimoto et. al., 1992; Sperduto, Thompson, & O'Brien, 1986). As a next step, researchers investigated how consistency of self-monitoring affects weight loss efforts. A series of self-monitoring intervention studies had participants record their eating behaviors, food intake, and physical activity using a paper-and-pencil self-monitoring booklet and found that more frequent self-monitoring is related to greater weight loss (Baker & Kirschenbaum, 1993; Baker & Kirschenbaum, 1998; Boutelle & Kirschenbaum, 1998). Boutelle and Kirschenbaum (1998) suggested self-monitoring all foods eaten on 75% or more of days in order to successfully lose weight. The conclusion that more consistent self-monitoring is related to greater weight loss is a recurring trend in the self-monitoring of exercise and food intake literature (Wadden et al., 2005). However, similar to the self-monitoring of body weight literature, the direction of the relationship between self-monitoring physical activity and food intake and weight loss is unknown. Self-monitoring these behaviors may lead to weight loss, or weight loss may encourage self-monitoring practices.

Once a relationship between more consistent self-monitoring and weight loss was established, researchers began to investigate the many factors that could improve adherence to a self-monitoring protocol, with the assumption that improved adherence would be related to increased weight loss. After a thorough literature review, a number of common factors that improve self-monitoring were identified. These are summarized in Table 1.2. Simplified diaries, Internet technology, PDAs, PEDs, and mobile phones (SMS) can be used as self-monitoring tools that can increase self-monitoring adherence (Beasley, 2007; Burke et al., 2009; Burke et al., 2011; Cushing, Jensen, & Steele, 2010; Helsel, Jakicic, & Otto, 2007; Micco et al., 2007; Morgan, Lubans, Collins, Warren, & Callister, 2011; Patrick et al., 2009; Tate, Wing, & Winett, 2001; Yon et al., 2007). Counselor support and feedback, accountability, human counseling, and reminders to self-monitor are features of self-monitoring programs that can increase self-monitoring adherence (Boutelle, Kirschenbaum, Baker, & Mitchell, 1999; Harvey–Berino et al., 2002; Tate, Jackvony, & Wing, 2006). Finally, individual differences, including understanding the importance of self-monitoring, using one's preferred self-monitoring method, social support, gender (being male), and race (being Caucasian) have all been linked to improved self-monitoring adherence (Burke, Swigart, Turk, Derro, & Ewing, 2009; Hollis et al., 2008; Shay, Seibert, Watts, Sbrocco, & Pagliara, 2009). The one factor that is consistently related to a decreased self-monitoring adherence is time (e.g., Carels et al., 2008; Polzien, Jakicic, Tate, & Otto, 2007). As time in a weight loss program increases, self-monitoring behavior tends to decrease.

Table 1.2

Factors that may impact adherence to self-monitoring

Self-monitoring tools	Program features	Individual differences	Barriers to self-monitoring
Simplified diaries	Human counseling (better than automated)	Understanding importance of self-monitoring	Time in weight loss program
Using a PDA, PED, or mobile phone (SMS)	Support, feedback, and accountability to a counselor	Using preferred method or tool	Access to/ acceptance of technology
Internet technology	Reminders to self-monitor	Social support	
Food scale		Gender (male)	
Pedometer		Race (Caucasian)	
Packaged meals (e.g., Weight Watchers, SlimFast)			

Note: The factors described are often combined to create a multi-component self-monitoring intervention.

Future efforts to increase adherence to self-monitoring could focus on improving self-monitoring tools, incorporating human counselor support, feedback, and reminders into self-monitoring programs, or accounting for individual differences when implementing these programs. Our research group has developed a new food intake self-monitoring tool, the bite counter device (Hoover, Muth, & Dong, 2009). It is possible that the bite counter will be able to simplify the food intake self-monitoring process and increase adherence to self-monitoring.

However, “bites” are a new construct in the weight loss literature. In order for the bite counter to be an effective self-monitoring tool, the reasons why bite count may vary must be understood by both the individuals implementing a self-monitoring intervention and by the people following the self-monitoring intervention. As a first step toward this understanding, the sources of variance in bite count must be identified and studied. In the next section, the bite counter design and functionality is described, and the foundation for predicted sources of variance in bite count is discussed.

The Bite Counter

The bite counter is a newly invented device designed to help people self-monitor their eating. It is worn on the wrist like a watch and tracks a pattern of wrist roll motion in order to detect that the wearer has taken a bite of food or drink of liquid, storing a log of time-stamped bite count data. It provides the capacity to detect, record, and store cumulative totals of bite counts over the day with little effort by the wearer.

Our research team has discovered that while eating, the wrist of a person undergoes a characteristic rolling motion that is indicative of the person taking a bite of food (Hoover, Muth & Dong, 2009). The roll motion takes place about the axis extending from the elbow to the hand. If, for the right hand, positive roll is defined as clockwise in direction as viewed from the elbow looking towards the hand, and negative roll as counterclockwise motion, the characteristic movement involves a cycle of roll motion that contains an interval of positive roll followed by an interval of negative roll.

For a typical person, the positive roll happens when a person is raising food from an eating surface (such as a table or plate) towards the mouth (see Figure 1.3). The negative roll happens when the hand is being lowered, or when food is being picked up by fingers or placed on a utensil. The actual placing of food into the mouth usually occurs between the positive and negative rolls. This characteristic roll is important because it differentiates wrist or arm motions caused by many other activities from a motion that can be directly associated with taking a bite of food or a sip or drink of a liquid.

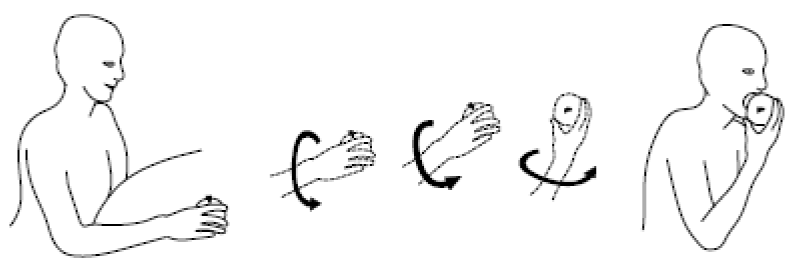


Figure 1.3. Positive wrist roll when taking a bite.

Initial research with the bite counter was completed with a tethered sensor, an InertiaCube3 (InterSense, Inc., Bedford, MA) with an attached athletic wrist-band (see Figure 1.4). To test the bite counter concept, a controlled study focused solely on a single food (Scisco, 2009). Fifty-one participants were presented with 870 kcal (276 grams) of Kellogg's Eggo® cinnamon toast waffles and allowed to eat as much as they liked using a fork. The waffles were pre-cut into uniform, bite-size pieces. The participant was seated at a table, and the bite counter was placed on the wrist of the dominant hand and connected to an external computer. A video camera was positioned to record the person while eating. The computer recorded the raw sensor data and the times at which bites were detected. The raw sensor data and bite detection times were correlated with the recorded video in order to evaluate the performance of the device. The participants ate a range of 8 to 95 bites, 34 bites on average. The sensitivity of the device was 94% and only 6% of the actual bites were undetected. The positive predictive value was 80%. While the conditions in this test were restrictive in terms of food type eaten and utensil used, it showed that our technique works across a large number of participants.

Figure 1.4. The tethered InertiaCube3 attached to an athletic wristband.

In a follow up study, a much smaller and less expensive sensor was used, the STMicroelectronics LPR530al, as shown in Figure 1.5 (Dong, Hoover, Scisco, & Muth, 2012). Participants wore this smaller sensor and the InterCube3 in order to compare performance between sensors. In this laboratory study with less control over the eating situation, 47 participants were recorded eating a meal that they brought with them to the study, using the utensil(s) of their choice, and given no particular instructions as to how to eat the meal. The meals chosen ranged from noodles eaten with a spoon to chicken tenders and french fries eaten with fingers to a pasta dish eaten with a fork. As with the controlled meal, a video camera was positioned to record the person while eating and the bite counter was placed on the person's dominant wrist and connected to an external computer. Data were also recorded and analyzed in the same manner as with the controlled meal. The sensitivity of the STMicroelectronics device was found to be 86%, with a positive predictive value 81%. The sensitivity of the InertiaCube sensor was found to be 85%, with a positive predictive value 81%. The first non-tethered ambulatory bite counters using the smaller sensor were developed by Bite Technologies and became available in summer 2011 (Figure 1.6).

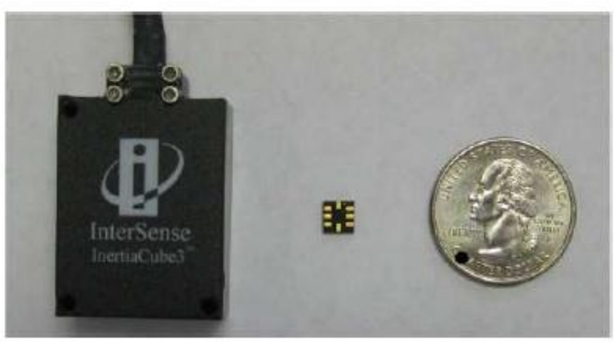


Figure 1.5. The smaller MEMS sensor (center) compared to the InterSense IneritaCube3 and a US quarter.

Figure 1.6. The ambulatory bite counter used in the current study.

Possible applications of the bite counter for weight loss are numerous. In the first study of a bite counter application, the bite counter's utility for slowing bite-rate and reducing energy intake was explored (Scisco, Muth, Dong, & Hoover, 2011). The study was a within-participants design with three conditions. Thirty university students ate three meals in the laboratory while wearing the bite counter: a baseline meal without feedback (Baseline), a meal during which participants received bite-rate feedback (Feedback), and a meal during which participants followed a 50% slower bite-rate target (Slow Bite-Rate). Bite-rate feedback was provided by displaying participant's bites in real-time on a step graph, with the x-axis representing time elapsed and the y-axis representing number of bites taken. Overall, participants ate 70 fewer kilocalories during the Slow Bite-Rate condition compared to the Feedback condition. Additionally, when baseline energy intake was added post-hoc as a grouping variable, participants who ate over 400 kilocalories at baseline (n = 11) ate 164 fewer kilocalories during the Slow-Eating condition compared to Baseline, and 142 fewer kilocalories in the Feedback condition compared to Baseline. However, the Slow Bite-Rate condition did not significantly affect participants who ate under 400 kilocalories at baseline (n = 19). The results from this initial study indicate that slowing bite-rate with the bite counter may be most effective for reducing energy intake for individuals who consume larger amounts of food.

These first studies with the bite counter were conducted in laboratory settings and were limited to only one meal or one food consumed by an individual. Ideally, the bite counter will be used by an individual for months or years to self-monitor their food intake in their daily life. Therefore, it is necessary to determine the variables that will explain variance in bite count in order to guide long-term bite counter use in real-life settings.

Bite Count Variance

An assumption of the bite counter method is that bites will serve as a proxy for energy intake. As number of bites taken during a meal increases for an individual, we assume that this increase will equate to an increase in energy intake. However, there are a number of other reasons why bite count may vary. We can parse these potential explanatory factors into within-person variance and between-person variance in bite count. For example, analyses of 24-hour dietary recalls have indicated that about half of the variation in daily energy consumption (kcal/day) is due to differences within people, with the other half being due to differences between people (Beaton et al., 1979). Although bite count variance and energy intake variance are not the same, the present study is assuming that they are positively related in order to generate predictor variables.

Some examples of within and between person variance are described in Table 1.3 and in the text that follows.

Table 1.3

Within and between person bite count variance examples

Within person variance in bite count	Between person variance in bite count
Energy of food (kilocalories)	Body size (e.g., body weight, BMI)
Energy density (kilocalories/gram)	Body fat percentage
How food is eaten (e.g., utensils used)	Waist-to-hip ratio (WHR)
Location of the meal	Age
Day of the week	Gender
Number of people at the meal	Energy needs (energy expenditure)
Meal duration	Dietary restraint
Bite size	

Within-person variance. Within-person variance in bite count can be conceptualized as reasons why bite count would change for a given individual. For instance, if Jane the graduate student is wearing a bite counter and tracking her bite count during meals, there are many possible reasons why her bite counts might vary. There may be differences between her meals, such as the caloric content or energy density of the foods, the utensils used to eat, and other activities engaged in while eating. There may be differences between the days that she tracks bite count. For example, she may be on vacation and eating all of her meals at Las Vegas buffets one day, and she may be at work and eating at her regular meal times another day. There may even be differences between weeks and seasons. For example, results of a one-year dietary intake study indicated that individuals ate more in summer and winter months compared to the spring and ate more on weekends than during the week (Basiotis, Thomas, Kelsay, & Mertz, 1989).

Between-person variance. Between-person variance in bite count can be conceptualized as reasons why bite count would differ between individuals. For example, if we compared the bite counts of Jane the graduate student and Greg the professional athlete, we might see large differences in bite count based on their body size, bite size, gender, and energy needs. Preliminary research in our laboratory indicates that, when the energy density and portion size of a food are controlled, the number of bites taken varies more between individuals than within individuals (Salley, Scisco, Hoover, & Muth, 2011). These findings are supported by the existing literature which has found large differences between people in their patterns of energy intake (Tarasuk & Beaton, 1991). Therefore, an important step in the bite counter project is to identify the characteristics of an individual that will predict bite counts.

Multi-level Linear Modeling

The variance structure just described is “nested” or “hierarchical”. Nested data is very common is social sciences research (Bickel, 2007). A classic example of nested data is students nested within classrooms (Hox, 2010). For example, a researcher may have a data set with 1,000 students, each of whom is a member of 50 different classrooms. If a researcher was interested in predicting academic performance, there may be individual characteristics, such as socio-economic status (SES) of the child, which might predict academic performance. However, there may also be features of the classroom, such as teacher experience, that might predict performance as well. Thus, it would be important to consider the relationship between SES and academic performance within the context of the teacher experience in each of the classrooms. The students are considered nested, or grouped, within the classrooms.

Data can also be nested when it comes from repeated measurements for the same individuals over time (Cohen, Cohen, West, & Aiken, 2003). For example, in the present study, human eating behavior is being measured over time. The variation in the number of bites recorded by the bite counter may be due to differences in the eating occasions, such as the energy of the food eaten at each occasion. However, there may also be differences between individuals that affect how many bites are recorded, such as gender or body weight. Therefore, it is important to consider the relationship between bites and the amount of energy consumed within the context of each individual's gender and body weight. The eating occasions are nested, or grouped, within the individuals.

An analysis technique that allows for nested data is multilevel linear modeling (MLM) also known as hierarchical linear modeling (HLM), random coefficients modeling, multilevel regression, and mixed models (Tabachnick & Fidell, 2007). For purposes of consistency and clarity, this analysis technique will be referred to as MLM throughout the remainder of this document. MLM is considered another method of regression analysis conducted under specific conditions, those conditions being nested data and relationships among the measurements that are nested (Bickel, 2007).

MLM allows the researcher to analyze nested data that violates some of the assumptions of ordinary least squares (OLS) regression or repeated-measures ANOVA analyses (Tabachnick & Fidell, 2007). Repeated measures ANOVA requires complete data for each individual at each measurement occasion, equal intervals between measurements, and uncorrelated errors. In MLM, there is no requirement for complete data for each individual or each measurement occasion, there is no need for equal intervals between measurements, and the sphericity assumption (uncorrelated errors over time) can be violated. That is, MLM allows for measurement occasions to be correlated. In the case of repeated measures analyses, measurements are correlated because they originate from the same individual (e.g., meals are eaten by the same person over time). MLM deals with these correlated measurements by estimating error separately for measurement occasions and for individuals (Tabachnick & Fidell, 2007). Additionally, repeated measures data is likely to have missing values due to participant drop-out or a participant missing a measurement occasion. In repeated measures analysis, a participant with a missing measurement occasion would be removed from the data set completely. In MLM, this participant can remain in the data set (Hox, 2010).

In the immediate text that follows, a simple example is used to conceptually demonstrate the research questions that can be answered with MLM. Starting with the raw data shown in Table 1.4, there are five students whose GPA was measured at five different years (2007, 2008, 2009, 2010, and 2011). When GPA was measured, job status was also measured and defined as the average number of hours worked per day (0 hours (unemployed), 1 hour, 2 hours, 3 hours, or 4 or more hours). The gender of each student is also known. The data is nested because the GPA and job status measurements can be grouped by the individual student who provided the data. GPA is the dependent variable (DV), job status is the level-1 independent variable (IV), and gender is the level-2 IV. Level-1 refers to a variable measured at the lowest level of analysis, in this case, the measurement occasion level. Level-2 refers to a variable measured at the second level of analysis, in this case, the individual level. The first three questions (Q1-Q3) discussed in this example reflect the fixed effects in MLM. Fixed effects examine the overall relationships between the IVs and the DV.

Table 1.4

Data for MLM example.

Student	Year	GPA	JobStatus	Gender
Scott	2007	2.5	0	Male
Scott	2008	2.6	1	Male
Scott	2009	2.9	4	Male
Scott	2010	2.7	2	Male
Scott	2011	2.8	3	Male
Greg	2007	2.4	3	Male
Greg	2008	2.5	4	Male
Greg	2009	2.1	0	Male
Greg	2010	2.2	1	Male
Greg	2011	2.3	2	Male
Kate	2007	3.1	0	Female
Kate	2008	2.9	1	Female
Kate	2009	2.3	4	Female
Kate	2010	2.5	3	Female
Kate	2011	2.6	2	Female
Liz	2007	3.2	4	Female
Liz	2008	3.8	1	Female
Liz	2009	3.6	2	Female
Liz	2010	3.4	3	Female
Liz	2011	4	0	Female
Ann	2007	3.5	0	Female
Ann	2008	3.4	1	Female
Ann	2009	3.3	2	Female
Ann	2010	3.2	3	Female
Ann	2011	3.1	4	Female

Q1: Does job status predict GPA?

Figure 1.7 shows all of the GPA measurements for all students and all years, with GPA on the y-axis and job status on the x-axis. Given this plot, the first question that can be asked of the data set is “does job status predict GPA”? As seen in Figure 1.7, the overall effect of job status on GPA is slightly negative. As the number of hours worked per day increases, GPA decreases.

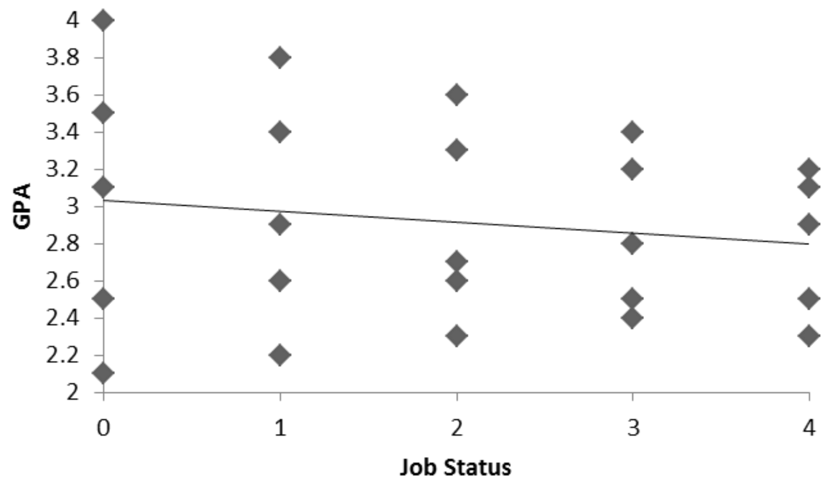


Figure 1.7. Relationship between job status and GPA.

Q2: Does gender predict GPA?

Figure 1.8 shows all of the GPA measurements for all students and all years, with GPA on the y-axis and gender on the x-axis. Given this plot, the second question that can be asked of the data set is “does gender predict GPA?” As seen in Figure 1.8, on average, females have higher GPAs than males. A line has been fit to the data to demonstrate that this would typically be shown for variables with more than two values and to demonstrate the group differences.

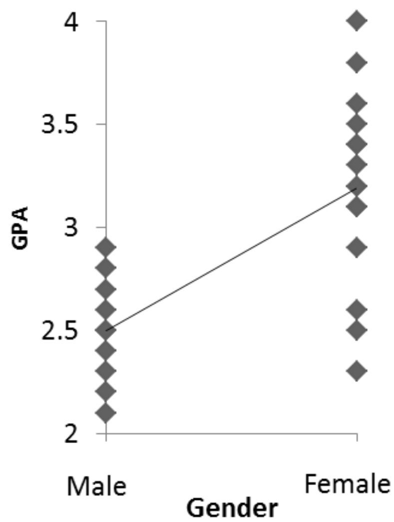


Figure 1.8. Scatterplot demonstrating the average difference in GPA between the genders.

Q3: Does the relationship between job status and GPA depend on gender?

Figure 1.9 shows all of the GPA measurements for all students and all years, with GPA on y-axis and job status on the x-axis. Given this plot, the third question that can be asked of the data set is, "does the relationship between job status and GPA depend on gender?" It can be seen in Figure 1.9 that the relationship between job status and GPA does appear to depend on gender, with an overall increase in GPA for males when they work more hours per day, and an overall decrease in GPA for females when they work more hours per day.

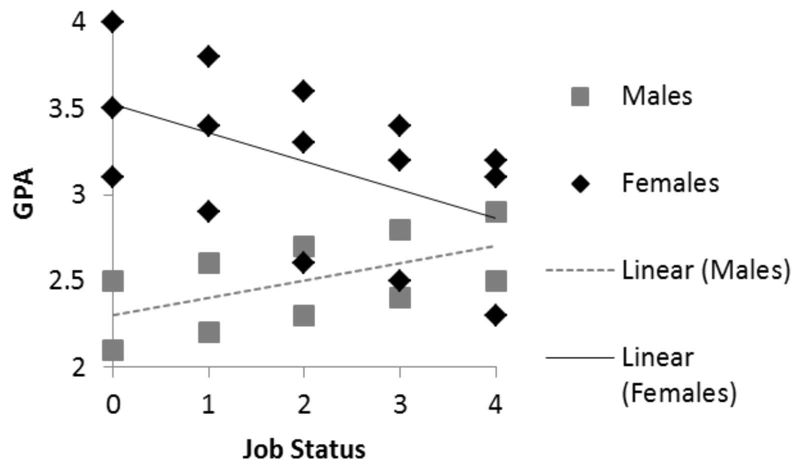


Figure 1.9. Scatterplot demonstrating how the relationship between job status and GPA depends on gender.

The next four questions (Q4-Q7) discussed in this example reflect the *random* effects in MLM. Random effects allow the mean of the DV (intercept) and the relationship between the level-1 IV and the DV (slope) to vary by the level-2 grouping variable.

Q4: Does GPA, when job status is average, vary by student?

. Figure 1.10 shows five individual scatterplots, one for each student, with GPA on the y-axis and job status on the x-axis. A line extends from the point for each individual when job status is at its mean (mean job status is 2 hours per day) to the y-axis. Given these plots, the fourth question that can be asked of the data set is “does GPA, when job status is average, vary by student?” It can be seen in Figure 1.10 that all five student have different GPAs when they work 2 hours per day. This provides evidence of nesting and support for using MLM.

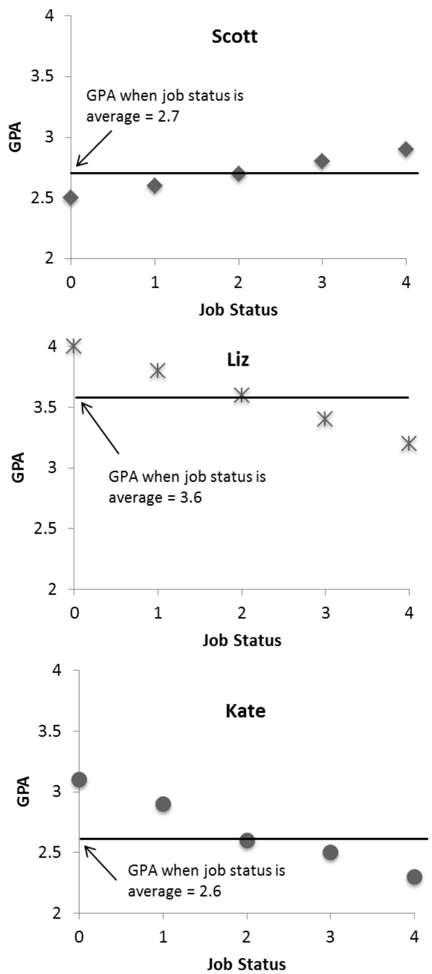


Figure 1.10. Student scatterplots demonstrating individual differences in GPA when job status is average.

Q5: Can the student-level variation in GPA, when job status is average, be explained by gender?

Examining Figure 1.10, it can now be asked if the differences in GPA, when working the average number of hours per day for the sample, can be explained by the gender of the students. It can be seen that gender may explain some of this variation. Scott and Greg (the top two scatterplots) are the male students, and their GPAs at job status 2 are 2.7 and 2.3. Liz, Ann, and Kate (the bottom three scatterplots) are the female students, and their GPAs at job status 2 are 3.6, 3.3, and 2.6. Overall, it seems that the females may have higher GPAs than males when working the average amount of time for this student sample.

Q6: Does the relationship between job status and GPA vary by student?

Figure 1.11 shows five individual scatterplots, one for each student, with GPA on the y-axis and job status on the x-axis. Linear regression lines are fit to each data set, and the slopes are indicated on the scatterplots. Given these plots, the sixth question that can be asked of the data set is "does the relationship between job status and GPA vary by student?" Examining the slopes of the five lines, it can be seen that the relationship between job status and GPA varies by student. Some students' GPAs increased as they worked additional hours, and some students GPAs decreased as they worked additional hours.

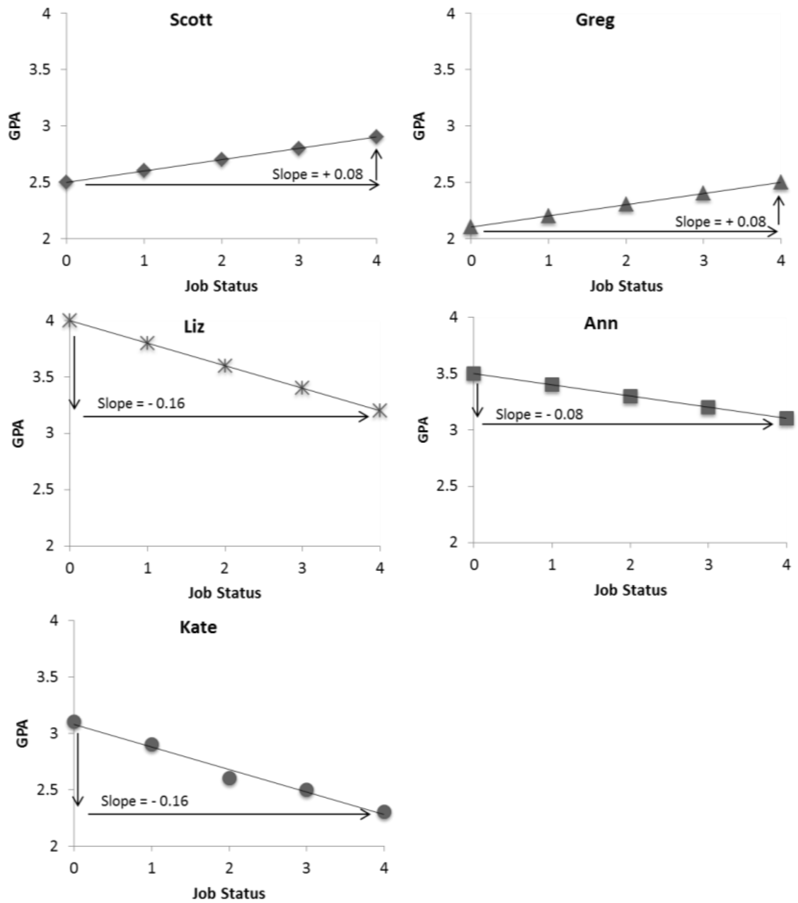


Figure 1.11. Student scatterplots demonstrating individual differences in the relationship between job status and GPA.

Q7: Can the student-level variation in the relationship between job status and GPA be explained by gender?

Examining Figure 1.11, it can now be asked if the differences in the relationships between GPA and job status (the slopes), can be explained by the gender of the students. It can be seen that Scott and Greg, the two males, have positive slopes. However, Liz, Ann, and Kate, the three females, have negative slopes. Therefore, it seems that gender can explain some of the variation in the student-level relationships between job status and GPA. Male GPAs increase when they work more hours per day, and female GPAs decrease when they work more hours per day. The difference between Q3 and Q7 is that in Q3 the slopes were originally grouped by gender; however, in Q7 the slopes were first allowed to vary by students, and then they were grouped by gender, a level-2 variable that could explain this level-1 slope variation.

MLM Estimation Method

Before demonstrating the MLM equations, it is important to acknowledge that MLM uses a different estimation method compared to OLS regression-based repeated-measures ANOVA. The OLS estimation method estimates intercept and slopes by seeking to make the sum of the squared differences between the observed value and the predicted value of the dependent variable across all observations as small as possible (Cohen et al., 2003). This is an analytic solution, meaning the values can be derived directly from a set of equations (Cohen et al., 2003). The most common estimation method for MLM analyses is maximum likelihood (ML) (Bickel, 2007; Hox, 2010). ML estimation provides values for the intercepts and slopes by seeking the values that have the greatest likelihood of resulting in the observed data (Bickel, 2007). That is, ML estimation uses the values of the predictors and the dependent variable to find the intercepts and slopes that make the sample as likely or as "typical" as possible (Cohen et al., 2003). This is an iterative process. Initial intercept and slope values are generated, the likelihood of the estimates given the predictor and dependent variable values is calculated, and this guides the next iteration which tries to increase the likelihood of the sample values (Cohen et al., 2003; Hox, 2010). The process continues until the likelihood does not improve by more than an amount known as the “convergence criterion” (Cohen et al., 2003). There is no analytic solution to ML estimation, meaning that there is not a set of equations from which the coefficients are directly calculated given its iterative nature (Cohen et al., 2003). ML estimation is made possible by high speed computers and an iterative computational procedure that can run hundreds to thousands of estimations until convergence is reached (Bickel, 2007; Cohen et al., 2003; Hox, 2010).

Restricted maximum likelihood (REML or RML) is a preferred method of ML for smaller samples because it uses a likelihood function to take into consideration the number of parameters being estimated in the model (Bickel, 2007) and is less biased (Hox, 2010). REML includes only the variance components in the likelihood function, and the parameter estimates are estimated separately (Hox, 2010). ML, which includes the variance components and the parameter estimates in the likelihood function (Hox, 2010), should be used when comparing fit across incremental models (Tabachnick & Fidell, 2007).

MLM Equations

Returning to the present example, with level-1 job status and level-2 gender predicting GPA, the full MLM regression equation can be built from a series of equations at each level. The level-one model is represented by equation 1.1 using conventional notation for MLM (Bickel, 2007; Hox, 2010). The interpretations of each symbol are provided in Table 1.5 (Tabachnick & Fidell, 2007).

$$GPA_{ij} = \beta_{0j} + \beta_{1j} jobstatus_{1ij} + e_{ij} \qquad \textbf{(1.1)}$$

Table 1.5

Symbols and Meanings for the Level-1 Equation

Symbol	Meaning
i	The measurement occasion (nested within an individual)
j	The individual
GPA_{ij}	The GPAs for measurement occasions *i* in individuals *j*; the DV
β_{0j}	For an individual *j*, the mean (intercept) of GPA
β_{1j}	For an individual *j*, the slope of the relationship between GPA and job status
$jobstatus_{1ij}$	The job status scores for measurement occasions *i* in individuals *j*; the level-1 IV
e_{ij}	Deviation of predicted GPA values from actual GPA values for measurement occasions *i* in individuals *j*; the error term for the level-1 equation

The level-2 model is shown in equations 1.2 and 1.3. The mean GPAs of the individuals (β_{0j}) and the slopes of the relationship between GPA and job status for the individuals (β_{1j}) become DVs in equations 1.5 and 1.6 (Bickel, 2007; Hox, 2010). The interpretations of each new symbol are provided in Table 1.6 (Tabachnick & Fidell, 2007).

$$\beta_{0j} = \gamma_{00} + \gamma_{01} gender_j + \mu_{0j} \quad \textbf{(1.2)}$$

$$\beta_{1j} = \gamma_{10} + \gamma_{11} gender_j + \mu_{1j} \quad \textbf{(1.3)}$$

Table 1.6

Symbols and Meanings for the Level-2 Equations

Symbol	Meaning
γ_{00}	The grand mean of GPA scores across all individuals when all predictors are zero
γ_{01}	The overall regression coefficient for the relationship (slope) between gender and GPA
$gender_j$	The gender for individuals *j*
μ_{0j}	The deviation of the mean GPA (intercept) of an individual *j* from the overall mean GPA; An error component for the Level-2 equations
γ_{10}	The overall regression coefficient for the relationship (slope) between job status and GPA
γ_{11}	The degree to which the relationship between job status and GPA depends on gender; The cross-level interaction term
μ_{1j}	The deviation of each individual *j* slope from the overall slope; An error component for the Level-2 equations

Combining the level-one and level-two equations through substitution results in equation 1.4.

$$GPA_{ij} = \gamma_{00} + \gamma_{01} gender_j + \mu_{0j} + (\gamma_{10} + \gamma_{11} gender_j + \mu_{1j}) * jobstatus_{1ij} + e_{ij}$$

(1.4)

Rearranged, this becomes the full model, shown in equation 1.5.

$$GPA_{ij} = \gamma_{00} + \gamma_{01} gender_j + \gamma_{10} jobstatus_{1ij} + \gamma_{11} gender_j * jobstatus_{1ij} + \mu_{1j} jobstatus_{1ij} + \mu_{0j} + e_{ij}$$

(1.5)

It can be seen that β_{0j} and β_{1j} have been dropped from the overall equation. These coefficients are not fixed values because they vary by the individual *j*. Thus, they are called *random* effects. MLM provides an estimate of the variance of each random effect (Tabachnich and Fidell, 2007). These two variances are described in Table 1.7.

Table 1.7

Symbols and Meanings for the Random Variance Components

Symbol	Meaning
τ_{00}	The variance of the random means (intercepts)
τ_{10}	The variance of the random slopes

When an MLM analysis in conducted, the three fixed coefficients in equation 1.5 (γ_{01}, γ_{10}, γ_{11}) and the two variance components in Table 1.7 (τ_{00}, τ_{10}) are the main parameters that are interpreted. In Table 1.8, these five parameters and their interpretations are referenced back to questions 1 through 7 and Figures 1.7 through 1.11.

Table 1.8 *Research questions with their corresponding parameter estimates, figures, and interpretations.*

Number	Question	Parameter Estimate	Corresponding Figure	Interpretation
Q1	Does job status predict GPA?	γ_{10} (slope between job status and GPA)	1.7: slope of the regression line between job status and GPA	Magnitude, direction, and statistical significance
Q2	Does gender predict GPA?	γ_{01} (slope between gender and GPA)	1.8: slope of the regression line between job status and GPA	Magnitude, direction, and statistical significance
Q3	Does the relationship between job status and GPA depend on gender?	γ_{11} (cross-level interaction term)	1.9: how male slope differs from female slope	Magnitude, direction, and statistical significance
Q4	Does GPA, when job status is average, vary by student?	τ_{00} (variance of the random intercepts)	1.10: variance of the student-level GPA values at job status 2	Greater than expected by chance?
Q5	Can the student-level variation in GPA, when job status is average, be explained by gender?	τ_{00} (variance of the random intercepts)	1.10: variance of the student-level GPA values at job status 2	Reduction in value from Q4?
Q6	Does the relationship between job status and GPA vary by student?	τ_{10} (variance of the random slopes)	1.11: variance of the student-level slopes	Greater than expected by chance?
Q7	Can the student-level variation in the relationship between job status and GPA be explained by gender?	τ_{10} (variance of the random slopes)	1.11: variance of the student-level slopes	Reduction in value from Q6?

MLM and Eating Research

This MLM analysis technique is particularly useful for eating research when the same participant's eating behaviors are measured at multiple meals. In a traditional two-level hierarchical structure, each meal can be defined as "Level 1" with multiple meal-level predictors occurring at this level. Then, each individual can be defined as "Level 2" with multiple individual-level predictors occurring at this level. The goal of the MLM analysis would be to determine the direct effect of meal- and individual-level explanatory variables on the Level 1 outcome (e.g., bites), and to determine if the individual-level variables serve as moderators of the meal-level relationships (Hox, 2010).

MLM has been used to successfully analyze repeated-measures eating behavior data. For example, O'Connor, Jones, Conner, McMillan, and Ferguson (2008) used MLM to analyze daily diary reports of hassles and between-meal snacking. Using a two-level hierarchical structure, they defined Level 1 as daily within-person variation in snacking behavior and hassles, and Level 2 as between-person variance (e.g., eating style, gender). This allowed them to examine the impact of daily hassles and individual differences on snacking behavior, as well as moderators of the hassles-snacking relationship. As another example, Fulton et al. (2009) examined the within-person and between-person predictors of children's BMI using MLM. Using a two-level hierarchical structure, they defined Level 1 as daily within-person variation in energy intake, physical activity, and sedentary activity, and Level 2 as between-person variation (e.g., gender, race). This MLM analysis allowed these researchers to examine how daily changes in energy intake and activity levels impact BMI, how individual differences impact BMI, and how these predictors might interact.

The Present Bite Counter Study

MLM allows for the exploration of meal-level and person-level variables that could predict bite count. In the present study, participants wore bite counters daily and recorded bite counts for each meal eaten. Every 24 hours, participants also completed dietary recalls for each meal and survey measures asking about features of each meal. This created a rich data set that allows for the investigation of predictors of bite count.

The current study used a two-level model. In MLM, the dependent variable is always at the first level of analysis (Hox, 2010). Thus, the dependent variable was meal-level bite count. This model has two levels of predictors. Level 1 is meal-level predictors: features of the meals, measured repeatedly across all meals, which could impact bite count. Level 2 is individual-level predictors: features of an individual that could impact bite count. Main effects of each predictor at each level on bite count were tested. MLM also allows within-level and cross-level interaction effects to be tested. An example of the hierarchical data structure for two individuals for this two-level model is shown in Figure 1.12.

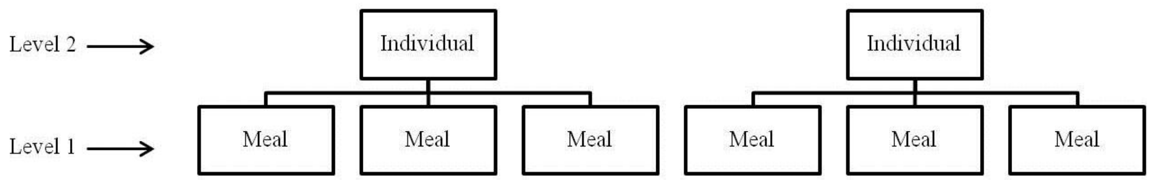


Figure 1.12. The two-level model, with meals at level 1and individuals at level 2.

In the sections below, possible predictors of bite count are identified at the two levels: meal and individual. When available, previous research relevant to the selected predictors is described. Because “bites”, the dependent variable, is a new construct in the literature, empirical support is not always available. However, support for these predictors is drawn from research using calories or grams of food as outcome measures, with the assumption that bites may serve as a proxy for the amount of food an individual consumes. In particular, the research by John de Castro and colleagues that investigated the predictors of energy intake in free-living humans using a diet-diary methodology is an excellent source that is used to support many of the research questions described below (e.g., de Castro & Plunkett, 2002). Given the large number of parameters that need to be estimated when using a multi-level design, it is recommended that the model remain “reasonably small” (Hox, 2010, p. 33). Therefore, only those predictors that are thought to have the strongest possible relationship with bite count and that are most theoretically meaningful were examined in this study. Because up to 86% of the variance in food intake is due to environmental factors, many of the predictors are environmental in nature (de Castro, 2010).

Meal-level Predictors of Bite Count

Meal-level predictors are variables that could affect meal-level bite count.

Total number of kilocalories. The first meal level-predictor to be examined is the total number of kilocalories consumed during the meal. Arguably, the relationship between kilocalories and bites is the most important relationship to understand for the bite counter project. The current standard for measuring energy intake is the kilocalorie, the quantity of heat necessary to raise the temperature of 1 kg (1 L) of water 1°C (McArdle, Katch, & Katch, 2005). The kilocalorie is more commonly referred to as a calorie on food packages and labeling. In order for the bite counter to be understood and well-accepted by the weight loss community as a measure of energy intake, it should provide a reasonable estimate of the number of kilocalories consumed.

Within an individual meal, it is possible that eating more kilocalories will be associated with taking more bites of the meal. For example, if an individual takes 15 bites to eat 300 kilocalories of a sandwich, we could predict that it might take 5 more bites to eat 100 kilocalories, assuming that bite size stays relatively constant. This prediction is supported by preliminary analyses from our research group. Across 38 meals, bite count and kilocalories at the meal level were positively related, $r = .723$, $p < .05$. However, there is some research to suggest that when an individual eats more of the same food, larger bites are taken and the number of bites does not increase. In a within-subjects laboratory study, Burger, Fisher, and Johnson (2011) found that when adult participants ate 220 more kilocalories of a pasta entrée, they did not take significantly more bites. This increase in food consumption was explained by the participants taking larger bites. Similarly, Fisher, Rolls, and Birch (2003) found that when children ate 25% more food at lunch, they did not take significantly more bites. Again, this increase in food consumption was explained by an increase in bite size. Also, Mishra, Mishra, and Masters (2012) used fork size as a proxy for bite size and found that restaurant patrons ate more food with smaller forks compared to larger forks, and lab participants ate more from larger forks compared to smaller forks. The authors attributed this result to the presence of a clear hunger satiation goal in the restaurant, and the absence of this goal in the laboratory. That is, the laboratory environment was more artificial, and participants may not have sought to reduce hunger which made them more susceptible to anchoring on the bite size cue. However, in a restaurant, they may have seen the small bite size as feedback that they were not making much progress on reducing their hunger, and thus they ate more in order to reach visual-cue based satiation.

Therefore, it is possible that there is a positive relationship, negative relationship, or no relationship between kilocalories and bites. Because there is no published research examining the relationship between bites and kilocalories in humans eating in their daily environments, this study will be the first to explore this kilocalorie-bite relationship.

<u>Research Question 1: Do kilocalories consumed during a meal predict number of bites recorded during a meal?</u>

Energy density. Energy density is defined as the number of kilocalories per gram in a given food (Rolls, Ello-Martin, & Ledwicke, 2005). Differences in water and fat contents between foods tend to have the largest impact on energy density (Yao & Roberts, 2001). More water in a food is associated with decreased energy density due to water's zero energy content, whereas more fat in a food is associated with increased energy content because fats are roughly twice as energy dense as proteins and carbohydrates (Yao & Roberts, 2001). Increasing the percentage of low energy density foods eaten is an eating strategy that may aid weight loss due to the increased volume of food consumed and the decreased caloric content of that food (Rolls, 2007).

Diet-diary research has found a positive relationship between the energy density of a meal and the amount of food consumed, $r = 0.26 – 0.30$ (de Castro, 2004a; de Castro, 2004b; de Castro, 2005). Reviews of studies that provided foods of varying energy density to individuals have concluded that consumption of low energy density diets is associated with reduced energy intake and comparable levels of satiety (Prentice, 1998; Yao & Roberts, 2001). Laboratory studies that manipulate energy density have found that increasing the energy density of a food increases the kilocalories of food consumed because individuals tend to consume a similar weight or volume of the same food across meals (Bell, Castellanos, Pelkman, Thorwart, & Rolls, 1998; Bell & Rolls, 2001).

The relationship between the energy density of a meal and the number of bites taken at a meal is unknown because there is no published research on the relationship between these two variables. The relationship between the energy density of a meal and the number of bites taken at a meal may not follow the pattern of results that has been uncovered by the energy density and kilocalorie research. That is, there may not be a positive relationship between energy density and the number of bites taken at a meal. For example, imagine an individual consumes about 500 kilocalories per day at breakfast. One day the individual has 500 kilocalories of watermelon, and another day the individual has 500 kilocalories of breakfast sausage.   This individual would need to take many more bites of the low energy density food (the watermelon) than the high energy density food (the sausage) to consume the same number of kilocalories for that meal. Thus, an individual may take more bites during a low energy density meal than a high energy density meal. Conversely, it is possible that individuals will take more bites of more energy dense meals because of their rich properties and high palatability to prolong and savor their hedonic properties, and fewer bites of less energy dense foods because of their lighter qualities and lower palatability, although one could also find a low energy density food to have pleasing qualities as well. The proposed study will be the first to explore the energy density-bite relationship. <u>Research Question 2: Does the average energy density of a meal predict number of bites recorded during a meal?</u>

Kilocalorie by energy density interaction. An interaction between two level 1 variables, total kilocalories and average energy density, is predicted. It is possible that the relationship between kilocalories and bites depends on the energy density of the food. Following the above example, when an individual is eating watermelon for breakfast, she may take 60 bites to eat 500 kilocalories. When that same individual is eating sausage for breakfast, she may only take 20 bites to eat 500 kilocalories. That is, it takes fewer bites to eat the same number of kilocalories when the energy density of the food is high, indicating that the relationship between bites and kilocalories is not as strong for high energy density foods compared to low energy density foods. This hypothetical relationship is shown in Figure 1.10.   As can be seen in Figure 1.13, the slope of the line for high energy density foods is less steep because it takes fewer bites to eat more kilocalories compared to low energy density foods. The slope of the line for low energy density foods is steeper because it takes more bites to eat more kilocalories compared to high energy density foods.

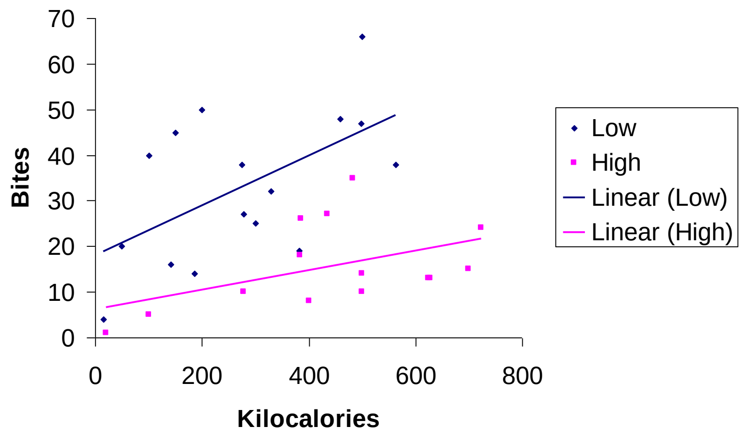


Figure 1.13. Hypothetical interaction between kilocalories and energy density.

Conversely, it is possible that an interaction with the opposite pattern could emerge if the individual takes more bites of an energy dense food and fewer bites of a less energy dense food. Then the relationship between bites and kilocalories would be weaker for high energy density foods compared to low energy density foods. <u>Research Question 3: Does the relationship between kilocalories consumed during a meal and number of bites recorded during a meal depend on the energy density of the food?</u>

Meal duration. Prior research has demonstrated a positive relationship between meal duration and the amount of food consumed. For example, in a laboratory study that manipulated meal duration, participants were given either 12 or 36 minutes to eat a meal consisting of pizza, cookies, and bottled water, and they ate almost 100 kilocalories more during the longer meal (Pliner, Bell, Hirsch, & Kinchla, 2006). In another study that manipulated music playing during the meal, listening to music was associated with longer meal times and increased food intake (Stroebele & de Castro, 2006). Examination of diet diary studies has shown that meal size and meal time are positively correlated, $r = 0.20$ to $r = 0.54$ (de Castro, 1991; de Castro, 2010; Feunekes, de Graaf, & van Staveren, 1995). At a broader level, over the past 30 years, the amount of time Americans spend eating each day has increased about half an hour for men (from 2.0 h to 2.4 h) and almost an hour for women (from 1.6 h to 2.5 h), a finding that parallels rising obesity rates (Zick & Stevens, 2011).

As time elapses during a bite counter recording session, it is likely that more bites are taken as people eat more food. It is also possible that a longer meal will allow people to engage in more activities that could trigger false bite counts (e.g., working, talking, and cooking). Additionally, longer meal times may indicate meals eaten with others, and thus they may reflect the social facilitation of energy intake. Preliminary analyses from our research group for 38 meals indicated that bite count and meal time are very strongly correlated, $r = .875$, $p < .05$. <u>Research Question 4: Does meal duration predict the number of bites recorded during a meal?</u>

Meal location. One environmental factor that can affect consumption is meal location. Many Americans consume meals outside of their homes at restaurants and fast food locations, and the number of commercially prepared meals eaten per week has increased in recent years (Kant & Graubard, 2004). This increase in eating outside of the home is associated with an increase in kilocalories consumed (Kant & Graubard, 2004). Increased energy intake outside of the home is partly the result of large portion sizes at these locations that are often much larger than recommended serving sizes (Condrasky, Ledikwe, Flood, & Rolls, 2007; Ledikwe, Ello-Martin, & Rolls, 2005). Humans use environmental cues like portion size to guide food intake; therefore, restaurants portions may cue us to consume more food (Wansink, 2010). For example, in a laboratory study that manipulated portion size, participants ate 30% more kilocalories when offered a large portion of macaroni and cheese compared to a small portion (Rolls, Morris, & Roe, 2002). Similarly, when participants were offered two portions of pasta, the larger portion size resulted in participants consuming 26% more kilocalories (Burger et al., 2011). However, at home we have familiar environmental cues such as the consistent sizes of our plates and bowls that can help us to regulate our portion sizes and our subsequent food intake (Sobal & Wansink, 2008). Increased energy intake outside of the home is also the result of increased energy density due to greater fat content in restaurant and fast food meals (Paeratakul, Ferdinand, Champagne, Ryan, & Bray, 2003). In support of these relationships, a daily diary study conducted in the US indicated that meals eaten in restaurants are 38% larger than meals eaten at home and 44% larger than meals eaten in other locations (de Castro et al., 1990). A 24-hour dietary recall study with children and adolescents in the US found that meals eaten at restaurants were 55% larger than meals eaten at home, and meals eaten in restaurants contained significantly more calories from fat (Zoumas-Morse, Rock, Sobo, & Neuhouser, 2001). Given increased energy intake at locations outside of the home, it is possible that more bites will be taken during meals eaten outside of the home than meals eaten at home. <u>Research Question 5: Does the location of a meal predict the number of bites recorded during a meal?</u>

Social facilitation. Meals are frequently eaten with other people, and the people that we eat with often reflect our social relationships (Sobal & Nelson, 2003). As the number of people an individual eats with increases, energy intake also increases, a finding often referred to as the social facilitation of food intake (Herman, Roth, & Polivy, 2003). This finding has been supported by 7-day diary studies by de Castro and colleagues that asked individuals to record detailed information about each meal, including the number of people present. de Castro and de Castro (1989) found that meals eaten alone contained about 180 fewer kilocalories than meal eaten with others. Additionally, the overall correlation between number of people and meal size, $r = 0.418$, indicated that 17.5% of the variance in meal size could be explained by the number of people present at the meal (de Castro & de Castro, 1989). This strong positive correlation between number of people and meal size is still present after controlling for time of day, meal location, snacks, and alcohol intake (de Castro, Brewer, Elmore, & Orozco, 1990). Analyses of over 3,800 meals have indicated that meals eaten in large groups are over 75% larger than meals eaten alone (de Castro & Brewer, 1991). Interestingly, it appears that social facilitation is a strong predictor of meal size but not of overall intake for an entire day (de Castro, 1996).

The positive relationship between number of people present at a meal and energy intake has also been supported by a number of studies that manipulate the number of people present at a meal (Redd & de Castro, 1992). For example, when children ate a snack in groups of nine, they consumed 30% more food than when they ate in groups of three (Lumeng & Hillman, 2007). In another study, adults eating with friends ate 18% more than when they ate alone (Hetherington, Anderson, Norton, & Newson, 2006). These experimental studies provide more support for a link between the number of people present at a meal and the amount of food consumed (Redd & de Castro, 1992).

Following from this social facilitation literature, one can assume that eating with more people will result in higher bite counts if bite counts reflect increase energy intake. Additionally, eating with other people involves more talking and gesturing which may trigger additional bite recordings by the bite counter device. <u>Research Question 6: Does the number of people an individual eats with predict the number of bites recorded during a meal?</u>

Day of the week. The day of the week a meal is eaten on is a cultural influence that may impact the amount of food consumed. Weekdays are typically devoted to routine work activities that constrain eating behavior, whereas weekends are reserved for leisure activities or celebrations that are associated with more food intake (e.g., birthday parties, picnics, social gatherings) (Basiotis et al., 1989; de Castro, 1991). Daily diary studies have shown that individuals tend to eat 18-20% more food on weekends than weekdays by eating larger meals (de Castro, 1991; Rhodes, Cleveland, Murayi, & Moshfegh, 2007). If larger meals are eaten on weekends, it follows that more bites may be detected during weekend meals than weekday meals. <u>Research Question 7: Does day of the week predict the number of bites recorded during a meal?</u>

An interaction between day of the week and number of people eating with is also predicted. The positive relationship between number of people and meal size is larger on weekends ($r = 0.4$) than weekdays ($r = 0.3$), indicating that the social facilitation of food intake may depend on the day of the week the meal is consumed (de Castro, 1991). That is, eating with others may not affect bite count as strongly when the social eating is part of the weekly routine (de Castro, 1991). <u>Research Question 8: Does the relationship between number of people an individual eats with and bite count depend on whether it is a weekend or a weekday?</u>

Individual-level Predictors of Bite Count

Gender. On average, males need to consume more calories than females due to their larger body size and greater lean body mass (McArdle, Katch, & Katch, 2005). There are also social pressures for men to eat more than women, with men desiring larger body types and females desiring a more slender figure (Rolls, Fedoroff, & Guthrie, 1991). Laboratory studies have demonstrated that men eat more kilocalories than women during a single meal with the degree of difference varying across studies. For example, in three different studies (Grunberg & Straub, 1992; Pliner et al., 2006; Rolls, Morris, & Roe, 2002) men have been found to eat 30-70% more kilocalories than women. This gender difference has also been found in humans in their natural eating environments. An analysis of a decade of diet diary research has indicated that about 16% of the variance in daily energy intake is due to the gender of the individual (de Castro, 1996). If bites and kilocalories are strongly correlated, one may predict that males will have higher bite counts than females. However, if males take larger bites than women in order to consume more food (Burger et al., 2011), it is possible that a reverse gender effect could be found for bite count. Research Question 9: Does gender predict bite count?

Weight. Individuals with larger body weights require more kilocalories to maintain their body weight (McArdle et al., 2005). Body weight has been found to be more strongly correlated with energy intake than BMI (Periwal & Chow, 2006). This is because two people can have the same BMI, but different heights and weights. For example, Jane is 5’ 3” and weighs 200 pounds; her BMI is 35.4. Greg is 5’ 9” and weighs 240 pounds; his BMI is 35.4. However, Greg is a much larger individual, and thus requires more kilocalories at each meal. If bites serve as a proxy for energy intake, then one may predict that individuals with larger body weights will consume more bites. Alternatively, individuals with larger body weights may take larger bites, resulting in no relationship, or even a negative relationship, between body weight and bites. Research Question 10: Does body weight predict bite count?

Additional Two-Level Model

Our research group has hypothesized that bite count may be a more meaningful measure when aggregated to the day-level compared to the meal-level because this will reduce the variation in bite count produced by bite counter errors that could originate from false detections, undetected bites, or device errors. Therefore, in a second analysis, the meal-level predictors were aggregated to the day-level, and a two-level model with day as level 1 and individual as level 2 were explored in addition to the two-level model with meals at level 1. Bite count for the entire day served as the dependent variable.

CHAPTER TWO

METHODS

Participants

Sample Size

Sample size determination for the statistical power of a MLM analysis must consider the multiple levels: (1) the sample size at level 1 nested within level 2 (*n*); (2) the sample size at level 2 (*N*); and (3) the total sample size (*n* x *N*) (Bosker, Snijders, & Guldemond, 2003). *n* varies from person to person (e.g., one person may have recorded 30 meals, and another person may have recorded 40 meals), but for simplicity, no subscripts will be used for *n* in this description. The goal of the present study, with important predictors at both levels of analysis, was to maximize all three samples to provide enough power for the analysis. As a rule of thumb, Bosker et al. (2003) suggest that *n* should be at least 6 and *N* should be at least 10. A total sample size of 60 is also suggested by Tabachnick and Fidell (2007) when only 5 or fewer parameters are being estimated. Hox (2010) suggests a larger sample size of $n = 30$ and $N = 30$ when most interested in the fixed parameters, and $n = 20$ and $N = 50$ when there is strong interest in cross-level interactions.

The present study operated under both equipment and time constraints. Both of these costs were considered when choosing sample size because decisions of sample size frequently involve decisions about optimal and feasible study design (Hox, 2010). It was assumed that participants would record three meals per day on average. In order to appropriately power the analysis at both levels with samples sizes of at least 30 at each level (Hox, 2010) and to maximize the total sample size, data was collected from a minimum of 80 participants, and each participant recorded bite count, dietary recalls, and additional measures for 2 weeks, which was predicted to provide an average of 42 total meals per person. To check this sample size decision against the ability to detect an expected effect size, the predicted correlation between kilocalories and bites was used. The kilocalorie-bite relationship is the most theoretically meaningful for the bite counter project. In order for the bite counter to be understood and well-accepted by the weight loss community as a measure of energy intake, it should provide a reasonable estimate of the number of kilocalories consumed. Therefore, at minimum, the current analysis should be appropriately powered to detect this effect. Preliminary analyses from free-living humans in our research group suggest a correlation of about 0.7 between kilocalories and bites. We can assume that this correlation will decrease with a larger sample size as more variance is introduced, but we still expect this effect to be large. Following Cohen's guidelines, a large effect size is 0.5 (Cohen et al., 2003). The necessary sample size to detect the relationship between two variables with an expected effect size of 0.5 with an alpha level of 0.5 and a power level of 0.80 is 28 (Cohen, 1992). Therefore, collecting data from at least 28 meals per participant is sufficient for detecting the expected relationship between kilocalories and bites.

A final approach to confirming that the sample size selected for the current study is appropriate is to examine articles that have used MLM analyses with similar numbers of variables entered into the model. If the sample sizes are comparable or smaller than the proposed sample sizes and the model was able to converge, then our sample size is likely to be adequate. For example, Grizzle, Zablah, Brown, Mowen, and Lee (2009) examined predictors of employee customer-oriented behavior and unit profits with a two-level multilevel model. Individuals were ate level 1, and restaurants were at level 2. An average of about 17 employees was nested within each of 38 restaurants, for a total sample size of 671. Six variables and two-cross-level interactions were entered into the model. As another example, Erdogan and Bauer (2010) examined the effects of leader-member exchange on employee outcomes and the moderating role of justice climate. Individuals were at level 1 and stores were at level 2. An average of about 11 respondents was nested within each of 25 stores, for a total sample size of 276. Seven variables and one within-level interaction were entered into the model. The present study had an average of 39 meals with Bite Counter and ASA24 data nested within 83 individuals and a total sample size of 3,246 meals with Bite Counter and ASA24 data. This was much larger than these studies and was sufficient for running the MLM analysis which estimated up to 14 parameters (see Results section for a description of the parameters).

Sample Recruitment and Compensation

Clemson University students and employees were recruited using an e-mail announcement sent to graduate students, an Inside NOW e-mail announcement and flyers hung on announcement boards in campus buildings. Community members were recruited using flyers hung in Fike Recreation Center, community centers, fitness centers, libraries, and coffee shops. Study announcements were put on the Clemson psychology department webpage, the Applied Psychophysiology Lab webpage, and the Bite Technologies Facebook page. All participants received $50 for two weeks of participation, $25 for less than 2 weeks of participation (drop outs), and a free data summary. The data summary included foods, kilocalories, bites, and average kilocalories per bite for each meal reported. The data summary was e-mailed as a Microsoft Excel file to the participant within four weeks after completing the study.

Sample Characteristics

The present study recruited and selected a representative sample of participants based on gender, BMI, and age. Demographic statistics for Clemson University, surrounding counties, South Carolina, and the US were gathered to guide recruitment and selection, and these are described in Table 2.1. Based on these demographic statistics, the present study aimed to recruit about 50% females and 50% males between the ages of 18 and 64 and to represent overweight and obesity trends.

Table 2.1

Demographic statistics used to guide sample recruitment and selection

Location	Gender	BMI	Age
Clemson University	46% female (students) 49% female (employees)[a]	Undergrad: 2-3% underweight, 70-77% normal, and 20-30% overweight/obese[b,c,d]	20[e] = mean age (undergraduates)
Pickens County	50.1% female[f]	29.4% obese in South Carolina[g]	11.8% ages 20-24 13.3% ages 25-34 14.3% ages 35-44 12.4% ages 45-54 4.8% ages 55-59 4.0% ages 60-64[f]
Oconee County	50.8% female[f]	29.4% obese in South Carolina[g]	5.7% ages 20-24 12.8% ages 25-34 14.5% ages 35-44 14.1% ages 45-54 6.4% ages 55-59 5.7% ages 60-64[f]
Anderson County	51.7% female[f]	29.4% obese in South Carolina[g]	5.9% ages 20-24 13.5% ages 25-34 15.5% ages 35-44 14.0% ages 45-54 5.7% ages 55-59 4.6% ages 60-64[f]
United States[g]		68% overweight (includes obese) Males 63.5% overweight ages 20-39 77.8% overweight ages 40-59 78.4% overweight ages 60+ Females 59.5% overweight ages 20-39 66.3% overweight ages 40-59 68.6% overweight ages 60+	

Note. [a]Clemson University Mini Fact Book for 2011 [b]Huang et al., 2003 [c]Lowry et al., 2000 [d]Fishel-Brown, 2010 [e] Clemson University College Portrait (2009) [f]U.S. Census Bureau, 2000 census [g] Centers for Disease Control and Prevention [h]Flegal et al., 2010

Data collection spanned 21 consecutive weeks from October 2011 to February 2012. Ninety-four participants started the study. Eleven participants dropped out of the study (4 females, 7 males), an 11.7% drop-out rate. These participants were not included in any data analyses because they provided no data or because any data provided were of very low quality. Reasons participants dropped out of the study were: not enough time in daily schedule to participate (3), illness (2), non-compliance (2), losing a bite counter (1), getting bite counters wet (1), unable to use ASA24 on computer (1), and not wanting to wear and use the bite counter (1).

Eighty-three participants completed the two-week study (43 females, 40 males, mean (*M*) age = 33.73, standard deviation (*SD*) = 13.02). Demographic characteristics of the sample are provided in Table 2.2.

Table 2.2.

Demographic characteristics of the 83 study participants.

Characteristic	N	% of total sample
Gender		
Male	40	48.2
Female	43	51.8
BMI category[a]		
Underweight (BMI < 18.5)	2	2.4
Normal weight (BMI 18.5-24.9)	38	45.8
Overweight (BMI 25.0-29.9)	23	27.7
Obese (BMI ≥ 30.0)	20	24.1
Ethnicity		
American Indian or Alaska Native	1	1.2
Asian or Pacific Islander	5	6.0
African American	5	6.0
Caucasian	67	80.7
Hispanic	2	2.4
Other[b]	3	3.6
Education level		
High school diploma or equivalent	3	3.6
Some college	17	20.5
Bachelor’s degree	31	37.3
Master’s degree	23	27.7
Doctoral or professional degree	9	10.8
Household income		
$0-30,000	36	43.4
$30,001-60,000	11	13.6
$60,001-100,000	19	22.9
More than $100,000	15	18.1
Handedness		
Right hand	78	94.0
Left hand	5	6.0
Trying to lose weight	35	42.4
Trying to gain weight	3	3.6
Following a certain diet or way of eating[c]	23	27.7

Note. [a]BMI calculated from orientation measured height and weight. [b]Other ethnicities reported were Persian, African-Black, and South Asian. [c]Open-ended responses included eating local, organic, and whole foods; limiting eating out, refined sugars, starches, fats, fried foods, carbs, junk food, sodium, snacking; eating “healthier”; diets including Weight Watchers, Type I diabetes , Type B blood type, figure competitor, yogi, and macrobiotic; counting calories; eating smaller meals and using smaller plates; following vegetarian practices (including lacto, lacto-ovo, and pescetarian); increasing fiber, fruits, vegetables, lean protein/seafood; and eating complex carbs, fats, and protein in every meal.

Materials

Bite Counters

Bite counters were 1400 through 1700 series devices from Bite Technologies (see Figure 1.6). Each device series used the same equipment and design, with improvements made over time to increase the daily battery life. The device was a 2.5 x 1.5 inch (64 x 38 mm) plastic rectangle that was 1 inch (25 mm) thick and weighed 2.7 oz (75 grams). A 1 inch (25 mm) wide, 6.5 - 8.5 inches (165 - 216 mm) long wrist band was attached to the device. The battery in the device ideally allowed for 14 hours of bite counting use per charge (approximately 2 weeks of regular use). It took 3 hours to fully recharge the battery. The bite counter stored data for up to 320 eating sessions. A USB connection was used for downloading data and recharging.

These bite counters operated as a typical watch when not in use as a bite counter. Prior to each eating session, the user pressed a single button on the device to put the device in bite counting mode. At the end of each eating session, the user again pressed the button to turn the device off.

Downloaded bite counter data provided a year, month, day, and time stamp for each meal recorded, the meal duration, and the number of bites recorded at each meal. The number of bites per meal recorded by the device was the main dependent variable for the present study. Meal duration recorded by the bite counter served as a main independent variable. Meal duration also allowed for the exploration of eating rate (average bites/minute or average kcal/minute) as a predictor of bite count.

ASA24 Dietary Recall

Dietary recalls were completed using the Automated Self-Administered 24-hour Recall (ASA24; National Cancer Institute, 2011). ASA24 is an Internet-based software tool that allows participants to complete 24-hour dietary recalls from a computer without the presence of a researcher. ASA24 is based on a modified version of the interviewer-administered Automated Multiple Pass Method (AMPM) 24-hour recall developed by the U.S. Department of Agriculture (USDA) and used in the U.S. National Health and Nutrition Examination Survey (NHANES). Food codes, portion sizes, and nutrient data in ASA24 originate from version 4.1 of the USDA's Food and Nutrient Database for Dietary Studies (FNDDS), and portion size photographs have been provided by Baylor College of Medicine (Zimmerman et al., 2009). Version 1 of ASA24 became available in September 2011 and is available free of charge to researchers. A demo version of ASA24 can be found here: http://asa24demo.westat.com/

The ASA24 interview process has five steps: (1) Meal-based Quick List, (2) Meal Gap Review, (3) Detail Pass, (4) Final Review, and (5) Forgotten Foods. During the first step, the Meal-based Quick List, participants were asked to select an eating occasion (breakfast, brunch, lunch, dinner, supper, snack, or just a drink), specify the time and location of the meal, indicate if a TV and/or computer was used during the meal, and indicate if the meal was eaten alone or with others (Figure 2.1). Then the participants added the main foods and drinks for each meal to the Quick List (Figure 2.2). In the second step, the Meal Gap Review, participants were asked if they consumed anything during all gaps between eating occasions that exceeded three hours (Figure 2.3). If the participants responded yes, they returned to the Quick List to add the food and/or drink. In the third step, the Detail Pass, participants were asked to provide details for the foods and drinks recorded in the Quick List, including the amount eaten and anything added to the main foods (Figure 2.4 and Figure 2.5). During the Final Review, participants were asked to review all foods, drinks, and details and to make edits if appropriate (Figure 2.6). Next, participants were asked if they consumed any commonly forgotten foods or drinks, questions to which they must have responded yes or no (Figure 2.7). If they responded yes, they returned to the Quick List to add the foods or drinks. Before finishing, the "Last Chance" option was provided for additions or changes to be made. The Last Chance question was followed by a Trailer Question that asked the participants to report if the amount of food consumed was more than usual, usual, or much less than usual.

A number of features make the ASA24 program unique and comprehensive, including a tutorial on how to complete the recall, an animated audible character to guide participants through the interview (a penguin), "Show Me" video clips for major sections, allowing participants to find foods by browsing through defined food groups or by searching for keyed text, using photographs to assist participants in reporting portion size, a module to asses who a participant was eating with, and a module to assess where a meal was consumed.

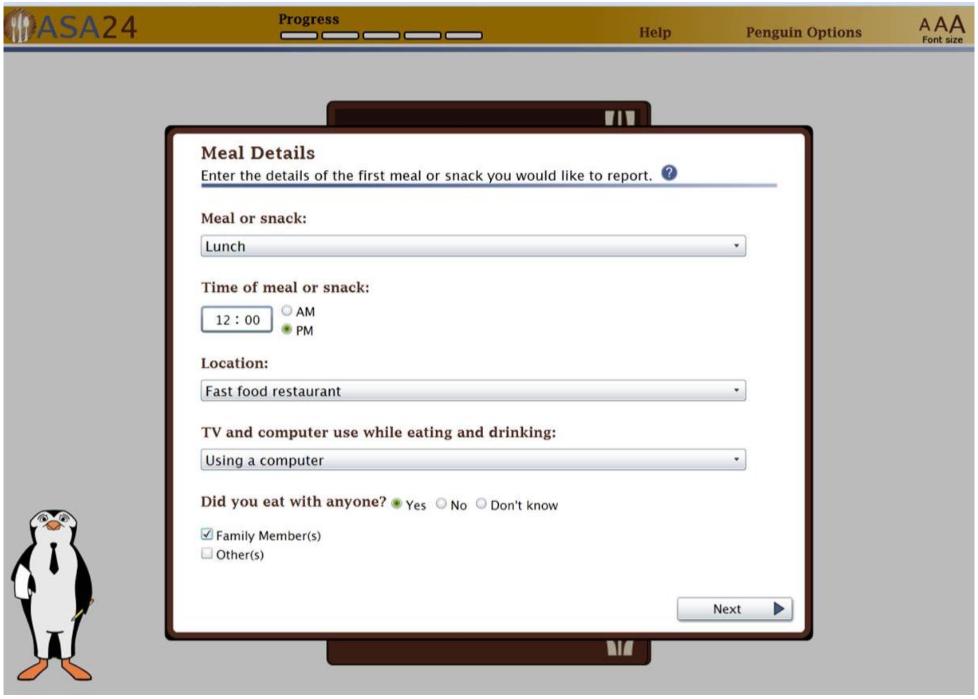


Figure 2.1. Selecting a meal, time, location, computer and/or TV use, and who the meal was eaten with.

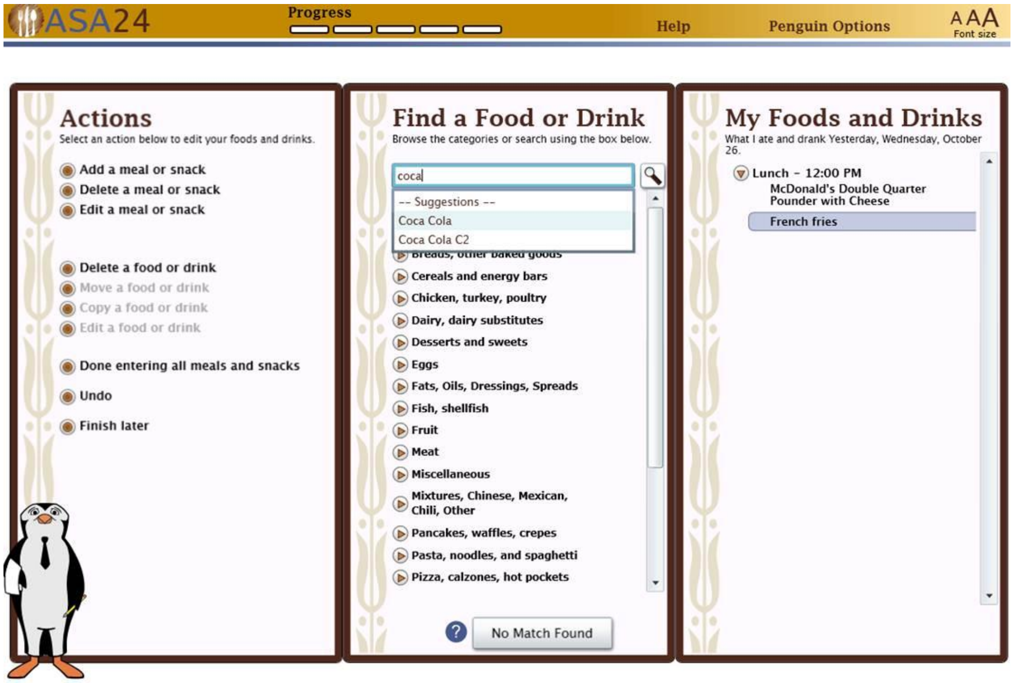


Figure 2.2. Adding foods and drinks to the Quick List for lunch.

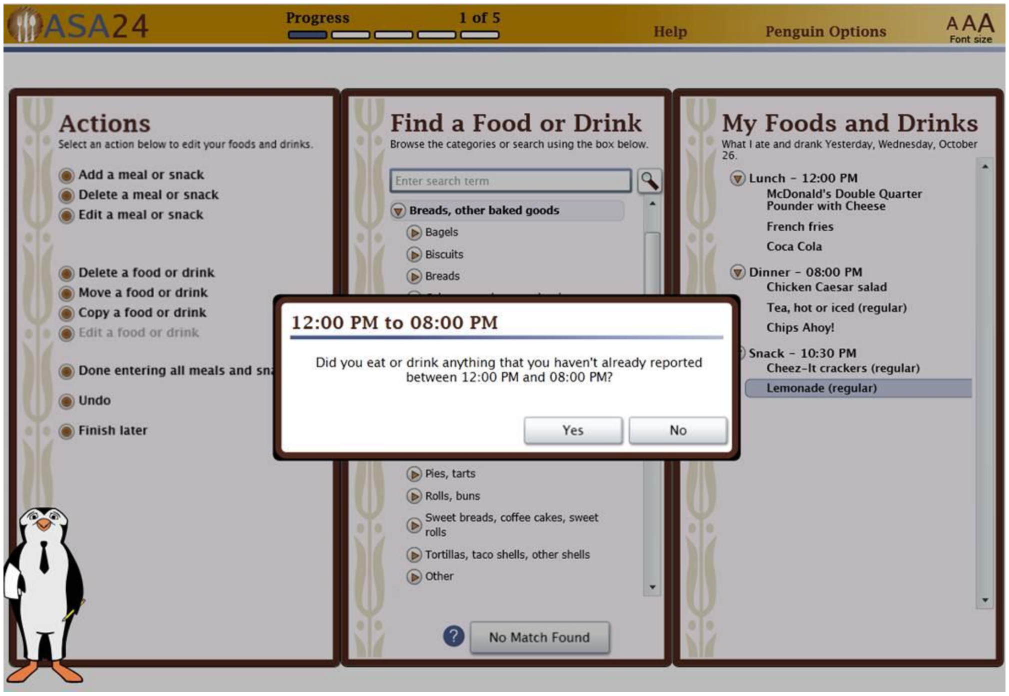


Figure 2.3. Meal Gap Review between lunch and dinner.

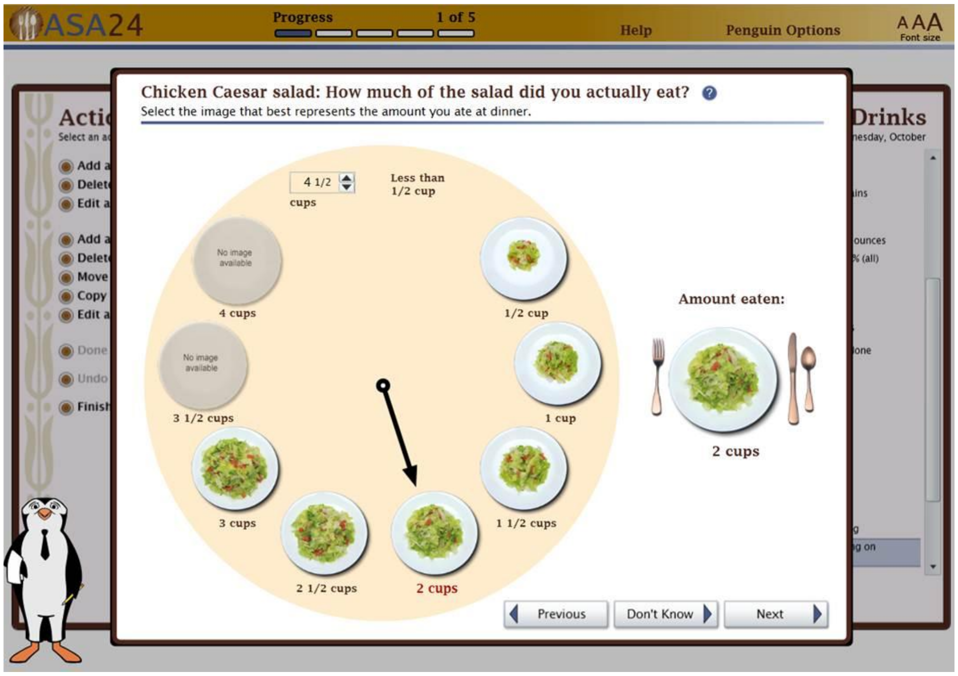


Figure 2.4. Portion size question for salad during the Detail Pass.

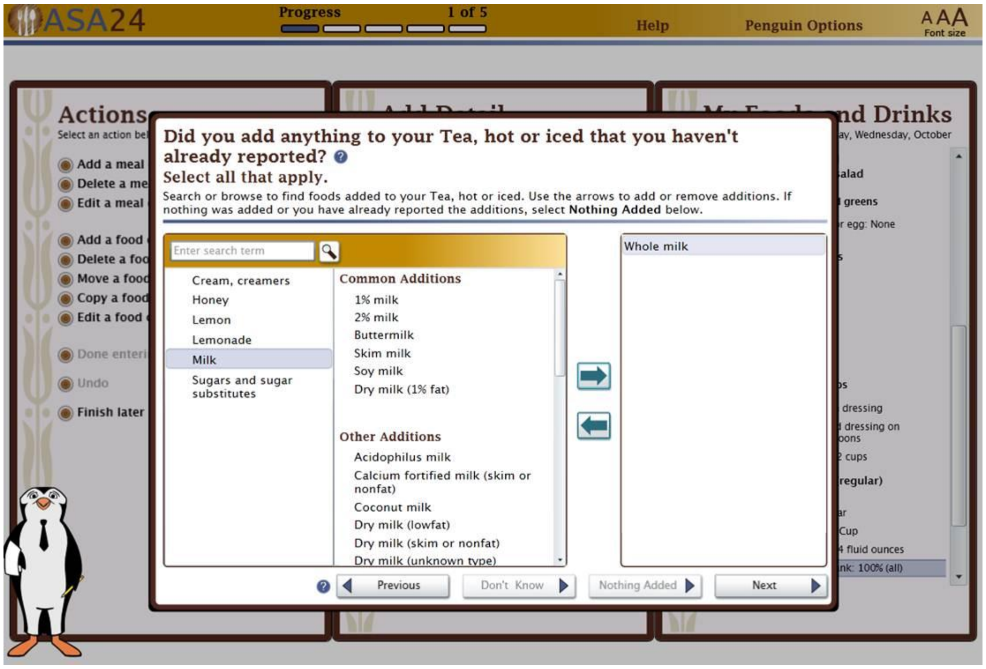


Figure 2.5. Adding milk to tea during the Detail Pass.

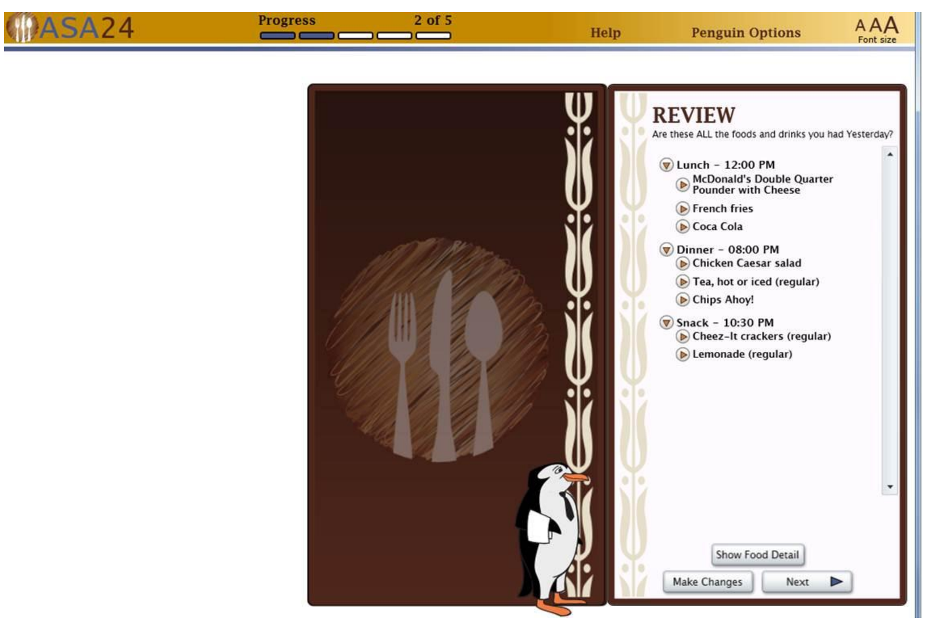


Figure 2.6. Final review of foods, drinks, and details.

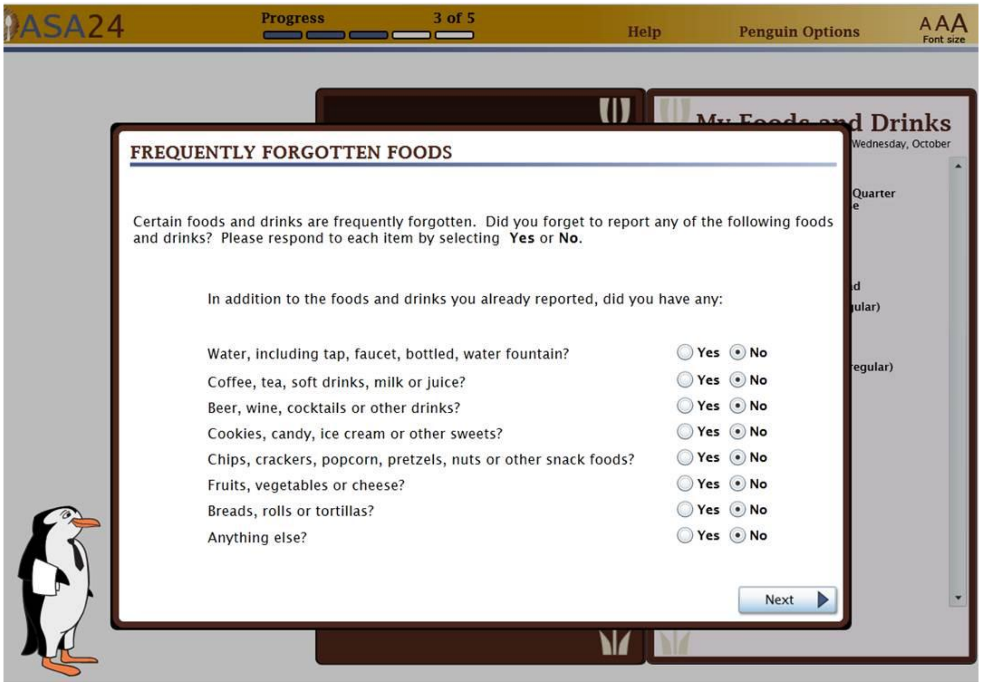


Figure 2.7. Forgotten foods prompt.

Different methods of dietary assessment have been thoroughly reviewed by Thompson and Subar (2008) who have identified a number of advantages of 24-hour dietary recalls. The immediacy of the recall period helps participants to recall most of their intake. Additionally, in comparison to keeping food records, participants find 24-hour recalls less burdensome. This reduces selection bias and allows for a more representative sample. Also, dietary recalls occur after the food has been consumed which reduces the chance of the assessment method interfering with food and drink selection and consumption. The main weakness of the 24-hour dietary recall is that participants may not report their intake accurately due to problems with knowledge or memory. Thompson and Subar's (2008) review of the literature indicates that underreporting of energy using 24-hour dietary recalls ranges from 3% to 26% with underreporting affecting up to 15% of all recalls.

However, the interviewer prompts and multiple pass approach of the AMPM 24-hour recall are designed to reduce underreporting (Thompson & Subar, 2008). In a controlled study of adult men, AMPM dietary recall accurately estimated energy intake regardless of BMI (Conway, Ingwersen, & Moshfegh, 2004). In a controlled study of adult women, AMPM dietary recall resulted in overestimation of energy intake by 8-10%, and there were no energy recall differences between normal and obese women (Conway, Ingwersen, Vinyard, & Moshfegh, 2003). The AMPM was also found to accurately reflect total energy intake in free-living humans, with underreporting of energy intake increasing for those with greater BMIs (Moshfegh et al., 2008). In addition, the AMPM has been shown to provide a more valid measure of total energy intake compared to other energy intake measures, such as the Block food-frequency questionnaire and National Cancer Institute's Diet History Questionnaire (Blanton, Moshfegh, Baer, & Kretsch, 2006).

Drawbacks to the AMPM recall are the costs associated with training interviewers and the impracticality of interviewers administering recalls in person or over the telephone in a large sample study (Subar et al., 2007). The ASA24 dietary recall addresses these problems by allowing participants to complete recalls unassisted at any time during a recall day using an Internet-based recall program. The majority of ASA24 development has been guided by experts in the field of dietary assessment (Zimmerman et al., 2009). Some studies with users of the ASA24 system have also guided software development. A pilot study of the Quick List indicated that participants preferred recalling by meal (e.g., breakfast, lunch) rather than recalling all foods for one day together (Subar et al., 2007). Additionally, this pilot study indicated that the act of scrolling through food lists helped to trigger memories of foods and beverages eaten, an advantage over the AMPM interview method. Another study that manipulated presentation of the serving size photographs found that eight photographs allow for more accurate estimations than four photographs, and participants preferred seeing all serving size options at once rather than sequentially (Subar et al., 2010).

Overall, the ASA24 dietary recall was selected for use in the proposed study because it is based on a well-validated intake measure (the AMPM recall) that results in accurate energy intake reports, and because it will allow for inexpensive and practical 24-hour dietary recalls from a large sample. The 24-hour recall is considered the best self-report instrument available for estimating dietary intake, and we can assume that the measure is unbiased across persons (Kirkpatrick, 2011). For the present study, the ASA24 recall data provided the number of kilocalories consumed at each meal, the average energy density of each meal, the date and time of the meal, the meal location, and whether the meal was consumed alone or with others.

Body Measurements

Tanita WB-3000 Digital Beam Scale. Body weight, height, and BMI were measured using the Tanita WB-3000 Digital Beam Scale (Tanita Corp., Arlington Heights, IL).

Omrom Body Logic Body Fat Analyzer. Body fat percentage was measured using the Omrom Body Logic Body Fat Analyzer (Omron Corp., Kyoto, Japan). This hand-held device analyzes the impedance of a small electrical current flowing between two electrical plates on the palms of the hands (McArdle et al. 2005). The current passes more quickly through hydrated fat-free body tissue and extracellular water than fat or bone tissues (McArdle et al., 2005). Impedance is entered into an equation with height, weight, age, and sex, and body fat percentage is estimated (Gibson, Heyward, & Mermier, 2000). The Omrom Body Logic Body Fat Analyzer provides an accurate estimate of body fat percentage ± 3.5% for approximately 7 out of every 10 men and 2 out of every 3 women when compared to hydrostatic weighing (Gibson et al., 2000). Additionally, the Omron Body Logic Fat Analyzer is a noninvasive and economical way to measure body fat percentage.

MyoTape™ Tape Measure. The MyoTape™ (Accu-Measure, Greenwood Village, CO) was used to measure waist and hip circumference. To measure waist circumference, the tape measure was wrapped around the smallest circumference around the abdomen. The tape measure was adjusted snugly without causing compressions on the skin. To measure hip circumference, the tape measure was wrapped around the biggest circumference around the buttocks.

Questionnaires

All questionnaires were administered electronically using Survey Monkey (Survey Monkey, Palo Alto, CA).

Demographics. A demographics questionnaire (Appendix A) asked participants to report a number of variables, including age, gender, ethnicity, handedness, education level, eating disorder history, and frequency of computer use.

Dietary restraint. Cognitive restraint, emotional eating, and uncontrolled eating were measured using the Three-Factor Eating Questionnaire R-18 (TFEQ R-18; Appendix B) (de Lauzon et al., 2004).

Daily meals questionnaire. Additional features of the meal not described by the bite counter data or the ASA24 data were obtained with an additional survey (Appendix C). The survey asked participants to report their bite counter usage and technical problems, additional activities they engaged in while the bite counter on, the utensils used, hunger, fullness, palatability, the number of people they ate with for each meal, and who prepared the meal. The survey also asked participants to estimate their daily physical activity.

Usability. Participants completed a usability questionnaire during their last visit to the laboratory on Survey Monkey (Appendix D). This questionnaire assessed problems, difficulties, likes, dislikes, and preferences for the ASA24 dietary recall and the bite counter.

Procedure

Pre-screening

The procedures for online pre-screening are described in Appendix E. When the participant contacted the researcher to participate in the study, the researcher sent the participant a link to complete an online consent form, the demographics questionnaire, and the TFEQ-R18 on Survey Monkey. Participants with a history of an eating disorder were excluded from the study, as using the bite counter and completing dietary recalls increases awareness of eating behavior. Participants with incomplete survey responses were also excluded (for example, skipping the last page of the survey). Participants were also excluded from the study if they did not have daily access to an Internet-connected computer with at least a 10 inch screen and the ability to install Microsoft Silverlight; this was necessary for completion of the dietary recalls. Eligible participants were added to a waiting list if no bite counters were available. Participants selected for the study were contacted by the researcher to attend an individual orientation meeting.

Orientation Meeting

The protocol for the Orientation meeting is described in detail in Appendix F. Upon arrival at the meeting, the participant read and signed a Clemson University IRB approved written consent form (see Appendix G). The experimenter stated that the purpose of the study was to investigate how well a new device, the bite counter, was able to estimate energy intake during a meal. The experimenter emphasized the importance of compliance with daily bite counter use and dietary recalls and confirmed that the participant would be able to complete these tasks for two weeks. Then the experimenter measured the participant’s height, weight, body fat percentage, hip circumference, and waist circumference.

The participant was given a bite counter and told how to wear the bite counter during the day, how to record bites during a meal, and how to charge the bite counter. The written instructions in Appendix H were reviewed in person and provided in a folder for the participant to take home. The experimenter instructed the participant to record all meals and snacks. However, if a meal or snack was going to last for a very long time (such as drinking coffee and nibbling on candy for over an hour at one's desk at work, or drinking a glass of wine in the evening while making dinner), the participant was told not record this intake because it would be too difficult to define a meal end time.

The participant was given a username and password for the ASA24 system. The participant completed a demonstration of the ASA24 program by entering two meals from their previous day. The experimenter was available for guidance and to answer questions. The participant was also shown how to complete the daily meals questionnaire on Survey Monkey. The participant was instructed to complete this questionnaire during the ASA24 Final Review so that meal details could be matched with the ASA24 entries. The participant received basic written instructions for completing the ASA24 program and the daily meals questionnaire (see Appendix I). The participant was also given a 50 page spiral notebook (3" x 5") to make notes about meal times and foods. Using this notebook was optional, and participants were encouraged to use other methods for taking notes if more convenient, such as on their mobile phone or personal computer.

The first day of data collection with the bite counter (typically the day after the orientation meeting) was scheduled. The participant was asked for their preferred e-mail address for daily reminders and their preferred e-mail delivery time. The data download meeting and the final meeting and meal were scheduled, and an appointment sheet was provided with dates, times, and meeting instructions (see Appendix J).

Data Collection

During the two week data collection period, the participant was instructed to wear the bite counter for the entire waking day, except when exercising, swimming, or showering. They were instructed to record bites using the bite counter for every meal and snack they consumed during the day that consisted of foods and/or beverages, excluding meals for which an ending time would be far in the future (greater than one hour) and difficult to define. Participants completed dietary recalls and surveys the day after a midnight to midnight period. For example, a participant completed a dietary recall on Wednesday, October 26, anytime from 12:00am-11:59pm, for the food and beverages consumed on Tuesday, October 25. Participants received an automated e-mail message at their preferred time reminding them to complete the recall and the survey. This reminder included links to the ASA24 recall system and the Survey Monkey survey. The participant was encouraged to contact the researcher via e-mail or telephone anytime they experienced any technical difficulties or had questions.

Data download meeting. The protocol for this 15 minute meeting is described in detail in Appendix K. After about 7 days of data collection, the participant came to the laboratory for data downloading and bite counter reset. If minor bite counter problems were seen in the data (typically trouble getting the bite counter to stay on, which looked like a series of zero or one bites followed by a full recording), the experimenter reviewed the correct way to turn the bite counter on and off with the participant and provided recommendations for getting the bite counter to stay on. These recommendations included charging the device overnight every night, not wearing the device too tightly on the wrist, and waiting an additional 10 seconds after the device said on to begin moving the wrist. If severe bite counter problems were detected (many zero and one bite sessions with few full recordings), the experimenter gave a new bite counter and charger to the participant to use for the remaining week. The experimenter also gave the recommendations described above for minor problems because the data errors could have been due to device failure, user error, or a combination of the two. In both cases, the experimenter also ran the device "test mode" to check that the sensor was operational and to check the battery level. If a low battery level was detected, this guided the experimenter's troubleshooting and participant instructions.

Final meeting and meal. The protocol for the final meeting and meal are described in detail in Appendix L. After 14 days of data collection, the participant returned to the laboratory to return the bite counter and complete the Usability Questionnaire on Survey Monkey. Weight, body fat percentage, waist circumference, and hip circumference were measured again.

In addition, the participant ate a meal in the laboratory in order to measure average bite size. The participant ate Amy's brand macaroni and cheese. This meal was selected because it is easy to prepare in the laboratory, is acceptable for either lunch or dinner, and is amorphous and thus can be eaten in different sized bites. Amy's brand received the highest taste ratings when compared to nine other commercially available macaroni and cheese varieties by three research assistants. A soy cheese variety was available for vegans, and a rice pasta variety was available for those allergic to gluten.

The participant was seated at the laboratory eating station set with a fork, napkin, plate, macaroni and cheese on top of the plate in its original container, and a glass of 500 mL of water. An Ohaus Scout Pro Balance SP4001 (Ohaus Corp., Pine Brook, NJ) with an RS232 interface was concealed under a tablecloth and sampled the weight of the meal every three seconds. Data was collected using TAL WinWedge RS232 data acquisition software (TAL Technologies, Inc., Philadelphia, PA) which imported real-time data into Microsoft Excel. The participant wore an InteriaCube3 (InterSense, Inc., Bedford, MD) on their dominant wrist, with a bite counter above their wrist on the lower part of the forearm. The meal was video recorded. Participants were instructed to eat normally and to stop eating when they felt full or when all of the food had been eaten. Satiety before and after the meal was measured using the Satiety Labeled Intensity Magnitude (SLIM) scale (Cardello, Schutz, Lesher, & Merrill, 2005; Appendix M). Liking or disliking the meal was measured after the meal using the Labeled Affective Magnitude (LAM) scale (Schutz & Cardello, 2001; Appendix N). At the conclusion of this laboratory session, the participant was debriefed and received the $50 incentive for participation.

Statistical Analyses

Data Merging and Error Screening

Data was prepared for statistical analysis using Microsoft Excel. Each participant's data was merged and screened for errors individually. The steps for merging the data from three sources (bite counter data files, ASA24 Individual Food and Nutrient (INF) data file, and Survey Monkey daily meals questionnaire data files) are outlined in Appendix O. Date and time were the primary indicators used to merge the data sets. After the data was merged, it was screened for errors using the steps outlined in Appendix O. Errors originated from the bite counter (device failure or user error) and the ASA24 recall (missing data, incomplete data, database error, pathway of questions error, or user entry error). Errors were either corrected or removed from the dataset. A flowchart describing the decision-making process for bite counter data error identification, correction, and removal is shown in Figure 2.8. A flowchart describing the decision-making process for ASA24 data error identification, correction, and removal is shown in Figure 2.9. The red parallelograms at the top of each figure refer to the possible errors that could be flagged when following the screening steps in Appendix O.

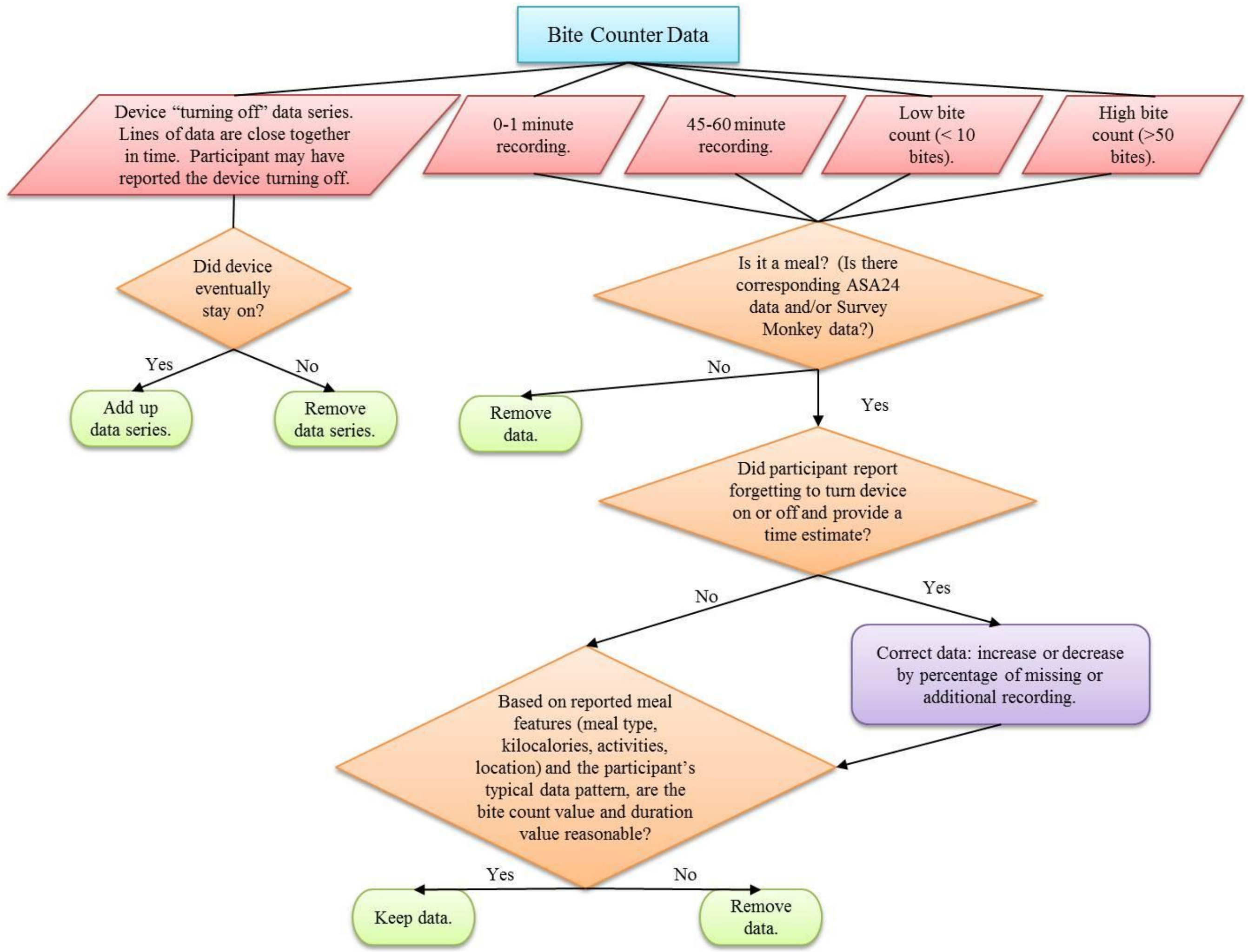


Figure 2.8. Bite counter data decision-making process for error identification, correction, and removal.

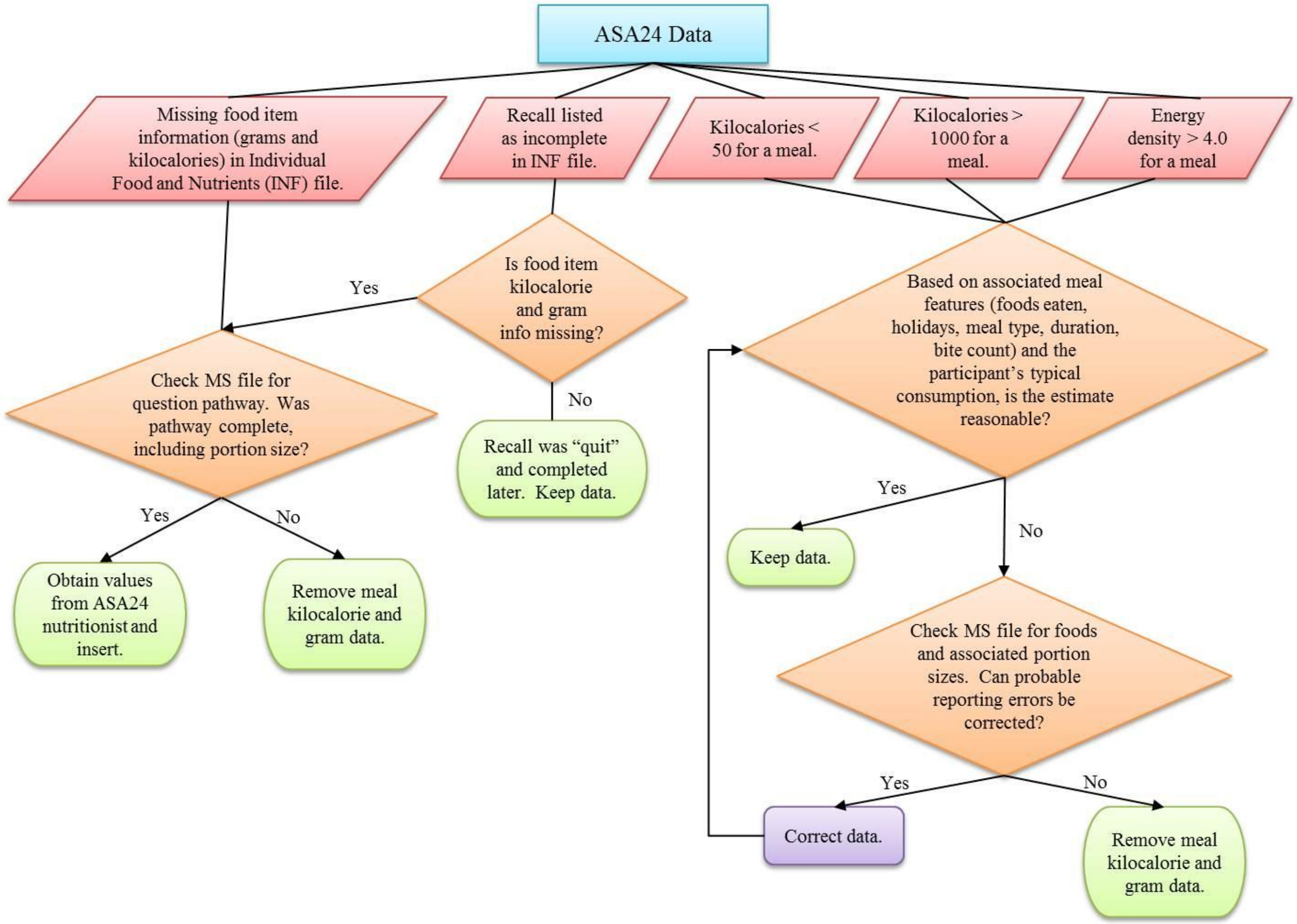


Figure 2.9. ASA24 data decision-making process for error identification, correction, and removal.

In order to demonstrate the decision-making process for error identification, correction, and removal, a number of examples are provided. Starting with the bite counter data, a "turning off" data series was a frequent error identified in the raw bite counter data. For example, participant BiteCD012 had a small snack of 108 kcal of Captain Crunch cereal reported at 11:07PM on November 20th. When this was matched with the bite counter data, three lines of data were found at that time: meals 97, 98, and 99. As can be seen in Figure 2.10, these three lines of data were short duration recordings (25, 7, and 58 seconds), and the bite count values were low (2, 0, and 3 bites). These three meals were summed up for a total of 5 bites and duration of 1 minute 30 seconds. Based on the low calorie snack description, this summed up data appeared to be reasonable and was retained as corrected data.

MealID	Start	Duration	Bites	Year	M	D	Time	Duration	What was	What time	Did you w	Did y
88	3.72E+08	1507	86	2011	11	20	11:34:39	25:07:00	Lunch	1:03 PM	Yes	Yes
91	3.72E+08	347	18	2011	11	20	15:40:02	5:47	Snack	4:00 PM	Yes	Yes
92	3.72E+08	685	26	2011	11	20	15:46:11	11:25				
93	3.72E+08	169	12	2011	11	20	17:02:51	2:49	Snack	5:00 PM	Yes	Yes
94	3.72E+08	1206	71	2011	11	20	18:21:37	20:06	Dinner	6:25 PM	Yes	Yes
95	3.72E+08	236	17	2011	11	20	21:27:08	3:56	Snack	9:34 PM	Yes	Yes
96	3.72E+08	25	2	2011	11	20	23:04:20	0:25	Snack	11:07 PM	Yes	Yes
97	3.72E+08	7	0	2011	11	20	23:04:52	0:07	sum up			
98	3.72E+08	58	3	2011	11	20	23:05:10	0:58	sum up			
99	3.72E+08	849	29	2011	11	21	8:51:36	14:09	Breakfast	8:52 AM	Yes	Yes
100	3.72E+08	127	4	2011	11	21	10:36:22	2:07	Snack	10:38 AM	Yes	Yes
101	3.72E+08	561	28	2011	11	21	12:25:10	9:21	Lunch	12:44 PM	Yes	Yes
102	3.72E+08	472	19	2011	11	21	13:53:25	7:52	Snack	2:02 PM	Yes	Yes
103	3.72E+08	706	38	2011	11	21	16:02:01	11:46	Snack	4:04 PM	Yes	Yes

Figure 2.10. Example of a "turning off" bite counter data series.

Examining the duration of the bite counter recordings and the participant's daily meals questionnaire allowed for the detection of possible meal duration errors. For example, participant BiteCD003's meal 26 originally had a 35 minute duration, one of the longest meals for this participant. This meal was associated with 1,111 kcal of bread, hummus, potatoes, chicken, and coffee consumed at lunch, and 112 bites were recorded at this meal. However, the participant reported leaving the device on for an extra 15 minutes, or 43% of the recorded meal. Thus, 15 minutes were removed from the bite counter recording, resulting in a total duration of 20 minutes, and bite count was reduced by 43% for a total bite count of 64. When compared to the existing duration and bite count values, this adjusted data appeared to match the data set, as can be seen in Figure 2.11. Thus, the decision was made to keep the data in its corrected form.

MealID	Start	Duration	Bites	Year	M	D	Time	Duration	What was	What time
44	3.7E+08	685	50	2011	11	4	19:57:36	11:25	Dinner	8:00 PM
47	3.7E+08	718	10	2011	11	5	14:36:05	11:58	Snack	2:36 PM
14	3.7E+08	729	35	2011	10	28	20:24:13	12:09	Snack	8:30 PM
12	3.7E+08	785	33	2011	10	28	10:22:39	13:05	Breakfast	10:15 AM
51	3.7E+08	811	20	2011	11	6	12:47:27	13:31	Snack	12:47 PM
21	3.7E+08	897	17	2011	10	30	15:40:03	14:57	missing data	
37	3.7E+08	924	22	2011	11	3	10:16:12	15:24	Breakfast	10:15 AM
64	3.7E+08	982	25	2011	11	8	19:10:46	16:22	Snack	7:10 PM
46	3.7E+08	1041	61	2011	11	5	13:42:10	17:21	Lunch	1:42 PM
58	3.7E+08	1120	80	2011	11	7	22:41:23	18:40	Dinner	10:41 PM
63	3.7E+08	1179	37	2011	11	8	15:09:25	19:39		
26	3.7E+08	1200	64	2011	10	31	12:42:34	20:00	Lunch	12:42 PM
50	3.7E+08	1302	91	2011	11	5	23:45:18	21:42	Dinner	10:45 PM
56	3.7E+08	1343	40	2011	11	7	16:46:29	22:23	Just a drin	4:46 PM
36	3.7E+08	1348	96	2011	11	2	22:25:42	22:28	Dinner	10:25 PM
17	3.7E+08	1439	98	2011	10	29	23:21:31	23:59	Dinner	11:20 PM
53	3.7E+08	1460	72	2011	11	6	23:00:54	24:20	Dinner	11:00 PM

Figure 2.11. Example of bite counter data with corrected duration and bite count, sorted by meal duration.

Examining the number of bites recorded also allowed for detection of possible errors. For example, participant BiteCD051 had a recording of 8 bites for meal 4. The associated meal data was then examined to see if the bite count value was reasonable. This meal was a breakfast of 250.8 kcal of white bread that lasted 3 minutes and 30 seconds. In Figure 2.12, it can be seen that this participant had a number of shorter meals with similar kcal and/or bite values. Based on all of this associated information, it was decided that this data was most likely correct, and the meal was retained.

MealID	Bites	Year	M	D	Time	Duration	What was	MealKCAL	Food_Description		
31	5	2011	10	12	11:24:53 AM	1:37	Snack	99.28	Cookie, brownie, fat free, without icing		
24	6	2011	10	10	12:34:41 PM	1:32	Snack	94.64	Apple, raw		
45	7	2011	10	17	2:50:46 PM	6:40	Missing su	77.48	Apple, raw		
4	8	2011	10	5	9:51:15	3:30	Breakfast	250.8	Bread, white, made from home recipe or purcha		
30	9	2011	10	12	7:38:35	1:59	Breakfast	215.3905	Cheese, c	Bread, pit	Milk, cow's, fluid, 1% fat
13	11	2011	10	7	7:57:25	2:44	Missing survey data				
17	11	2011	10	8	12:32:49 PM	3:01	Just a drin	138.348	Milk, cow's, fluid, 1% fat		
29	11	2011	10	11	6:26:52 PM	5:02	Snack	94.64	Apple, raw		
32	12	2011	10	12	3:53:41 PM	10:22	Snack	77.48	Apple, raw		
1	13	2011	10	4	10:06:04 AM	2:49	Breakfast	107.2014	Cheese sp	Bread, pita, wheat or cracked wheat	
5	13	2011	10	5	10:11:35 AM	3:12	Snack	58.5	Peach, raw		
9	13	2011	10	5	10:35:28 PM	4:58	Snack	5.74	Carrots, raw		
6	16	2011	10	5	12:19:54 PM	3:31	Snack	121.365	Pudding, canned, chocolate, fat free		

Figure 2.12. Example of screening for a low bite count error with data sorted by bite count.

Possible ASA24 program, database, and reporting errors were identified by screening the data file for abnormal values. For example, when participant BiteCD014's data was sorted by total meal kcal, a snack of 37 kcal of Ovaltine® powder was found with an associated bite count of 20 and duration of 5 minutes 33 seconds. This meal, number 8, can be seen in Figure 2.13. Typically, Ovaltine powder would be reconstituted with a liquid, such as milk, but no reconstituting liquid was reported. This was judged to be an error in either participant reporting or the ASA24 program, and the meal kcal data was removed from the data set.

MealID	Duration	Bites	Duration	What was	What time	MealKCAL	FoodComp	Food_Description
8	333	20	5:33	Snack	9:50 PM	37.344	1	Milk, malted, dry mix, fortified, r
11	362	26	6:02	Snack	10:56 AM	46.995	1	Chicken noodle soup
63	112	7	1:52	Snack	12:25 PM	52.095	1	Grapes, raw, NS as to type
13	174	7	2:54	Snack	4:47 PM	77.48	1	Apple, raw
34	368	20	6:08	Snack	10:52 AM	77.48	1	Apple, raw

Figure 2.13. Example of a low kcal value that was removed from the data set sorted by kcal values.

Additional errors identified in the ASA24 data were large kcal values that stemmed from food entry errors or ASA24 program errors. When participant BiteCD056's data was sorted by meal kcal, a large meal of 1678 kcal was found, the largest meal for this participant. Inspection of the food kcal values, as shown in Figure 2.14, indicated that 1269 of the kcal came from a report of two cups of whole dry milk. This participant frequently reported drinking whole milk, but not dry milk. Additionally, two cups of dried milk was judged to be an excessive amount to consume at one meal, so it was assumed that the participant reported this food incorrectly. Therefore, the values were converted to two cups of whole milk (296 kcal), and the meal was reduced to 705 kcal.

IntakeDay	Occ_No	Occ_Time	MealFood	FoodAmt	MealKCAL	KCAL	FoodComp	Food_Description
2	3	6:00 PM	421.516	52	1678.27	138.32	1	Bread, wheat or cracked wheat
2	3	6:00 PM		76		219.64	1	Chicken patty, fillet, or tenders, breaded, cooked
2	3	6:00 PM		32.125		27.9488	1	Tomato sauce
2	3	6:00 PM		1.19119		6.34904	1	Margarine-like spread, tub, salted
2	3	6:00 PM		256		1269.76	1	Milk, dry, whole, not reconstituted
2	3	6:00 PM		4.2		16.254	1	Sugar, white, granulated or lump

Figure 2.14. Example of an error in ASA24 that inflated the kcal value for a food.

Another error found in the ASA24 data files were missing values for kcals and grams. If the missing values were missing because the participant failed to report all food details or because the pathway of questions failed to prompt the participant, these meals then had missing kcal and gram values. However, in one instance, the missing food was the result of a database writing error for apple juice. Although the participants reported apple juice type and amount consumed (found in the My Selection file), these drinks showed up as a missing value (in the Individual Foods and Nutrients file). Upon request from the author, the ASA24 nutritionist provided information that could be used to replace missing values: one ounce of apple juice was equal to 31 grams and 14.26 kcals. Multiplying the amount reported by the participant resulted in amounts that could replace missing values. For example, if a participant reported drinking 100% of a 12 oz. glass of apple juice, then 372 grams and 171.12 kcals of apple juice were inserted to replace the missing values.

Multilevel Linear Modeling Analysis

Data were analyzed using IBM SPSS Statistics 19. Data were cleaned using the guidelines provided by Tabachnick & Fidell (2007) for cleaning grouped data. The MLM analysis began with an intercepts-only model (null model) without predictors to determine if MLM was appropriate (Heck, Thomas, & Tabata, 2010; Hox, 2010). The amount of dependence on the individual was calculated as the intraclass correlation

(ICC1), with values of 0.05 or greater indicating that significant nesting is present (Heck, Thomas, & Tabata, 2010).

Then the predictor variables were transformed with centering to improve interpretation of the intercept values (Hox, 2010). In the present MLM analysis, the intercept was the expected value of bites when the predictors had a value of zero. The problem with this is that zero was originally not meaningful (e.g., the expected value for bites when kilocalories were zero). Therefore, the predictors were grand-mean centered, which resulted in the zero point for each predictor representing the mean for that predictor (Hox, 2010). Thus, the intercept indicated the expected value of bites when the predictors were at their means (for example, the expected value for bites when kilocalories were at the mean). Grand-mean centering was also chosen for the present analysis because it allowed for comparison of parameter estimates across models with predictors at both level-1 and level-2, and it substantially reduced collinearity of interaction terms (Bickel, 2007; Hofmann & Gavin, 1998; Hox, 2010).

The research questions for the proposed study were tested with nested models using a bottom-up (hierarchical) approach (Hox, 2010). That is, parameters were entered into the model one at a time, and their unique contribution to the model was assessed. If predictors did not improve model fit, explain bite variance, or have significant fixed coefficients, they were dropped from subsequent models.

After running the intercept-only model as described above, level-1 variables were entered into the model as fixed effects one at a time. After each level-1 variable was added, the level-1 interactions were added. Model fit was compared using the -2 log likelihood χ^2 deviance difference test with degrees of freedom as the number of added parameters (Hox, 2010). If the χ^2 difference between two models was above the critical value for the associated number of degrees of freedom, this was evidence of improved model fit. The change in residual variance as level-1 variables were added to the model indicated the unique amount of within-participants variance explained by each predictor. The fixed coefficient for each predictor was examined for significance using its associated *t*-test.

Then level-2 variables were entered into the model as fixed effects one at a time. In addition to examining the χ^2 deviance difference test and the significance of the fixed coefficient, the change in intercept variance indicated the unique amount of between-participants variance explained by each level-2 predictor. Next, the slopes between level-1 predictors and Bites were allowed to vary one at a time, and random slope variance that significantly improved model fit and was significantly greater than would be expected by chance, as assessed by the Wald *Z* test of significance, was retained in the model (Hox, 2010). Heterogeneity of variance was allowed by specifying a specific covariance type for estimates of random effects: Compound Symmetry Heterogeneous. Cross-level interaction terms were then added to the model to examine reduction in random slope variance in addition to change in model fit and significance of cross-level interaction terms.

CHAPTER THREE

RESULTS

Original Data

After error removal, the total number of meals reported across all participants was 4,256. Of these meals, 3,767 meals had bite counter data (88.5%), 3,976 meals had Daily Meals Questionnaire responses (93.4%), and 3,882 meals had ASA24 data (91.2%). 3,406 meals had both bite counter and ASA24 data (80.0%). 3,346 meals had complete data from all three sources (78.6%).

MLM Analysis

Data Cleaning

Data for the primary variables of interest were inspected for correct values, outliers, normality, linearity, homogeneity of variance, and multicollinearity. First, the five level-1 continuous variables (Bites, Meal Kilocalories, Meal Duration, Number of People, and Meal Energy Density) were inspected for appropriate means, minimum values, maximum values, skewness, kurtosis, and univariate outliers within each of the 83 participants (Tabachnick & Fidell, 2007). Boxplots, histograms, and expected normal probability plots (q-q plots) were evaluated in addition to skewness and kurtosis values. Bites and Meal Kilocalories had positive skew and positive kurtosis values within participants. Inspection of within participant histograms, boxplots, and q-q plots indicated that the positive skew and kurtosis values were most likely the result of outliers on the positive end of the distributions. In order to determine if transformation of these variables was appropriate and to examine linearity, bivariate scatterplots of Bites and Meal Kilocalories were examined within participants. The pattern of data was mostly linear and oval-shaped, indicating that the positive skewness and kurtosis were not contributing to nonlinearity. Therefore, transformation was not appropriate for Bites and Meal Kilocalories (Tabachnick & Fidell, 2007). Outliers for Bites and Meal Kilocalories were removed within participant if the standardized value (z-score) of the data point was greater than approximately 3.29 and if the data point was clearly separated from the rest of the distribution for the participant (Tabachnick & Fidell, 2007). Fifty-five Bites outliers were removed (1.4% of the meals with Bites data), and 45 Meal Kilocalorie outliers were removed (1.2% of the meals with Meal Kilocalorie data). Re-inspection of the skewness, kurtosis, and plots of Bites and Meal Kilocalories within participants revealed reduced positive skewness and kurtosis values and relatively normal distributions.

Meal Duration also had positive skew and kurtosis. Examination of bivariate scatterplots revealed almost perfect linear relationships between Bites and Meal Duration within participants. Within participant correlations were examined to evaluate multicollinearity, or the degree of relationship between the two variables (Tabachnick & Fidell, 2007). The average within participant correlation between Bites and Meal Duration was 0.81 with one-third of correlations ≥ 0.90. This indicated that Bites and Meal Duration may have represented the same variable, and multicollinearity was present. Because both Bites and Meal Duration were obtained from the Bite Counter recordings, the longer the device was on, the more bites were counted by the device. The decision was made to remove Meal Duration from the analysis because it would be likely to explain almost all of the variance in Bites, leaving little opportunity for additional predictors to explain variance in Bites.

Number of People had extreme positive skewness and kurtosis values within participants. Overall, 61.2% of meals were eaten alone (value = 0), 18.1% of meals were eaten with one other person, 6.4% of meals were eaten with two people, 6.4% of meals were eaten with three people, and 7.9% of meals were eaten with 4 or more people (values ranged from 4 to 50). Bivariate scatterplots of Bites and Number of People were non-oval shaped, with the majority of the data points centered on 0 people. Logarithmic transformation of Number of People reduced skewness and kurtosis values somewhat, and a histogram of Number of People revealed visible positive skew and positive kurtosis. An inverse transformation of Number of People did not improve skewness and kurtosis, and skew became highly negative. Since neither transformation seemed to adequately correct the variable, the decision was made to create a dichotomous predictor variable named Social with the groups Alone or With Others which could still represent social facilitation of eating. The new variable Social is described in more detail with the other dichotomous predictors at level-1 below.

Meal Energy Density had positive skewness and kurtosis values within participants. Removal of Bites and Meal Kilocalorie outliers did not improve Meal Energy Density skewness and kurtosis values. Examination of plots revealed that the positive skewness and kurtosis were most likely due to a few high energy density meals reported by participants that differed from the energy density of the majority of their meals. In order to determine if transformation of this variable was appropriate and to examine linearity, bivariate scatterplots of Bites and Meal Energy Density were examined within participants. The scatterplots were mostly linear and oval-shaped, indicating that transformation of this variable was not necessary. However, the plots did reveal that for some participants, there were a few outlying meals of very high energy density with very few bites, again indicating high energy density snacks. Outliers for Meal Energy Density were removed within participant if the standardized value (z-score) of the data point was greater than approximately 3.29 and if the data point was clearly separated from the rest of the distribution for the participant (Tabachnick & Fidell, 2007). Sixty-eight Meal Energy Density outliers were removed (1.8% of the meals with Meal Energy Density data). Re-inspection of the skewness, kurtosis, and plots of Meal Energy Density within participants revealed reduced positive skewness and kurtosis values and relatively normal distributions.

Then the dichotomous level-1 variables Location (Home vs. Not at Home), Intake Day (Weekday vs. Weekend), and the new variable Social (Alone vs. With Others) were examined to see if the split between categories was 90:10 or greater within participants which would indicate reduced variability (Tabachnick & Fidell, 2007). For Location, 2 participants ate over 90% of meals at home, 2 participants ate over 90% of their meals not at home, and 1 participant ate all of their meals at home. Across all meals for all participants, 56.9% of meals were eaten at home, and 43.1% of meals were eaten outside of the home. For Intake Day, 1 participant had 90% of reported meals that occurred on weekdays. Across all meals for all participants, 73.1% of meals were eaten on weekdays, and 26.9% of meals were eaten on weekends. This is expected for 2 out of every 7 days being weekends (28.6%). For Social, 5 participants ate alone for over 90% of their meals, and 1 participant ate with others for over 90% of their meals. Across all meals for all participants, 61.1% of meals were eaten alone, and 38.9% of meals were eaten with others. Because the majority of participants had acceptable variability for the dichotomous predictors, all data was retained at this step.

Then the level-2 continuous variable Body Weight was examined for correct values, outliers, normality, and linearity with descriptive statistics, a histogram, a q-q plot, and a bivariate scatterplot with Bites. Skewness and kurtosis values and graphs indicated a normal distribution of body weight and no evidence of nonlinearity. The level-2 dichotomous variable Gender was split almost evenly with 40 males and 43 females.

Next, multivariate outliers among all level-1 predictors were identified within each participant using Mahalanobis distance. Values were obtained by running a regression for each participant with all level-1 predictors entered and saving Mahalanobis distance values. A Mahalanobis distance value greater than 20.515, the critical χ^2 value for $p < .001$ and $df = 5$ (the number of IVs), indicated the presence of a multivariate outlier (Tabachnick & Fidell, 2007). Twenty meals were identified as multivariate outliers. The sources of these outliers were examined, and they included abnormal dichotomous predictor values for the participant (e.g., the only meal eaten with someone else or the only meal eaten at home) and high values for continuous predictors (e.g., highest Meal Energy Density value for a participant). All 20 multivariate outlier meals were removed from the data set.

Then correlations among the remaining variables of interest were examined for evidence of multicollinearity (r's > 0.90) (Tabachnick & Fidell, 2007). All correlations were < 0.50, so no additional evidence of multicollinearity was found.

Finally, homogeneity of variance of the DV Bites was examined using the ratio of the largest participant variance to the smallest participant variance (F_{max}). The variance ratio for bites was 62.47, indicating a severe violation of homogeneity of variance (value much higher than 10) (Tabachnick & Fidell, 2007). As a result, Bites variances were allowed to vary by person, or be heterogeneous, by using the *Compound Symmetry: Heterogeneous* covariance type when multi-level linear modeling analyses were performed (Snijders & Bosker, 2011).

Data for MLM analysis

After outlier removal, 4,065 meals remained (95.5% of the original meals). Of these remaining meals, 3,606 meals had bite counter data (88.7%), 3,794 meals had Daily Meals Questionnaire responses (93.3%), and 3,691 meals had complete ASA24 data (90.8%). 3,246 meals had both bite counter and ASA24 data (79.9%). The number of meals with both bite counter and ASA24 data for each participant ranged from 15 to 100 (M = 39, SD = 15). 3,190 meals had complete data from all three sources (78.5%). The number of meals with data from all three sources for each participant ranged from 13 to 99 (M = 38, SD = 15). These frequencies and additional features of these meals are described in Table 3.1. Participants engaged in other activities for at least 68% of their reported meals. Talking, using a computer, and watching TV were the most common activities engaged in while eating. Participants ate most often with their hands, a fork, or a spoon.

Table 3.1

Frequencies and percentages of participant meal reporting and meal features.

Meals	*N*	*% of analysis data set*
All meals	4065	100
Bite counter data	3606	87.7
Daily meals questionnaire (DMQ)	3794	93.3
ASA24 data	3691	90.8
Bite counter and ASA24 data	3246	79.9
Bite counter, ASA24, and DMQ data	3190	78.5
Engaged in other activities during the meal	2772	68.2
Talking / conversation	1012	24.9
Using a computer	758	18.6
Watching TV / movie	719	17.7
Reading	176	4.3
Driving	141	3.5
Cooking / food preparation	31	0.8
Feeding a child or pet	23	0.6
Using phone to talk or text	25	0.6
Utensil used		
Hands	2354	57.9
Fork	1221	30.0
Spoon	885	21.8
Knife	412	10.1
Chopsticks	29	0.7
Straw	17	0.4
Toothpick	2	0.05

Descriptive statistics for main Level 1 and Level 2 analysis variables are presented in Table 3.2. ICC1 represents the amount of between-person variance for each variable.

Table 3.2

Descriptive Statistics for the Meal (Level-1) and Participant (Level-2) Variables

Level and Variable	*N*	*Mean*	*SD*	*ICC1*
Level-1				
Bites	3,606	39.15	26.62	0.24
Kilocalories	3,691	479.77	359.19	0.20
Energy Density	3,691	1.18	1.00	0.14
Location	3,749	0.43	0.50	0.19
Social	3,794	0.39	0.49	0.17
Intake Day	3,749	0.27	0.44	0.00
Level-2				
Gender	83	0.57	0.49	N/A
Body Weight	83	172.58	42.79	N/A

Note. Location coded 0 = Home, 1 = Not at Home. Social coded 0 = Alone, 1 = With Others. Intake Day coded 0 = Weekday, 1 = Weekend. Gender coded 0 = Male, 1 = Female.

Within-participant correlations between level-1 study variables are presented in Table 3.3. These within-participant correlations assume that these relationships are the same within each participant (Snijders & Bosker, 2011) and provide some preliminary information about the relationships among the variables. Interestingly, Kilocalories, Location, and Social are positively correlated with Bites, indicating that, on average, eating a larger number of kilocalories at a meal, eating outside of the home, and eating with others is related to taking a greater number of bites of food during a meal. However, Energy Density is negatively correlated with bites, indicating that fewer bites are taken during high energy density meals.

Table 3.3

Within-participant correlations between level-1 variables.

Variable	1	2	3	4	5
1. Bites	--				
2. Kilocalories	0.45*	--			
3. Energy Density	-0.14*	0.07*	--		
4. Location	0.05*	0.08*	0.03	--	
5. Social	0.25*	0.30*	-0.02	0.11*	--
6. Intake Day	0.01	0.08*	0.01	-0.16*	0.18*

Note. * $p < 0.05$. Location coded 0 = Home, 1 = Not at Home. Social coded 0 = Alone, 1 = With Others. Intake Day coded 0 = Weekday, 1 = Weekend.

Total correlations are presented in Table 3.4 for all level-1 and level-2 variables. These total correlations represent the relationships for the complete meal-level data set without taking into account within-participant nesting (Snijders & Bosker, 2011). Correlations between level-1 predictors and Bites remained similar in size and direction compared to the within-participant correlations. The level-2 variables Gender, Body Weight, BMI, and Height were not related to the number of bites taken during a meal.

Table 3.4

Total correlations between level-1 and level-2 variables.

Variable	1	2	3	4	5	6	7	8	9
1. Bites	--								
2. Kilocalories	0.39*	--							
3. Energy Density	-0.14*	0.09*	--						
4. Location	0.04*	0.07*	0.06*	--					
5. Social	0.23*	0.29*	-0.01	0.12*	--				
6. Intake Day	0.01	0.06	0.01	-0.15*	0.17*	--			
7. Gender	-0.02	-0.30*	0.00	0.03*	-0.02	0.00	--		
8. Body weight	0.01	0.22*	-0.04*	-0.04*	0.05*	0.01	-0.47*	--	
9. BMI	0.00	0.14*	-0.07*	-0.01	0.04*	0.01	-0.19*	0.91*	--
10. Height	0.00	0.26*	0.04*	-0.07*	0.04*	0.00	-0.72*	0.48*	0.07*

Note. * $p < 0.05$. Location coded 0 = Home, 1 = Not at Home. Social coded 0 = Alone, 1 = With Others. Intake Day coded 0 = Weekday, 1 = Weekend. Gender coded 0 = Male, 1 = Female.

Model 1: Is Nesting Present? The Intercepts-Only Model

Model building began with an intercepts-only model, with Bites as the DV, participants as the grouping variable, and no predictors. ICC1, the ratio of between participants variance to total variance, was 0.24. This indicated that 24% of the variance in bites was between participants, and 76% of the variance in bites was within participants. Nesting was present, and MLM analysis could be used to explain variance at both levels (Heck, Thomas, & Tabata, 2010).

Model fit statistics and estimates of random effects for the intercepts-only and subsequent models are presented in Table 3.5 to allow for comparison across models. Similarly, estimates of fixed effects for all models are presented in Table 3.6. As can be seen in Table 3.4, the null model consisted of both significant within-participants variance (563.43) and significant between-participants variance (180.57) that could be explained by the addition of level-1 and level-2 predictor to the model.

Table 3.5

Estimates of model fit and random effects.

Model fit			Random effects							
#	# par.	-2LL	e_{ij}(SE)	τ00(SE)	τ10 Kcalories	τ10 EDensity	τ10 Location	τ10 Social	τ10 Intake Day
1	3	29468.49	563.43(14.30)*	180.57(30.93)*					
2	4	28722.97^	442.76(11.24)*	192.22(32.18)*					
3	5	28617.07^	428.28(10.87)*	186.19(31.19)*					
4	6	28611.13^	427.43(10.85)*	186.86(31.30)*					
5	7	28550.99^	419.41(10.64)*	183.99(30.81)*					
6	8	28543.71^	418.42(10.62)*	184.26(30.84)*					
7	9	28497.60^	412.27(10.46)*	184.17(30.80)*					
8	10	28495.70	411.98(10.46)*	184.79(30.90)*					
9	10	28493.51^	412.27(10.46)*	174.64(29.31)*					
10	11	28491.73	412.27(10.46)*	170.72(28.69)*					
11	12	28312.93^	378.09(9.74)*	164.56(28.26)*	.0004(<.001)*				
12[a]	13	28479.86	407.46(10.40)*	175.23(29.30)*		a			
13	13	28308.11^	374.35(9.99)*	167.01(28.99)*	.0004(<.001)*		18.90(17.72)		
14	13	28305.56^	373.29(9.78)*	160.94(27.65)*	.0004(<.001)*			28.16(15.52)	
15	13	28312.81	377.91(9.76)*	164.84(28.30)*	.0004(<.001)*				0.45(2.79)
16	13	28309.40	378.03(9.74)*	162.45(27.69)*	.0004(<.001)*				

Note. [a]Model 12 estimates were unstable and thus were not included; -2LL = -2 log-likelihood; SE = Standard Error; e_{ij} = residual (within-participant) variance; τ00 = random intercept (between-participants) variance; τ10 = random slope variance; ^Significant model improvement from previous significant model using the Chi-square deviance difference test; * p < .05.

Table 3.6 *Estimates of fixed effects for level-1 and level-2 predictors.*

Model #	# Parameters	γ00 (SE)	γ10 (SE)	γ20 (SE)	γ30 (SE)	γ40 (SE)	γ50 (SE)	γ120 (SE)	γ560 (SE)	γ01 (SE)	γ02 (SE)	γ11 (SE)
1	3	40.24* (1.54)										
2	4	38.51* (1.57)	.04* (.001)									
3	5	38.50* (1.55)	.04* (.001)	-4.28* (.41)								
4	6	38.51* (1.55)	.04* (.001)	-4.31* (.41)	2.04* (.84)							
5	7	38.65* (1.54)	.03* (.001)	-4.13* (.41)	1.49 (.83)	6.77* (.87)						
6	8	38.62* (1.54)	.03* (.001)	-4.11* (.41)	1.05 (.85)	7.20* (.88)	-2.32* (.86)					
7	9	38.84* (1.54)	.04* (.001)	-6.12* (.50)	.84 (.84)	6.46* (.88)	-2.02* (.85)	-.01* (.002)				
8	10	38.92* (1.54)	.04* (.001)	-6.11* (.50)	.88 (.84)	6.53* (.88)	-1.82* (.87)	-.01* (.001)	-2.38 (1.70)			
9	10	39.16* (1.51)	.04* (.001)	-6.13* (.05)	.81 (.84)	6.41* (.88)	-2.02* (.85)	-.01* (.001)		6.18* (3.02)		
10	11	39.14* (1.49)	.04* (.001)	-6.14* (.50)	.80 (.84)	6.42* (.88)	-2.03* (.85)	-.01* (.001)		4.18 (3.34)	-.05 (.04)	
11	12	40.27* (1.47)	.04* (.002)	-5.84* (.50)	.75 (.82)	5.76* (.85)	-1.85* (.82)	-.01* (.002)		3.14 (2.50)		
13[a]	13	40.33* (1.48)	.04* (.003)	-5.86* (.50)	.27 (.97)	5.87* (.86)	-1.78* (.83)	-.01* (.002)		3.31 (2.62)		
14	13	40.33* (1.46)	.04* (.002)	-5.75* (.50)	.75 (.83)	5.74* (1.06)	-1.70* (.82)	-.01* (.002)		4.70 (2.65)		
15	13	40.27* (1.47)	.04* (.003)	-5.83* (.50)	.74 (.82)	5.76* (.85)	-1.91* (.83)	-.01* (.002)		3.31 (2.51)		
16	13	40.56* (1.47)	.04* (.003)	-5.84* (.50)	.79 (.82)	5.71* (.85)	-1.87* (.82)	-.01* (.002)		6.03* (2.93)		.01 (.01)

Note. [a]Model 12 estimates were unstable and thus were not included. γ00 = grand mean of bites; γ10 = kilocalories-bites slope; γ20 = energy density-bites slope; γ30 = location-bites slope; γ40 = social-bites slope; γ50 = intake day-bites slope; γ120 = kilocalories x energy density interaction; γ560 = social x intake day interaction; γ01 = gender-bites slope; γ02 = body weight-bites slope; γ11 = gender x kilocalories interaction; **p* < .05.

Model 2: Do Kilocalories predict Bites?

Kilocalories was entered into the model as a fixed effect at level-1 in order to address research question 1: Do kilocalories consumed during a meal predict number of bites recorded during a meal? First, change in model fit was assessed by comparing model 2 to the null model. Results of the χ^2 deviance difference test (29468.49-28722.97 = 745.52, *df* = 4-3 = 1, *p* < .05) indicated that the addition of Kilocalories significantly improved model fit. Next, the change in within-participants variance from the null model to model 2 was examined. Kilocalories explained 21.4% ((563.43-442.76)/563.43*100) of the within-participants variance. Lastly, a significant positive relationship between Kilocalories and Bites was observed in the Kilocalories-Bites slope of 0.04. Each one Kilocalorie increase during a meal corresponded, on average, to a 0.04 Bite increase. Stated in a more practically meaningful way, each 25 Kilocalorie increase during a meal corresponded, on average, to a 1 Bite increase. Kilocalories was retained as a level-1 predictor for all subsequent models.

Model 3: Does Energy Density predict Bites?

Energy Density was added to the model as a fixed effect at level-1 in order to address research question 2: Does the average energy density of a meal predict number of bites recorded during a meal? First, change in model fit was assessed by comparing model 3 to model 2. Results of the χ^2 deviance difference test (28722.97-28617.07 = 105.90, *df* = 5-4 = 1, *p* < .05) indicated that the addition of Energy Density significantly improved model fit. Next, the change in within-participants variance from model 2 to model 3 was examined. Energy Density explained an additional 3.3% ((442.76-428.28)/442.76*100) of the within-participants variance. Lastly, a significant negative relationship between Energy Density and Bites was observed in the Energy Density-Bites slope of -4.28. Each 1 kcal/gram increase in Energy Density corresponded, on average, to a 4.28 decrease in number of Bites. Thus, the bite counter recorded fewer bites when participants ate mote energy dense meals. Energy Density was retained as a level-1 predictor for all subsequent models.

Model 4: Does Location predict Bites?

Location was added to the model as a fixed effect at level-1 in order to address research question 5: Does the location of a meal predict the number of bites recorded during a meal? First, the change in model fit was assessed by comparing model 4 to model 3. Results of the χ^2 deviance difference test (28617.07-28611.13 = 5.94, df = 6-5 = 1, $p < .05$) indicated that the addition of Location significantly improved model fit. Next, the change in within-participants variance from model 3 to model 4 was examined. Location explained an additional 0.2% ((428.28-427.43)/428.28*100) of the within-participants variance. Lastly, a significant positive relationship between Location and Bites was observed in the Location-Bites slope of 2.04. On average, 2.04 more bites were recorded when eating outside of the home compared to eating at home. Because Location significantly improved model fit and explained a percentage of the within-participants variance, it was retained as a level-1 predictor for all subsequent models despite its relatively small contribution.

Model 5: Does Social predict Bites?

Social was added to the model as a fixed effect at level-1 in order to address research question 6: Does the number of people an individual eats with predict the number of bites recorded during a meal? First, the change in model fit was assessed by comparing model 5 to model 4. Results of the χ^2 deviance difference test (28611.13 – 28550.99 = 60.14, *df* = 7-6 = 1, *p* < .05) indicated that the addition of Social significantly improved model fit. Next, the change in within-participants variance from model 4 to model 5 was examined. Social explained an additional 1.9% ((427.43-419.41)/427.43*100) of the within-participants variance. Lastly, a significant positive relationship between Social and Bites was observed in the Social-Bites slope of 6.77. On average, 6.77 more bites were recorded when eating with others compared to eating alone. Social was retained as a level-1 predictor for all subsequent models.

It was also noted that when Social was added to the model, the Location-Bites relationship became nonsignificant. Therefore, when controlling for the effects of Social and the other predictors in the model, the effect of Location was diminished.

Model 6: Does Intake Day predict Bites?

Intake Day was added to the model as a fixed effect at level-1 in order to address research question 7: Does day of the week predict the number of bites recorded during a meal? First, the change in model fit was assessed by comparing model 6 to model 5. Results of the χ^2 deviance difference test (28550.99-28543.71 = 7.28, *df* = 8-7 = 1, *p* < .05) indicated that the addition of Intake Day significantly improved model fit. Next, the change in within-participants variance from model 5 to model 6 was examined. Intake Day explained an additional 0.2% ((419.41-418.42)/419.41*100) of the within-participants variance. Lastly, a significant negative relationship between Intake Day and Bites was observed in the Intake Day-Bites slope of -2.32. On average, 2.32 fewer bites were recorded for weekend meals than weekday meals. Intake Day was retained as a level-1 predictor for all subsequent models.

Model 7: Do Kilocalories and Energy Density interact to predict Bites?

An interaction between Kilocalories and Energy Density was added to the model in order to address research question 3: Does the relationship between kilocalories consumed during a meal and number of bites recorded during a meal depend on the energy density of the food? First, the change in model fit was assessed by comparing model 7 to model 6. Results of the χ^2 deviance difference test (28543.71-28497.60 = 46.11, df = 9-8 = 1, $p < .05$) indicated that the addition of the Kilocalorie x Energy Density interaction significantly improved model fit. Next, the change in within-participants variance from model 6 to model 7 was examined. The Kilocalorie x Energy Density interaction explained an additional 1.5% ((418.42-412.27)/418.42*100) of the within-participants variance. Lastly, the Kilocalorie x Energy Density interaction term was negative and significant: -0.01. In order to examine the nature of the interaction, simple slopes were calculated in accordance with Cohen et al. (2003) using the fixed effects coefficients at high (+1 SD) and low (-1 SD) values of Kilocalories. These slopes were significant at low (B = 0.05, SE = 0.002), t = 21.92, $p < .05$, moderate (B = 0.04, SE

= 0.001), t = 30.97, $p < .05$, and high (B = 0.03, SE = 0.002), t = 17.97, $p < .05$ values of Energy Density. Figure 3.1 shows that the relationship between Kilocalories and Bites is strongest for low Energy Density meals. The Kilocalorie x Energy Density interaction was retained in all subsequent models.

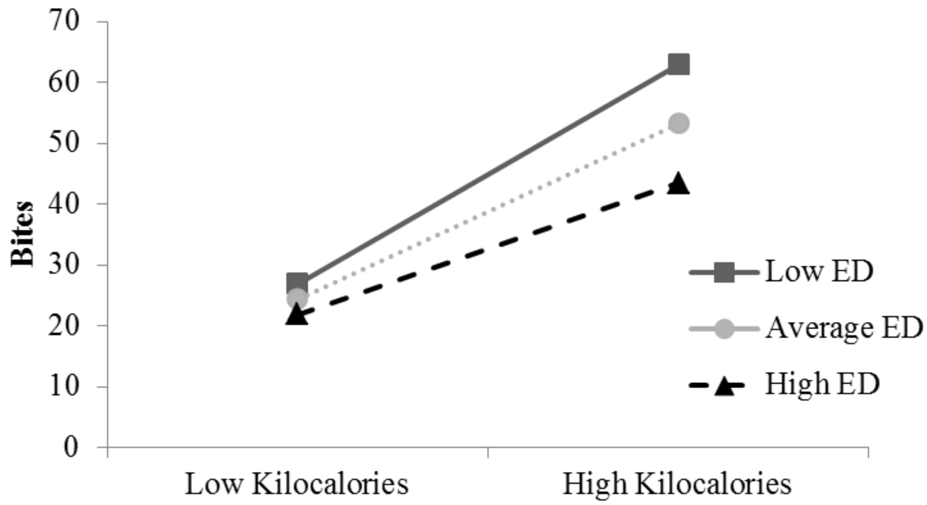


Figure 3.1. The Kilocalorie x Energy Density interaction demonstrating that the relationship between Kilocalories and Bites is strongest for low Energy Density meals.

Model 8: Do Social and Intake Day interact to predict Bites?

An interaction between Social and Intake Day was added to the model in order to address research question 8: Does the relationship between number of people an individual eats with and bite count depend on whether it is a weekend or a weekday? First, the change in model fit was assessed by comparing model 8 to model 7. Results of the $\chi 2$ deviance difference test (28497.60-28495.70 = 1.9, df = 10-9 = 1, $p > .05$) indicated that the addition of the Social X Intake Day interaction did not improve model fit. Next, the change in within-participants variance from model 7 to model 8 was examined. The Social X Intake Day interaction explained an additional 0.0007% ((412.27-411.98)/412.27*100) of the within-participants variance. Finally, the Social X Intake Day interaction term was non-significant (-2.38). Because the Social X Intake Day interaction did not improve the model or its interpretation, it was dropped from subsequent models.

Model 9: Does Gender predict Bites?

Gender was added to the model as a fixed effect at level-2 in order to address research question 9: Does gender predict bite count? First, the change in model fit was assessed by comparing model 9 to model 7. (Model 9 was not compared to model 8 because model 8 was not a significant improvement over model 7, and its interaction term was dropped from subsequent models.) Results of the χ^2 deviance difference test (28497.60-28493.51) = 4.09, df = 10-9 = 1, $p < .05$) indicated that the addition of Gender significantly improved model fit. Next, the change in between-participants (intercept) variance from model 7 to model 9 was examined. Gender explained 5.2% ((184.17-174.64)/184.17*100) of the between-participants variance. Lastly, a significant positive relationship between Gender and Bites was observed in the Gender-Bites slope of 6.18. On average, 6.18 more bites per meal were recorded for females compared to males. Gender was retained as a level-2 predictor for all subsequent models.

Model 10: Does Body Weight predict Bites?

Body weight was added to the model as a fixed effect at level-2 in order to address research question 10: Does body weight predict bite count? First, the change in model fit was assessed by comparing model 10 to model 9. Results of the χ^2 deviance difference test (28493.51-28491.73) = 1.78, *df* = 11-10 = 1, $p > .05$) indicated that the addition of Body Weight did not significantly improve model fit. Next, the change in between-participants (intercept) variance from model 9 to model 10 was examined. Body Weight explained 2.24% ((174.64-170.72)/174.64*100) of the between-participants variance. However, the Body Weight-Bites slope was non-significant (-0.05). Because Body Weight did not improve the model or its interpretation, it was dropped from subsequent models.

Model 11: Does the Relationship between Kilocalories and Bites vary by participant?

Models 11-15 allowed the slopes between Bites and a level-1 predictor to vary by participant one variable at a time (Hox, 2010). If a significant random slope variance was found, this was retained in the model, and a cross-level interaction was added to try to explain these varying slopes with a level-2 predictor.

In model 11, the relationship between Kilocalories and Bites was allowed to vary by participant (random Kilocalories-Bites slope variance). First, the change in model fit was assessed by comparing model 11 to model 9. (Model 11 was not compared to model 10 because model 10 was not a significant improvement over model 9, and its predictor was dropped from subsequent models.) Results of the χ^2 deviance difference test

(28493.51-28312.93) = 180.58, *df* = 12-10 = 2, $p < .05$) indicated that the addition of Kilocalories-Bites slopes varying by participants significantly improved model fit. The random Kilocalories-Bites slope variance of 0.0004 was significant, indicating that the relationship between Kilocalories and Bites did vary by participant. Therefore, the random Kilocalories-Bites slope variance was retained for all subsequent models.

Model 12: Does the Relationship between Energy Density and Bites vary by participant?

In model 12, the relationship between Energy Density and Bites was allowed to vary by participant (random Energy Density-Bites slope variance). The χ^2 deviance difference test comparing model 12 to model 11 (28312.93-28497.86) = -184.93, *df* = 13-12 = 1, $p < .05$) indicated that the addition of the random Energy Density-Bites slope variance significantly harmed the model fit. Additionally, the remaining model estimates were unstable because the Hessian matrix was not positive definite. Therefore, the random Energy Density-Bites slope variance was dropped from subsequent models.

Model 13: Does the Relationship between Location and Bites vary by participant?

In model 13, the relationship between Location and Bites was allowed to vary by participant (random Location-Bites slope variance). The χ^2 deviance difference test comparing model 13 to model 11 (28312.93-28308.11) = 4.82, *df* = 13-12 = 1, $p < .05$) indicated that the addition of the random Location-Bites slope variance significantly improved the model fit. However, the random Location-Bites slope variance (18.90) did not significantly differ by participant. Due to the small increase in model fit but non-significant slope variation, the random Location-Bites slope variance was dropped from subsequent models.

Model 14: Does the Relationship between Social and Bites vary by participant?

In model 14, the relationship between Social and Bites was allowed to vary by participant (random Social-Bites slope variance). The χ^2 deviance difference test comparing model 14 to model 11 (28312.93-28305.56) = 7.37, df = 13-12 = 1, $p < .05$) indicated that the addition of the random Social-Bites slope variance significantly improved the model fit. However, the random Social-Bites slope variance (28.16) did not significantly differ by participant. Due to the small increase in model fit but non-significant slope variation, the random Social-Bites slope variance was dropped from subsequent models.

Model 15: Does the Relationship between Intake Day and Bites vary by participant?

In model 15, the relationship between Intake Day and Bites was allowed to vary by participant (random Intake Day-Bites slope variance). The χ^2 deviance difference test comparing model 15 to model 11 (28312.93-28312.81) = 0.12, df = 13-12 = 1, $p > .05$) indicated that the addition of the random Intake Day-Bites slope variance did not significantly improve the model fit. In addition, the random Intake Day-Bites slope variance (0.45) did not significantly differ by participant. Because the random Intake Day-Bites slope variance did not improve model fit and did not vary by participant, it was dropped from subsequent models.

Model 16: Can the varying Kilocalorie-Bite slopes by explained by Gender?

Because the relationship between Kilocalories and Bites varied significantly by participant, a cross-level interaction between Kilocalories and Gender was added to the model to examine if Gender could explain some of this random slope variance. The χ^2 deviance difference test comparing model 16 to model 11 (28312.93-28309.40) = 3.53, *df* = 13-12 = 1, $p > .05$) indicated that the addition of the Kilocalories x Gender interaction did not significantly improve the model fit. In addition, the interaction term was nonsignificant (0.01). Therefore, the varying Kilocalorie-Bites slopes could not be explained by the Gender of the participant. The cross-level interaction term was dropped from subsequent models.

Exploration of Additional Level-2 variables

With the significant random slope variance for the relationship between Kilocalories and Bites, additional Level-2 variables (individual difference variables) were explored to determine if they might help explain this variation (Hox, 2010). Model 11 was determined to be the best model, with five fixed predictors at level-1 (Kilocalories, Energy Density, Location, Social, and Intake Day), a Kilocalorie x Energy Density interaction at level-1, one fixed predictor at level-2 (Gender), and the significant random slope variance between Kilocalories and Bites. All exploratory models were compared to model 11 to see if model fit would improve and if the random slope variance could be explained. Model estimates are provided in Table 3.7 and Table 3.8.

Table 3.7

Estimates of model fit and random effects for model 11 and exploratory models.

Model fit			Random effects		
Model #	# parameters	-2LL	e_{ij}(SE)	τ00(SE)	τ10 Kcalories
11	12	28312.93	378.09(9.74)*	164.56(28.26)*	.00041(<.001)*
17	14	28310.25	378.10(9.74)*	161.17(27.60)*	.00041(<.001)*
18	14	28312.04	378.14(9.74)*	163.22(28.03)*	.00041(<.001)*
19	14	28306.08^	378.09(9.74)*	157.83(26.94)*	.00037(<.001)*

Note. -2LL = -2 log-likelihood; SE = Standard Error; eij = residual (within-participant) variance; τ00 = random intercept (between-participants) variance; τ10 = random slope variance; ^Significant model improvement from previous significant model using the Chi-square deviance difference test; * p < .05.

Table 3.8

Estimates of fixed effects for level-1 and level-2 predictors for model 11 and exploratory models.

#	# Parameters	γ00 (SE)	γ10 (SE)	γ20 (SE)	γ30 (SE)	γ40 (SE)	γ50 (SE)	γ120 (SE)	γ01 (SE)	γ02 (SE)	γ03 (SE)	γ04 (SE)	γ12 (SE)	γ13 (SE)	γ14 (SE)
11	12	40.27* (1.47)	.04* (.002)	-5.84* (.50)	.75 (.82)	5.76* (.85)	-1.85* (.82)	-.01* (.002)	3.14 (2.50)						
17	14	40.35* (1.46)	.04* (.003)	-5.85* (.50)	.76 (.82)	5.75* (.85)	-1.87* (0.82)	-.01* (.002)	1.92 (2.78)	-.06 (.04)			8E-5 (6E-5)		
18	14	40.27* (1.46)	.04* (.003)	-5.86* (.50)	.75 (.82)	5.76* (.85)	-1.85* (.82)	-.01* (.002)	2.82 (2.50)		-.24 (.25)			1E-4 (4E-4)	
19	14	40.94* (1.45)	.04* (.003)	-5.81* (.50)	.79 (.82)	5.73* (.86)	-1.88* (.82)	-.01* (.002)	1.50 (3.70)			-.83 (.54)			-.002* (7E-4)

Note. γ00 = grand mean of bites; γ10 = kilocalories-bites slope; γ20 = energy density-bites slope; γ30 = location-bites slope; γ40 = social-bites slope; γ50 = intake day-bites slope; γ120 = kilocalories x energy density interaction; γ01 = gender-bites slope; γ02 = body weight-bites slope; γ03 = BMI-bites slope; γ04 = height-bites slope; γ12 = kilocalories x body weight interaction; γ13 = kilocalories x BMI interaction; γ14 = kilocalories x height interaction. *$p < .05$.

Model 17: Can the varying Kilocalorie-Bite slopes be explained by Body Weight?

First, although Body Weight did not explain bites directly, it was possible that Body Weight might have been an individual difference that could explain some of the random Kilocalorie-Bite slope variance. A Body Weight fixed effect at level-2 and a Body Weight x Kilocalorie interaction term were added to create Model 17. The χ^2 deviance difference test comparing model 17 to model 11 (28312.93-28310.25) = 2.68, df = 14-12 = 2, $p > .05$) indicated that the addition of the Body Weight fixed effect and the Body Weight x Kilocalorie interaction did not significantly improve model fit. Random slope variance was not reduced (.00041-.00041 = 0) indicating that Body Weight did not explain any of the random Kilocalorie-Bite slope variance. Finally, the Body Weight x Kilocalorie interaction term (0.00008) was non-significant. Therefore, the Body Weight fixed effect and the Body Weight x Kilocalorie interaction term were dropped from further exploratory models.

Model 18: Can the varying Kilocalorie-Bite slopes be explained by BMI?

It was thought that BMI, the ratio of a participant's weight to their height, might be an individual difference variable that could explain some of the random Kilocalorie-Bite slope variance. A BMI fixed effect at level-2 and a BMI x Kilocalorie interaction term were added to create Model 18. The χ^2 deviance difference test comparing model 18 to model 11 (28312.93-28312.04) = 0.89, df = 14-12 = 2, $p > .05$) indicated that the addition of the BMI fixed effect and the BMI x Kilocalorie interaction did not significantly improve model fit. Random slope variance was not reduced (.00041-

.00041= 0) indicating that BMI did not explain any of the random Kilocalorie-Bite slope variance. Finally, the BMI x Kilocalorie interaction term (0.0001) was non-significant. Therefore, the BMI fixed effect and the BMI x Kilocalorie interaction term were dropped from further exploratory models.

Model 19: Can the varying Kilocalorie-Bite slopes be explained by Height?

It was thought that Height could be another individual difference variable that could explain some of the random Kilocalorie-Bite slope variance. A Height fixed effect at level-2 and a Height x Kilocalorie interaction term were added to create Model 19. The χ^2 deviance difference test comparing model 19 to model 11 (28312.93-28306.08) = 6.85, df = 14-12 = 2, $p < .05$) indicated that the addition of the Height fixed effect and the Height x Kilocalorie interaction significantly improved model fit. Height explained 9.8% ((0.00041-0.00037)/0.00041*100) of the random Kilocalories-Bites slope variance. The Height fixed effect (-0.83) was non-significant, indicating no direct relationship between Height and Bites. However, the Height x Kilocalories interaction term (-0.002) was negative and significant. In order to examine the nature of the interaction, simple slopes were calculated in accordance with Cohen et al. (2003) using the fixed effects coefficients at high (+1 SD) and low (-1 SD) values of Kilocalories. These slopes were significant at low (B = 0.047, SE = 0.004), t = 12.51, $p < .05$, moderate (B = 0.040, SE = 0.003), t = 15.62, $p < .05$, and high (B = 0.033, SE = 0.003), t = 9.67, $p < .05$ values of Height. Figure 3.2 shows that the positive relationship between Kilocalories and Bites is stronger for shorter participants and weaker for taller participants.

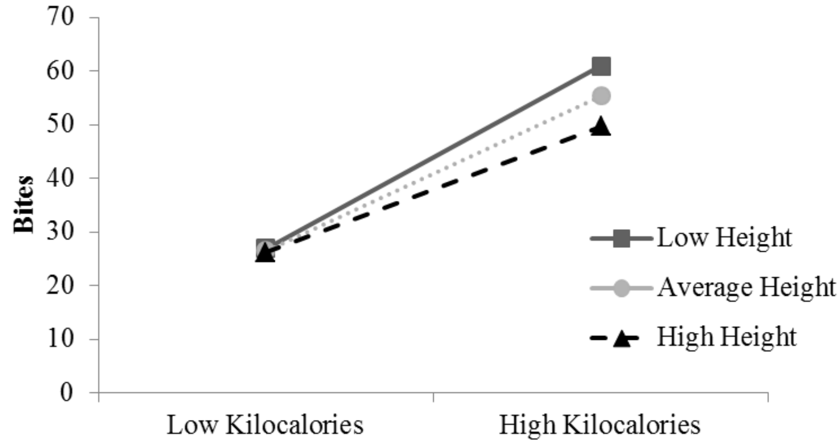


Figure 3.2. The Kilocalorie x Height interaction at the meal-level demonstrating that the relationship between Kilocalories and Bites is strongest for shorter participants.

The Final Model

Model 19 was the best-fitting model for explaining variance in bites. In order to calculate the overall effect size for the model, all predictors in the model needed to be fixed with no random slopes (Bickel, 2007). Therefore, model 19 was run without the random Kilocalories-Bites slope variance. For this model, the residual variance was 408.13 and the intercept variance was 162.59. The overall effect size was calculated as $1- [(\text{residual}_{\text{fixed}} + \text{intercept}_{\text{fixed}}) / (\text{residual}_{\text{intercepts-only}} + \text{intercept}_{\text{intercepts-only}})] =$ $1- [(408.13+162.59) / (563.43+180.57)] = 0.233$. Therefore, the final model explained 23.3% of the overall variance in bites.

The fixed coefficients from model 19 (shown in Table 3.8 above) indicate the nature of the relationships between predictors and Bites for the final model. The positive relationship between Kilocalories and Bites and the negative relationship between Energy

Density and Bites were main effects that were qualified by a significant interaction between Kilocalories and Energy Density. The simple slopes of the Kilocalories x Energy Density interaction term for model 19 had the same values as the simple slopes for Model 11 and were still significant. Thus, the size and the nature of the interaction did not change, and Figure 3.1 was still appropriate for interpretation of the interaction for the final model. The relationship between Kilocalories and Bites depended on the Energy Density of the meal being eaten, with a stronger relationship between Kilocalories and Bites for meals of lower Energy Density.

The relationship between Location and Bites remained nonsignificant in the final model. Therefore, when controlling for the effects of the other predictors, Location was no longer a significant predictor of Bites. The relationship between Social and Bites remained significant and indicated that, on average, participants took 5.73 more bites when eating with others than when eating alone. The relationship between Intake Day and Bites remained significant and indicated that, on average, participants took 1.88 fewer bites when eating on weekends compared to weekdays. The relationship between Gender and Bites became nonsignificant, indicating that when controlling for the effects of the other predictors, Gender was no longer a significant predictor of Bites. The nonsignificant relationship between Height and Bites was qualified by a significant cross-level interaction between Height and Kilocalories, as seen in Figure 3.2. The relationship between Kilocalories and Bites depended on the Height of the participants, with a stronger positive relationship between Kilocalories and Bites for shorter participants and a weaker positive relationship between Kilocalories and Bites for taller participants.

Additional Two-Level Model

In a second analysis, the level-1 variables (meal-level variables) were aggregated to the day-level. In order to provide support for aggregation, ICC2, an index of reliability, was calculated for all level-1 variables (Snijders & Bosker, 2011). ICC2 is the ratio of (between-participants variance – within-participants variance) / between participants variance, and a recommended cut-off value is 0.60 (Glick, 1985). Essentially, the ICC2 indicates the degree to which variables aggregated up to the day level can serve as a substitute for variables at the meal level. Table 3.9 shows the ICC2 values for each level 1-variable. Because Intake Day was naturally a day-level variable, an ICC2 value did not need to be calculated.

Table 3.9

ICC2 values for level-1 variables

Variable	ICC2
Bites	.44
Kilocalories	.42
Energy Density	.19
Location	.50
Social	.49

All ICC2 values were less than 0.60, and typically one would not aggregate these variables up to the day-level because important variability would be lost. Nonetheless, in order to explore a model with level-1 representing the day, these variables were aggregated up to the day-level.

In the day-level model, the sum of day-level values within a participant were used for each aggregated variable. Meal energy density for this model was calculated as the sum of the kilocalories for the day divided by the sum of the grams for the day. All rows in the data set represented a day; thus, day become level 1, and participant remained level 2. The sums were used in this model because this might be a practical way for an individual to interpret bite counter data (i.e., someone might want to know how the total number of bites for a day is related to the total number of kilocalories for a day). All predictor variables were centered at the grand mean. Model 19, the final model at the meal level, was run using the data at the day level.

The random Kilocalories-Bites slope variance became non-significant in the day-level model (τ_{01} = 1E-4, *SE* = 8E-5, Wald *Z* = 1.70, $p > .05$). This indicated that the relationship between Bites and Kilocalories at the day level did not vary between participants. This random effect was subsequently removed from the model, as was the cross-level interaction between Kilocalories and Height. A final model at the day-level was evaluated with Kilocalories, Energy Density, Kilocalories x Energy Density, Location, Social, Intake Day, Gender, and Height in the model as fixed effects.

Table 3.10 provides the random effects for the final meal-level model and the final day-level model, and Table 3.11 provides the fixed effects for the final meal-level model and the final day-level model to aid in comparison across the models.

Table 3.10

Random effects for the meal-level and the day-level models.

Model	e_{ij}(SE)	τ00(SE)	τ01 Kcalories
Meal-level	378.09(9.74)*	157.83(26.94)*	.00037(<.001)*
Day-level	1615.17 (73.36)*	2086.17(345.05)*	n/a

Note. SE = Standard Error; eij = residual (within-participant) variance; τ00 = random intercept (between-participants) variance; τ10 = random slope variance; *p < .05.

Table 3.11

Fixed effects for the meal-level and the day-level models.

Model	γ00 (SE)	γ10 (SE)	γ20 (SE)	γ30 (SE)	γ40 (SE)	γ50 (SE)	γ120 (SE)	γ01 (SE)	γ04 (SE)	γ14 (SE)
Meal-level	40.94* (1.45)	.04* (.003)	-5.81* (.50)	.79 (.82)	5.73* (.86)	-1.88* (.82)	-.01* (.002)	1.50 (3.70)	-.83 (.54)	-.002* (7E-4)
Day-level	121.77* (5.18)	.03* (.003)	-27.57* (4.57)	1.30 (1.30)	5.30* (1.43)	-8.15* (3.06)	-.01* (.005)	26.31 (15.53)	-1.52 (2.13)	n/a

Note. γ00 = grand mean of bites; γ10 = kilocalories-bites slope; γ20 = energy density-bites slope; γ30 = location-bites slope; γ40 = social-bites slope; γ50 = intake day-bites slope; γ120 = kilocalories x energy density interaction; γ01 = gender-bites slope; γ04 = height-bites slope; γ14 = kilocalories x height interaction. *p < .05.

The day-level model had significant within-participants variance and between-participants variance, as can be seen in Table 3.10. In Table 3.11, it can be seen that all of the significant relationships in the meal-level model remain in the day-level model. The significant positive relationship between Kilocalories and Bites and the significant negative relationship between Energy Density and Bites were qualified by the significant Kilocalories x Energy Density interaction. In order to examine the nature of the interaction, simple slopes were calculated in accordance with Cohen et al. (2003) using the fixed effects coefficients at high (+1 SD) and low (-1 SD) values of Kilocalories. These slopes were significant at low ($B = 0.034$, $SE = 0.003$), $t = 10.06$, $p < .05$, moderate ($B = 0.03$, $SE = 0.002$), $t = 12.33$, $p < .05$, and high ($B = 0.026$, $SE = 0.003$), $t = 9.57$, $p < .05$, values of Energy Density. Figure 3.3 shows that the relationship between Kilocalories and Bites is strongest for days with overall lower Energy Density. However, when compared to Figure 3.1 which shows the relationship for the meal-level model, it can be seen that the relative strength of the interaction has decreased when Bites and Kilocalories are at their totals for the day.

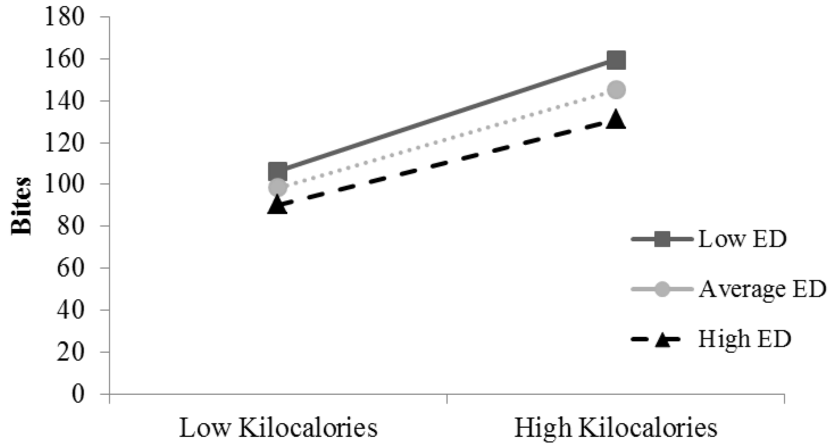


Figure 3.3. The Kilocalorie x Energy Density interaction at the day-level demonstrating that the relationship between Kilocalories and Bites is strongest for days with overall lower Energy Density.

The relationship between Location and Bites remained nonsignificant in the day-level model. Therefore, when controlling for the effects of the other predictors, Location was not a significant predictor of Bites at the day-level. The relationship between Social and Bites remained significant and indicated that, on average, participants took 5.3 more bites per day for each additional meal eaten with others. The relationship between Intake Day and Bites remained significant and indicated that, on average, participants took 8.15 fewer bites per day when eating on weekends compared to weekdays. The relationship between Gender and Bites was nonsignificant, indicating that when controlling for the effects of the other predictors, Gender was not a significant predictor of Bites. Finally, the relationship between Height and Bites was nonsignificant, meaning that the number of bites taken during a day could not be predicted by a participant's height.

Additional Model with Outlier Participants Removed

Further inspection of the within-participant correlations between Bites and Kilocalories revealed 14 participants with correlations ranging from -0.01 to 0.3, as can be seen in Figure 3.4. The remaining 69 participants' correlations were normally distributed within a range of 0.31 to 0.80.

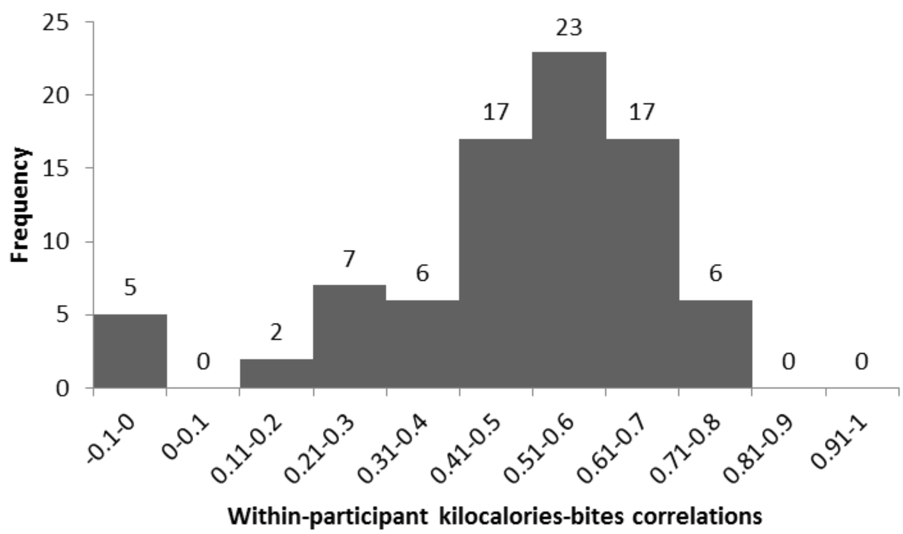


Figure 3.4. Within-participant correlations between Kilocalories and Bites for the original 83 participants.

Descriptions of the quality of the data from each participant are provided in Appendix P, and these 14 outlying participants are indicated by an asterisk next to the participant ID. There were a number of reasons why these participants may have had poor data quality: the bite counter turning off frequently during meals, a broken bite counter speaker resulting in decreased turning off feedback, low battery levels from not charging the bite counter, difficulty remembering to turn the bite counter on and off, holding down the button on the bite counter to get past the calibration screen, abnormal eating patterns, indications that some meals may have been incorrectly reported in ASA24, feeling overwhelmed by the study requirements, and a low sample size for matched meals. With these justifications, these 14 participants were removed from the data set, and analyses were conducted on the data for the 69 remaining participants.

For the new data set, 3,474 meals remained. Of those meals 2,783 (80.1%) had bite counter and ASA24 data, and 2,741 (78.9%) had data from all three sources. Removing data from 14 participants (16.9% of the 83 original participants) resulted in 449 meals removed from the data set (14.1% of 3,190 original meals).

Within-participant correlations between level-1 variables are presented in Table 3.12. Overall, these correlations were very similar to the correlations in the original model (see Table 3.3). The Bites and Kilocalories correlation increased by 0.06 and remained significant ($r = 0.51$, $p < 0.05$).

Table 3.12

Within-participant correlations between level-1 variables for outliers-removed model.

Variable	1	2	3	4	5
1. Bites	--				
2. Kilocalories	0.51*	--			
3. Energy Density	-0.14*	0.04*	--		
4. Location	0.06*	0.09*	0.03	--	
5. Social	0.28*	0.32*	-0.04*	0.11*	--
6. Intake Day	0.03	0.08*	0.01	-0.16*	0.18*

Note. * $p < 0.05$. Location coded 0 = Home, 1 = Not at Home. Social coded 0 = Alone, 1 = With Others. Intake Day coded 0 = Weekday, 1 = Weekend.

Total correlations among all variables of interest are presented in Table 3.13. With outlier removal, the correlation between Bites and Kilocalories increased by 0.07 and remained significant ($r = 0.46$, $p < .05$). The negative correlation between Gender and Bites became significant ($r = -0.05$, $p < .05$) and indicated that females took fewer bites than males. A positive correlation emerged between Body Weight and Bites ($r = 0.05$, $p < .05$) which indicated that people with heavier body weights took more bites. The correlation with Bites was similar for BMI ($r = 0.04$, $p < .05$), which reflected the overall near perfect correlation between Body Weight and BMI ($r = 0.92$, $p < 0.05$).

Table 3.13

Total correlations between level-1 and level-2 variables for the outliers-removed model.

Variable	1	2	3	4	5	6	7	8	9
1. Bites	--								
2. Kilocalories	0.46*	--							
3. Energy Density	-0.14*	0.06*	--						
4. Location	0.07*	0.08*	0.07*	--					
5. Social	0.27*	0.31*	-0.02	0.12*	--				
6. Intake Day	0.03	0.06*	0.01	-0.15*	0.17*	--			
7. Gender	-0.05*	-0.29*	0.01	0.06*	-0.04*	-0.01	--		
8. Body weight	0.05*	0.22*	-0.05*	-0.07*	0.06*	0.02	-0.45*	--	
9. BMI	0.04*	0.13*	-0.08*	-0.06*	0.04*	0.03	-0.19*	0.92*	--
10. Height	0.01	0.28*	0.05*	-0.07*	0.07*	0.01	-0.72*	0.54*	0.17*

Note. * $p < 0.05$. Location coded 0 = Home, 1 = Not at Home. Social coded 0 = Alone, 1 = With Others. Intake Day coded 0 = Weekday, 1 = Weekend. Gender coded 0 = Male, 1 = Female. Bite size calculated as kilocalories per bite during the lab meal.

All predictors were centered at the grand mean, and model building was conducted on this outliers-removed sample in the same manner as described for the previous model building with all participants. Results from Models 1 through 16 are presented in Tables 3.14 and 3.15. Exploratory models 17 through 19 are compared to model 11 in Tables 3.16 and 3.17.

The results of model 1 indicated that there was still significant nesting (ICC1 = 0.22) with 22% of the variance in bites occurring between participants. Models 2 through 5, 7 through 8, and 10 through 16 were in-line with full sample findings. Examining the unique effect of each level-1 predictor for explaining within-participants variance in bites, it was found that Kilocalories explained 28.4%, Energy Density explained 2.7%, Kilocalories x Energy Density explained 1.4%, Location explained 0.3%, and Social explained 2.1%. However, in Model 6, the significant effect of Intake Day found in the full sample was non-significant for the outliers-removed sample, did not improve model fit, and explained 0% of the within-participants variance. This indicated that the number of Bites taken during meals did not differ between Weekends and Weekdays. Therefore, Intake Day was dropped from further models. Additionally, in Model 9, the significant effect of Gender found in the full sample was non-significant for the outliers-removed sample, did not improve model fit, and explained 0% of between-participants variance. This indicated that the number of Bites taken during meals did not differ between males and females. Thus, Gender was dropped from future models. Results of exploratory models 17 and 18 were in-line with full sample findings. However, in Model 19 the direct effect of Height was significant in addition to the Height by Kilocalories cross-level interaction.

Table 3.14

Estimates of model fit and random effects for the outliers-removed model.

Model fit			Random effects						
#	# par.	-2LL	e_{ij}(SE)	τ00(SE)	τ10 Kcalories	τ10 EDensity	τ10 Location	τ10 Social	τ10 Intake Day
1	3	25288.71	559.38(15.30)*	154.31(28.97)*					
2	4	24403.35^	400.67(10.96)*	175.03(31.92)*					
3	5	24326.24^	389.67(10.66)*	168.02(30.68)*					
4	6	24317.73^	388.47(10.63)*	167.44(30.59)*					
5	7	24259.93^	380.48(10.41)*	161.86(29.58)*					
6	8	24257.40	380.48(10.40)*	162.13(29.62)*					
7	8	24222.20^	375.23(10.27)*	160.50(29.32)*					
8	10	24220.06	374.91(10.26)*	160.84(29.38)*					
9	9	24218.62	375.22(10.27)*	152.06(27.84)*					
10	9	24218.76	375.21(10.27)*	152.51(27.90)*					
11	10	24060.94^	347.34(9.61)*	151.43(27.87)*	.0004(<.001)*				
12[a]	11	24210.11	372.13(10.22)*	160.66(29.34)*		a			
13	11	24056.47^	346.29(9.60)*	153.44(28.22)*	.0004(<.001)*		4.26(4.15)		
14	11	24058.54	346.29(9.66)*	150.88(27.87)*	.0003(<.001)*			5.17(8.09)	
15	12	24059.41	347.09(9.61)*	154.23(28.53)*	.0004(<.001)*				.52(1.37)
16	12	24056.79	347.34(9.61)*	143.38(26.45)*	.0004(<.001)*				

Note. [a]Model 12 failed to converge; -2LL = -2 log-likelihood; SE = Standard Error; e_{ij} = residual (within-participant) variance; τ00 = random intercept (between-participants) variance; τ10 = random slope variance; ^Significant model improvement from previous significant model using the Chi-square deviance difference test; * $p < .05$.

Table 3.15. *Estimates of fixed effects for level-1 and level-2 predictors for the outliers removed model.*

Model #	# Parameters	γ00 (SE)	γ10 (SE)	γ20 (SE)	γ30 (SE)	γ40 (SE)	γ50 (SE)	γ120 (SE)	γ560 (SE)	γ01 (SE)	γ02 (SE)	γ11 (SE)
1	3	39.75*										
		(1.57)										
2	4	38.09*	.04*									
		(1.64)	(.001)									
3	5	38.10*	.04*	-3.69*								
		(1.61)	(.001)	(.42)								
4	6	38.11*	.04*	-3.73*	2.49*							
		(1.61)	(.001)	(.42)	(.85)							
5	7	38.21*	.04*	-3.51*	1.94*	6.90*						
		(1.58)	(.001)	(.41)	(.85)	(0.90)						
6	8	37.95*	.04*	-3.50*	1.68	7.17*	-1.40					
		(1.59)	(.001)	(.41)	(.86)	(.92)	(.88)					
7	8	38.32*	.40*	-5.45*	1.80*	6.28*		-.01*				
		(1.58)	(.001)	(.52)	(.84)	(.90)		(.002)				
8	10	38.20*	.40	-5.40*	1.64	6.29*	-.93	-.01*	-1.44			
		(1.59)	(.001)	(.52)	(.86)	(.95)	(.89)	(.002)	(1.75)			
9	9	38.61*	.04*	-5.47*	1.78*	6.24*		-.01*		5.90		
		(1.54)	(.001)	(.52)	(.84)	(.90)		(.002)		(3.09)		
10	9	38.38*	.04*	-5.47*	1.78*	6.27*		-.01*			-.06	
		(1.54)	(.001)	(.52)	(.84)	(.90)		(.002)			(.03)	
11	10	39.60*	.04*	-5.50	1.84*	5.80*		-.01*				
		(1.54)	(.001)	(.51)	(.81)	(.87)		(.002)				
13	11	39.59*	.04*	-5.53	1.54	5.76*		-.01*				
		(1.55)	(.003)	(.51)	(.85)	(.87)		(.002)				
14	11	39.54*	.04*	-5.47	1.83	5.67*		-.01*				
		(1.53)	(.003)	(.51)	(.82)	(.92)		(.002)				
15	12	39.43*	.04*	-5.47	1.67*	5.96*	-.89	-.01*				
		(1.56)	(.003)	(.51)	(.83)	(.89)	(.85)	(.002)				
16	12	39.98*	.04*	-5.51	1.86*	5.75*		-.01*		5.61		.01
		(1.51)	(.003)	(.51)	(.82)	(.87)		(.002)		(3.01)		(.005)

Note. Model 12 estimates were unstable and thus were not included. γ00 = grand mean of bites; γ10 = kilocalories-bites slope; γ20 = energy density-bites slope; γ30 = location-bites slope; γ40 = social-bites slope; γ50 = intake day-bites slope; γ120 = kilocalories x energy density interaction; γ560 = social x intake day interaction; γ01 = gender-bites slope; γ02 = body weight-bites slope; γ11 = gender x kilocalories interaction; **p* < .05.

Table 3.16. *Estimates of model fit and random effects for model 11 and exploratory models for the outliers-removed model.*

	Model fit			Random effects	
Model #	# parameters	-2LL	e_{ij}(SE)	τ00(SE)	τ10 Kcalories
11	10	24060.94	347.34(9.61)*	151.43(27.87)*	.00038(<.001)*
17	12	24058.08	347.40(9.61)*	145.62(26.81)*	.00036(<.001)*
18	12	24060.04	347.39(9.61)*	149.49(27.50)*	.00038(<.001)*
19	12	24055.14^	347.37(9.61)*	139.64(25.83)*	.00034(<.001)*

Note. -2LL = -2 log-likelihood; SE = Standard Error; eij = residual (within-participant) variance; τ00 = random intercept (between-participants) variance; τ10 = random slope variance; ^Marginally significant model improvement from Model 11 using the Chi-square deviance difference test; * p < .05.

Table 3.17. *Estimates of fixed effects for level-1 and level-2 predictors for model 11 and exploratory models for the outliers removed model.*

#	# Parameters	γ00 (SE)	γ10 (SE)	γ20 (SE)	γ30 (SE)	γ40 (SE)	γ120 (SE)	γ02 (SE)	γ03 (SE)	γ04 (SE)	γ12 (SE)	γ13 (SE)	γ14 (SE)
11	10	39.60* (1.54)	.04* (.001)	-5.50* (.51)	1.84* (.81)	5.80* (.87)	-.01* (.002)						
17	12	39.69* (1.51)	.04* (.003)	-5.51* (.51)	1.84* (.81)	5.78* (.87)	-.01* (.002)	-.05 (.03)			9E-5 (5E-5)		
18	12	39.60* (1.53)	.04* (.003)	-5.52* (.51)	1.83* (.81)	5.79* (.87)	-.01* (.002)		-.24 (.26)			3E-4 (4E-4)	
19	12	39.87* (1.48)	.04* (.003)	-5.49* (.51)	1.85* (.82)	5.76* (.87)	-.01* (.002)			-.96* (.42)			-.002* (7E-4)

Note. γ00 = grand mean of bites; γ10 = kilocalories-bites slope; γ20 = energy density-bites slope; γ30 = location-bites slope; γ40 = social-bites slope; γ50 = intake day-bites slope; γ120 = kilocalories x energy density interaction; γ01 = gender-bites slope; γ02 = body weight-bites slope; γ03 = BMI-bites slope; γ04 = height-bites slope; γ12 = kilocalories x body weight interaction; γ13 = kilocalories x BMI interaction; γ14 = kilocalories x height interaction. *p < .05.

The Final Model for the Outliers-Removed Sample

Model 19 was the best-fitting model for explaining variance in bites. The overall effect size for this model was 0.431 (Bickel, 2007). Therefore, the final model explained 43.1% of the overall variance in bites for the outliers-removed sample. This was an improvement over the model for the full sample which explained 23.3% of the variance in bites.

The fixed coefficients from model 19 (shown in Table 3.17 above) indicate the nature of the relationships between predictors and Bites for the final model for the outliers-removed sample. The positive relationship between Kilocalories and Bites and the negative relationship between Energy Density and Bites were main effects that were qualified by a significant interaction between Kilocalories and Energy Density. The simple slopes for the outliers-removed sample were calculated in accordance with Cohen et al. (2003) using the fixed effects coefficients at high (+1 SD) and low (-1 SD) values of Kilocalories. These slopes were significant at low (B = 0.05, SE = 0.003), t = 15.13, p < .05, moderate (B = 0.04, SE = 0.003), t = 14.90, p < .05, and high (B = 0.03, SE = 0.003), t = 9.87, p < .05 values of Energy Density. As can be seen in Figure 3.5, the relationship between Kilocalories and Bites depended on the Energy Density of the meal being eaten, with a stronger relationship between Kilocalories and Bites for meals of lower Energy Density.

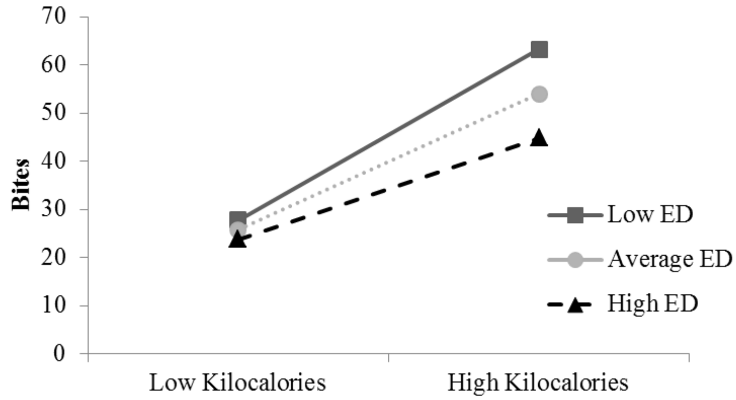


Figure 3.5. The Kilocalorie x Energy Density interaction for the outliers-removed model demonstrating that the relationship between Kilocalories and Bites is strongest for meals with lower Energy Density.

The relationship between Location and Bites remained significant in the final model. This differed from the model for the full sample for which Location became a nonsignificant effect. The relationship between Location and Bites indicated that, on average, participants took 1.85 more Bites when eating out of the home than when eating at home. The relationship between Social and Bites remained significant and indicated that, on average, participants took 5.76 more bites when eating with others than when eating alone. The significant positive relationship between Height and Bites was qualified by a significant cross-level interaction between Height and Kilocalories. In order to examine the nature of the interaction, simple slopes were calculated in accordance with Cohen et al. (2003) using the fixed effects coefficients at high (+1 SD) and low (-1 SD) values of Kilocalories. These slopes were significant at low (B = 0.047, SE = 0.006), t = 7.02, $p < .05$, moderate (B = 0.040, SE = 0.003), t = 14.90, $p < .05$, and high (B = 0.033, SE = 0.006), t = 5.32, $p < .05$ values of Height. Figure 3.6 shows that the positive relationship between Kilocalories and Bites is stronger for shorter participants and weaker for taller participants.

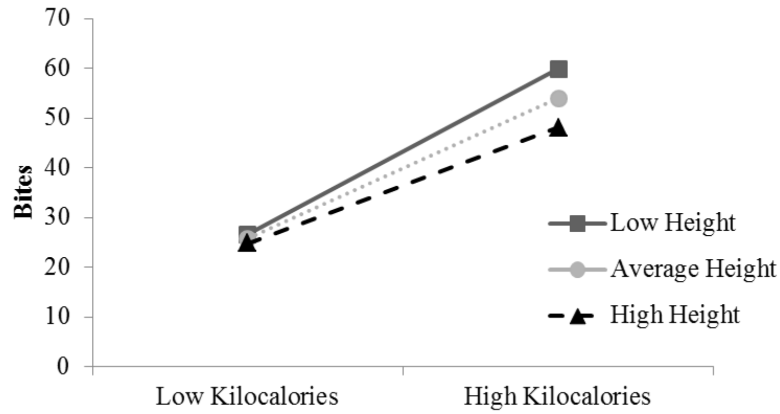


Figure 3.6. The Kilocalorie x Height interaction for the outliers-removed model demonstrating that the relationship between Kilocalories and Bites is strongest for shorter participants.

Day-Level Model for the Outliers-Removed Sample

Data for the day-level model using the sums for each day were prepared for the outliers-removed sample following the same procedures as described for the day-level model with the full sample. The best fitting model for the outliers-removed sample (Model 19) was run using this day-level data. Tables 3.18 and 3.19 compare the meal-level model and the day-level model for the outliers-removed sample. Significant within-participants variance, between-participants variance, and random Kilocalories-Bites slope variance remained in the day-level model. This differed from the day-level model for the full sample which did not have significant random Kilocalories-Bites slope variance. Therefore, the cross-level interaction between Kilocalories and Height was retained.

Table 3.18

Random effects for the meal-level and the day-level models for the outliers-removed sample.

Model	e_{ij}(SE)	τ00(SE)	τ01 Kcalories
Meal-level	347.37(9.61)*	139.64(25.83)*	.00034(<.001)*
Day-level	1507.75(74.42)*	1860.48(340.78)*	.00016(<.001)*

Note. SE = Standard Error; eij = residual (within-participant) variance; τ00 = random intercept (between-participants) variance; τ10 = random slope variance; **p* < .05.

Table 3.19

Fixed effects for the meal-level and the day-level models for the outliers removed sample.

Model	γ00 (SE)	γ10 (SE)	γ20 (SE)	γ30 (SE)	γ40 (SE)	γ120 (SE)	γ04 (SE)	γ14 (SE)
Meal-level	39.87* (1.48)	.04* (.003)	-5.49* (.51)	1.85* (.82)	5.76* (.87)	-.01* (.002)	-.96* (.42)	-.002* (9E-4)
Day-level	125.33* (5.42)	.04* (.003)	-31.81* (4.99)	.95 (1.25)	3.80* (1.45)	-.01 (.005)	-4.49* (1.54)	-.002* (9E-4)

Note. γ00 = grand mean of bites; γ10 = kilocalories-bites slope; γ20 = energy density-bites slope; γ30 = location-bites slope; γ40 = social-bites slope; γ50 = intake day-bites slope; γ120 = kilocalories x energy density interaction; γ01 = gender-bites slope; γ04 = height-bites slope; γ14 = kilocalories x height interaction. **p* < .05.

Examining the fixed effects in Table 3.19, it can be seen that the interaction between Kilocalories and Energy Density became nonsignificant in the day-level model for the outliers-removed sample. This indicated that when variability was reduced by aggregating to the day level, the relationship between Kilocalories and Bites no longer depended on Energy Density. Thus, the main effects of Kilocalories and Energy Density were interpreted. For every additional Kilocalorie consumed during a day, participants took 0.04 more bites on average. Stated in a more practical way, for every 25 Kilocalories consumed, participants took 1 more bite on average. Also, for every 1 point increase in daily energy density, participants took 31.81 fewer bites on average.

Location also became nonsignificant in the day-level model. This indicated that when variability was reduced by aggregating to the day level, Location was no longer a significant predictor of Bites. Social remained significant and indicated that for each additional meal eaten with someone else, participants took 3.80 more bites on average. The significant positive relationship between Height and Bites was qualified by a significant cross-level interaction between Height and Kilocalories.

In order to examine the nature of the interaction, simple slopes were calculated in accordance with Cohen et al. (2003) using the fixed effects coefficients at high (+1 SD) and low (-1 SD) values of Kilocalories. These slopes were significant at low (B = 0.047, SE = 0.005), t = 9.16, p < .05, moderate (B = 0.040, SE = 0.003), t = 12.07, p < .05, and high (B = 0.033, SE = 0.004), t = 8.72, p < .05 values of Height. The magnitude and the direction of the slopes did not change from the meal-level model (Figure 3.6) to the day-level model. Figure 3.7 shows that the positive relationship between Kilocalories and Bites is stronger for shorter participants and weaker for taller participants.

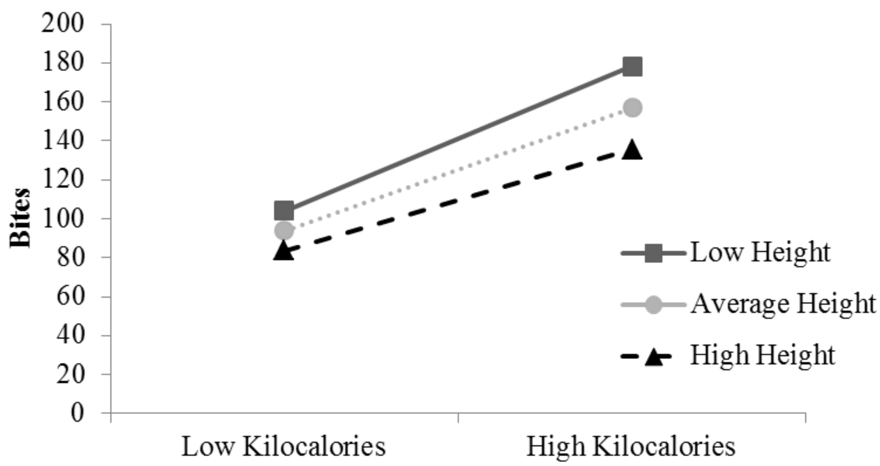


Figure 3.7. The Kilocalorie x Height interaction for the outliers-removed model at the day-level demonstrating that the relationship between Kilocalories and Bites is strongest for shorter participants.

Bite Size Model

Because Height was a significant moderator of the Kilocalories to Bites relationship, it was hypothesized that Height was a proxy for Bite Size. That is, taller participants might have had larger mouths capable of holding more food, and thus taller participants might have taken larger bites. Therefore, participants with a measure of average Bite Size (kilocalories per bite) from the lab meal were retained in the model for a total of 60 participants and 2,388 meals with matching data. BiteCD251 was removed from this model because his average Bite Size was an outlying case (41 kcals/bite). Correlations among variables of interest are provided in tables 3.20 and 3.21. It can be seen that Bite Size and Bites are negatively correlated ($r = -0.10$, $p < 0.05$), indicating that participants with a larger average Bite Size may take fewer Bites during meals. Additionally, Bite Size and Height are positively correlated ($r = 0.28$, $p < 0.05$), suggesting that taller participants take larger bites.

Table 3.20

Within-participant correlations between level-1 variables for bite size model with 60 participants.

Variable	1	2	3	4	5
1. Bites	--				
2. Kilocalories	0.50*	--			
3. Energy Density	-0.14*	0.05*	--		
4. Location	0.06*	0.10*	0.03	--	
5. Social	0.29*	0.32*	-0.04*	0.12*	--
6. Intake Day	0.03	0.08*	0.01	-0.15*	0.18*

Note. * $p < 0.05$. Location coded 0 = Home, 1 = Not at Home. Social coded 0 = Alone, 1 = With Others. Intake Day coded 0 = Weekday, 1 = Weekend.

Table 3.21

Total correlations between level-1 and level-2 variables for the bite size model with 60 participants.

Variable	1	2	3	4	5	6	7	8	9	10
1. Bites	--									
2. Kilocalories	0.46*	--								
3. Energy Density	-0.14*	0.05*	--							
4. Location	0.08*	0.09*	0.08*	--						
5. Social	0.31*	0.32*	-0.03	0.14*	--					
6. Intake Day	0.04*	0.07*	0.01	-0.15*	0.17*	--				
7. Gender	-0.06*	-0.29*	0.04	0.04*	-0.04*	-0.02	--			
8. Body weight	0.10*	0.25*	-0.04*	-0.07*	0.05*	0.02	-0.51*	--		
9. BMI	0.09*	0.18*	-0.06*	-0.06*	0.05*	0.02	-0.28*	0.92*	--	
10. Height	0.05*	0.29*	0.02	-0.06*	0.03	0.01	-0.71*	0.61*	0.27*	--
11. Bite size	-0.10*	0.20*	0.00	-0.04*	0.07*	-0.01	-0.36*	0.26*	0.19*	0.28*

Note. * $p < 0.05$. Location coded 0 = Home, 1 = Not at Home. Social coded 0 = Alone, 1 = With Others. Intake Day coded 0 = Weekday, 1 = Weekend. Gender coded 0 = Male, 1 = Female. Bite size calculated as kilocalories per bite during the lab meal.

The final model identified in the outliers-removed sample with Kilocalories, Energy Density, Kilocalories x Energy Density, Location, Social, Height, and Kilocalories x Height as fixed effects and Kilocalories as a random effect was run with the addition of Bite Size and Bite Size x Kilocalories as fixed effects. All variables were centered at the grand mean for the data set with 60 participants. When Bite Size and Bite Size x Kilocalories were added to the model, the main effect of Height and the Height x Kilocalories interaction became non-significant. This indicated that when controlling for the effect of Bite Size, Height no longer explained significant variance in Bites. Location also became a non-significant effect, indicating that when controlling for the effect of Bite Size, Location no longer explained significant variance in Bites in this sample. Thus, Height, Height x Kilocalories, and Location were dropped from the model to create a more parsimonious model with significant predictors of Bites. This final model was also run at the day-level for the 60 participants. The results of the final meal-level and day-level models including Bite Size are presented in Tables 3.22 and 3.23.

Table 3.22

Random effects for the meal-level and the day-level bite size models for 60 participants.

Model	e_{ij}(SE)	τ00(SE)	τ01 Kcalories
Meal-level	331.26(9.83)*	89.68(18.34)*	.000217(<.001)*
Day-level	1426.39(77.05)*	1347.67(269.80)*	.000181(<.001)*

Note. SE = Standard Error; eij = residual (within-participant) variance; τ00 = random intercept (between-participants) variance; τ10 = random slope variance; **p* < .05.

Table 3.23

Fixed effects for the meal-level and the day-level bite size models for 60 participants.

Model	γ00 (SE)	γ10 (SE)	γ20 (SE)	γ40 (SE)	γ120 (SE)	γ05 (SE)	γ15 (SE)
Meal-level	38.87* (1.29)	0.04* (.002)	-5.29* (.52)	6.57* (.90)	-.01* (.002)	-1.34* (.29)	-.003* (.0005)
Day-level	121.11* (4.99)	0.04* (.004)	-28.58* (5.19)	4.42* (1.53)	-.01* (.006)	-4.40* (1.11)	-.002* (.0008)

Note. γ00 = grand mean of bites; γ10 = kilocalories-bites slope; γ20 = energy density-bites slope; γ40 = social-bites slope; γ120 = kilocalories x energy density interaction; γ05 = bite size-bites slope; γ15 bite size x kilocalories interaction. **p* < .05.

At the meal-level, the positive relationship between Kilocalories and Bites, the negative relationship between Energy Density and Bites, and the negative interaction term between Kilocalories and Energy Density were nearly identical to the previous meal-level model for the outliers-removed sample. Therefore, the relationship between Kilocalories and Bites was stronger for meals of lower energy density compared to meals of higher energy density, as shown in Figure 3.6. The positive relationship between Social and Bites was also very similar and indicated that participants in this sample took 6.57 more bites, on average, during meals eaten with others compared to meals eaten alone.

New to this analysis, the positive relationship between Bite Size and Bites indicated that for every 1 kilocalorie per bite increase in individual bite size, the average number of bites taken during a meal decreased by about 1.34 bites. The addition of Bite Size explained 24.26% of the between-participants variance in Bites. However, there was also a significant interaction between Bite Size and Kilocalories, and the addition of this interaction explained 35.22% of the random Kilocalories-Bites slope variance. Simple slopes were calculated in accordance with Cohen et al. (2003) using the fixed effects coefficients at high (+1 SD) and low (-1 SD) values of Kilocalories. These slopes were significant at low (B = 0.053, SE = 0.003), t = 19.72, $p < .05$, moderate (B = 0.040, SE = 0.003), t = 16.44, $p < .05$, and high (B = 0.026, SE = 0.002), t = 12.01, $p < .05$ values of Bite Size.

As can be seen in Figure 3.8, the relationship between Kilocalories and Bites is stronger for individuals with smaller bite sizes than individuals with larger bite sizes. That is, participants with larger bite sizes took fewer bites to eat high kilocalorie meals compared to participants with smaller bite sizes who took more bites to eat high kilocalorie meals. Overall, compared an intercepts-only model, the final meal-level model explained 38% of the total variance in Bites.

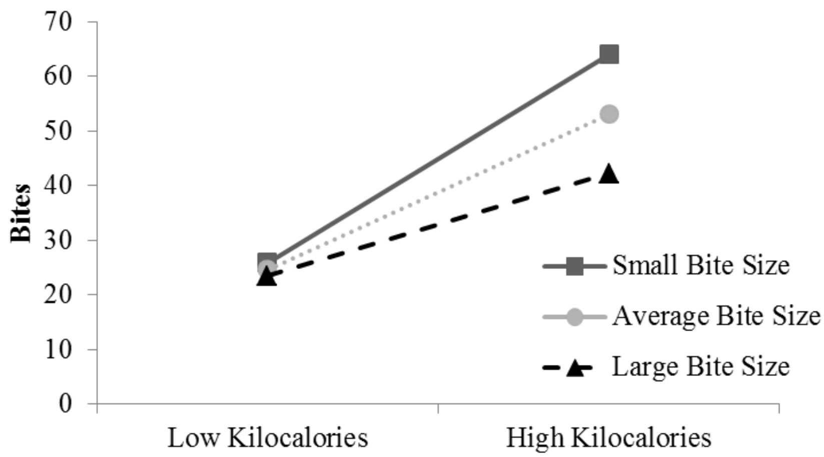


Figure 3.8. The Kilocalorie x Bite Size interaction at the meal-level demonstrating that the relationship between Kilocalories and Bites is strongest for participants with smaller bite sizes.

All of these relationships remained significant and in the same direction in the day-level model. The interaction term between Kilocalories and Bite Size decreased slightly. Simple slopes were calculated in accordance with Cohen et al. (2003) using the fixed effects coefficients at high (+1 SD) and low (-1 SD) values of Kilocalories. These slopes were significant at low (B = 0.049, SE = 0.004), t = 13.27, $p < .05$, moderate (B = 0.040, SE = 0.003), t = 11.71, $p < .05$, and high (B = 0.03, SE = 0.002), t = 15.81, $p < .05$ values of Bite Size. As can be seen Figure 3.9, these slopes are similar to the slopes in Figure 3.8, and indicate that the relationship between Kilocalories and Bites is stronger for individuals with smaller bite sizes than individuals with larger bite sizes at the day-level.

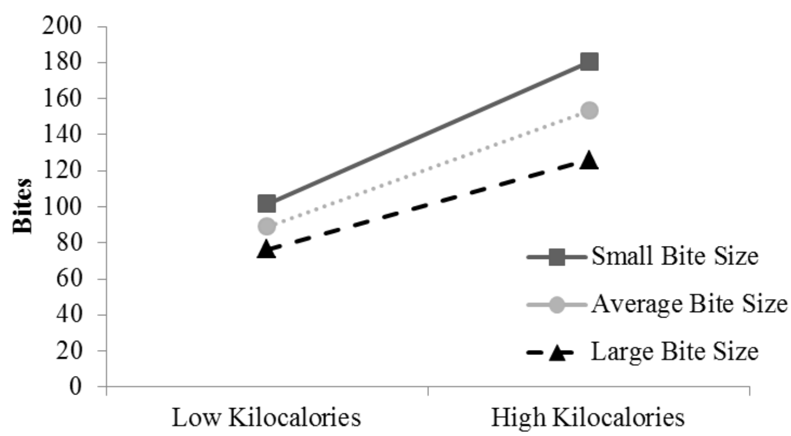


Figure 3.9. The Kilocalorie x Bite Size interaction at the day-level demonstrating that the relationship between Kilocalories and Bites is strongest for participants with smaller bite sizes.

Lab Meal

At the end of the study, 75 participants ate a meal in the laboratory. Eight participants declined to eat the macaroni and cheese either because they did not like the food or because it did not fit into their diet (i.e., it was not low-sodium or low-fat). Of those who ate the meal, two participants had missing data on variables of interest and seven participants had outlying values across variables of interest (z-scores > 3.29, separate from the rest of the data set when examining histograms) that could have overly influenced relationships among variables (e.g., ate for a very long time in the lab or ate very fast in the lab). After dropping these nine participants, 66 participants remained in the lab meal data set for analysis. Descriptive statistics and correlations among variables are provided in Tables 3.24 and 3.25. In addition to the variables measured in the lab under the “Lab Meal” heading, averages for five variables from the real-world meals were calculated for each participant and are listed under the “Average Real-World” heading.

As can be seen in Tables 3.24 and 3.25, participants took significantly fewer bites in the lab (M = 22.20, SD = 6.92) than during average real-world meals (M = 39.63, SD = 14.03, $t(66) = -9.84$, $p < .05$), and the two were not correlated ($r = .19$, $p > .05$). Kilocalories per bite, a proxy for bite size, did not differ significantly between the lab (M = 17.15, SD = 4.51) and the real-world (M = 16.52, SD = 6.56, $t(66) = 0.79$, $p > .05$), and the two were positively related ($r = .37$, $p < .05$). Meal duration was significantly shorter in the lab (M = 400.45, SD = 110.49) than in the real world (M = 783.66, SD = 269.72, $t(66) = -11.75$, $p < .05$), but the two were positively correlated ($r = .25$, $p < .05$). Eating rate calculated as kilocalories per minute was marginally faster in the lab (*M* = 56.99, *SD* = 17.70) than in the real-world (*M* = 52.25, *SD* = 21.39, $t(66) = 1.93$, $p = .05$), but the two were positively correlated ($r = .49$, $p < .05$). Eating rate calculated as bites per minute was not different in the lab (*M* = 3.44, *SD* = 1.00) compared to the real-world (*M* = 3.22, *SD* = 0.32, $t(66) = 1.84$, $p > .05$), and the two were positively correlated ($r = .33$, $p < .05$).

Table 3.24.

Descriptive statistics for lab meal variables and real-world variables.

Variable	Min	Max	*Mean*	*SD*	*t*	Mean difference
Lab Meal						
Kilocalories	142	410	359.91	76.31		
Water (ml)	0	500	320.91	135.32		
Bites	8	45	22.20	6.92		
Kcals/bite	6	26	17.15	4.51		
Duration (sec)	242	698	400.45	110.49		
Rate (kcal/min)	26.46	96.85	56.99	17.70		
Rate (bites/min)	1.47	5.78	3.44	1.00		
SLIM - Before	13	68	33.77	10.96		
SLIM - After	24	90	67.48	13.85		
LAM	34	87	65.89	13.12		
Average Real-World					Lab – Real world	
Bites	20.58	80.29	39.63	14.03	-9.84*	-17.43
Kcals/bite	6.82	34.46	16.52	6.56	0.79	0.63
Duration (sec)	367.62	1418.58	783.66	269.72	-11.75*	-383.20
Rate (kcal/min)	19.33	113.64	52.25	21.39	1.93^	4.74
Rate (bites/min)	2.48	4.02	3.22	0.32	1.84	0.21

Note. SLIM scores below 50 indicate hunger and above 50 indicate fullness. LAM scores below 50 indicate disliking and above 50 indicate liking. All *t*-test *df* = 65. **p* < .05. ^ p = .05.

Table 3.25

Correlations between lab meal variables and real-world variables.

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
	Lab Meal														
1	Kilocalories														
2	Water (ml)	.22													
3	Bites	.37*	.01												
4	Kcals/bite	.35*	.17	-.68*											
5	Duration (sec)	.23	.17	.43*	-.26*										
6	Rate (kcal/min)	.57*	.06	-.09	.49*	-.64*									
7	Rate (bites/min)	.24	-.12	.62*	-.44*	-.41*	.53*								
8	SLIM - Before	-.49*	-.28*	-.05	-.38*	-.06	-.36*	-.02							
9	SLIM - After	-.21	.09	.02	-.18	.16	-.31*	-.14	.12						
10	LAM	.07	.09	.02	.13	-.04	.09	.02	-.15	.17					
	Average Real-World														
11	Bites	.06	.18	.19	-.17	.30*	-.21	-.06	.15	-.07	-.13				
12	Kcals/bite	.21	.07	-.19	.37*	-.36*	.46*	.14	-.15	-.2	-.06	-.45*			
13	Duration (sec)	.02	.26*	.06	-.03	.25*	-.20	-.18	.05	-.06	-.05	.91*	-.43*		
14	Rate (kcal/min)	.26*	.04	-.13	.33*	-.35*	.49*	.21	-.16	-.22	-.11	-.41*	.96*	-.47*	
15	Rate (bites/min)	.12	-.22	.29*	-.30*	.02	.08	.33*	.10	-.07	-.23	.19	-.05	-.19	.18

Note. **p* < .05.

Body Measurements

Height and weight were self-reported during pre-screening, and BMI was calculated from height and weight as (pounds/inches^2) x 703. Height, weight, BMI, body fat percentage, and waist-to-hip ratio (WHR) were measured at the beginning of the two week study and again at the end of the two week study. Means, standard deviations, and results of within-subjects *t*-tests are reported in Table 3.26 for 82 study participants. Participant BiteCD232 was excluded from body measurement comparisons due to third-trimester pregnancy. Overall, participants overestimated their height and underestimated their weight, resulting in an underestimation of BMI for self-report. Participants lost an average of 0.5 pounds over the course of the two week study, equivalent to an average BMI reduction of 0.1.

Table 3.26

Body measurements from self-report, pre-study, and post-study.

Measurements	Min	Max	*M*	*SD*	*t*	Mean difference
Self-report						
Height (inches)	60.0	77.0	67.9	3.9		
Weight (pounds)	102.0	275.0	168.7	39.8		
BMI	17.7	39.5	25.6	5.0		
Pre-study					Pre-study – Self-report	
Height	60.0	76.0	67.5	3.7	-4.97*	-0.4
Weight	102.4	288.4	171.5	42.0	4.75*	2.8
BMI	17.1	42.4	26.4	5.5	6.77*	0.77
WHR	0.67	1.06	0.84	0.09		
Body fat percent	4.8	44.7	26.3	9.30		
Post-study					Post-study – Pre-study	
Weight	103.0	285.4	171.0	41.8	-2.06*	-0.54
BMI	17.3	41.5	26.3	5.5	-2.13*	-0.1
WHR	0.68	1.11	0.84	0.09	-0.34	0.00
Body fat percent	7.7	44.3	26.4	9.2	0.67	0.10

Note. * $p < 0.05$. All *t*-test $df = 81$.

Usability Questionnaire

At the end of the study, participants had the opportunity to provide feedback about their experience in the study, specifically about their impressions of the ASA24 dietary recall program and the bite counter. Table 3.27 shows the frequency of responses for questions about the ASA24 dietary recall program. The majority of participants (67.5%) reported completing the ASA24 for most foods and beverages they consumed.

In associated open-ended responses, participants with a favorable view of ASA24 described the interface as “simple”, “straight-forward”, “well-organized”, “user friendly”, and “easy to follow”. They liked the “comprehensive” list of food choices, the food categories, the search feature, the “good layout”, the pictures of the foods, being able to add forgotten foods at any time, the prompting pathway of questions, being able to see the meal breakdown and summary, its presence on the Internet and being able to use a computer to complete it, the instructions provided, and the e-mail reminders with links. Participants described that the ASA24 became routine, that it was easy to complete if they were already tracking their meals, and that writing things down during the day made it easier to complete. Participants liked seeing what they ate and how much, explaining that it held them accountable and increased their awareness of behaviors like snacking and their overall intake patterns.

Table 3.27

Responses to usability questions about the ASA24 dietary recall.

Question	*N*	% of total sample
Frequency of completing ASA24		
For every food and beverage	18	21.7
For most foods and beverages	56	67.5
For main meals and beverages	3	3.6
Forgot some meals and beverages	2	2.4
Forgot one or more days	4	4.8
Ease or difficulty of use		
Extremely easy	5	6.0
Very easy	22	26.5
Somewhat easy	30	36.1
Neither easy nor difficult	13	15.7
Somewhat difficult	10	12.0
Very difficult	3	3.6
Liked or disliked		
Liked very much	10	12.0
Liked somewhat	26	31.3
Neither liked nor disliked	28	33.7
Disliked somewhat	19	22.9
Experienced ASA24 problems		
Yes	28	33.7
No	55	66.3
ASA24 resulted in eating behavior change		
Yes	45	54.2
No	38	45.8
Recorded dietary intake elsewhere		
Yes	49	59.0
No	34	41.0

Participants also described why the ASA24 was difficult to complete, what they disliked about the program, and problems they had with the website. Some found it difficult to remember meal details, such as specific foods, portion sizes, and the time at which the meal was eaten. Many participants expressed a desire for a "favorites" option, being able to save commonly eaten foods for quick entry. They sometimes had trouble finding foods, especially if the food was international cuisine, and thought that some options were incomplete or unclear. Many participants described frustration with the penguin interviewer providing instructions and slowing down the recall process. When ASA24 was initially released, the penguin would provide instructions for every recall. About halfway through data collection (December 28, 2011), ASA24 was updated so that participants were asked on their second and all subsequent recalls if they wanted the penguin's help or if they wanted to turn him off. This appeared to eliminate frustration with the penguin. Participants described the interface as "unwieldy" and "not stream-lined" with too much mouse clicking and not enough opportunity to use the keyboard. Needing Internet access was sometimes troublesome, and sometimes the program would slow down or freeze, which was the source of many of the reported problems with ASA24. Participants who wanted to use Apple products (e.g., iPhone, iPad) or the Linux operating system were disappointed to learn that ASA24 was not compatible. Downloading the new version of Microsoft Silverlight was difficult for some participants, but this problem was always resolved through troubleshooting. Finding the time to complete the recall was difficult for participants with busy schedules. Some participants wanted to enter the meals during the day instead of all at once the following day.

When asked how they changed their eating behavior as a result of using ASA24, participants described that becoming more aware of what they were eating and portion sizes helped them to eat healthier and eat smaller portions. Participants reported not eating foods that were difficult to find in the database or unnecessary snacks so that they would not have to enter them into ASA24 later. Some participants focused on consuming food and beverage during meals and snacking less between meals. One participant stated, "[I] felt like I had to be sitting down and have organized meals". One participant reported eating simpler foods with fewer ingredients which would make the food easier to report in ASA24. One participant described eating more than usual in order to provide more data for the study.

Participants recorded their meals in a variety of places other than ASA24 to aid their daily reporting. Many participants used the small notebook provided which was described as "invaluable". Others used their day planners, calendars, tablets, phones, computer "sticky notes", and e-mails chains to themselves to record details about their intake during the day. In addition to ASA24, other recall-type programs were used by some participants, including Fat Secret, Livestrong, and My Fitness Buddy.

Table 3.28 shows the frequency of responses for questions about the bite counter. While 26.5% of participant wore the bite counter all day as instructed, 30.1% wore it only during meal times, and 42.4% found a middle ground between all day and just mealtimes. Participants found the bite counter easy to use because they only had to press a button to turn it on and off. Some people liked that it was on the wrist, easily portable, functioned as a watch, and could be strapped to a lunch bag or the refrigerator handle. They described using the device as "not rocket science", a "no brainer", "user friendly", and that it "became second nature". The audible and visual feedback was helpful for knowing when the device was turned on and off. Some participants liked being asked about the device by friends and coworkers so that they could tell them about their participation in the study. Participants liked that it increased their awareness of eating.

Table 3.28

Responses to usability questions about the bite counter.

Question	*N*	% of total sample
Frequency of wearing bite counter		
All day everyday (from morning to evening)	22	26.5
Only part of the day (more often than meals)	35	42.2
Only during meals, took it off other times	25	30.1
Did not wear it during some meals	1	1.2
Ease or difficulty of use		
Extremely easy	26	31.3
Very easy	38	45.8
Somewhat easy	11	13.3
Neither easy nor difficult	5	6.0
Somewhat difficult	2	2.4
Very difficult	1	1.2
Liked or disliked		
Extremely liked	2	2.4
Liked very much	9	10.8
Liked somewhat	21	25.3
Neither liked nor disliked	38	45.8
Disliked somewhat	12	14.5
Disliked very much	1	1.2
Problems wearing: physical discomfort		
Yes	19	22.9
No	64	77.1
Experienced problems with bite counter		
Yes	36	43.4
No	47	56.6
Bite counter changed eating behavior		
Yes	43	51.8
No	40	48.2
Preferred tool		
Bite counter	63	75.9
ASA24 dietary recall	20	24.1

Overall, the most difficult aspect of the bite counter was remembering to turn it on and off. Some participants found it harder to remember as they became more accustomed to wearing the bite counter, when at social functions, or when engaged in other activities while eating. Some participants had trouble remembering to charge the device at night, and some participants had difficulty remembering to wear the device. The device was also "frustrating" when it would shut off automatically during meals and when the display malfunctioned. Participants disliked that it was not waterproof, that it could not be worn during exercise, that it got in the way of long-sleeves and jackets, and that they did not receive bite count or charging feedback from the device. In terms of physical discomfort and appearance, the device was described as unattractive, uncomfortable, "too big", "bulky", "cumbersome", not "trendy", and "ugly". Some participants found the Velcro to be irritating, and some participants disliked having something on their wrist. A few participants wanted a longer wristband so that they could slide their hand through the band without having to separate the two ends. As described above, friends and coworkers often asked about the device, but some participants disliked describing their "weird-looking watch" to others. When asked how the device could be improved, participants suggested a smaller device with a curved back, a thinner non-Velcro wristband, optional beeping, less frequent charging, different colors, additional watch features like the date and a stop watch, syncing to devices like the iPhone, water-resistance, impact-resistance, and automatic detection of eating.

For the 43.4% of participants who experienced bite counter problems, the main problem with the bite counter was that it would sometimes shut off during meals and would need to be turned back on. A few participants thought that 18:88 was an error message, although this indicated that the device was calibrating. Some participants thought they had to hold down the button to pass through the 18:88 message, which resulted in difficulty getting the device to stay on. Finally, the devices did not automatically adjust for daylight savings time, which was a small inconvenience until the experimenter could adjust the time for them.

For the 51.8% of participants who described changing their eating behavior as a result of using the bite counter, many participants described snacking less and eating fewer meals. Sometimes these meals were described as smaller than usual, but others described these meals a larger than usual. Participants became more aware of when they ate, how often they ate, and “more aware of ‘mealtime’ vs. ‘not mealtime’”. Some participants described becoming more aware of how fast they ate, and one participant described paying more attention to when they became full. One participant would not eat at night after the device had been plugged in to charge. Some participants described eating more often with their dominant hand, trying not to move their dominant hand around too much for other activities while eating, and noticing that they sometimes ate with their non-dominant hand.

When asked which tool they preferred, the majority of participants (75.9%) reported preferring the bite counter because it took less time, was easier and simpler, and because it was new and different. For those who preferred using the ASA24 dietary recall, they preferred this tool because it allowed them to receive feedback about what foods they were eating and how much they were eating.

CHAPTER FOUR

DISCUSSION

The purpose of this study was to identify sources of variance in bite count during meals from people using the bite counter during their daily lives. In the discussion that follows, the results for each variable of interest are summarized. Practical implications for the bite counter, study strengths, limitations, and future research directions are discussed.

Sources of Variance in Bite Count

Kilocalories

Research question 1 investigated if kilocalories could predict bite count. Kilocalories were found to explain the most variance in bite count: 21.4% of within-participants variance was explained for the full sample model, and 28.4% of within-participants variance was explained for the outliers-removed model. Average within-participant correlations were 0.45 and 0.51 for the two models, and total correlations across all meals were 0.39 and 0.46 for the two models, indicating that taking more bites was associated with greater energy intake. The slope between Kilocalories and Bites held reliably at 0.04 throughout model building at the meal-level and the day-level, with the exception of a slope of 0.03 at the day-level for the full sample. This translated to an average of 25 kilocalories per bite across all meals. Practically, this could translate to using the bite counter as a calorie counter, with bites multiplied by 25 to create kilocalorie feedback during meals.

It is important to acknowledge that this relationship between kilocalories and bites was moderated by energy density, height, and bite size, as will be discussed below. A simple kilocalorie multiplier may work well when averaged across all meals for all people, but it may be important to consider features of the meals and individual differences before using this kilocalorie multiplier and providing feedback at the meal-level. Additionally, the relationship between kilocalories and bites leaves over 70% of the variance in bites within-participants unexplained. While additional predictors discussed below help to account for additional variance, the final model for the outliers-removed sample still had over 50% of the variance in bites unexplained. This indicates that there may be other predictors of bites explaining significant meal-level variation, or there may be error in the measurements obtained by the bite counter or the ASA24 dietary recall, as will be discussed in subsequent sections.

Energy Density

Research question 2 investigated if the average energy density of a meal could predict bite count. Energy density explained 3.3% of within-participants variance in the full sample and 2.7% of within-participants variance in the outliers-removed sample, indicating that it had a much smaller effect on the number of bites taken during a meal compared to kilocalories. Within-participant and total correlations across both samples were -0.14, indicating the increased energy density was associated with taking fewer bites. The slopes between energy density and bites were -5.81 and -5.49 for the meal-level models for the full sample and the outliers removed sample, respectively. This indicated that as the average number of kilocalories per gram per meal increased by 1, participants took about 5 to 6 fewer bites per meal. The slopes between energy density and bites were -27.57 and -31.81 for the day-level models for the full sample and the outliers removed sample, respectively. This indicated that as the average number of kilocalories per gram for a *day* increased by 1, participants took about 27 to 32 fewer bites *per day*.

To make these results more meaningful, it is important to put them in the context of average food energy densities. Rolls (2007) describes four energy density categories: (1) Very Low Energy Density (0-0.6 kcals/g) foods such as non-starchy fruits and vegetables, nonfat milk, and broth-based soups; (2) Low Energy Density (0.6-1.5 kcals/gram) foods such as starchy fruits and vegetables, grains, breakfast cereals with low-fat milk, low fat meats, beans and legumes, and low fat mixed dishes such as chili and spaghetti; (3) Medium Energy Density (1.5-4.0 kcals/gram) foods such as meats, cheeses, pizza, French fries, salad dressings, bread, pretzels, ice cream, and cake; and (4) High Energy Density (4.0-9.0) foods such as crackers, chips, chocolate candies, cookies, nuts, butter, and oils. Applying this information to the study results, if a person was eating a very low energy density meal (e.g, 0.5 kcals/gram) consisting of a fruit and vegetable salad, it could be expected that they would take about 18 more bites compared to eating a medium energy density (e.g., 3.5 kcals/gram) meal of a burger and fries. However, a significant interaction between kilocalories and energy density as described below indicates that the main effect of energy density should also take into consideration the number of kilocalories being consumed at a meal.

Although no prior research has investigated a relationship between energy density and bites, previous research has investigated the relationship between energy density and kilocalories, finding that people tend to consume more kilocalories when they eat more energy dense foods (e.g., Bell et al., 1998; de Castro, 2004a). In this case, bites cannot be substituted for kilocalories when describing the relationship with energy density because more bites are associated with meals consisting of overall lower energy density. Again, this points to the importance of examining the kilocalorie by energy density interaction as discussed below.

Kilocalories by Energy Density Interaction

Research question 3 investigated if the relationship between kilocalories and bites would depend on the average energy density of the foods being consumed. For both the full sample and the outliers-removed sample, the kilocalories by energy density interaction explained about 1.5% of the variance in bites, indicating that this effect was relatively small compared to the overall effect of kilocalories. For both the full sample and the outliers-removed sample, the simple slopes revealed that when energy density was at its mean across all meals (1.18 kcals/g, low energy density), about 25 kilocalories were consumed per bite. When energy density was one standard deviation below its mean (0.18 kcals/g, very low energy density), about 20 kilocalories were consumed per bite. When energy density was one standard deviation above its mean (2.18 kcals/g, medium energy density), about 33 kilocalories were consumed per bite. The strength of this interaction was reduced for the day-level model for the full sample, it was eliminated in the day-level model for the outliers-removed sample, but it remained the same in the day-level model that included Bite Size as a predictor.

These results indicate that if individuals use the bite counter to monitor energy intake in the future at the *meal-level*, the energy density of the meal should be considered. A smaller kilocalorie multiplier could be applied to meals with lower energy densities, and a larger kilocalorie multiplier could be applied to meals with higher energy densities. Rolls' (2007) four categories of energy density could serve as a guide for future bite counter features. For example, a participant could enter 1 through 4 into the bite counter to indicate the energy density of the meal, and the appropriate multiplier could then be applied. However, if an individual is going to use the bite counter to monitor energy intake at the *day-level* or higher, then the variability in energy density might be reduced such that it would have a smaller impact on the relationship between kilocalories and bites. In this case, the user could continue to input the energy density of the meal to improve overall accuracy of the kilocalorie estimations, or the user could skip this energy density input step knowing that its effect on day-level or greater kilocalorie sums will not be as great as it averages out over time.

Meal Duration

Research question 4 investigated if meal duration could predict bite count. During data exploration, Meal Duration was identified as a variable with an almost perfect correlation with Bites. This indicated that Meal Duration and Bites were representing the same construct. The longer the device was on, the more bites (either true detections or false positives) were recorded by the device. There are two practical implications of this finding. First, for over half of the meals, participants were engaged in other activities while eating, and some of these activities could involve the use of the hands, such as using a computer. Thus, while the device is on, it could be detecting these activities (false positives) in addition to true bites which may explain why there was such a strong correlation between Meal Duration and Bites. Second, Meal Duration itself could potentially be used as an outcome variable from the bite counter. It is possible that the detection of Bites could be used as one indicator of eating activity, which might enable automatic detection of eating behavior by the device (Dong, Hoover, Scisco, & Muth, under review). Then Meal Duration could be used by an individual as part of an eating diary, which might also include the time eating began and ended, eating rate, and perhaps even foods consumed and kilocalorie estimates if bite counter recordings are paired with an eating diary. This combination of information could be very useful for an individual trying to change their eating patterns. For example, if someone sees that they typically eat all of the their daily meals in under 10 minutes and they would like to begin increasing their meal durations in order to slow their overall eating rate, they could use the eating calendar to help them accomplish this goal. The bite counter could also have an additional feature indicating how long someone has been eating, like a stop-watch, to provide real-time feedback about Meal Duration.

Meal Location

Research question 5 investigated if meal location could predict bite count. Specifically, meals eaten outside of the home were compared to meals eaten at home. Within-participant correlations between location and bites were 0.05 and 0.06 for the full sample and the outliers-removed sample, respectively. Total correlations between location and bites were 0.04 and 0.07 for the full sample and the outliers-removed sample, respectively. These small correlations indicated that participants might take more bites when eating outside of the home than when eating at home. For both the full sample and the outliers-removed sample, the kilocalories by energy density interaction explained about 0.2-0.3% of the variance in bites, indicating that this effect was very small.

The slopes between location and bites were .79 and 1.03 for the meal-level models for the full sample and the outliers-removed sample, respectively. Although in the expected direction, these slopes were not significantly different from zero. The slope between location and bites was 1.85 for the meal-level for the outliers-removed sample, and indicated that when this sample ate a meal outside of the home, they took about 2 additional bites during the meal compared to eating a meal at home. This translates into consuming about 50 additional kilocalories when eating outside of the home compared to eating at home. However, the day-level model slope of 0.95 between location and bites was not significantly different from zero. Location was a non-significant predictor in the model with Bite Size that included only 60 participants.

Taken together, these results suggest that people may take a few more bites when they eat meals outside of the home, which may be an indicator of increased energy intake during these meals and larger portion sizes available when eating outside of the home (e.g., Condrasky et al., 2007; de Castro et al., 1990). However, location was not a very strong or reliable predictor of bites across models. Therefore, individuals using the bite counter could be made aware of a tendency to take more bites outside of the home, and they could watch for this pattern in their personal bite count data from meal to meal. If they did see that they tended to take more bites when eating outside of the home, they could try to target these locations as an opportunity to reduce the number of bites being taken.

Social

Research question 6 investigated if eating with others versus eating alone could predict bite count. Within-participant correlations between social and bites were 0.25 and 0.28 for the full sample and the outliers-removed sample, respectively. Total correlations between social and bites were 0.23 and 0.27 for the full sample and the outliers-removed sample, respectively. These positive correlations for social were the second largest correlations with bites found for the tested model and indicated that participants took more bites when they ate with others than when they ate alone. Social explained 1.9% and 2.1% of the within-participants variance for the full sample and the outliers removed sample, respectively. This was the second largest unique effect at the meal-level for the tested model. The slopes between social and bites at the meal-level were 5.73 and 5.76

for the full sample and the outliers-removed sample, respectively. These slopes indicated that participants took about 5 to 6 more bites during meals that they ate with others compared to meals that they ate alone. Translated to the average number of kilocalories consumed per bite, this equates to eating 125 to 150 additional kilocalories during a meal eaten with others compared to a meal eaten alone, a finding that is very similar to the de Castro and de Castro (1989) finding that meals eaten with others contained about 180 more kilocalories than meals eaten alone.

The slopes between social and bites at the day-level were 5.76 and 3.80 for the full sample and the outliers removed sample, respectively. This indicated that for every additional meal eaten with others during a day, participants took between 4 and 6 additional bites per day. The reduction in the number of additional bites taken for the day-level model for the outliers-removed sample suggests that eating with others may not have as strong of a relationship with number of bites taken for the entire day compared to number of bites taken during a meal. This is similar to the finding by de Castro (1996) that social facilitation is a stronger predictor of meal size than daily food intake. Also, findings were very similar for Social in the meal-level and day-level models with Bite Size that included 60 participants.

The practical implication of this finding is that the bite counter may provide individuals with some information about their eating patterns when they eat with others. If individuals are made aware of the tendency to take more bites when eating with others, they could try to monitor bites during these meals and keep their number of bites taken during meals eaten with others similar to the number of bites taken during meals eaten alone. That is, a social eating situation may provide a cue to an individual that they should monitor their bite count more closely during those meals in order to avoid over-eating. An individual could do this by setting an alarm when eating with others to go off at their average number of bites per meal when eating alone.

Intake Day

Research question 7 investigated if day of the week, dichotomized as weekday vs. weekend, could predict bite count. The within-participant correlations (0.01) and total correlations (0.03) between intake day and bites were small and non-significant. In the meal-level model with the full sample, 0.2% of the variance in bites was explained by intake day, which indicated that intake day was a very small effect. The relationship between intake day and bites indicated that about 2 additional bites were taken during meals on weekdays than meals on weekends, and 8 additional bites were taken overall for weekdays compared to weekends. This translated to eating 50 additional kilocalories during weekday meals and 200 additional kilocalories during weekdays overall. This result is opposite the finding in previous research that people tend to eat more on weekends than weekdays (e.g., Rhodes et al., 2007). However, intake day explained 0% of the variance in bites for the outliers-removed model and the relationship between intake day and bites was non-significant. This indicates that the finding that participants took more bites on weekdays could not be reproduced in a sample that had higher quality bite counter and ASA24 data overall. Practically, future bite counter users seeking to reduce bite counts would not need to focus on whether intake occurs on a weekend or a weekday, and instead should focus on if they are eating with other people, as this would indicate greater potential for taking more bites.

Social by Intake Day Interaction

Research question 8 investigated if the relationship between eating with others and bites depend on whether it is a weekend or a weekday. No significant interaction between social and intake day was found for any of the models, with the interaction explaining close to 0% of the within-participants variance. This finding did not coincide with previous research that found greater social facilitation of eating on weekends compared to weekdays (de Castro, 1991). Practically, this finding indicates that bite counter users should be cognizant of their bite count when eating with others every day of the week.

Gender

Research question 9 investigated if gender could predict bite count. Overall, correlations between gender and bites were very small, negative, and only significant for the outliers-removed sample. This indicated that females may take fewer bites than males during meals. Gender explained 5.2% of the between-participants variance in full sample model, but none of the between-participants variance in the outliers-removed model. Slopes between gender and bites in the final models were not significantly different from zero. Gender also did not explain any differences in the relationships between kilocalories and bites between participants. It is possible that men might take more bites in order to consume more kilocalories (McArdle et al., 2005), but women might take more bites if they are taking smaller bites (Burger et al., 2011). These two effects could possibly counteract each other, resulting in no consistent relationship between gender and bites found in the present study. This indicates that gender is most likely not an individual difference characteristic that could guide bite counter kilocalorie calibration settings.

Body Weight and BMI

Research question 10 investigated if body weight could predict bite count. Overall, correlations between body weight and bites were very small, positive, and only significant for the outliers-removed sample. This indicated that a higher body weight might be associated with taking more bites during meals. Body weight explained 2.2% of the between-participants variance in full sample model, and 5.0% of the between-participants variance in the outliers-removed model. Slopes between body weight and bites in the final models were not significantly different from zero. Body weight also did not explain any differences in the relationships between kilocalories and bites between participants. Thus, although a higher body weight has been found to be associated with increased energy intake in previous research (Periwal & Chow, 2006), body weight does not seem to be associated with the number of bites taken during a meal. This indicates that body weight is most likely not an individual difference characteristic that could guide bite counter kilocalorie calibration settings.

Body weight and BMI were highly correlated. Thus, BMI had similar small, positive correlations with bites that were only significant for the outliers-removed model. This indicated that a higher BMI might be associated with taking more bites during meals. In exploratory analyses, BMI did not significantly predict bites or explain individuals' differences in the relationship between kilocalories and bites. This indicates that BMI is most likely not an individual difference characteristic that could guide bite counter kilocalorie calibration settings.

Height

In exploratory analyses, participant height did not have a positive correlation with the number of bites taken during a meal. However, for the outliers-removed sample at the meal-level, the slope between height and bites was -0.96 and significant, indicating that as height increased by one inch, participants took about one fewer bite per meal on average. When aggregated to the day-level for the outliers-removed model, the slope between height and bites was -4.49 and significant, indicating that as height increased by one inch, participants took about 4 to 5 fewer bites per day on average.

Additionally, height explained 9.8% of individual differences in the relationships between kilocalories and bites. The interaction between kilocalories and bites was significant for the full sample at the meal-level and for the outliers-removed sample at the meal-level and the day-level. Simple slopes were consistent across these three models and indicated that participants of average height (about 5' 7" in both samples) ate about 25 kilocalories per bite, taller participants (about 5' 10.5" in both samples) ate about 30 kilocalories per bite, and shorter participants (about 5' 3.5" in both samples) ate about 21 kilocalories per bite. This leads to the possibility that taller individuals take larger bites, and height could possibly serve as an individual difference variable approximating bite size.

To explore this idea, the total correlation between bite size in the lab (kilocalories per bite) and height was calculated for the 60 participants in the bite size model, and a significant positive correlation of 0.28 indicated that bite size and height are somewhat related. However, bite size and body weight were also significantly positively correlated (0.26), and body weight was not a significant moderator of the kilocalories-bites relationship. This suggests that there may be something unique about height that potentially allows it to be related to bite size in the real world, such as the overall size of one's skeletal frame and possibly increased mouth volume. Human body size measurements including height and body surface area (m^2) have been found to be associated with larger bite sizes in a laboratory setting (Hill & McCutcheon, 1984). The relationship between body size and bite size in animals has also been investigated as it could have important implications for species fitness. Cope, Loonen, Rowcliffe, and Pettifor (2005) found that geese with longer bills had larger bite sizes over a range of grass heights, and that bite size was proportional to body mass to the power 2.99. Wilson and Kerley (2003) found that larger animals such as the rhinoceros had larger bite sizes over a range of plants than smaller animals such as goats, although differences between animals of similar size depended on the type of plant being consumed.

To test the hypothesis that height might be a proxy for bite size, bite size was added as a predictor to a model with 60 participants who had average bite sizes from the lab meal. When bite size was added, height was no longer a significant predictor of bites and it no longer moderated the relationship between kilocalories and bites. This suggests that when controlling for bite size, height does not provide any additional predictive power for the number of bites taken during a meal.

Therefore, in the absence of a bite size measurement, height is an individual difference variable that could be used to calibrate the kilocalorie setting for the bite counter. Shorter participants could receive a smaller kilocalorie multiplier, and taller participants could receive a larger kilocalorie multiplier. This suggestion should be taken with caution, however, noting that a bite size measurement may be a better way to calibrate the bite counter kilocalorie setting, as discussed below.

Bite Size

When bite size was entered into a model with 60 participants with bite size measurements, bite size was able to explain 24.6% of the between-participants variance. Every additional 1 kilocalorie per bite increase in bite size was associated with a decrease of about 1 to 2 bites taken per meal on average. The interaction between kilocalories and bite size explained 35.22% of the variance in individual relationships between kilocalories and bites. The simple slopes indicated that participants with smaller bite sizes ate about 19 kilocalories per bite on average, participants with average bite sizes ate about 25 kilocalories per bite on average, and participants with larger bite sizes ate about

39 kilocalories per bite on average. This finding was still significant at the day-level: participants with smaller bite sizes ate about 20 kilocalories per bite on average, participants with average bite sizes ate about 25 kilocalories per bite on average, and participants with larger bite sizes ate about 33 kilocalories per bite on average.

Furthermore, as described above, the addition of bite size to the model eliminated the significant height main effect and interaction with kilocalories. This suggests that bite size would be a better individual difference variable that could be used to calibrate a bite counter kilocalorie setting. Individuals with smaller bite sizes could be given a smaller kilocalorie multiplier, and individuals with larger bite sizes could be given a larger kilocalorie multiplier. Also, individuals with different bite sizes might need to be given different bite reduction goals. Individuals with larger bite sizes may need to reduce their intake by fewer bites than individuals with smaller bite sizes in order to reduce energy intake.

These recommendations make an assumption that bite size is constant across meals for the same person. There is evidence in the literature that bite size is fairly constant within individuals (Medicis & Hiiemae, 1998; Westerterp-Plantega et al., 1990) with greater variation between individuals (Hutchings et al., 2009). This has been observed in our own laboratory study, during which participants consistently took the same bite sizes (kcals/bite) of the same food over three separate sessions, but there was greater variation in bite size between participants (Salley et al., 2011).

Hence, it follows that a person's bite size could serve as a calibration step for the bite counter. This idea is analogous to calibrating a pedometer, or step counter, for running or walking. Before using a pedometer to estimate distance, the user can calibrate it by running or walking a set distance (e.g., ½ mile on the inside of a track). The number of steps that it takes the user to travel this distance is then used to calculate future distances. For example, if it took someone 1,000 steps to travel ½ mile, then their pedometer would tell them that they went 1 mile when 2,000 steps were recorded. A similar calibration step could be imagined for the bite counter. A standard food with known calorie content and energy density could be eaten by a new bite counter user. For example, 500 kilocalories of low energy density food like pasta with an energy density of 1.5 kcals/g could be eaten by a new user. If the bite counter detected 20 bites for this meal, 25 kcals/bite would serve as the user's calibrated bite size. This could then be held constant across all meals, or for improved accuracy, it could be adjusted based on the energy density of the foods being eaten, with a decrease in kcals/bite for lower energy density foods and an increase in kcals/bite for higher energy density foods.

Manipulating bite size also has some applicability to the bite counter. When bite size is manipulated, taking smaller bites is associated with less energy intake (Walden, Martin, Ortego, Ryan, & Williamson, 2004; Zijlstra, de Wijk, Mars, Stafleu, & de Graaf, 2009) or no change in energy intake (Spiegel, Kaplan, Tomassini, & Stellar, 1993) in controlled laboratory and clinical settings. If an individual wanted to reduce their bite size in order to slow their eating rate (that is, take more bites of a meal of the same size), they could use the bite counter to help them do so in their daily lives. For example, if a participant knows they typically take 30 bites when they eat two slices of pizza, they could try taking 60 bites of the same pizza. This would slow down their eating rate and, if their goal was to eat less as a result, it would give them more time to consider feelings of hunger and satiety during the meal and perhaps even become tired or bored of the food being eaten (Scisco, 2009).

Lab Meal

Positive correlations between lab meal and real world measures provided support for using measures obtained in the lab to predict eating behavior in the real world. Perhaps most relevant to the current study was the finding that bite size in the lab and real world were positively correlated and not significantly different from one another. This supports the idea that bite size is consistent within individuals and demonstrates that bite size from a single laboratory meal could be a possible way to calibrate the bite counter in future research. The findings that participants ate for a shorter amount of time and ate faster in the lab compared to real world meals indicated that the controlled laboratory environment may have been unnatural for many participants. Participants ate alone in silence without being able to do any other activities and while being video-recorded. They frequently told the experimenter about almost always doing something else while they eat, and as a result the lab meal felt strange or uncomfortable to them. Thus, it is possible that participants ate quickly in order have the lab meal experience end as soon as possible. Future research should aim to create a more natural eating environment in which participants are free to do other activities or perhaps eat with others. Because bite size should remain constant within individuals, introducing other activities and a social element should not overly influence bite size, although the features of laboratory meals that could impact bite size should also be topics of future research (Mishra et al., 2012).

Weight Loss

Participants lost an average of 0.5 pounds over the two-week study period. Weight loss was not a goal of the study, and the study was not advertised as such. However, 42.4% of participants who completed the study were trying to lose weight, and they used the study as an opportunity to help them self-monitor their eating behaviors. Recruitment at the beginning of January was particularly successful as some of these participants used the study to kick off their New Year's weight loss resolution.

The significant weight loss was most likely the result of self-monitoring eating over two weeks, a behavior that is consistently related to weight loss (Wadden et al., 2005). Results from the usability questionnaire indicated that participants became much more aware of what they were eating, how much they were eating, and when they were eating. This increased awareness could be attributed to completing the ASA24 dietary recall and using the bite counter daily, although the unique effect of each one cannot be completely disentangled. The ASA24 most likely made them more aware of food details and quantity, whereas the bite counter most likely increased their awareness of when they were eating and meal duration since the device had to be turned on and turned off. This awareness of food intake may have provided opportunities for individuals to make behavioral changes, such as deciding to turn the device off and stop eating when feeling full or when a certain amount of food had been consumed.

The weight loss observed in the study also may have resulted from decreased snacking. Participants described not wanting to snack because they did not want to turn the device on again for something small and/or because they did not want to report another meal in ASA24. It appears that the costs of the minimal effort to use the bite counter and/or the greater effort of entering a snack into ASA24 sometimes outweighed whatever benefits participants might have obtained from snacking.

However, suggesting that individuals reduce snacking to lose weight actually goes against current guidelines from the Academy of Nutrition and Dietetics (2012) that recommend distributing caloric intake throughout the day in 4-5 meals and snacks. Research supporting this official recommendation seems to be mixed. In a review of cross-sectional and longitudinal studies of adults, snacking behaviors were found to be associated with increased body weight (Mesas, Munoz-Pareja, Lopez-Garcia, & Rodriguez-Artalejo, 2012). However, in a review of weight-loss and weight-maintenance interventions, eating frequency (one definition of snacking behavior) was not associated with body weight or related health outcomes (Palmer, Capra, & Baines, 2009). Identifying relationships between snacking, body weight, and health is difficult because definitions of snacking are not consistent in the literature, and changes in eating frequency may be difficult for individuals to sustain over time (Palmer, Capra, & Baines, 2011). Therefore, if reduced snacking was a mechanism by which this study led to weight loss, it is possible that this effect may not persist over the long-term.

Implications of ASA24 and Bite Counter Usability

The usability questionnaire provided important insights into participant's impressions of the study tools. The ASA24 dietary recall is a new Internet-based automated recall system designed by the National Cancer Institutes to be a dietary intake research tool. Most participants completed about 12 to 14 recalls which indicated that the ASA24 was acceptable for daily use. However, the recall itself has a large number of questions and steps, and recalling more meals and more foods requires a greater time investment by the participant. Participants cited the time needed to complete the recall as one of their main frustrations. This could have resulted in participants trying to get through the recall process quickly, which might have led to incorrect responses to questions about foods, details, and portion sizes. Incorrect responses as well as difficulty finding food items could have led to error in estimation of kilocalories from ASA24.

Additionally, ASA24 uses pictures to help participants estimate portion sizes. However, these pictures could lead to perceptual errors and subsequent over- or under-estimation of the amount of food that was actually consumed (Scisco, Blades, Zielinski, & Muth, under review). Furthermore, the ASA24 is designed for participants to use their memory to complete the recall, and reviews of 24-hour dietary recall approaches indicate that participants can typically remember most of their meals with a tendency to underreport (Thompson & Subar, 2008). Although the interviewer prompts and the multiple pass method of the ASA24 are designed to reduce underreporting (Thompson & Subar, 2008), the time needed to complete the recall electronically could potentially lead to underreporting. Also, participants in this study expressed great difficulty remembering their meal details unless they used another method to record their meal details at the time of the meal, such as the “invaluable” small notebook. This recording of details in the notebook most likely reduced another cited benefit of 24-hour recalls, that they have less of an influence over eating behavior at the time of the meal (Thompson & Subar, 2008).

An alternative to the ASA24 for future studies could be a dietary intake recording tool that allows meal details to be entered at the time of the meal. This might be preferred by some participants because they could input their meal information during smaller time periods throughout the day, rather than dedicating a larger, single period of time in the morning or evening trying to remember details from the previous day. There are a number of popular programs available for mobile devices, such as FatSecret and LiveStrong, but the accuracy of the kilocalorie databases would need to be examined prior to use in a research study. An advantage of the ASA24 is that it uses the USDA’s Food and Nutrient Database for Dietary Studies (FNDDS). Although the 24-hour recall is considered the best self-report instrument available for estimating dietary intake (Kirkpatrick, 2011), there may be other methods that participants in future bite counter studies may find easier to complete. If participants are already turning the bite counter on and off and making notes about details of bite counter use, taking a few more minutes to record the foods eaten may not place too much additional burden upon participants. While one single method of recording dietary intake may not be preferred by all participants, efforts should be made to provide them with tools that are easy to use and quick to complete, yet accurate.

The bite counter was perceived as much easier to use than the ASA24. Although not an equal comparison by any means, 75% of participants reported that they would prefer to use the bite counter over the ASA24, mainly due to its simplicity and the minimal amount of time needed to engage with the device. However, device problems and user difficulties could have reduced the accuracy of bite counter recordings. Some of the devices in the study would shut off during meals due to an internal battery power problem. Although participants were instructed to keep turning the device on to record their meal, it is possible that some bites were not recorded. However, steps were taken during data screening to correct these errors by adding up these “turning off” sequences which may have reduced bite count underestimation.

Additionally, participants reported difficulty remembering to turn the device on and off. When this was noted by participants during their recall, steps were taken during data screening to correct for these errors. However, participants may not have remembered to report errors in device recording, or participants’ reports of the durations for which the device was off at the beginning of meals or on after the conclusion of meals may have been incorrect. Any of these possibilities could have led to under- or overestimation of bite counts. Some participants also found the device uncomfortable and unattractive and chose not to wear it during the day. This could have led to forgetting to use the device to record meals.

Future device design improvements should make the bite counter more attractive and comfortable for daily use. This would help participants to remember to wear the bite counter and record their meals with the device. Additionally, research on the ability to automatically detect eating should continue, as this could potentially eliminate the need for participants to activate and deactivate the device (Dong et al., under review). However, any recording errors associated with detecting meals automatically should be less severe than the recording errors associated with participants forgetting to turn the device on and off in order for automatic detection of meals to improve device accuracy. This is another area for future research.

Study Strengths

Large Sample Size and Success of Data Collection

Overall, data collection efforts were successful. This was one of the first studies to collect eating behavior data from naturalistic settings with the bite counter. The study required a significant time commitment by participants who used the bite counter for 14 consecutive days while spending up to an hour each day completing the ASA24 dietary recall and the Daily Meals Questionnaire. Only 11.7% of the participants who began the study withdrew for various reasons; 3,190 complete meals across 83 participants were analyzed after outlier meal removal; and 2,741 complete meals across 69 participants were analyzed after outlier participant removal. This large sample size provided sufficient power for the MLM analyses conducted (Hox, 2010).

Data collection was successful due to a combination of factors. Wide advertisement to students, university employees, and community members attracted over 260 interested participants. The $50 compensation seemed to be an adequate motivator for some participants. However, many participants expressed greater interest in receiving their data summary with details about how many kilocalories they were eating and how many bites they were taking. Future studies with ambulatory bite counters should continue to provide data summaries to participants as this seems to be a strong motivating factor. Additionally, the participants were given in-depth instructions during a one hour orientation meeting, reminded to begin using their bite counter on the start date, sent daily e-mails with links to the ASA24 recall website and the Daily Meals Questionnaire website, and sent reminders to attend the data download meeting and the final meeting. These factors held the participants accountable for their participation in the study and also made it easier for them to remember to complete the study requirements. The Lettermelater.com website was an invaluable resource for delivering reminder e-mails at participants' preferred times without placing excessive burden on the experimenter.

Participant Recall of Bite Counter Use

An extremely important step in data collection is that participants accurately report the time that they ate their meals. For example, if the bite counter was turned on at 7:16AM on Monday, October 1, and a meal was reported at 7:16AM on Monday, October 1 in ASA24, then these meals are easily matched during the data matching process. The farther apart in the time the bite counter recording and the ASA24 report become, the more difficult it becomes to match the meals. Thanks to pilot testing and early data collection with the bite counter (Jasper, Scisco, Parker, Hoover, & Muth, 2012), it was known that this meal start time information would be crucial. During the orientation meeting, the fact that meal start time information would be critical for future data matching was emphasized to participants, and they were encouraged to use the small notebook or another tool to take notes about the time they turned the device on. As a result, matching meals based on time for this study was much easier than during previous data collection efforts, with many participants accurately reporting their meal start time within a few minutes of the start time recorded by the bite counter. Future research with the bite counter and dietary recall methods should continue to emphasize the importance of accurately recording meal start time.

An additional strength of the study was that participants reported a number of details about their bite counter use in the Daily Meals Questionnaire that aided data matching and error identification (see Appendix C). Without these details, a researcher would not have much information to guide their error identification and decision-making process. However, the format of this questionnaire made reporting these details tedious for some participants. Future research should continue to collect these reports of bite counter use from participants, but this questionnaire format should be simplified to reduce participant reporting burden.

Objective Measurement of Eating Behavior

The bite counter is a unique device that can measure eating behaviors objectively in naturalistic, real world settings. Variables like bites, meal duration, and eating rate (bites/minute) were measured without relying on participant self-report or experimenter observations in laboratory settings. This allowed for comparisons between objectively measured laboratory variables and objectively measured real world variables, comparisons that were previously not possible without the bite counter.

Study Limitations

Accuracy of Bite Counter and ASA24 data

As previously described, technical difficulties and user errors could have contributed to error in bite counter recordings. Furthermore, bite counter algorithm development has been limited to laboratory studies under controlled and uncontrolled conditions (Dong, Hoover, Scisco, & Muth, 2012). Further bite counter algorithm improvement may be able to reduce the occurrence of false positives and to increase true detections. A cafeteria study is currently underway with 300 participants which will provide an exceptionally large database of bites taken in a more naturalistic setting. This future database could be used to improve device accuracy over a wide range of wrist motions resulting from eating different foods, using different utensils, and individual differences in bite behavior. It could also be used to answer important questions relevant to the algorithm, such as the average time elapsed between bites during meals. In addition, the present study identified behaviors that participants frequently engaged in while eating, such as talking to others, using a computer, watching TV, reading, and driving. These behaviors could be studied closely in laboratory and naturalistic settings to examine how they impact device accuracy.

Potential errors in ASA24 reporting by participants or features of the ASA24 that could lead to inaccurate kilocalorie estimates were also previously described. Future published work about the validity of the ASA24 for estimating energy intake should be applied to the results of the present study. Combined with the possible errors from the bite counter recordings, it can be assumed that the average within-participants correlation when outliers were removed of 0.51 is just a starting point. As improvements are made to the bite counter and the ASA24 or other dietary intake recording tools, it is possible that error in bite and kilocalorie recordings could be reduced, thus potentially improving the correlation between these two variables.

Lack of Bite Counter Training and Feedback

Another limitation of this study was that participants did not receive bite counter training. They were simply told how to use the device to record their meals. Participants were encouraged to eat as they normally would, which could have included engaging in other activities while eating and use of the non-dominant hand. Participants did not receive feedback from the device other than an “on” message and beeping when it was turned on and off, so they did not develop an understanding of when the device was recording bites and when it was not. This could have resulted in participants using the device in a way that would differ from someone who knows how the device works and what is being detected. Perhaps more knowledgeable participants that are given meaningful device feedback would use the device “correctly”, and the correlation between bites and kilocalories could possibly improve.

Study Sample

The majority of participants in the study were students or employees of Clemson University. As students and employees of a university, many of these participants were interested in and understood the importance of research. Through conversations with these participants during meetings, the experimenter learned that many of these participants were motivated to comply with instructions and provide quality data for this study. Additionally, almost half of the sample was motivated to change their weight during the study which could have served as a motivator to comply with the study instructions. Thus, this university-based sample that included individuals trying to change their weight may have had higher rates of compliance and better data quality than might be expected in the general population. Additionally, over 80% of the sample was Caucasian. Therefore, results cannot be generalized to all racial and ethnic groups.

Future Research Directions

Five key areas of future research have been identified for improving the relationship between kilocalories and bites as detected by the bite counter.

First, as discussed above, the bite counter algorithm and design should be improved to reduce false positive detection, increase true bite detections, and reduce user errors associated with device use. This research could range from the current database of bites being developed by the cafeteria study to ongoing usability studies during device development to automatic detection of eating by the bite counter device.

Second, future research should investigate what type of dietary intake reporting is most accurate and acceptable for participants in bite counter studies. It may be that real-time recording of intake with a mobile, Internet-capable device would be a better approach. A study comparing participant perceptions of their reporting accuracy and usability of different dietary intake tools while simultaneously recording meals with the bite counter could inform future bite counter validation studies. The tool selected should also have an accurate kilocalorie database, be a validated measure of energy intake, and provide data in a way that can be managed by researchers. It may be that the ASA24 will be the best tool available considering all of these factors especially as improvements are made to ASA24 over time, but further exploration is necessary.

Third, bite counter training and feedback could be provided to participants in order to improve the quality of the bite counter recordings. It may be the case that participants should refrain from other activities while eating in order to reduce the occurrence of false positives. Perhaps participants should be able to see when bites are being recorded on the device in real-time so that they can adjust their behavior to make sure that bites are being recorded during meals. This training and feedback could take a number of forms, from a small manual provided with the bite counter at the beginning of the study, to videos explaining how to use the bite counter, to detailed one-on-one instructions and demonstrations with an experimenter. This feedback and training could also occur in stages during a study, and improvement in the relationship between bites and kilocalories could be assessed over time. Future research could also examine a number of these approaches and compare them to each other and to bite counter use without any training or feedback. The goal of this research would be to determine what kind of training and feedback, if any, is necessary to improve the relationship between bites recorded by the device and kilocalories consumed during a meal.

Fourth, future research should examine improvement in the kilocalories to bites relationship when the bite counter is calibrated based on an individual's bite size. The research questions in this area are numerous. The foods, utensils, and laboratory settings most appropriate for a calibration meal should be investigated. There may be features of a meal experience that could alter bite size, and these should be fully understood when designing a calibration meal. Investigating the possibility of calibrating at home with an individual's own utensils and foods would have interesting applications for future calibration instructions for devices sold commercially. The effect of food energy density on calibration should be investigated. It would also be interesting to examine if participants trust bite counter kilocalorie estimates more if they know that the device has been calibrated to them. Bite size may be one very important key to a bite counter that can accurately estimate kilocalories consumed during meals.

Fifth, future research should explore adding an energy density feature to the bite counter in order to adjust kilocalorie estimates to the energy density of the meal being eaten. There are numerous research questions in this area as well. It is unknown if people can accurately estimate the energy densities of meals. Meals are sometimes comprised of many different foods and beverages, making energy density estimates potentially very difficult. The heuristics that could be used to guide energy density judgments should be identified and tested. The Volumetrics categories (Rolls, 2007) may be appropriate, or there might be different categories that could be applied to overall meal judgments. Accurate meal energy density input from the user may be another key to a bite counter that can accurately estimate kilocalories consumed during meals.

The Future Bite Counter

The future goal of the bite counter is to be a device that can not only count bites but also can count kilocalories during a meal. Based on the main findings from this research, energy density and bite size are two features that should be implemented into a future bite counter in order to provide a user with more accurate kilocalorie estimates. A future bite counter is imagined as a device that can provide real-time kilocalorie feedback to the user.

Imagine a bite counter that is shipped to a future user along with a microwavable calibration meal. The user would eat this low energy density calibration meal while recording bites with the device. The kilocalories/bites ratio determined with this low energy density calibration meal would be used to set the bite counter's kilocalorie conversion setting for that individual:

$$\text{Kilocalories Low ED} = (\text{Kilocalories/bites ratio})*(\text{Bites})$$

For example, if a person eats a 500 kilocalorie calibration meal in 20 bites, the kilocalories to bites ratio would be 500/20 = 25. Inserted into the above equation:

$$\text{Kilocalories Low ED} = 25(\text{Bites})$$

This equation would then be modified by the person before eating meals by entering the energy density of the meal into the bite counter. For example, if four categories of energy density are used (Very Low, Low, Medium, and High), the user would select the energy density of the meal using an energy density menu feature, and one of four equations would be used to adjust the kilocalories-bites relationship:

$$\text{Kilocalories Very Low ED} = 0.8*[25(\text{Bites})]$$

$$\text{Kilocalories Low ED} = 1*25(\text{Bites})$$

$$\text{Kilocalories Medium ED} = 1.3*[25(\text{Bites})]$$

$$\text{Kilocalories High ED} = 2*[25(\text{Bites})]$$

The coefficients for these equations are based on the simple slopes obtained from the kilocalorie-energy density interaction, and these coefficients would need to be replicated and tested in future studies. However, they may provide a useful starting point for the future bite counter. With these two simple steps, a bite size calibration before using the device and an indication of meal energy density before eating, the bite counter could become an exciting new tool for self-monitoring kilocalorie intake in real-time during meals.

Conclusion

The present study was motivated by the obesity epidemic that affects millions of individuals worldwide. Although changes to the food and physical activity environments are necessary to reverse obesity trends, those who are already obese can use tools to help them self-monitor their energy intake. The bite counter is a tool that has the potential to help individuals self-monitor a number of different eating behaviors in real-time, including the number of bites taken, meal duration, bite-rate, and perhaps even the number of kilocalories consumed. The present study identified meal energy density and individual bite size as two important factors to consider for future bite counter development. Once the relationship between kilocalories and bites has been improved through a possible combination of device calibration to the individual and to the meal type, participants who receive device feedback and appropriate training may be able to use the device to reduce their energy intake. This reduction of energy intake could lead to successful weight loss and weight maintenance.

APPENDICES

Appendix A

Demographics Questionnaire

1. Please enter your unique participant ID provided by the experimenter. (If you do not remember your participant ID, please e-mail jscisco@clemson.edu or call 864-656-1144 to receive your ID.) ___________________________
2. What is your age in years? ______ years
3. What is your gender?

   ☐ Male

   ☐ Female
4. What is your ethnicity? (optional)

   ☐ American Indian or Alaska Native

   ☐ Asian or Pacific Islander

   ☐ African American

   ☐ Caucasian

   ☐ Hispanic

   ☐ Other (please specify): ______________________________
5. What level of education have you obtained?

   ☐ Less than a high school diploma

   ☐ High school diploma or equivalent

   ☐ Some college

   ☐ Bachelor’s degree

□ Master's degree

□ Doctoral or professional degree (PhD, MD, JD, DPharm, DPT, etc.)

6. What is your annual household income? (optional)

□ $0-10,000	□ $60,001-70,000
□ $10,001-20,000	□ $70,001-80,000
□ $20,001-30,000	□ $80,001-90,000
□ $30,001-40,000	□ $90,001-100,000
□ $40,001 – 50,000	□ More than $100,000
□ $50,001-60,000	

7. How frequently do you use a computer?

□ Never

□ Once per month

□ Once per week

□ A few times per week

□ Daily

8. Do you have DAILY access to a computer with:

- a high-speed Internet connection (such as cable, DSL, or FIOS)
- a screen size of at least 10 inches, and
- Microsoft Silverlight version 4.0 (or the ability to install this program)?

□ Yes

□ No

□ I don't know.

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

   ☐ Yes

   ☐ No

10. What hand do you use most often for eating a meal? (For example, what hand do you use most often for eating with a fork?)

    ☐ Right hand

    ☐ Left hand

11. What is your height in feet and inches?

    ________ Feet

    _______ Inches

12. What is your weight in pounds?

    _______ pounds

13. Please indicate the normal, or typical time, at which you eat the following meals during a <u>weekday</u>. If you do not eat one of more of these meals during a weekday, please enter 00:00AM for that meal's time.

	HH		MM	AM/PM
Breakfast	____	:	___	______
Morning snack	____	:	___	______
Lunch	____	:	___	______
Afternoon snack	____	:	___	______
Dinner	____	:	___	______
Evening snack	____	:	___	______

Other ____ : ___ ______

14. Please indicate the normal, or typical time, at which you eat the following meals during a weekend. If you do not eat one of more of these meals during a weekend, please enter 00:00AM for that meal's time.

	HH		MM	AM/PM
Breakfast	____	:	___	______
Morning snack	____	:	___	______
Lunch	____	:	___	______
Afternoon snack	____	:	___	______
Dinner	____	:	___	______
Evening snack	____	:	___	______
Other	____	:	___	______

15. Are you currently trying to lose weight?

- ☐ Yes
- ☐ No

16. Are you currently trying to gain weight?

- ☐ Yes
- ☐ No

17. Do you have any food allergies?

- ☐ Yes
- ☐ No

If yes, please list the foods you are allergic to: ______________________________

18. Are you currently following a specific diet, or way of eating?

☐ Yes

☐ No

If yes, please describe your diet: ____

Appendix B

Three-Factor Eating Questionnaire R-18 (TFEQ R-18)

1. **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

2. **I deliberately take small helpings as a means of controlling my weight.**

1	2	3	4
Definitely false	Mostly false	Mostly true	Definitely true

3. **When I feel anxious, I find myself eating.**

1	2	3	4
Definitely false	Mostly false	Mostly true	Definitely true

4. **Sometimes when I start eating, I just can't seem to stop.**

1	2	3	4
Definitely false	Mostly false	Mostly true	Definitely true

5. **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

6. **When I feel blue, I often overeat.**

1	2	3	4
Definitely false	Mostly false	Mostly true	Definitely true

7. **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

8. **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

9. **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

10. **When I feel lonely, I console myself by eating.**

1	2	3	4
Definitely false	Mostly false	Mostly true	Definitely true

11. **I consciously hold back at meals in order not to weight gain.**

1	2	3	4
Definitely false	Mostly false	Mostly true	Definitely true

12. **I do not eat some foods because they make me fat.**

1	2	3	4
Definitely false	Mostly false	Mostly true	Definitely true

13. **I am always hungry enough to eat at any time.**

1	2	3	4
Definitely false	Mostly false	Mostly true	Definitely true

14. **How often do you feel hungry?**

1	2	3	4
Only at meal times	Sometimes between meals	Often between meals	Almost always

15. **How frequently do you avoid "stocking up" on tempting foods?**

1	2	3	4
Almost never	Seldom	Usually	Almost always

16. **How likely are you to consciously eat less than you want?**

1	2	3	4
Unlikely	Slightly likely	Moderately likely	Very likely

17. **Do you go on eating binges though you are not hungry?**

1	2	3	4
Never	Rarely	Usually	Almost always

18. **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 C

Daily Meals Questionnaire

The following questions will help the researchers link your questionnaire responses to the ASA24 dietary recall.

1. Please enter your unique participant ID provided by the researcher. (If you do not remember your participant ID, please e-mail jscisco@clemson.edu or call 864-656-1144 to receive your ID.)

   ____

2. Please enter yesterday's date which is the day you are completing the ASA24 dietary recall for:

   MM/DD/YYYY

   ___/___/____

3. How many meals and snacks from yesterday will you be recalling using ASA24?

☐ 0	☐ 6
☐ 1	☐ 7
☐ 2	☐ 8
☐ 3	☐ 9
☐ 4	☐ 10
☐ 5	☐ More than 10

Participants were asked to answer the following questions about each meal:

Please answer the following questions for one meal you recalled for yesterday using ASA24.

1. What was this meal or snack?

   ☐ Breakfast

- ☐ Brunch
- ☐ Lunch
- ☐ Dinner
- ☐ Supper
- ☐ Snack
- ☐ Just a drink

2. What time did you eat this meal?

   HH MM AM/PM

   ___ : ___

3. Did you wear the Bite Counter on your wrist during this meal?
   - ☐ Yes
   - ☐ No
   - ☐ I do not remember

4. Did you turn the Bite Counter ON at the beginning of this meal?
   - ☐ Yes
   - ☐ No
   - ☐ I do not remember
   - ☐ Yes, but I turned it on after I began eating

5. If you turned the Bite Counter ON after you began eating, how many minutes did you eat before you turned the bite counter ON?

   ______________ minutes

6. Did you turn the bite counter OFF after you finished eating your meal?

 - ☐ Yes
 - ☐ No
 - ☐ I do not remember
 - ☐ Yes, but I turned it off a few minutes after I finished eating

7. If you turned the bite counter off a few minutes after you finished eating, how many minutes elapsed between the end of your meal and when you turned the Bite Counter OFF?

 ______________ minutes

8. Did you turn the Bite Counter on and off multiple times during this meal? (You might do this for a multi-course meal with break in between.)

 - ☐ Yes
 - ☐ No

9. If you turned the Bite Counter on and off multiple times for this meal, please indicate how many times you turned the Bite Counter on and off in the box below.

 Number of times on/off ___________________

10. Did you have any problems with the Bite Counter during this meal?

 - ☐ Yes
 - ☐ No

11. If you had problems with the Bite Counter during this meal, please explain the problems below:

 ____

12. Did you spend some or all of this meal time doing other activities? (For example: talking, reading a book, watching TV, using the computer, working, cooking, etc.)

☐ Yes

☐ No

13. If you spent some or all of this meal time doing other activities, please list the percentage of meal time spent doing those activities and a description of the activities below.

Here are some examples:

Activity 1 "For 50% of this meal, I used my computer."

Activity 2 "For 30% of this meal, I talked to my family."

Activity 1 ____

Activity 2 ____

Activity 3 ____

Activity 4 ____

Activity 5 ____

14. What utensils did you use to eat your meal? (Check all that apply)

☐ Fork

☐ Knife

☐ Spoon

☐ Chopsticks

☐ Hands

☐ Other (please specify): ______________

15. How hungry were you before you ate this meal?

☐ Not hungry at all

☐ Somewhat hungry

☐ Moderately hungry

☐ Very hungry

☐ Extremely hungry

16. How full were you after you ate this meal?

☐ Not full at all

☐ Somewhat full

☐ Moderately full

☐ Very full

☐ Extremely full

17. How much did you like your meal in terms of its taste?

☐ I did not like it at all.

☐ I liked it somewhat.

☐ I liked it moderately.

☐ I liked it very much.

☐ I liked it extremely

18. How many people did you eat with during this meal? (If you ate alone, enter zero).

____

19. Who prepared this meal? (Select all that apply.)

- ☐ I prepared the meal.
- ☐ A family member prepared the meal.
- ☐ A friend prepared the meal.
- ☐ A restaurant, cafeteria, grocery store, or other location prepared the meal.

After answering all of the above questions for each meal, the participant will be asked:

20. How physically active were you yesterday?

- ☐ I was sedentary.
- ☐ I was somewhat active.
- ☐ I was moderately active.
- ☐ I was very active.
- ☐ I was extremely active.

Appendix D

Usability Questionnaire

1. Please enter your unique participant ID provided by the researcher. (If you do not remember your participant ID, please e-mail jscisco@clemson.edu or call 864-656-1144 to receive your ID.)

   ____

2. In the past two weeks, how hungry have you felt?

   ☐ Not hungry

   ☐ Somewhat hungry

   ☐ Moderately hungry

   ☐ Very hungry

   ☐ Extremely hungry

3. In the past two weeks, how full have you felt?

   ☐ Not full at all

   ☐ Somewhat full

   ☐ Moderately full

   ☐ Very full

   ☐ Extremely full

4. In the past two weeks, how often did you complete the 24 hour dietary recall?

   ☐ For every food and beverage I consumed

   ☐ For most food and beverages I consumed

☐ For only my main meals and the beverages consumed with those meals

☐ I forgot some meals and beverages I consumed

☐ I forgot many meals and beverages I consumed

☐ I forgot to complete the dietary recall on one or more days

5. In the past two weeks, how easy or difficult did you find it to complete the 24 hour dietary recall?

   ☐ Extremely easy

   ☐ Very easy

   ☐ Somewhat easy

   ☐ Neither easy nor difficult

   ☐ Somewhat difficult

   ☐ Very difficult

   ☐ Extremely difficult

6. What about the 24 hour dietary recall made it easy or difficult to complete?

   ____

   ____

7. In the past two weeks, how much did you like or dislike completing the 24 hour dietary recall?

   ☐ Extremely liked

   ☐ Liked very much

   ☐ Liked somewhat

☐ Neither liked nor disliked

☐ Disliked somewhat

☐ Disliked very much

☐ Extremely disliked

8. What did you like or dislike about completing the 24 hour dietary recall?

____

9. In the past two weeks, did you have any problems using the 24 hour dietary recall?

☐ Yes

☐ No

10. Please describe any problems you had with the 24 hour dietary recall.

____

11. Did you feel that completing the 24 hour dietary recall changed your eating behavior?

☐ Yes

☐ No

12. How did you feel the 24 hour dietary recall changed your eating behavior?

____

13. Did you record your dietary intake anywhere other than the Internet-based ASA24 system?

☐ Yes

☐ No

14. If you did record your intake in another way, please explain how you recorded your intake.

15. In the past two weeks, how often did you wear the bite counter? (Select the option that most applies.)

- ☐ All day everyday (from morning to evening)
- ☐ Only part of the day (more often than just meal times)
- ☐ Only during meal times, the other times I took it off
- ☐ I did not wear it during some meals
- ☐ I did not wear it during many meals
- ☐ I did not wear it for one or more days

16. In the past two weeks, how easy or difficult did you find it to use the bite counter?

- ☐ Extremely easy
- ☐ Very easy
- ☐ Somewhat easy
- ☐ Neither easy nor difficult
- ☐ Somewhat difficult
- ☐ Very difficult
- ☐ Extremely difficult

17. What about the bite counter made it easy or difficult to use?

____

____

18. In the past two weeks, how much did you like or dislike using the bite counter?

☐ Extremely liked

☐ Liked very much

☐ Liked somewhat

☐ Neither liked nor disliked

☐ Disliked somewhat

☐ Disliked very much

☐ Extremely disliked

19. What did you like or dislike about using the bite counter?

____

20. In the past two weeks, did you have any problems wearing the bite counter due to physical discomfort or other reasons?

☐ Yes

☐ No

21. What could be done to make it easier to wear the bite counter for longer periods of time?

____

22. In the past two weeks, did you have any problems using the bite counter?

☐ Yes

☐ No

23. Please describe ant problems you had with the bite counter.

____

24. Did you feel that using the bite counter changed your eating behavior?

- ☐ Yes
- ☐ No

25. How did you feel the bite counter changed your eating behavior?

____

26. Which did you prefer using, the 24 hour dietary recall or the bite counter?

- ☐ 24 hour dietary recall
- ☐ Bite counter

27. Why did you choose the 24 hour dietary recall or the bite counter as your preferred tool?

____

Appendix E

Initial Participant Contact and Online Pre-screening Protocol

1. Assign the interested participant the next available ID number in the Excel worksheet: MyDropbox/Dissertation!/Data!/**ParticipantIDinfo**.
    a. Record the participant's name, e-mail, and phone number.

2. Send the interested participant the following e-mail:

    Dear [name],

    Thank you for your interest in our research study being conducted by the Department of Psychology at Clemson University. In order to determine your eligibility for the study, please complete the following survey by clicking the link below or copying and pasting it into your web browser address bar:

    https://www.surveymonkey.com/s/prescreening

    You will be asked for a participant ID. Your unique participant ID is [insert 9 letter-number ID here].

    If you have any questions, you may contact me by e-mail at jscisco@clemson.edu or by phone at 864-656-1144.

    Sincerely,

    Jenna Scisco
    Department of Psychology
    Clemson University

3. Download the Survey Monkey data in Advanced Spreadsheet form and save in MyDropbox/Dissertation!/Data!/SurveyMonkey/Prescreening.
    a. Save the ZIP file as Prescreening_MonthDDYYY_Time
    b. Extract to a folder by the same name.
    c. Drag ZIP file into new folder with data.
    d. Open CSV file Sheet_1 and check for:
        i. History of an eating disorder = excluded
        ii. No daily access to an Internet-connected computer = excluded
        iii. Age, gender, and BMI status = add description to **ParticipantIDinfo** spreadsheet.

4. If the participant is eligible *and* there are available bite counters, schedule the first session by sending the following e-mail:

Dear [name],

Thank you for completing the eligibility survey for our research study being conducted by the Department of Psychology at Clemson University. Your responses have indicated that you are eligible to participate in the study.

I would like to schedule a meeting with you to provide participation instructions and your wrist-worn device. This meeting will take approximately one hour. Please let me know some times that you are available to meet within the next week [insert dates here], and I will select a time for this meeting.

Sincerely,

Jenna Scisco
Department of Psychology
Clemson University
864-656-1144

4. a. When the participant responds, send the following e-mail to schedule the meeting:

Dear [name],

Thank you for your response. We will have your first meeting at [insert time] on [insert day]. We will meet in Brackett Hall room 422 for approximately one hour.

Please bring your personal calendar to this meeting. This will allow us to schedule two follow-up meetings and your two weeks of participation.

Sincerely,

Jenna Scisco
Department of Psychology
Clemson University
864-656-1144

5. If the participant is eligible and there are *not* available bite counters, send the following e-mail for future participation:

Dear [name],

Thank you for completing the eligibility survey for our research study being conducted by the Department of Psychology at Clemson University. Your responses have indicated that you are eligible to participate in the study, and I look forward to your participation.

At this time, all of the wrist-worn devices for the study are in use or are reserved. I have added you to the study waiting list. As soon as a device becomes available for you, I will contact you to set up a time for our first meeting. This is an ongoing study, and you may be contacted anytime from [current month year] to April 2012.

Sincerely,

Jenna Scisco
Department of Psychology
Clemson University
864-656-1144

5. a. Add the participant to the waiting list in the **ParticipantIDinfo** spreadsheet

6. If the participant is *not* eligible send the following e-mail:

Dear [*insert participant's name here],*

Thank you for completing the eligibility survey for our research study being conducted by the Department of Psychology at Clemson University. Your responses have indicated that you are not eligible to participate in the study.

Sincerely,

Jenna Scisco
Department of Psychology
Clemson University
864-656-1144

7. When a device becomes available, select the next participant from the waiting list and send the following e-mail:

Dear [name],

Good news! We currently have an opening in our study and would like to begin your participation.

I would like to schedule a meeting with you to provide participation instructions and your wrist-worn device. This meeting will take approximately one hour. Please let me know some times that you are available to meet from [5 days here], and I will select a time for this meeting. There is currently a waiting list for this study, and a prompt reply is appreciated.

Sincerely,

Jenna Scisco
Department of Psychology
Clemson University
864-656-1144

7 a. When the participant responds, send the e-mail described in 4 a.

8. When a participant has been scheduled, add their session to the lab calendar as "ParticipantID orientation" and reserve their bite counter on the Bite Counter Status white board. Record the date and time of the orientation in the ParticipantIDinfo spreadsheet.

Appendix F

Orientation Protocol

1 day before participant arrives:

1. Bite Counter preparation:
    a. Record the participant's bite counter number on **ParticipantIDinfo** spreadsheet.
    b. Connect the device to the bite counter software.
        i. Download and save all previous data. Clear the data from the device.
        ii. Sync the time with the computer time
        iii. Verify that the display settings are set to "on" with no review of calories, bites, or charge.
        iv. Disconnect the device.
    c. Confirm the "on" setting and no review of calories, bites or charge.
    d. Run the device "Diagnostics". You do this by holding the device steady, pressing and holding the right button down and pressing the left button and then releasing both buttons. The first diagnostic is a "Display Test". During this test you should see the entire display activated. Following this test the device goes into "Sensor Test" mode. During the sensor test, you should slowly roll the device away from you and then back towards you as if it were being rolled on the wrist. The numbers on the display should go positive and then negative and a corresponding auditory cue will go high and low in pitch. You should do this rolling motion once or twice and at some point stop the rolling motion in any position. When the motion is stopped and the device held steady, the number should stay within +/-10 and the sound will cease.
    e. Charge the device overnight.

Day of orientation:

1. Prepare participant's "take home" folder. It should include:
    a. ASA24 Dietary Recall and Daily Meals Survey Instructions.
        i. Assign the participant a password from the password excel spreadsheet. Write password and unique participant ID on these instructions.
    b. Bite Counter instructions
    c. Appointment slip
    d. Small notebook
    e. Extra copy of consent form

2. Prepare participant's "in lab" folder.
    a. Consent form

b. Download Survey Monkey prescreening data for the participant as a PDF. Include open-ended responses. Print and add to participant folder.
c. Add prescreening sheet. Label pre-screening sheet with participant number, date, and time. Add age, bite counter number, ASA24 user name, ASA24 password, email, and phone number (if provided) to the sheet.

3. Get out scale, MyoTape, and body fat analyzer. Confirm that they are working.

4. Turn on laptop computer and place on lab table.
   a. Confirm that Internet is working.
   b. Load ASA24 demo page, survey monkey page, and Google lab calendar.

5. Put a pencil, pen, and both folders on lab table. Now you're ready! Wait patiently for the participant. ☺

When participant arrives:

1. Welcome the participant to the laboratory and ask them to have a seat at the conference table. Put up "Please Do Not Disturb" signs on all 3 lab doors.

2. Ask the participant to read and sign the consent form. ***Emphasize that participation will last for two weeks and will require about one hour of effort per day.***

3. Explain the purpose of the study and general procedure:

   "<u>The purpose of the study you will be participating in is to learn about the relationship between number of bites taken during a meal, measured with the bite counter, and a number of important variables that we are interested in studying, including the number of calories in the foods you eat. Today, I am going take body measurements including height, weight, body composition, waist, and hip circumference. After these measurements are taken, I will describe the study procedures and instructions. Do you have any questions before we begin?</u>"

4. Measure the participant's height and weight using the Tanita scale.
   a. Have participants remove shoes but not socks and empty their pockets.
   b. If between two height measurements (e.g., between ½ inch and ¾ inch), round down (e.g., ½ inch).
   c. Record height and weight values on the prescreening sheet.

5. Measure the participant's body fat percentage using the handheld Omron device:
   a. Press blue **On** button. Will flash *Guest*.
   b. Press **Set**. Will flash *Normal*.
   c. Press **Set**. Use **Up** and **Down** to enter height, weight, age, and gender. Press **Set** after each.
   d. Will say *Ready*.
   e. Have participant stand with feet shoulder width apart. Ask them to grasp both sides of the analyzer firmly, with their arms straight out in front of them at a 90 degree angle to the floor.

f. Press **Start**.
g. Record BMI and body fat percentage on the pre-screening sheet.

6. Measure waist and hips using the MyoTape.
   a. Waist is the smallest circumference, typically just above the belly button.
   b. Hips are the largest circumference around the buttocks.
   c. Record measurements on the pre-screening sheet.

7. Explain study instructions, broadly:

   "For this study, you will be wearing a device called the Bite Counter on your wrist during the day for two weeks. This device can measure how much you are eating, just like a pedometer can measure how much you are exercising. Then, each day after you use the bite counter, you are going to use your computer to tell me about the foods that you ate, some features of the meal, and your experience with the bite counter. First, we will go over the bite counter, how it is used, and when you will use it."

8. Explain bite counter instructions by reading through the participant bite counter instructions and demoing each step.

9. Schedule 14 days of bite counter use with the earliest start date as tomorrow.
   a. Record dates on prescreening sheet and participant take home instructions.

10. Schedule 14 days of recalls.
    a. Record dates on prescreening sheet and participant take home instructions.

11. Explain ASA24 and daily meals questionnaire by reading through the participant instructions. Demo both by having the participant recall two meals that they ate yesterday.
    a. Demo website: http://asa24demo.westat.com/#
    b. Demo ID for survey: BiteCD999
    c. Suggest using a small notebook (provided) or another immediate method (e.g., typing into your phone) to record times and important information that will help to improve recall accuracy. This is not required, but recommended.

12. Schedule reminders for preferred e-mail address and preferred daily time.
    a. Record e-mail address, phone number, and preferred recall time on pre-screening sheet.

13. Schedule dates and time for 2 follow up meetings and record on appointment slip. One date should be on the 6^{th}, 7^{th}, or 8^{th} day of data collection. The other date should be the day of the last recall or the following day.
    a. Record dates and time on prescreening sheet and appointment sheet. Add meetings to lab scheduler.
    b. Remind participant to bring the bite counter to both meetings, and to not eat or drink anything other than water for about two hours before the final meeting.

14. Describe incentives:

"Upon completion of the study, you will receive $25. If you have completed all of your recalls and used your bite counter every day, you will receive an additional $25 bonus. It is okay to miss one day of recalls if you are unable to complete the recall or use the bite counter one day (for example, can't get to a computer, leave your bite counter at home, etc.). You will also receive a data report with your bite counts and calorie counts for each meal via e-mail after study completion."

15. Give participant their take home folder, bite counter, USB cord, and charger. Remind them that you can be contacted by phone during normal business hours and by e-mail at any time. Thank them for their participation. Any questions?

After participant leaves:

1. Enter data in Prescreening spreadsheet.

2. Add participant to ASA24 using the load participants file.

3. Add e-mail reminders to LetterMeLater.com
    a. Bite Counter start date reminder
    b. 14 days of dietary recall reminders

4. Identify recruitment group and add to the "in progress" list.

Appendix G

Written Consent Form

Information Concerning Participation in a Research Study
Clemson University

Ambulatory Monitoring of Food Intake

Description of the Research and Your Participation
You are invited to participate in a research study conducted by Eric Muth. The purpose of this research is to detect food intake during the day.

Your participation will involve:

- completing a short form about yourself
- completing a survey about your eating behavior
- having your height, weight, body composition, waist, and hips measured
- wearing a wrist-worn watch-like device called the Bite Counter during meals and throughout the day
- completing daily questionnaires about what you ate and related behaviors during the previous day
- completing a post study interview about your eating habits during the study and about the Bite Counter and diet questionnaires
- eating one meal in the laboratory that will be video-recorded.

The amount of time required for your participation will be about 1 hour/day of participation up to 14 consecutive days. You may be paid a maximum of $50 for participating. You may also receive a data summary including Bite Count and dietary recall records.

Risks and Discomforts
There are certain risks or discomforts associated with this research. They include increasing sensitivity to food intake during the day. For this reason, individuals with a current or previous eating disorder are asked not to participate in this study.

Potential Benefits
There are no direct benefits to you for participating in this study. However, this research may help us to understand food intake patterns during the day and improve our device for measuring food intake.

Protection of Confidentiality
We will do everything we can to protect your privacy. Your identity will not be revealed in any publication that might result from this study.

In rare cases, a research study will be evaluated by an oversight agency, such as the Clemson University Institutional Review Board or the federal Office for Human Research Protections, that would require that we share the information we collect from you. If this happens, the information would only be used to determine if we conducted this study properly and adequately protected your rights as a participant.

Voluntary Participation

Your participation in this research study is voluntary. You may choose not to participate and you may withdraw your consent to participate at any time. You will not be penalized in any way should you decide not to participate or to withdraw from this study.

Contact Information

If you have any questions or concerns about this study or if any problems arise, please contact Eric Muth at Clemson University at 864-656-6741. If you have any questions or concerns about your rights as a research participant, please contact the Clemson University Office of Research Compliance (ORC) at 864-656-6460 or irb@clemson.edu. If you are outside of the Upstate South Carolina area, please use the ORC's toll-free number, 866-297-3071.

Consent

I have read this consent form and have been given the opportunity to ask questions. I give my consent to participate in this study.

Participant's signature: ______________________________ Date: _________________

A copy of this consent form will be given to you.

Appendix H

Bite Counter Instructions

How do I wear the Bite Counter?
The Bite Counter should be worn on your dominant wrist that you normally eat with. It is worn like a watch. The Velcro or leather strap should be adjusted so that it fits snugly.

When do I wear the Bite Counter?
Please wear the Bite Counter at all times except when exercising, showering, swimming, or sleeping. By wearing the Bite Counter during most of the day, it will be easier for you to remember to turn the Bite Counter on when you are eating. **Warning: This device is not waterproof or water resistant.**

What is the Bite Counter default mode?
The default mode for the Bite Counter is "Time" mode. The display will show the time, with an arrow to the left of the screen to indicate PM when appropriate.

How do I use the Bite Counter to record bites during a meal?

1. Once you have prepared all of your food and you are ready to take your first bite, press the left button once. A beep will indicate that the device has turned on. This action will turn on Bite Count mode, and the device will now display the word "on" to indicate that it is in Bite Count mode.

This picture shows the Bite Counter in "Time" mode before the left button is pressed.
Press the left button to begin counting bites and to stop counting bites.

2. Continue to eat and drink normally.
3. Once you have finished and have taken your last bite, press the left button again to turn off Bite Count mode. A beep will indicate that the device has turned off. Your data will save automatically and the display will return to "Time" mode.

What is a meal?
A meal is anytime that you are eating and/or drinking that has a definite beginning and end. That is, you know that you will begin eating and/or drinking, and you can predict when the eating or drinking will end, either by finishing all of the food/drink or becoming full or satisfied.

What should I do during a multi-course meal?
If you are eating a multi-course meal with extended periods of no eating in between, turn the bite counter on and off for each course. For example, at a restaurant, you might turn the bite counter on and off three different times if there are breaks in between each course – once for the appetizer, once for the entrée, and once for the dessert.

How do I charge the Bite Counter?
To charge the Bite Counter, insert the large end of the USB cable into the power supply and plug the small end of the USB cable into the Bite Counter. Plug the power supply into an electrical outlet. The display will read "chr" when the battery is charging and will display "Time" mode when charging is complete.

How often should I charge the Bite Counter?
You should charge the bite counter **every night** while you are sleeping. The bite counter will not work properly if it is not fully charged every 24 hours.

Appendix I

ASA24 Dietary Recall and Daily Meals Survey Instructions

When do I complete the ASA24 dietary recall and daily meals survey?
Complete them every 24 hours for the previous day that you recorded your meals with the bite counter. You can complete then anytime from midnight to midnight. You cannot complete an ASA24 dietary recall after more than 24 hours have passed.

Your days of Bite Counter use: __________________ - ____________________
Days to complete ASA24 dietary recall and daily meal survey: ____________ - _____________

How do I access the ASA24 dietary recall?
1. In your web browser, go to https://asa24.westat.com/
2. Enter your unique participant ID: ______________________
3. Enter your password: ____________________________

How do I access the daily meals survey?
In your web browser, go to https://www.surveymonkey.com/s/dailymeals

How do I complete the ASA24 dietary recall and the daily meals survey?
- Start the ASA24 dietary recall first. When you are on the *final review* page, start the daily meals survey in another web browser window.
- Follow the instructions provided by the "interviewer" in the ASA24 dietary recall. Report all meals, foods, and drinks you ate and drank during the previous day. Remember to report all details of your meals, including portion sizes and added foods. Help buttons are available in ASA24 if you are unsure of how to complete a step in the recall.
- The daily meals survey will ask for additional details about each meal as well as your experience with the bite counter for each meal. Please report all problems you experience with the bite counter. This will help the researchers troubleshoot bite counter problems for you.

How are the ASA24 dietary recall, daily meals survey, and bite counter data linked?
Researchers will link these three using your unique participant ID number and the **TIME** of the meal. Because time is so important, please enter the meal times into the ASA24 dietary recall and the daily meals survey as accurately as possible.

Appendix J

Appointment Slip

You're scheduled for two more Bite Counter meetings!

Please come to Brackett Hall, room 422, on

______________________________________ at _____:_____AM / PM

and

______________________________________ at _____:_____ AM / PM

Please bring your Bite Counter, USB cord, and charger to both meetings.

A meal will be provided for you to eat at the last meeting.

Please refrain from eating or drinking anything other than water for at least 2 hours prior to this last meeting.

Questions? Contact:

Jenna Scisco: E-mail jscisco@clemson.edu or call 864-656-1144

Appendix K

Data Download Meeting Protocol

One day before meeting:

1. Send participant a reminder e-mail:

> Dear [name],
>
> This is a reminder that we will have our first bite counter data download meeting on [date] at [time] in Brackett Hall room 422. Please bring your bite counter, USB cord, and charger to this meeting. The meeting will last approximately 15 minutes.
>
> Thanks!
>
> Jenna Scisco
> Department of Psychology
> Clemson University
> 864-656-1144

Day of meeting:

1. Add Data Download Meeting sheet to the participant folder. Note any reported bite counter problems and ASA24 problems on the sheet. Also write the scheduled final meeting date and time on the sheet. Also write down how many recalls and surveys have been completed.

2. Set up laptop with Bite Counter software.

When participant arrives:

1. Record the Bite Counter number on the sheet.

2. Download the Bite Counter data and save to: Dropbox/Dissertation!/Data!/BiteCounterRaw/ParticipantID
   a. Name the file ParticipantID_DeviceNumber_MonthDayYear
   b. Check the data for errors, and ask the participant about any error-like data. For example, if there are a lot of zeros or short meals with few bites, is the device turning off, or are they testing the device?
   c. If the problems are severe, replace the bite counter with the reserve bite counter and record the new bite counter number on the sheet.

3. Ask the participant about any difficulties they are experiencing with the device, recall, or the survey. Record these on the sheet.

4. Remind the participant of their final meeting and not to eat or drink anything other than water two hours beforehand.

5. Any questions?

Appendix L

Final Meeting and Meal Protocol

One day before meeting:

1. Send participant a reminder e-mail:

> Dear [name],
>
> This is a reminder that we will be meeting tomorrow [date] at [time] in Brackett 422. This meeting will last approximately 45 minutes, and you will eat a meal in the laboratory.
>
> Please bring your bite counter, USB cord, and charger with you to this meeting to return them. Please do not eat or drink anything other than water for at least two hours prior to this meeting.
>
> Thanks!
>
> Jenna Scisco
> Department of Psychology
> Clemson University
> 864-656-1144

Day of meeting & meal:

1. **Check food allergies to see if a special meal is needed.**

2. Turn on the desktop computer.
   a. Check the IntertiaCube3 by double clicking the Blue "I" indicator on the right of the Windows Taskbar. The InterSense Server should show that the IntertiaCube3 is operational. There will be a green circle, and the yaw, pitch, and roll will be responsive to sensor movement.
   b. Look in the C:/Jenna folder and make sure there are no Original Data, Bite Detect, or Human Detect data files. If there are, rename and move them.
   c. Put a stop watch next to the computer.

3. Set up the video camera:
   a. Put the camera in the tripod stand. It can be plugged in or unplugged if the battery indicator is full.
   b. Make sure the camera is positioned so that you can see as much of the area where the participant will be sitting as possible.

c. Turn off video camera.

4. Set up the food scale:
   a. Pull back the tablecloth.
   b. Turn the scale on. Wait until the scale reads 0.0g.
   c. Put an empty plate on top of the scale. Make sure it is centered and not touching any wood. Wait a few seconds for the weight to steady.
   d. Press zero. Wait a few seconds for the scale to read 0.0g.
   e. Press PRINT to begin sending data to the computer
   f. Remove plate and pull table cloth back over the table.
   g. Center the empty plate on the scale. Again, make sure it is not touching any wood.
   h. From the desktop, open the WinWedge document **JennaDissrtn.SW3** and the excel document **scale.xls.**
      i. Confirm that data is being sent from the scale to the excel file.
      ii. Close the excel file.

5. Set the table with a fork, napkin, and flowers. Put the chair without arm rests at the table.

6. Turn on the laptop at the conference table. Open the usability questionnaire on Survey Monkey.

7. Add the following to the participant folder and label with participant number, date, and time:
   a. Start SLIM scale
   b. End SLIM scale
   c. End LAM scale
   d. Final meeting sheet
      i. Add age and weight to the sheet, as well as any problems from the last week.

8. Check ASA24 and survey monkey for the total number of completed recalls and surveys. Obtain the participant payment from the safe and the participant compensation sheet. Put with the participant folder on the conference table.

When the participant arrives at the laboratory:

1. Welcome the participant to the laboratory and ask them to have a seat at the conference table.

2. Record the returned bite counter number on the final meeting sheet. Download the Bite Counter data and save to: Dropbox/Dissertation!/Data!/BiteCounterRaw/ParticipantID

a. Name the file ParticipantID_DeviceNumber_MonthDayYear
b. Check the data for errors, and ask the participant about any error-like data. For example, if there are a lot of zeros or short meals with few bites, is the device turning off, or are they testing the device?
c. Record any problems on the final meeting sheet.

3. Measure the participant's height and weight, body fat percentage, and waist and hip circumference. Record values on the final meeting sheet.

4. Ask participant to complete the usability survey on the computer.

5. While participant completes the survey, prepare macaroni and cheese according to package instructions in the microwave. Pour 500 mL of water into a glass for drinking. Place the water and macaroni and cheese on the table. The macaroni and cheese should be placed in its container on top of the plate that is on the scale.

6. When the participant is done with the survey, explain the purpose of the meal:

   "<u>Today we will be collecting some data on feelings of hunger and fullness and enjoyment of a meal. I have prepared macaroni and cheese for you to eat today. The session will be video-taped. Additionally, you will be wearing two different bite counters on your dominant wrist. Before we begin with the meal, I would like you to fill out a quick scale asking about feelings of hunger or fullness. Please make a slash mark crossing the vertical line to indicate your current feeling of hunger or fullness."</u>

7. Have the participant sit at the eating table. Put the Inertia cube on the dominant wrist with the cord pointing toward the elbow. Put the Bite Counter above the Inertia cube on the same wrist.

8. "<u>I would like you to eat as you usually would. You can take as much time as you like to complete the meal, and I would like you to stop when you are full or when all of the food has been eaten. While you eat, I will be monitoring the sensor on the computer. Do not start eating until I tell you to do so. First, I need to turn on the video camera and activate the sensor on the computer. Do you have any questions before we begin?</u>"

9. Turn on the video camera. Press the start/stop button to begin recording. The green circle should turn to red when you are recording.

10. Start scale recording by opening the **scale.xls** file.

11. Open **Summer2010.exe** from the desktop. Select **Start**. Select **RightHand** or **LeftHand**.

12. "Please turn on your bite counter. You may begin eating. I will be sitting right here behind the divider. Please let me know when you are done eating by saying 'I'm done' or 'I'm finished.'"

13. Start stop watch/timer.

14. When the participant says 'I'm done':
    a. Stop the stop watch/timer.
    b. Record meal time on the final meeting sheet.
    c. Stop the Intertia cube by selecting **Stop**.
    d. Stop the scale by pausing Winwedge. Immediately save the excel file with the participant number and date to the JennaDissrtn/Scaledata folder.
    e. Press the start/stop button on the video camera to stop recording. Then turn off the video camera.
    f. Take off the two bite counters.

15. Ask the participant to move back to the conference table. Have the participant complete the SLIM scale and LAM scale.

    "Now that you have finished the meal, I would like you to fill out two quick scales. One scale will ask you about your feelings of hunger or fullness, and one will ask you how much you liked the meal."

16. Ask the participant if there is any other feedback they would like to provide about their experience in the study. Record comments on final meeting sheet.

17. Debrief the participant:

    "We're all done! Now I can tell you about the purpose of the study. As you know, this study is trying to describe the relationship between the number of bites detected by the bite counter during a meal and the number of calories in that meal. Additionally, I am interested in a number of other predictors of bites, including the energy density of the food, the duration of the meal, the number of people someone eats with, where the meal was eaten, day of the week, gender, and body weight. Additionally, I will use the data from today's meal to calculate your average bite size which may play a role in these relationships. Do you have any questions about your participation in the study?"

18. Ask the participant to fill out the compensation form. Tell the participant they will receive their data summary via e-mail within 4 weeks.

After the participant leaves:

1. Save the Intertia cube data: **It is important to do this step immediately after the participant leaves because the data will be written over if the files are not renamed and moved.**
   a. Go to Computer → Local disk C: → **Jenna**
   b. There will be two files: BiteDetect.txt and OriginalData.txt.
   c. Rename the files **BiteDetect_Participant#.txt**, and **OriginalData_Participant#.txt.**
   d. Cut the files and paste them to the Desktop/JennaDissrtn/**Bite Counter Data** folder. Upload to dropbox.

2. Save the bite counter data.

3. Measure the remaining water by pouring it into the graduated cylinder. Record the total amount of water remaining on the final meeting sheet.

4. Weigh the macaroni and cheese container and record the weight on the final meeting sheet.

5. Transfer the video from the video camera to the computer.
   a. Plug in the power cord and the USB cord for the video camera.
   b. Turn on, and rotate mode button.
   c. Open up the video camera on the computer: Canon_HDD → AVCHD → BDMV → Stream
   d. Select the latest video (.MTS) and rename ParticipantNumber_Date.MTS
   e. Copy the file into the Videos folder on the desktop.
   f. Unplug from the computer.
   g. Turn off video camera.

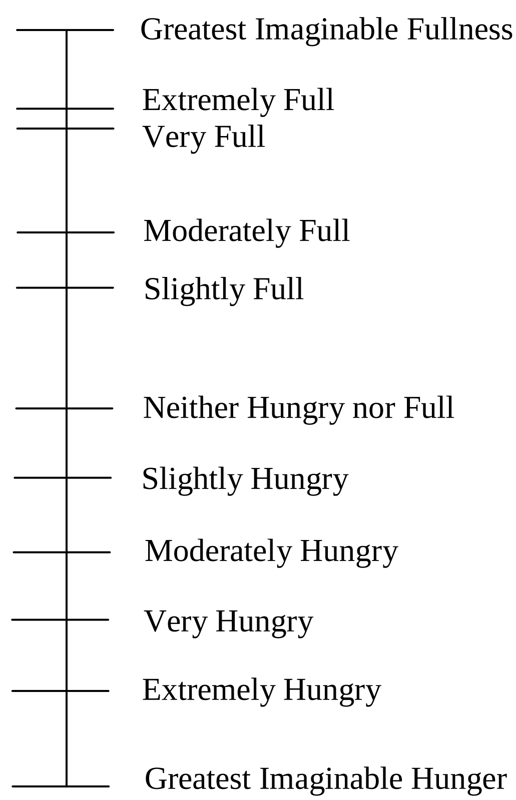
6. Watch the video and record the number of bites taken manually on the sheet.

7. Transfer the information from the final meeting sheet to the corresponding excel spreadsheet.

Appendix M

Satiety Labeled Intensity Magnitude (SLIM) Scale

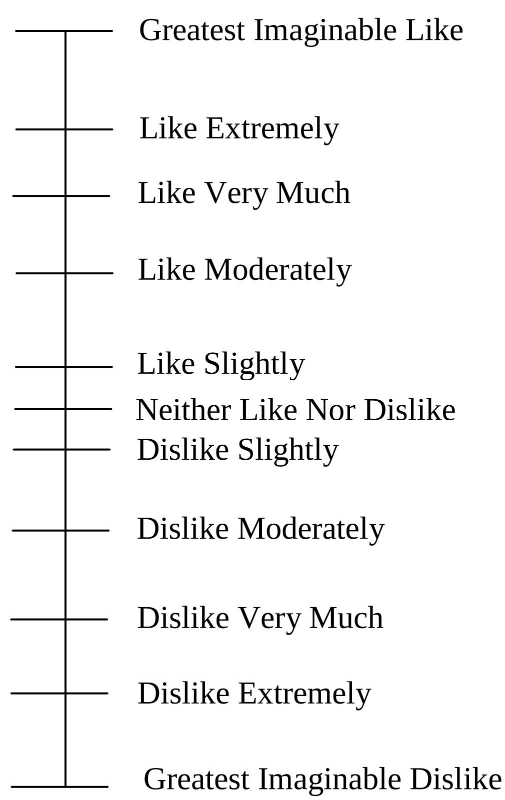
Please rate the degree of hunger/fullness that you *currently* feel by putting a slash (/) mark somewhere on the line below.



Appendix N

Labeled Affective Magnitude (LAM) Scale

How much did you like the macaroni and cheese? (Please put a slash (/) mark somewhere on the line below.)



Appendix O

Data Merging and Error Screening Steps

Step 1: Merge data for the meals.

1. In the *Dissertation!/Data!/Merged and screened data* folder, create a new folder named *ParticipantID.*
2. In the *ParticipantID* folder, create a new Excel workbook named ParticipantID.xls. All of the raw meal data is imported into this file.
    a. Name this first sheet Merged Data.
    b. Name the second sheet INF.
    c. Name the third sheet Removed.
3. In the *ParticipantID* folder, create a new Word document named ParticipantID data merging and screening history.docx and save in the *Merged and screened data* folder. This Word document is used to keep a record of what has been done to the data in Excel for this participant.
4. **Bite Counter data**: Original Bite Counter data is in *Dissertation!/Data!/BiteCounterRaw/ParticipantID.* Files are named by participant number, device number, and download date (e.g., BiteCD001_Device1413_Oct132011). There are typically two files per participant because data was downloaded twice. Data was cleared off of the device after the first download. Thus, data will not repeat from the first file to the second file.
    a. Copy all of the original bite counter data and paste it into the first sheet of ParticipantID.xls. Each row on this sheet represents a recording period by the bite counter (ultimately, a meal).
5. **Daily meals questionnaire data**: In *Dissertation!/Data!/SurveyMonkey/Daily meals questionnaire/ParticipantID/CSV*, open Sheet_1.csv and Sheet_2.csv for this participant (originally downloaded as an Advanced Spreadsheet from Survey Monkey using a participant ID filter).
    a. The data is split into two .csv files by Survey Monkey but can be combined into one to make merging the data easier. Sheet 2 is just an extension of Sheet 1. Simply copy the data from Sheet 2 and paste it onto the end of Sheet 1. Save Sheet 1 (yes, keep it a .csv file).
    b. Using meal date and time, match the daily meals questionnaire data to the bite counter data. This is made easier if the two spreadsheets are viewed side by side. Copy each meal from the Daily meals questionnaire and paste into the Merged Data sheet next to the associated bite counter data. If data from the

questionnaire is missing, write "missing data" in the empty cells. If the bite counter data is missing, create a new row and insert the questionnaire data.

6. **ASA24 data**: In *Dissertation!/Data!/ASA24/BiteCD_Request196_AllData*, open BiteCD-776_INF.csv. Copy and paste all of the data for the participant into the INF sheet in ParticipantID.xls.
    a. Hide cells so that the following are visible: UserName, RecallNo, RecallStatus, IntakeDate, IntakeDay, Occ_No, Occ_Time, FoodAmt, KCAL, FoodComp, Food_Description
    b. If foods are incomplete, check the MS file in *Dissertation!/Data!/ASA24/BiteCD_Request196_AllData* for the food, portion, and detail responses. Insert any known values into the INF file based on this information from MS. If values are unknown and the data set is thus missing necessary KCAL and gram data, mark this as missing data in the INF sheet in ParticipantID.xls.
    c. Create MealFoodAmt and MealKCAL columns
    d. Sum up FoodAmt and KCALs for each meal.
        i. =SUMIFS(FoodAmt range, RecallNo range, RecallNo, Occ_No range, Occ_No)
        ii. =SUMIFS(KCAL range, RecallNo range, RecallNo, Occ_No range, Occ_No)
        iii. The first row for each meal will have the correct totals.
        iv. Move additional food descriptors up to the first row for each meal using copy and paste (transpose).
        v. Hide rows below each meal's first row.
    e. Create a "New Window" in Excel and view the Merged Data and INF sheets side by side. Using the date and time from the bite counter data and the Daily meals questionnaire, match the data. Copy and *PASTE VALUES* from the INF sheet into the Merged Data sheet as appropriate. (If you do not paste values, the MealKCAL and MealFoodAmt will not transfer correctly.) Make note of any missing or incomplete ASA24 data on the Merged Data sheet.
    f. Create a new column named MealED and calculate Meal Energy Density as MealKCAL/MealFoodAmt.
7. On the Merged Data sheet, create a new first column named MealID. Number all meals sequentially, regardless of missing or incomplete data. (This will help with sorting and identification of errors and outliers by number.)

Step 2: Identify data errors.

*Note: Figures 2.10 and 2.11 describe the decision-making process for how to deal with the flagged data described below (i.e., potential data errors).

1. **Daily meals questionnaire data**:
    a. Was the bite counter turned on and off multiple times? If yes, flag data and sum up rows. Record which meals were summed in ParticipantID data merging and screening history.docx. Move the deleted meals to the Removed sheet in ParticipantID.xls.
    b. Were bite counter problems reported? If yes, determine if problem may have negatively affected the data. (For example, participant reported the device turning off, and there are 10 rows of data where the participant tried to get the device to turn on.) If there may be a need to remove or correct the data, flag the data.
    c. Was there a delay in turning on the bite counter or turning off the bite counter? If so, flag the data.
2. **Bite Counter data**:
    a. Bite Counts: Flag values < 10 and > 50.
    b. Meal duration: Flag values < 1 minute and > 45 minutes
3. **ASA24 data**:
    a. MealKCAL: Flag values < 50 and > 1000
    b. MealED: Flag values 0 and > 4.0
    c. Flag incomplete recalls
    d. Flag incomplete foods
4. **Data sheets**:
    a. Did the participant report any problems at either the data download meeting or the final meeting? If so, flag affected meals.
5. **E-mails**:
    a. Did the participant report any problems at any time via e-mail? If so, flag affected meals.
6. **Usability questionnaire**:
    a. Did the participant report any new problems in their usability questionnaire? If so, flag affected meals.
7. Go back to the flagged meals. Using the decision-making flow charts in Figure 2.10 and 2.11, decide if data should be removed, corrected, or kept the same. Take the appropriate action.
    a. When a meal is “removed”, add it to the removed tab. This will allow you to keep all of the data if you decide to use it later.
    b. Record all actions in ParticipantID data merging and screening history.docx.

Step 3: Create data summary for the participant.

1. In the *Dissertation!/Data!/Merged and screened data*/*ParticipantID* folder, create a new Excel workbook named ParticipantID data summary.xls.
2. Copy the data from the Merged Data sheet in ParticipantID.xls and paste into ParticipantID data summary.xls.
3. Delete rows so that MealID, Bites, Year, M, D, Duration, Meal or snack?, Meal time, MealKCAL, and Food_Description remain.
4. Create a new column names "calories per bite". Calculate for each meal with matching data as MealKCAL/Bites.
5. Calculate the average number of bites, calories, and calories/bite for each column. Highlight each average at the bottom of the respective columns for the participant to see easily.
6. Email ParticipantID data summary.xls to the participant as an attachment with the following message:

   Dear (first name),

   Attached please find your data summary from the Bite Counter study. This spreadsheet contains all of the meals for which Bite Counter data and/or ASA24 data were recorded. Each row is a meal. Your average number of bites per meal, calories per meal, and calories per bite are highlighted at the bottom of the spreadsheet.

   Thank you for your participation!

   Jenna Scisco
   Department of Psychology
   Clemson University

Appendix P

Description of Data Quality for Each Participant

ID	# matched meals	% matched meals	Bites-Kilocalories correlation	Bite Counter problems/data quality	# ASA24 completed	ASA24 problems/data quality
BiteCD001*	20	60.6	.171	First bite counter had time drift and display problems. Second bite counter turned off during meals. Meals were very short in duration.	11	One meal was overestimated (removed).
BiteCD003	35	77.8	.637	Good.	14	Some meals were underestimated (removed).
BiteCD006	36	87.8	.533	Bite counter turned off once.	14	Good.
BiteCD007	51	98.1	.480	Time drift. Sometimes did not calibrate right away.	14	Good.
BiteCD011	47	94.0	.384	Participant thought 18:88 was an error and tried to hold down the button to get past calibration. Device would turn off, but participant would eventually get it to stay on.	13	Good.
BiteCD012	89	92.7	.557	Bite counter turned off twice.	14	Good.
BiteCD014	59	76.6	.451	Good.	14	Nutritional supplement shakes were corrected (pathway of questions error). One underestimated meal removed.

ID	# matched meals	% matched meals	Bites-Kilocalories correlation	Bite Counter problems/data quality	# ASA24 completed	ASA24 problems/data quality
BiteCD015	31	81.6	.636	Bite counter turned off once. Display problems.	12	Good.
BiteCD018	41	83.7	.684	Bite counter turned off during a few meals. Time drift.	16^	Good.
BiteCD023	54	88.5	.762	Good.	14	Good.
BiteCD025	40	69.0	.426	Bite counter turned off during a few meals.	11	Good.
BiteCD026	45	81.8	.409	Bite counter turned off once.	14	Good.
BiteCD028*	100	82.0	.244	First bite counter turned off frequently and had a broken speaker. Second bite counter was better but battery level was very low when returned which indicated a possible user error. Many long duration meals.	17^	Good.
BiteCD029	52	89.7	.767	Bite counter turned off during a few meals.	14	Good.
BiteCD030	28	82.4	.491	First bite counter turned off frequently. Second bite counter had no problems.	13	Good.
BiteCD032	45	77.6	.696	Good.	14	Good.

ID	# matched meals	% matched meals	Bites-Kilocalories correlation	Bite Counter problems/data quality	# ASA24 completed	ASA24 problems/data quality
BiteCD034*	25	78.1	.223	Bite counter turned off during a few meals. Time drift.	13	Good.
BiteCD038	26	65.0	.513	First bite counter turned off during a few meals. Second bite counter was better, but a number of errors (long duration meals with few bites) were removed.	13	Good.
BiteCD041*	15	55.6	-.066	No bite counter problems. Possible poor quality recordings (very long durations and high bite counts).	13	Some meals were very large, which matched the participant's description of eating one large meal per day.
BiteCD043	39	83.0	.321	Good.	14	Good.
BiteCD051	32	76.2	.481	Bite counter turned off once.	12	Good.
BiteCD055*	42	95.5	.207	Good.	14	Difficulty reporting protein shakes, modified eating to avoid protein shakes, abnormal eating (less food) for 3-4 days due to ear infection.
BiteCD056	40	87.0	.548	Good.	14	Good.
BiteCD060	25	69.4	.494	Bite counter turned off during a few meals.	11	Good. Missing data due to shift in sleeping schedule.

ID	# matched meals	% matched meals	Bites-Kilocalories correlation	Bite Counter problems/data quality	# ASA24 completed	ASA24 problems/data quality
BiteCD063	44	74.6	.644	Time drift.	13	Missed 4 recalls out of 17.
BiteCD065	31	79.5	.667	Good.	12	Good.
BiteCD069	37	88.1	.323	Bite counter turned off during a few meals.	13	Good.
BiteCD073	43	78.2	.517	Bite counter turned off during a few meals.	13	Good.
BiteCD074	50	66.7	.539	Bite counter turned off once.	13	Good.
BiteCD075*	32	86.5	.247	Bite counter turned off during a few meals.	12	Good.
BiteCD077	25	59.5	.314	Bite counter turned off during a few meals.	11	Carnation instant breakfast errors (pathway of questions errors) removed.
BiteCD078	28	62.2	.660	Bite counter turned off during a few meals.	12	Incomplete recalls removed.
BiteCD083	32	88.9	.543	Time drift.	13	Good.
BiteCD084	44	75.9	.381	Good.	14	Good.
BiteCD094	35	68.6	.419	Good.	13	Good.

ID	# matched meals	% matched meals	Bites-Kilocalories correlation	Bite Counter problems/data quality	# ASA24 completed	ASA24 problems/data quality
BiteCD095*	32	84.2	-.017	Bite counter turned off during a few meals. Time drift.	14	Good.
BiteCD096	38	63.3	.409	Good.	14	Good.
BiteCD097	50	86.2	.678	Good.	14	Good.
BiteCD100	30	88.2	.519	Good.	14	Good.
BiteCD101	45	95.7	.580	Bite counter turned off twice.	14	Good.
BiteCD104	35	89.7	.553	Good.	14	Good.
BiteCD108	39	90.7	.532	Good.	15^	Good. (Extended data collection due to personal emergency).
BiteCD125	18	72.0	.575	Good.	12	Missed 8 recalls out of 20 due to exam schedule.
BiteCD129*	27	87.1	.285	Device turned off once.	13	Good.
BiteCD132	36	97.3	.507	Time drift.	14	Good.
BiteCD138	31	73.8	.721	Display problems.	13	Good.
BiteCD148	18	52.9	.666	Difficulty remembering to wear and use.	13	Good.
BiteCD151*	33	71.7	-.081	Good. Reported difficulty remembering to turn on and off.	14	One over-estimated meal (corrected).
BiteCD152	39	73.6	.475	Fast meals confirmed by participant.	13	Good.

ID	# matched meals	% matched meals	Bites-Kilocalories correlation	Bite Counter problems/data quality	# ASA24 completed	ASA24 problems/data quality
BiteCD153	27	57.4	.471	Good.	12	Good.
BiteCD170	26	40.0	.548	Good.	14	Good.
BiteCD175	49	94.2	.553	First bite counter turned off frequently. Second bite counter had no problems.	14	One over-estimated meal (corrected).
BiteCD178*	30	81.1	.136	Bite counter turned off during a few meals. (Not reported by participant, but seen in data).	12	Good.
BiteCD196	43	82.7	.636	Bite counter turned off during a few meals.	14	Good.
BiteCD197	60	88.2	.749	Bite counter turned off during a few meals.	14	Good.
BiteCD208	49	98.0	.626	Bite counter turned off during a few meals.	14	Good.
BiteCD210	54	98.2	.631	Bite counter turned off once.	14	Good.
BiteCD211	36	72.0	.454	Bite counter turned off during a few meals. Display problems. Time drift.	14	Good.
BiteCD213*	36	92.3	-.088	Bite counter turned off frequently.	14	Good.
BiteCD214*	15	46.9	.203	Participant tried to hold down the button to get past calibration. Many zero bite recordings.	9	Good. Participant found study overwhelming.

ID	# matched meals	% matched meals	Bites-Kilocalories correlation	Bite Counter problems/data quality	# ASA24 completed	ASA24 problems/data quality
BiteCD215*	36	94.7	.254	Bite counter turned off frequently.	14	Good.
BiteCD216	41	89.1	.543	Bite counter turned off during a few meals.	12	Missed 5 out of 17 recalls due to Internet access.
BiteCD217	46	75.4	.617	Bite counter turned off during a few meals.	12	Over-estimated two meals (corrected).
BiteCD218	31	70.5	.591	Bite counter turned off during a few meals.	13	Good.
BiteCD219	39	70.9	.576	First device had display problems. Second device was good.	14	Good.
BiteCD222*	20	57.1	-.099	Good.	9	Many missing recalls and did not seem to understand purpose of the study.
BiteCD224	22	64.7	.338	First device turned off frequently. Second device was good.	12	One over-estimated meal (corrected).
BiteCD227	69	93.2	.492	First device turned off during a few meals. Second device was good.	14	Good.
BiteCD231	42	91.3	.529	Bite counter turned off during a few meals.	13	Good.
BiteCD232	59	92.2	.767	Bite counter turned off during a few meals.	14	Good.

ID	# matched meals	% matched meals	Bites-Kilocalories correlation	Bite Counter problems/data quality	# ASA24 completed	ASA24 problems/data quality
BiteCD237	21	41.2	.578	Good.	11	Good.
BiteCD240	36	87.8	.584	Good.	14	Good.
BiteCD241	25	78.1	.531	Bite counter turned off during a few meals.	12	Good.
BiteCD242	47	66.2	.608	Good.	13	One over-estimated meal (corrected).
BiteCD245	40	90.9	.407	Participant tried to hold down the button to get past calibration for the first week.	14	Good.
BiteCD246	46	100.0	.419	Good.	14	Good.
BiteCD251	51	100.0	.769	Bite counter turned off during a few meals.	14	Good.
BiteCD258	53	96.4	.572	Bite counter turned off during a few meals.	14	Good.
BiteCD260	71	87.7	.652	Good.	14	Good.
BiteCD261	35	92.1	.613	Good.	13	Good.
BiteCD266	43	87.8	.643	Good.	13	Good.
BiteCD268	44	66.7	.402	Good.	14	Good.
BiteCD270	15	51.7	.423	Good.	10	Good.

Note. *Outlier with a Bites-Kilocalories correlation < 0.31. ^Some participants completed extra recalls to make up for missing Bite Counter days.

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