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ACCURACY OF A BITE-COUNT BASED CALORIE ESTIMATE COMPARED TO HUMAN ESTIMATES WITH AND WITHOUT CALORIE INFORMATION AVAILABLE

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ACCURACY OF A BITE-COUNT BASED CALORIE ESTIMATE COMPARED TO HUMAN ESTIMATES WITH AND WITHOUT CALORIE INFORMATION AVAILABLE

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ABSTRACT

Obesity is an increasing health problem in the US, associated with such dangerous health risks as heart disease and diabetes. Self-monitoring in the form of calorie counting is a critical aspect of successful weight loss. However, calorie estimations are subject to several perceptual and cognitive biases, and there are limited tools available to assist these estimations. The present study seeks to assess the accuracy of participants' estimations of the calorie content of meals in the presence or absence of calorie information, and to compare their accuracy with calorie estimations based on bite count. Data were analyzed for 87 participants from a study in which participants were allowed to select from a wide variety of meals in a cafeteria setting, which they consumed while wearing a device designed to count bites of food. They were asked to estimate the number of calories they consumed either with or without calorie information available. True calorie intake and a calorie intake estimation based on bite count were calculated for each participant. A 2x2 Mixed-Design ANOVA revealed a significant main effect for estimation method ($F(1, 83) = 14.381$, $p < .001$), a marginally significant effect for the presence of calorie information ($F(1, 83) = 3.835$, $p = .054$), and a significant interaction between estimation method and the presence of calorie information ($F(1, 83) = 6.384$, $p < .05$). Post-hoc tests revealed that errors in human calorie estimations were significantly improved by the presence of calorie information ($t(45.89) = -2.731$ $p < .01$). Calorie estimations based on bite count were significantly more accurate than human estimates without the aid of calorie information ($t(32) = -3.578$, $p < .005$), but there was no significant difference between estimations based on bite count and human estimates with

the aid of calorie information ($t(52) = -1.116$, $p = .270$). The results suggest that bite count may aid individuals with calorie estimation when other aids are unavailable or be a less burdensome alternative to certain calorie estimation aids.

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INTRODUCTION

Objective

The purposes of this study were to: 1) examine the accuracy of individuals' estimations of calories eaten during a meal with and without the presence of a menu containing calorie information; and 2) compare the accuracy of an individualized bite-based measure of calorie intake to individuals' estimates.

The Obesity Epidemic

Since the 1980's obesity has increased dramatically to the point of being labeled a national epidemic. The most recent annual National Health and Nutrition Examination Survey (NHANES) report states that currently a third of the U.S. population is classified as overweight (having a body-mass index between 25 and 29.9 kg/m^2), and another third is classified as obese (having a body-mass index of greater than or equal to 30 kg/m^2) (Flegal et al., 2010). Obesity is associated with numerous health risks, including high blood pressure, coronary heart disease, and diabetes (Pi-Sunjyer, et al. 1998). Total medical costs associated with obesity in 2008 were estimated at $147 billion, with average insurance payouts being $1,429 higher for obese than non-obese patients (Finkelstein et al., 2009).

Despite increasing social awareness, the rise in the prevalence of obesity is showing no signs of slowing down (Flegal, 2005). Societal and personal level interventions to counter the increase in obesity are confounded by an increase in restaurant portion sizes, easy access to foods high in calorie content, and lifestyles that have led to an increased reliance on restaurants and fast foods rather than home cooked meals (Ello-Martin et al., 2005; Rolls et al., 2002; Rosenheck, 2008; Young & Nestle, 2003). Efforts to solve the societal problems associated with the obesity epidemic by increasing awareness and encouraging healthy lifestyles have had little influence on the national trend towards overweight and obesity. However, a variety of interventions at the individual level have been shown to be effective.

Interventions

The various interventions aimed at combating obesity for individuals tend to fall into one of three categories: surgical, pharmaceutical, and behavioral. Bariatric surgical procedures, such as gastric bypass surgery, vertical banded gastroplasty, and the adjustable gastric band, manage obesity be restricting appetite. The surgical treatment of obesity is currently the most effective method of treating severely obese patients (those with a BMI of 40 kg/m^2 or greater) (Maggard et al. 2005). While bariatric surgery has advanced to the point that morbidity rates are as low as 1%, there is still a tradeoff in quality of life, and should only be considered as a last resort for patients with BMIs higher than 40 kg/m^2 (Bult et al., 2008; Karlsson et al., 2007; Maggard et al., 2005). Drug treatments have been shown to slightly increase weight loss when coupled with behavioral treatments. However, these are only effective as assistants to behavioral interventions, and can be dangerous if used by patients with various comorbidities associated with obesity, such as hypertension, dyslipidemia, CHD, type-2 diabetes, and sleep apnea (Pi-Sunyer et al., 1998).

Behavioral interventions attempt to combat obesity by reinforcing behaviors that lead to a negative energy balance, such as healthy eating and high levels of physical activity, and discouraging behaviors that lead to a positive energy balance, such as overeating, emotional eating, and sedentary lifestyles. The term ‘energy balance’ describes the relationship between energy intake (EI) during eating, in the form of calories or kilocalories, and energy expenditure (EE), a summation of an individual’s energy usage due to physical activity and metabolism. Calories come in the form of three macronutrients in human metabolism: protein, carbohydrate, and fat. A positive energy balance occurs when more calories are being brought into the body than are being used, and results in the storage of energy. Excessive energy storage leads to overweight and obesity. A negative energy balance occurs when more calories are being burned than are being stored, resulting in weight loss. While this relationship is generally true, recent studies have found differences in calorie-reduced diets emphasizing the reduction of one macronutrient over another, indicating that the different sources of calories may not be equal when it comes to energy balance, either through differences in thermodynamic efficiency or psychological cues, such as satiety (Buchholz & Schoeller, 2004; Fine & Feinman, 2004; Schoeller & Buchholz, 2005).

Behavioral interventions prescribe the use of low calorie diets and reduced portion sizes to decrease calorie intake. Low calorie diets result in weight loss of an average of 8% body weight within a year (Pi-Sunyer et al., 1998). Physical activity can help contribute modestly to weight loss, but is primarily helpful in reducing some of the risk factors associated with obesity. Physical activity is most effective when combined with low calorie diets, as it can lead to improved weight loss maintenance (Pi-Sunyer et al., 1998). The primary weakness of behavioral interventions is that compliance rates tend to be low, as does weight-loss maintenance beyond the first year. Nevertheless, due to the low risk-levels and significant results in those who remain compliant, the behavioral treatment of obesity is still the recommended method for treating obesity in overweight and obese people with BMIs lower than 40 kg/m^2 (Burke et al., 2009; Foster et al., 2005).

Factors that Influence the Success of Behavioral Interventions

There are various factors that can contribute to both the short term and long term success or failure of behavioral weight-loss interventions. While the short term effectiveness of behavioral interventions has shown steady improvement in recent years, those who have received treatment are still having trouble maintaining weight loss after a year (Pi-Sunyer et al., 1998). A few factors have been shown to increase the likelihood of long term weight loss maintenance including: encouraging physical activity; prolonging the duration of the weight-intervention programs; and continuing counseling upon completion of the program (Svetkey et al., 2008). Svetkey et al. (2008) also found that those who adhere to and complete weight-intervention programs are more likely to maintain weight loss than those who do not complete them. In addition, Wing & Hill (2001) found that if weight loss is maintained for a set duration (2 to 5 years), then success rates for weight loss maintenance for even longer durations is increased dramatically, suggesting that healthy habits that maintain healthy weight levels have been formed. Many of the factors that are indicative of short term success also influence long term success, including physical activity levels and positive reinforcement through counseling (Burke et al., 2009). According to Foster et al. (2005), successful weight loss requires “significant planning, proficiency in making healthy choices and estimating portion sizes, and diligence in monitoring calorie intake and activity,” leading most researchers to investigate ways of making these things easier.

Perhaps the most critical component of successful behavioral interventions is consistent and frequent self-monitoring of EI (Burke et al., 2009). Baker & Kirschenbaum (1998) found that during a weight loss intervention, only the participants who most consistently monitored intake were able to lose weight during the holiday weeks, whereas those with lower consistency gained up to five times as much weight during the holiday weeks compared to non-holiday weeks. Likewise, Burke et al. (2008) found that frequency of food diary use correlated significantly with weight loss.

Monitoring Energy Intake

The accurate monitoring of EI is important to both researchers who are studying eating behavior and individuals who are trying to lose weight. In laboratory and clinical studies, EI is easily monitored through direct observation. However, in field studies and behavioral interventions, more indirect methods must be used which have varying levels of accuracy and cost.

The most accurate method of measuring EE in the field is the doubly labeled water (DLW) method. DLW has also been used to indirectly measure EI by combining

EE with weight gain or loss to derive EI. DLW has been shown to estimate EI within 2% to 8% in inpatient clinical studies and within 8% to 15% in field studies (Black & Cole, 2000; Schoeller, 1988). Because of its high degree of accuracy, the DLW method is often used as an EI benchmark to compare other methods against (Johnson et al., 1994; Muhlheim et al., 1998; Speakman & Thomson, 1997; Tooze et al., 2004). However, because of the high costs associated with obtaining the isotopes, the DLW method is only available to the most well-funded and equipped laboratories and clinics. Many researchers fall back on the use of various methods of self-monitoring to obtain estimates of free-living EI such as food diaries.

Methods used to Self-Monitor

Self-monitoring and self-reporting are often used to estimate the EI of participants outside of laboratory or clinical settings. Self-reports come in the form of food diaries, food frequency questionnaires, and 24-hour dietary recalls. Food frequency questionnaires are designed to assess usual EI over a given period of time, but are subject to large amounts of systematic and random error (Subar et al., 2003). Food diaries require participants to write down exactly what they ate and how much of each item they ate after every meal. These records are later reviewed by experts who then derive EI. However, in an early study assessing the validity of food diaries, Lansky & Brownell (1982) found that only 53% of food reports in the study were specific enough to allow for accurate estimates of calorie intake. 24-hour dietary recalls have many of the advantages of food diaries, in that they can get meal-specific calorie counts, and they do not burden the participant with filling out a report after every meal. However, these require participants to make the same estimations that food diaries require (i.e., foods chosen and portion size consumed), and they rely on the participant's accurate memory rather than the immediate recall of diaries. Subsequently, users tend to underreport on these as well (Johansson, Wikman, Ahren, Halllmans, & Johansson, 2001).

Despite their shortcomings, self-reports do provide some general information about EI, and can greatly improve the success of behavioral interventions. The act of self-monitoring itself is enough to facilitate weight loss, even if the food records are abbreviated or inaccurate (Helsel et al., 2007). However, when using self-reports, participants notoriously underreport EI. This may be due to a variety of factors, including portion size underestimation, forgetting, and intentional misreporting (Lichtman et al., 1992; Livingstone & Black, 2003; Martin et al., 1996; Muhlheim et al., 1998; Rumpler et al., 2008; Subar et al., 2003; Tooze et al., 2004; Trabulsi & Schoeller, 2001). Underreporting can range from 20% for normal weight individuals up to 50% for overweight individuals (Schoeller et al., 1995). Underreporting persists even after receiving training in the use of food records (Mertz et al., 1991).

While participants do not make calorie estimations during self-monitoring for behavioral interventions, it is a critical part of the everyday self-monitoring of someone who is trying to monitor their energy balance outside of structured, behavioral interventions. Even in interventions, accurate portion size estimations on the part of the participant are critical for transforming the reports into a measure of EI. While self-reporting and calorie estimation are technically two different processes, errors in both can be explained by many of the same influences (Martin et al., 2007). Additionally, while self-reporting has been studied extensively, few studies have directly examined how accurately people can estimate the calorie content of meals. An appropriate understanding of the factors that influence self-reporting and calorie estimation is necessary for improving the methods currently used for self-monitoring.

Calorie Estimation

A kilocalorie (kcal, or Calorie) is a metric unit of energy measurement defined as the amount of heat needed to raise the temperature of 1kg of water 1^{o} Celsius and is currently the most popular form of food energy measurement in nutritional research and nutrition labeling in the United States (Hargrove, 2006). Since the 1990 Nutrition Labeling and Education Act, all food manufacturers have provided nutrition labeling showing calorie content on nearly all packaged food (Backstrand et al., 1997). However, many people do not have an understanding of the appropriate number of calories an average adult should be consuming on a daily basis. Elbel (2011) found that only one third of respondents to a survey properly responded that adults should consume, on average, around 2,000 calories daily.

Intake monitoring is an essential part of reducing EI in order to lose weight and counting calories is the most common method for monitoring intake. Counting calories requires the dieter to make estimations of portion sizes and to have knowledge of the relative energy density (ED), or ‘calories per gram,’ of the food. Accurate calorie counting requires multiplying the portion size of each individual food item, typically established by weighing the food, by its ED. However, weighing individual foods and looking up their EDs is cumbersome and not practical for daily calorie counting. Most people make estimations of calorie content of meals by guessing portion sizes relative to assumed standard serving sizes, or by simply relying on their own knowledge and simple heuristics (Carels et al., 2006).

As with self-reporting, studies have shown that participants perform poorly when estimating the calorie content of meals. For example, Stanton & Tips (1990) found that only 28% of participants were able to estimate within 100 kcals of actual calorie content. While calorie estimation hasn't been studied as extensively as self-reporting, errors in calorie estimation have been shown to be associated with many of the same factors associated with inaccurate self-reporting (Chandon & Wansink, 2007; Stanton & Tips, 1990; Wansink, 2006). These factors include BMI, portion size and portion size estimation, perceived 'healthiness' of food items, and diet history (Carels et al., 2007; Chandon & Wansink, 2007; Harris & George, 2010; Stanton & Tips, 1990). However, other factors, such as forgetting and intentional misreporting, are specific to self-reports and do not contribute to calorie estimations.

Factors Associated with Errors in Self-Reporting and Calorie Estimation

Association with BMI. Studies investigating the changes in the accuracy of calorie estimations and the extent of underreporting intake associated with BMI have reported mixed results. Kretsch et al. (1999) found that obese participants underreported calorie intakes by 10% more than normal weight participants. Likewise, Johnson et al. (1994) found that as BMI increased, so did the amount of error in reporting intake. However, this effect was only found for women. Stanton & Tips (1990) found that higher BMI resulted in overestimations of calories. Carels et al. (2006) found that people with a higher BMI tended to have lower calorie estimation accuracy. However, Carels et al. (2007) found no difference between overweight and normal weight participants' calorie estimations. Likewise, Martin et al. (1996) found no relationship between underreporting and BMI.

It is possible that results showing a relationship between calorie estimation and BMI are being mediated by portion size. Wansink and Chandon performed two studies investigating the relationship between BMI and calorie estimations and found that accuracy declined as BMI rose, but this effect disappeared once portion size was added as a covariate (Chandon & Wansink, 2007, Wansink & Chandon, 2006).

Portion Size Estimation. Perhaps the most significant contributor to inaccurate calorie estimations is poor estimation of portion size. Portion estimations depend on human size and volume perception, which is subject to error, biases, illusions, and oversimplified heuristics. In an early study on human size perception, Teghtsoonian (1965) found that apparent size increases with actual size by a power function of about 0.6, meaning that an object looks like it increases in size more slowly than it actually does. This can lead to perceptual underestimations of portion size.

Most studies have shown declining portion estimation accuracy with increases in portion size. Chandon & Wansink (2007) found that sensitivity to changes in meal size decreases with meal size, implying that estimations of absolute portion size (and subsequently overall calorie content) would decrease in accuracy with increases in meal size. Oddly enough, the findings that accuracy decreases with increases in portion size do not hold true for all studies investigating calorie estimation. Holmstrup, Stearns-Bruening, & Fairchild (2008) found that participants were more accurate at estimating the calorie content of large meals than that of small meals.

Several studies have shown that food shape can have a significant impact on portion size perception. Chandon & Ordabayeva (2009) found that consumers perceive changes in all three dimensions (length, width, and height) to be less dramatic than changes of equal volumes in only one dimension, showing that human volume perceptions are not influenced by all dimensions the same. Specifically, when a glass is increased in height by the same volume as another glass that is increased in width and height, we perceive the change in height alone to be a more dramatic change than the change in both height and width. Garber et al. (2008) found that package shape can also affect volume perceptions. In a study investigating the effects of breaking a fixed portion into more numerous, smaller pieces, Scisco et al. (2012) found that participants perceived a fixed amount of Jell-O to be a larger portion when it was split into several smaller pieces.

Some researchers refer to errors in portion size estimation as the result of heuristics and biases. Raghubir and Krishna (1999) found that height is a vital dimension used as a simplifying heuristic to make volume judgments. However, height has a negative effect on perceived consumption, but a positive effect on actual consumption. Geier & Rozin (2009) found that estimators tend to devalue portion size in making calorie estimations; that is, people tend to give more weight to other factors such as 'healthiness', and devalue or disregard portion size. In this example, when making calorie estimations participants increased their estimations to a much smaller magnitude due to portion size changes than they did for changes in the ED of foods.

Various other factors can contribute to the accuracy of portion size estimations. External influences, such as advertising claims, can also have a significant effect on portion size perceptions. Size labels that infer smaller portion size (such as "bite size") can lead consumers to underestimate portion size and, subsequently, eat more (Aydinoglu & Krishna, 2010). However, participants still feel like they've eaten less than they did when eating out of a package with no size claims. Yuhas et al. (1989) found that training could also improve portion size estimation accuracy.

The effect of diet history. There is some evidence that people can be trained to improve their calorie and portion size estimations (Martin et al., 2007). Dieticians are better at estimating EI because of their familiarity with counting calories (Champagne et al., 2002). Aoki et al. (2006) found that trained dieticians could estimate the calorie content of meals with an accuracy of around 85%. Carels et al. (2007) found that dieters were more accurate at estimating calories than non-dieters. Visona & George (2002) examined the accuracy of calorie estimations among dieters and non-dieters. They found that while dieters are better at estimating calorie intake than non-dieters, they still underestimate by about 30% compared to non-dieters who underestimated EI by about 40%. Stanton & Tips (1990) found that those who reported disordered or restricted eating had a tendency to overestimate the calorie content of foods, providing evidence that being conscious of a food's energy content doesn't necessarily improve accuracy. Harris & George (2010) found that men underestimated calories by approximately the same amount regardless of physical activity levels.

The effect of gender. A small number of studies have investigated the relationship between gender and knowledge about daily energy requirements, energy balance, and calorie intake. Most significantly, Krukowski, Harvey-Berino, Kolodinsky, Narsana, and DeSisto (2006) examined the relationship between gender and an understanding of daily energy requirements and nutrition labeling use among college students and community members. They found that only 61.2 percent of men could accurately state typical daily energy requirements (2000 kcals) to within plus or minus 500 kcals, compared to 80.9% of college females. Furthermore, 64 percent of college males reported that they would not use nutrition labeling information even if it was presented to them compared to 28.4 percent of college females.

The effect of nutrition labeling. Another factor that contributes to calorie estimation, and subsequently accurate self-monitoring, is the presence or absence of nutrition labeling. The effect of Nutrition Labeling on self-monitoring has not been extensively studied because it is not relevant to most forms of self-report used for behavioral interventions. However, nutrition labeling is the most readily available source of calorie information for most meals, and is one of the most critical factors in determining energy intake outside of structured behavioral interventions. That is, it is the primary means of determining the calorie content of a meal for routine monitoring of EI.

In an effort to curb the obesity epidemic, legislation has been passed in many states requiring chain restaurants to post nutrition labeling information on their menus (Berman & Lavizzo-Mourey, 2008; Burton et al., 2006). The effectiveness of this method hinges on several assumptions (Roberto et al., 2009). First, nutrition labeling must be accurate to the actual nutrition content of the meals. Urban et al. (2011) measured the actual calorie content in a fast food chain using a bomb calorimeter and found that, with the exception of a few menu items, actual calorie content was very close to the labeled calorie content. Second, people need to have an understanding of healthy calorie intake levels, and be willing to use nutrition labeling. In a study investigating the potential effectiveness of menu labeling, Krukowski et al. (2006) found that around 50% of respondents reported that they wouldn't even use the labeling information if it were available in restaurants. Third, people have to be willing to alter their food choices. Several studies have shown that the presence of nutrition labeling information has had minimal effect on food choices (Elbel et al., 2009; Elbel, 2011). However, other studies have shown the opposite. For example, Bollinger, Leslie, & Sorensen (2010) found that the presence of nutrition labeling reduced calories per transaction by 6% at a Starbucks.

Despite the requirements of the 1990 Nutrition Labeling and Education Act, there are still questions about how much nutrition labels utilized in monitoring EI and how easily they are understood. According to the 2005 - 2006 National Health and Nutrition Examination Survey, 61.6% of U.S. citizens report using nutrition labels (Ollberding et al., 2010). Also, women, people with higher education, and individuals with higher income levels are more likely to report nutrition label use, and people who report using nutrition labeling also report lower levels of EI.

Even though the effectiveness of the use of nutrition labeling in altering food choices remains inconclusive, nutrition labeling has been shown to improve calorie estimations. After the use of calorie content information on menus was mandated in New York City, Elbel (2011) found that the number of people who were able to estimate the calorie content of their fast-food meals to within 100 kcals increased from 15% before labeling to 24% after labeling. Roberto et al. (2010) found that nutrition labeling improved calorie estimations, reduced the number of calories ordered and consumed, and reduced calories consumed later in the day.

New Self-Monitoring Tools

There is a dire need for tools that can accurately monitor EI in a field setting. More accurate clinical methods, such as the DLW method, are too costly and impractical for use by individuals. Other more commonly used methods, such as 24-hour dietary recalls and food frequency questionnaires, rely on human memory and perception, and are notoriously inaccurate. Traditional pen-and-paper methods of self-monitoring increase both the short-term and the long-term success of weight loss, but can discourage compliance because they are burdensome to remember and use (Burke et al., 2009). Newer methods attempt to improve compliance, convenience, and accuracy by automating part or all of the dietary assessment process.

Automated self-reports. Automated self-reports are digitized versions of their pen-and-paper or interview counterparts, and include tools such as web-based 24-hour dietary recalls and PDA-based food records. Digital food records offer the advantages of ease of entry, alerting the user to enter meals, and providing feedback in real time (Beasley et al., 2005). Additionally, they are portable, socially acceptable, and they can also make it so that the user doesn't need to look up the calorie content of each food item, increasing convenience and compliance (Burke et al., 2009).

Beasley, Riley, & Jean-Marie (2005) assessed the accuracy of a PDA-based food record, finding that it correlated moderately with a 24-hour dietary recall ($r = .713$) and observed intake ($r = .720$), showing good agreement with both. Fifty percent of the error in the PDA assessment was due to portion size estimation error, and omissions and misreporting of food items accounted for the other fifty percent.

Unfortunately, automated self-reports fail to eliminate many of the problems with pen-and-paper methods and bring some new problems to the table. Some participants find the software on these PDA-based food records to be difficult to use (Burke et al., 2009). There is a tradeoff between accuracy and convenience; as automated food records get more detailed and accurate, it becomes more difficult to navigate through the food selection menus (Chen, Lee, Rabb, & Schatz, 2010). Also, despite the added convenience, digital food records have been shown to be subject to many of the same sources of error as pen-and-paper methods, such as inaccurate portion size estimation, forgetting, and underreporting (Ngo et al., 2009). Beasley et al. (2005) found comparable errors in dietary intake estimation using a PDA based assessment program due to errors in portion-size estimation.

Digital photography. Digital photography is a new method for monitoring EI in the field that attempts to mimic direct observation. Participants take pictures of their own meals, and the pictures are sent to a nutritionist via the web for nutritional analysis. Over the past ten years, several studies have attempted to validate the use of digital photography by comparing it to other methods used for determining EI in the field. Williamson et al. (2003) found nutritionist analysis of portion sizes, plate waste, and food intake to be highly correlated with weighed calculations. Aoki, Nakai, and Yamauchi (2006) found that dieticians and licensed nutritionists were able to estimate the calorie and protein content of digital pictures with an accuracy of about 85%. Martin et al. (2007) validated the digital photography method as a means of monitoring food intake in children, finding strong inter-rater reliability and accuracy among dieticians for the use of digital photography for estimating macronutrient intake. Matthiessen et al. (2011) found that nutritionist estimations based on digital photography correlated strongly with estimations based on food records. Martin et al. (2009) used digital photos taken with a camera phone, estimating EI to within 6.6% in free-living environments.

The digital photography method allows for accurate estimation of calorie content for meals in a field setting. However, it requires the use of trained dieticians to analyze the photographs and estimate calorie content. Recently, pattern-recognition software has been incorporated into the digital photography method to attempt to automate the nutritional analysis aspect of the digital photography method (Martin, Kaya, & Gunturk, 2009). While this method is still being developed, and as of yet has limited applicability, it shows great potential as a device that may assist the routine self-monitoring of energy intake.

Devices for monitoring ingestive behavior. With the exception of the DLW method, methods for monitoring EI in the field and for routine self-monitoring rely on subjective estimations and reporting, which are themselves subject to cognitive and perceptual limitations. One way to get around this subjectivity is to develop devices that can directly monitor ingestive behavior and translate that into a measure of energy intake. Lopez-Meyer, Schuckers, Makeyev, & Sazonov (2010) describe devices for monitoring ingestive eating behavior as "objective tools… that can detect and characterize food intake." Lopez-Meyer et al. (2010) describe a device that can detect food intake with an accuracy of 94% by using a device that detects chewing and swallowing. Unfortunately, this tool has yet to be studied as a device for estimating calorie intake. Another tool that offers the potential of objectively and automatically calculating energy intake through monitoring ingestive behavior is the Bite Counter, developed by Hoover, Muth, & Dong (2010). The Bite Counter tracks the ingestive behavior of taking a bite of food, where a bite is defined as putting food in the mouth.

Present Study

Routine, personal self-monitoring outside of behavioral intervention programs requires people to estimate portion size and relative energy density to determine the overall calorie content of the meal. Generally, the only tools available to assist in measuring portion size are normal kitchen measuring utensils. Often, these will be neglected in favor of simple portion size estimations (e.g. "this looks like about a serving and a half"). Portion size estimations are affected by a variety of factors. Information about relative energy density must be gathered (in most cases) from nutrition labeling if it is present, or from personal estimations if no nutrition labeling is available. ED estimations are themselves subject to perceptions of healthfulness. The wide margins of error tend to lead towards generally poor overall calorie estimations.

The present study examined how calorie estimation accuracy is affected by the presence of calorie information. Since nutrition labeling has been shown to increase accuracy of calorie estimations, if calorie information is not given, then accuracy should decline.

This study compared calories as estimated by humans in the previously mentioned conditions (calories per serving information present and absent) and compared them to an estimate of EI derived from bite count. Bite count is a largely unstudied, physiological measure that has the potential to serve as a proxy for EI. A recent dissertation by one of our lab members examining bite count and energy intake over a two week period found an average of 15 calories-per-bite for women and 18 calories-per-bite for men, and this ratio could be further refined by accounting for gender, age, height, and weight (Scisco, 2012). Further evidence for the relationship between bite count and EI is needed to assess its utility for monitoring EI. Specifically, a bite count proxy for EI needs to be compared to human estimations of EI with varying levels of information. If calorie estimations based on bite count can be shown to be more accurate than individual estimates with and without calorie information present, then a device that monitors bite count could be used to monitor free-living EI and improve currently available calorie estimation methods.

Hypotheses

There were two primary hypotheses of this study: 1) Human estimates of calorie intake would be better in the presence of calorie information than in its absence, 2) An estimation of calorie intake derived from bite count using the previously mentioned equations would be more accurate than a human's ability to estimate calorie intake, at least in the absence of calorie information. There was also a third, secondary hypothesis: 3) In line with previous research, human calorie estimates will be related to BMI, caloric intake, body fat %, and gender.

METHOD

Participants

Participants were recruited from the student population of Clemson University and the surrounding area via fliers, e-mails, and word of mouth. Participants were given $10 and offered a free meal for participating in the study. Those with a self-report history of eating disorders were excluded from the study. Participants were also screened to achieve a demographic spread that was representative of the area population.

Of the 361 participants who volunteered and completed the online pre-screening survey, a total of 280 participants were enrolled in this study. Data were excluded from 193 participants: 7 because of faulty recordings, 2 because they did not provide calorie estimations and 184 because we could not confidently determine their actual calorie intake, leaving a sample size of 87 (48 male) for analysis. Participants had a mean age of 27.38 (*SD* = 11.10, range = 18 to 63). Nine identified themselves as African American, 12 as Asian or Pacific Islander, 62 as Caucasian, 2 as Hispanic, and 2 as other. Seven participants were left-handed. Participants had a mean body fat percentage of 22.8 (*SD* = 8.95, range = 6.4 to 42) and a mean BMI of 24.96 (*SD* = 4.92, range = 17.4 to 46.2).

Design

This study was a mixed design. There was one between-subjects variable, calorie information (CI) presence, with two conditions: CI given and CI not given. Both conditions also had a within-subjects variable with two conditions: human calorie estimation error (HCE error) and bite count calorie estimation error (BCE error).

Additional analyses were performed to examine the relationship between BMI, body fat percentage, gender, and calorie intake and HCE error and BCE error.

It is important to distinguish between HCE and HCE error, as well as between BCE and BCE error. HCE is the human's estimate of their caloric intake, whereas HCE error is HCE minus actual calorie intake. BCE is the bite count based estimated of caloric intake and BCE error is BCE minus actual calorie intake. HCE error and BCE error provide an estimate of the method's accuracy for an individual participant. For example, if a participant ate 750 kcals and their HCE was 1000 kcals, their HCE error would be 250, showing an overestimate of 250 kcals. It is also important to note that while an automated measure of bite count was obtained, the purpose of this study was to examine true bite count as a measure of energy intake rather than to validate the algorithms used to detect bites. Therefore, true bite count was used for all analyses. The process for finding true bite count is described in further detail below.

Materials

Eating station. To simulate a real-world environment, participants ate in a cafeteria setting at a four-person table customized for the purpose of monitoring bite count and food weight (Figure 2.1). Four scales were hidden in recesses cut out at each place setting. There were four cameras mounted above the eating station, each monitoring one participant. Each participant also wore a tethered bite counter. All of the measuring equipment was connected to two laptops (Dell Lattitude E6520) that were located near the eating station (Figure 2.2). The eating station was set up in Harcombe dining hall, an on-campus cafeteria at Clemson University.

Food items. Participants were allowed to select from any of the food items available in Harcombe during the day and time of their session. A record was kept of all of the food items available for each day and time of the study.

Tanita WB-3000 Digital Beam Scale. The Tanita Wb-300 Digital Beam Scale was used to measure participant height and weight, which was then used to calculate BMI (Tanita Corp., Arlington Heights, IL).

Omron Body Logic Body Fat Analyzer. The Omron Body Fat Analyzer was used to calculate body fat percentage based on electrical impedance and an individual's demographics (Omron Corp., Kyoto, Japan).

Cisco PVC300 cameras. Four cisco PVC300 cameras were mounted above the eating station, each positioned to monitor food as it was brought from the plate to the mouth (Cisco Systems, Inc., San Jose, CA). The cameras had a resolution of 640 x 480. The video recordings were used to ascertain true bite count. A bite was be defined as food being brought from the plate to the mouth and entering the mouth.

Figure 2.1. The Eating Station

Figure 2.2. Two Dell Lattitude E6520 laptops were used to store raw sensor data

Calorie information. Upon completion of the meal, participants in the CI given condition were given a copy of the menu containing all of the food items available for that session with calorie information for each one. Calorie information was copied from Harcombe Dining Hall's website. They were instructed to use the information provided to assist them in their calorie estimations. An example of a daily menu as used by participants can be seen in Appendix A.

Questionnaires. An online pre-screening questionnaire asked participants to report height, weight, food allergies, dieting status, and history of eating disorders (Appendix B). An online demographics questionnaire asked participants about age, gender, height, weight, handedness, and ethnicity (Appendix C). Upon completion of the eating session, participants were given a questionnaire, which asked them to estimate overall calories consumed (Appendix D).

Software. Video footage was recorded using video monitoring software that was included with the Cisco cameras and raw sensor data was recorded using custom software (Figure 2.3). True bite count was measured using customized software that synchronized video footage with wrist-sensor and scale data. Figure 2.4 shows the interface of the software, where experimenters could move the video forward or backwards at 1 frame or 15 frame intervals.

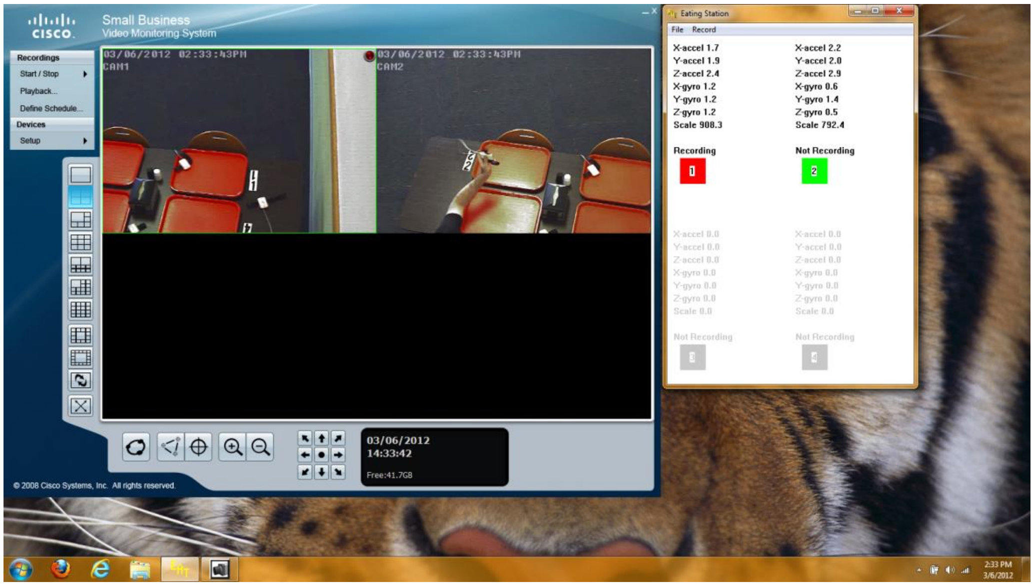


Figure 2.3. Video monitoring and raw sensor recording software.

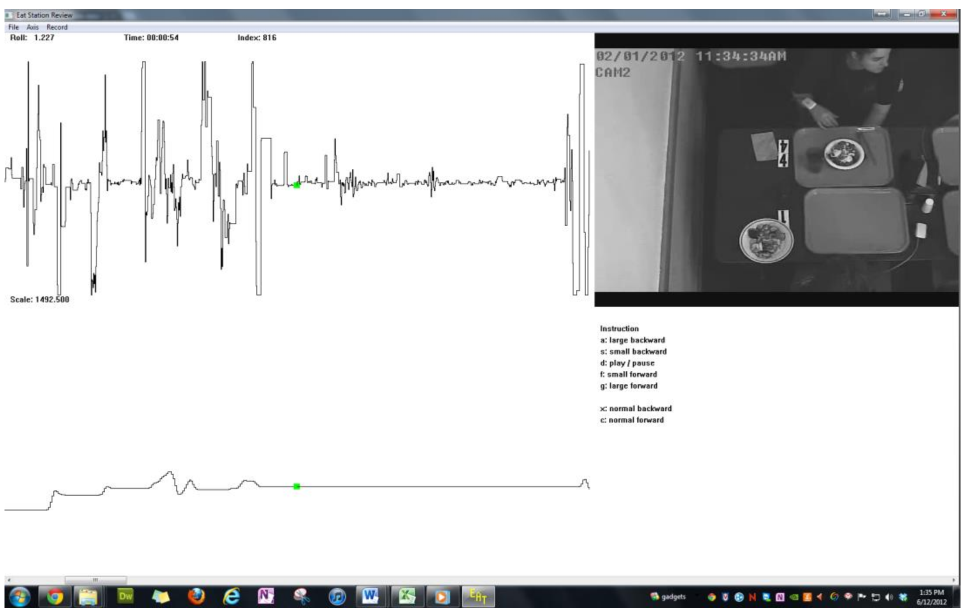


Figure 2.4. Custom Software for detecting true bite count.

Procedure

Experimental protocol. Detailed protocols for both the experimenters and the undergraduate assistants can be found in Appendices E and F respectively. The order in which participants were placed into one of the two groups was randomized. Upon recruitment, participants completed the online demographics and pre-screening questionnaire. Participants completed the eating session in groups of four. Upon arrival, their height and weight were measured using the digital beam scale. Participants were then led to Harcombe Dining Hall, where they received further instructions.

The participants were instructed to eat as much as they liked. To allow portion size and food selection to vary, participants will be allowed to serve themselves any of the food items in Harcombe that day, and were allowed to go back for as many courses as they wished. A course was defined as the time between sitting down with food and being connected to the wrist-worn sensor and being disconnected from the sensor, either to get another course or to complete the meal. Data recording was stopped between courses and restarted once the participant had been reseated for the next course. Participants were then connected to the Bite Counters and instructed to eat and interact naturally.

After each participant had made their food selections, the assistants wrote down each food item, the portion size, who served the item, and any customization made to the item. A daily menu was included in the subjects' folders each day that contained each food item that was supposed to be served in the cafeteria that day, along with a reference portion size for each item (as determined by what Aramark would consider to be a “standard” portion of that food item) and calorie content for that portion. Food items would be listed on each daily menu in the following format:

Food item	*Reference Portion Size*	*Calorie Content*

For example, the following entry is taken directly from a daily menu:

Seasoned Corn	**1 cup**	**103.15 (calories)**

An example daily menu can be found in Appendix A. The assistants were instructed to cross-reference each food item with the menu and to make alterations of any items were mismatched.

Upon completion of the meal, participants were given the post-meal questionnaire, which recorded their overall calorie estimations. Participants in the CI condition were also given the daily menu with calorie information for their session to assist them in their estimations. After completing the questionnaire, the participants were debriefed and dismissed.

Data Reduction

From the initial sample of 280 participants, 7 participants were immediately excluded from all further data reduction because of recording errors. True bite count was calculated for the entire remaining sample of 273. This sample was further reduced to the final sample of 87 used for analysis during the “determining calorie intake” phase, described below.

Determining true bite count. Bites were manually identified using custom software that paired video footage with data obtained from the scales and wrist-worn sensors. Participant meals were split up by courses. For the sample of 273 participants who had useable recordings, bites were counted for a total of 518 courses, averaging 1.9 courses per participant. The final sub-sample of 87 participants had a total of 160 courses, averaging 1.84 courses per participant.

Figure 2.4 above shows the interface used by the experimenters to count bites. Experimenters watched the videos and placed markers where bites occurred, noting what the food item was, what utensil was used, what container the item was eaten out of, and what hand was used. To account for inter-rater variability, an intra-class correlation using a two-way, random effects model and an absolute agreement definition was calculated for a subset of 57 courses that were counted by 3 groups of independent raters (Shrout & Fleiss, 1979). This subset of 57 was taken from the sample of 273 participants who had usable recordings via a convenience sampling of the first 1/3rd of the dataset. The intra-class correlation was found to be very strong at .929. Based on this, true bite count was measured for each participant based off of one rater's counted bites. For those courses that had already been counted by more than one rater, the count from the rater whose first initial came first alphabetically was used as the ground truth bite count for that course. For a detailed protocol on this procedure, see Appendix G.

Determining BCE and HCE. Human calorie estimations were provided by each participant at the end of their experimental session. Calorie estimations based on bite count were determined by applying equations that were derived from data from an unpublished dissertation by Scisco (2012). This was a field study that compared bite count to calorie intake as measured by a 24-hour dietary recall. These equations used gender, height (in inches), weight (in pounds), and age to calculate a kilocalories-per-bite (KPB) ratio that is tailored to each individual. The equation for males was:

$$KPB = (.2455 \times height) + (.0415 \times weight) - (.2597 \times age)$$

The equation for females was:

$$KPB = (.1342 \times height) + (.0290 \times weight) - (.0534 \times age)$$

These same equations were used in the present study to calculate a KPB ratio for each of the 273 participants with usable data recordings. The ratios were then multiplied by that participant's bite count to determine BCE.

Determining calorie intake. True calorie intake was determined using a four step process. All 273 participants with useable data recordings were included in the first step. After step one, 59 participants were excluded from all future steps for selecting food items with a high level of customization leaving a sample of 214. An example of an item with a high level of customization would be a sandwich from the sandwich station. Participants could build sandwiches using whatever bread type, meat type, cheeses, and toppings they desired. This made it particularly difficult to determine the calorie content of these items. This sample of 214 was used in steps two through four, after which 127 additional participants were excluded for selecting salads and pastas, for which calorie information could not be confidently determined, leaving the final sample of 87.

The process, described in detail below, is summarized as follows: 1) First, the food items selected by each participant were identified and verified. 2) Then, for each item that was absent from Harcombe's daily menus, reference information (defined in further detail below) was obtained from an online database. 3) Each participant's selected portion of each food item was then defined as a percentage of the reference portion of that food item. 4) The percentage of the selected portion of each food item consumed by each participant was then visually estimated by three raters.5) Finally, calories were determined for each food item by multiplying the reference calorie content of the selected food item by the percentage of the reference portion selected and the percentage of the selected portion consumed. Each participant's total calorie intake was then determined by summing their calorie intake for each selected food item.

Food item identification. A simplified decision tree for this procedure is shown in Figure 2.5. All 273 participants who had useable data recordings were included in this procedure. For these 273 participants, a total of 1,840 food items were consumed at an average of 6.74 items per participant. Food selection was initially documented during each experimental session by the undergraduate assistants on hand written records as described above and in Appendix F. Unfortunately, there were several unforeseen problems with this procedure. Many days' items that were available in the cafeteria were not listed on the menu for that day. Some items, such as drinks, deserts, and soups, were never or almost never listed on the menu. Additionally, the undergraduate assistants were under significant time pressure and had several responsibilities to keep track of, and subsequently often failed to cross-reference recorded food selections with menu items available that day. These problems required recorded food selections to be verified post data collection.

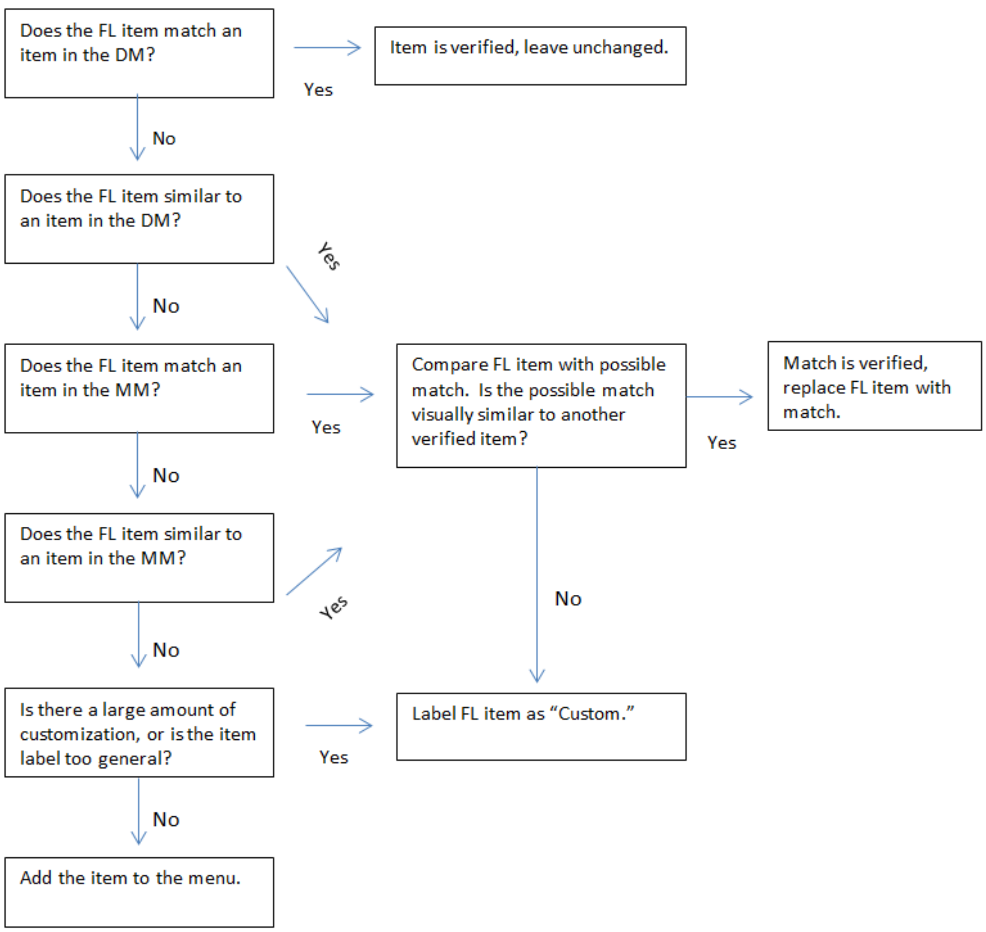


Figure 2.5. Decision tree for the food item verification process.

Selected food items were verified post data collection using a multi-step process. First, a master menu (MM) file was created by combining each day's daily menu (DM) items into one document and deleting duplicate items. Then, two experimenters cross-referenced each recorded food item in the food log database (FL), which contained every food item consumed by every participant, with items that were available on the DM for that participant's meal time. If the item matched an item from the DM exactly, it was considered "verified" and left unchanged. If the two experimenters agreed that a recorded item matched a similarly labeled item from DM, the recorded food item was changed to match the item from the DM. If no similar item was listed in the DM, the MM was scanned for matches. If the item in the FL matched an item in the MM, the item was left unchanged. If the two experimenters agreed that a recorded item matched a similarly labeled item from MM, the recorded food item was changed to match the item from the MM. If an item in the FL was changed, it was visually compared to images of other verified items with the same label. If the experimenters then agreed that the similar food items looked the same, then the name of the item in the FL was replaced with the agreed upon name of the similar food item and considered "verified". If no match could be found for the food item or if no consensus could be reached, one of two actions was taken.

If the experimenters could not agree upon a match for an item in the FL, either because the initial recorded item was not specific enough and the item could not be determined using the video recordings, or because the item contained a level of customization that made determining calorie content very difficult (such a sandwich from the sandwich station where participants could choose their own bread, meat, and toppings), it was labeled as "custom" and it was assumed that kcal information could not be confidently determined for that food item. If the item consistently appeared and was a reasonably simple item (such as a "brownie" or "coca-cola") but could not be found on the MM, it was added to the MM. At the end of this procedure, 59 food items had been labeled as "custom." Fifty-nine participants were found to have selected "custom" food items. These participants (and all of their food items) were excluded from all following steps, leaving a sample of 1,438 food items for step 2 through step 4.

Determining Reference Information for Missing Items. A simplified decision tree for this procedure is shown below in Figure 2.6. For items that were added to the MM during the food selection verification procedure, kilocalorie information and reference portion size information were obtained from a database on myfitnesspal.com, which contained all food items served by Aramark Cafeterias, uploaded by Aramark employees (Personal Communication, December 2012).

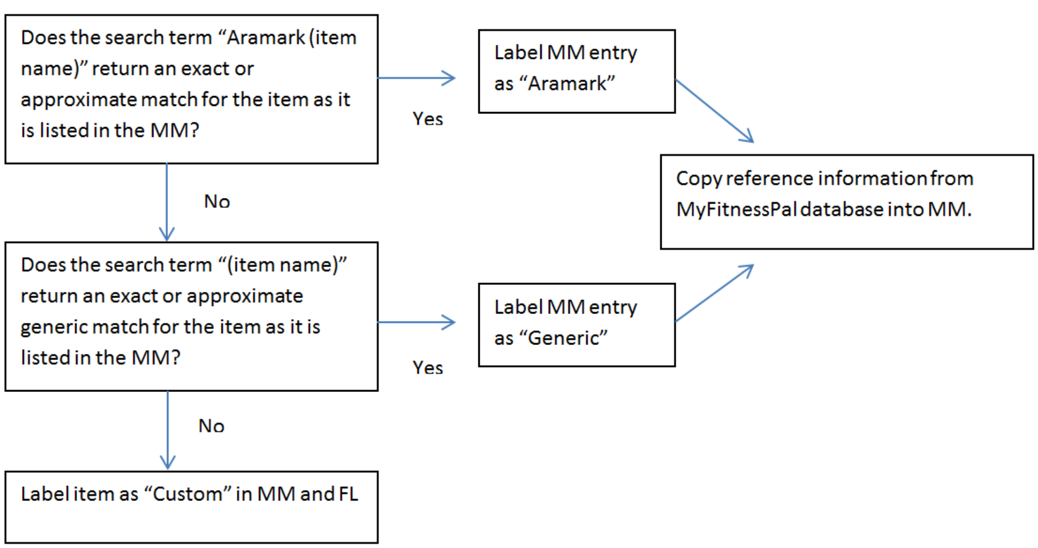


Figure 2.6: Decision Tree for Missing Reference Information Replacement

The database was searched for each item in the MM file that was added in the above procedure by using the search terms “Aramark (item name)”. For example, the item “vanilla pudding” was added to the MM during the food selection verification procedure. Reference information was added to the MM by searching the MyFitnessPal database using the search terms “Aramark vanilla pudding.” This search returned with one search result: “Vanilla Pudding w/ Whip cream (Aramark).” This is a very close match to the terms used in the MM, so the reference information for “Vanilla Pudding” in the MM was changed to the information listed in the MyFitnessPal database.

The MyFitnessPal database contained nutrition information obtained from a variety of sources other than Aramark. If no match could be found in the MyFitnessPal database that was uploaded by Aramark (that is, the search terms “Aramark (item name)” turned up no results), a generic version of that food item obtained from the same database was used. For example, Aramark had no listing for “Coca Cola” in the MyFitnessPal database. For this item, the database was searched for “Coca Cola,” excluding the search term “Aramark” and information from the positive search result was used as reference information.

If no approximate generic match could be found for an item in the MM, that item was changed to a “Custom” item, as described in the food selection verification procedure. Each food item on the MM was labeled according to the source from which its information was obtained: either from the original menus provided by Harcombe, uploaded to the MyFitnessPal database by Aramark employees, or listed as a generic item obtained from the MyFitnessPal database.

Portion size determination. During each experimental session, portion size selection was also recorded by the undergraduate assistants. If the food item was served by a cafeteria worker, then the selected portion was just recorded as the reference portion defined by the menu information that was provided daily by Harcombe Dining Hall. For example, the menu lists "buttermilk mashed potatoes" as having a standard portion size of one cup and 124 kcals. The cafeteria workers are instructed to serve these items by the reference portions unless a diner requests otherwise. These items were therefore assumed to be consistent with the reference portion size unless otherwise recorded by the undergraduate assistant. If the item was served by the participant themselves, then the portion was recorded as what seemed appropriate (1 glass of coke, 1 bowl of ice cream, etc.).

Post-experimental session portion size selection was verified for the 1,438 items that remained after step 1 using a two-step process. First, three raters visually estimated initial portion sizes of each food item using videos recorded during the experimental session. If the food item was divided into discreet portions (e.g. 2 chicken fingers or 1 cheeseburger) it was labeled according to those discreet portions. If the food item was amorphous (e.g. mashed potatoes or peas) or if it was a drink, it was labeled according to the percentage of its container that it occupied (e.g. 80% of a glass, or 40% of a plate). This information was only used for those items that were self-served by the participants, as items that were served by cafeteria workers were assumed to be a “standard portion” with an accepted amount of variability. This procedure was performed at the same time as the procedure for determining portion consumption, and additional details are described below. Finally, each food item was labeled according to what percentage of a ‘standard portion’ it consisted of (e.g. 2 servings of mashed potatoes would be 200% of a standard portion).

Portion consumed. A detailed protocol for this procedure is shown in Appendix H. Portion consumed was measured using a method similar to the Digital Photography method described by Williamson et al., who found visual estimations of portion consumption based on photographs to be highly correlated with visual estimations based on direct observation (2003). This process was applied to the sample of 1,438 food items consumed by participants who had useable data recordings and had not selected “custom” items. Three raters compared screenshots, taken from the videos recorded during an experimental session, of courses prior to meal commencement to screenshots of courses after meal completion (Figures 2.7a and 2.7b).

a. 

b. 

Figure 2.7. Before (a) and after (b) screenshots used to visually estimate starting portions and portions consumed.

The experimenters rated portions using course by course screenshots. Experimenters were given a list of foods consumed by that participant for that course (as listed in the food log that was created and verified in step one). The raters first had to identify which items present in the screenshots matched up to which items on the list of foods for that course. Regardless of their confidence in their decision, each rater was forced to estimate percentages for each food item. The raters then visually estimated the starting portions using the "before" screenshot (seen in Figure 7a), as described in step 3 above. Finally, the raters visually estimated what percentage of each starting portion of each item was consumed by comparing before and after (seen in Figure 7b) screenshots.

An intra-class correlation was calculated for the percentage ratings using a 2-way, random effects model using an absolute agreement definition and found to be very strong at 0.859 (Shrout & Fleiss, 1979). Still, some food items were found to have very different ratings for one rater as opposed to the other two. For example, nine items from the food log were rated by two raters as being 100 percent consumed and by the third to be 0 percent consumed. To mitigate the effects of such extreme ratings, the two raters whose ratings were closest to each other were averaged together. If all 3 raters rated a food item as the same percentage consumed (e.g. 30, 30, and 30), or if one rating was equidistant from the other two and two raters were not equal (e.g. 20, 30, and 40), all three ratings were averaged together. This process was applied to food items who met a minimum criterion of having at least two raters within 25 percent of one other. This criterion of 25% was chosen because it captured a majority of the food items, but was still stringent enough that items had large gaps between ratings could be reexamined. Only 20 out of 1,438 food items examined had 3 ratings with a difference of greater than 25 percent. A fourth rater rated each of these items, and their score was averaged with the nearest of the original 3 (this fourth rating was found to be within 25% of at least one other rater for each of the 20 items). To better adhere to the procedure described by Williamson et al., who had their experimenters rate items to the nearest ten percent, the averaged ratings of our three raters were rounded to the nearest ten percent.

Once food selection, portion selection, and portion consumption had all been verified, total calorie intake for a specific food item was determined by multiplying **kcals of the "standard" portion of that item** (provided by the master menu) by **percentage of a "standard" portion selected** and **percentage of selected portion consumed**:

$$\text{Total Caloric Intake} = \text{Kcals of Reference Portion} \times \text{\% of Reference Portion Selected} \times \text{\% of Reference Portion Consumed}$$

For example, say a participant selected buttermilk mashed potatoes. The master menu lists this item as 1 cup having 124 calories, and the item is served by a cafeteria employee. The participant reported having asked for only half of a serving of the item. The average rating for the two closest raters for portion consumed was 80%. Total caloric intake for that item would be determined by:

124 (kcals of standard) x .5 (% of standard) x .8 (% of portion consumed) = 49.6 kcals

Total calorie intake for a participant was calculated by summing that participant's kcal intake for all items that individual selected. After computing total calories, it was found that pastas from the pasta bar and salads from the salad bar had to be excluded due to the large amount of variability in energy density between these items and an inability to precisely determine their total calorie intake. Out of 1,438 items, 31 were pastas from the pasta bar and 114 were salads from the salad bar. A total of 127 participants who selected these items were excluded from further analysis, leaving a final sample size of 87.

Statistical analyses. The distribution of estimations for each of the four conditions were checked to ensure that the estimations followed a normal distribution using Q-Q plots, a graphical assessment of normality that plots observed values against values that would be expected of a sample with a normal distribution. Hypotheses 1 and 2 were tested using a 2 x 2 mixed-design ANOVA to assess differences between the CI conditions as a between subjects factor and HCE error and BCE error as a within subjects factor, with post-hoc t-tests examining the effects of CI condition and estimation method separately. Hypothesis 3 was tested using Pearson's r correlations to examine the relationships between age, body fat percentage, BMI, caloric intake, HCE error, and BCE error. To examine gender effects, analyses were again performed with gender as a between subjects factor. All analyses were performed with a set alpha level of .05.

RESULTS

Outliers and Descriptive Statistics

Outlier analyses were conducted by standardizing HCE error and BCE error scores and calculating Cook's Distance for each score. Cook's Distance provides an estimate of an individual score's impact on a given analysis, or leverage, relative to other scores. Outlier analyses showed two cases of human kcal estimations that were extreme outliers, having z-scores of 5.04 and 5.27 and Cook's Distances of .25 and .43. Each of these participants estimated consuming 4,500 calories (an unusually high estimate) and were excluded from all analyses. Outlier analyses revealed no significant outliers for BCE error in either CI condition.

Descriptive statistics for calorie intake, HCE, and BCE overall and across both CI conditions are displayed in Table 3.1. Mean calorie intake, HCE, and BCE are shown in Figure 3.1 for both CI conditions, showing general underestimations of calorie intake for both estimation methods in both conditions. Q-Q plots (Figure 3.2a - d) reveal normal distributions for estimate error across all conditions.

Descriptive Statistics				
		Calorie Intake	HCE	BCE
Overall	Sample Size		85	
	Mean	1177.69	900.61	1123.4
	SD	508.87	424.06	551.83
	Min	143	100	371.42
	Max	2618	2541.67	2981.2
CI Given	Sample Size		52	
	Mean	1119.77	978.39	1065.76
	SD	450.78	447.27	504.88
	Min	329	254	371.42
	Max	2143	2541.67	2777.66
CI Not Given	Sample Size		33	
	Mean	1268.97	778.03	1214.23
	SD	584.68	357.6	615.77
	Min	143	100	450.04
	Max	2618	1600	2981.2

Table 3.1. Descriptive statistics for calorie intake, HCE, BCE

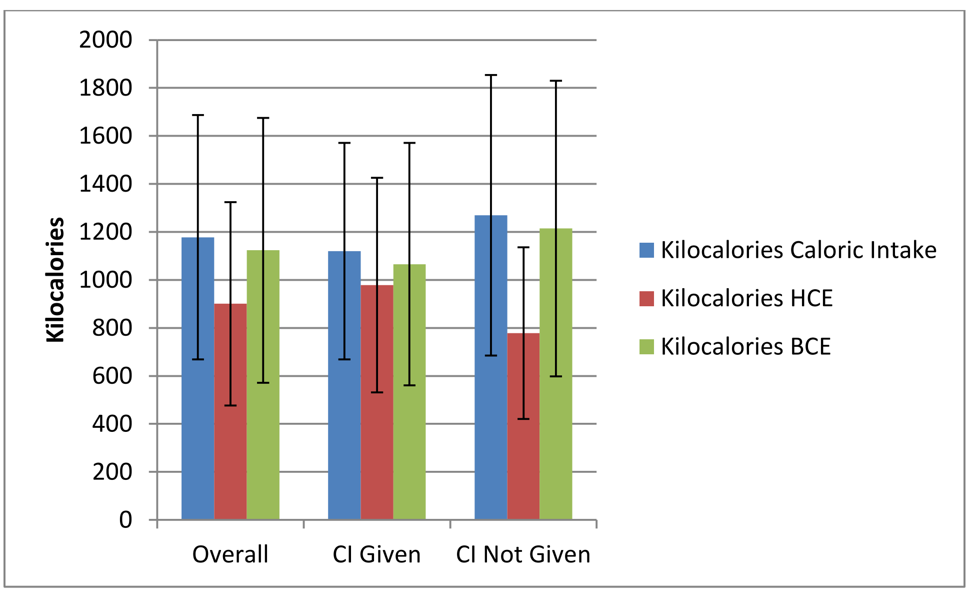


Figure 3.1. Mean calorie intake, HCE, and BCE overall and for both CI conditions. Error bars represent standard deviations.

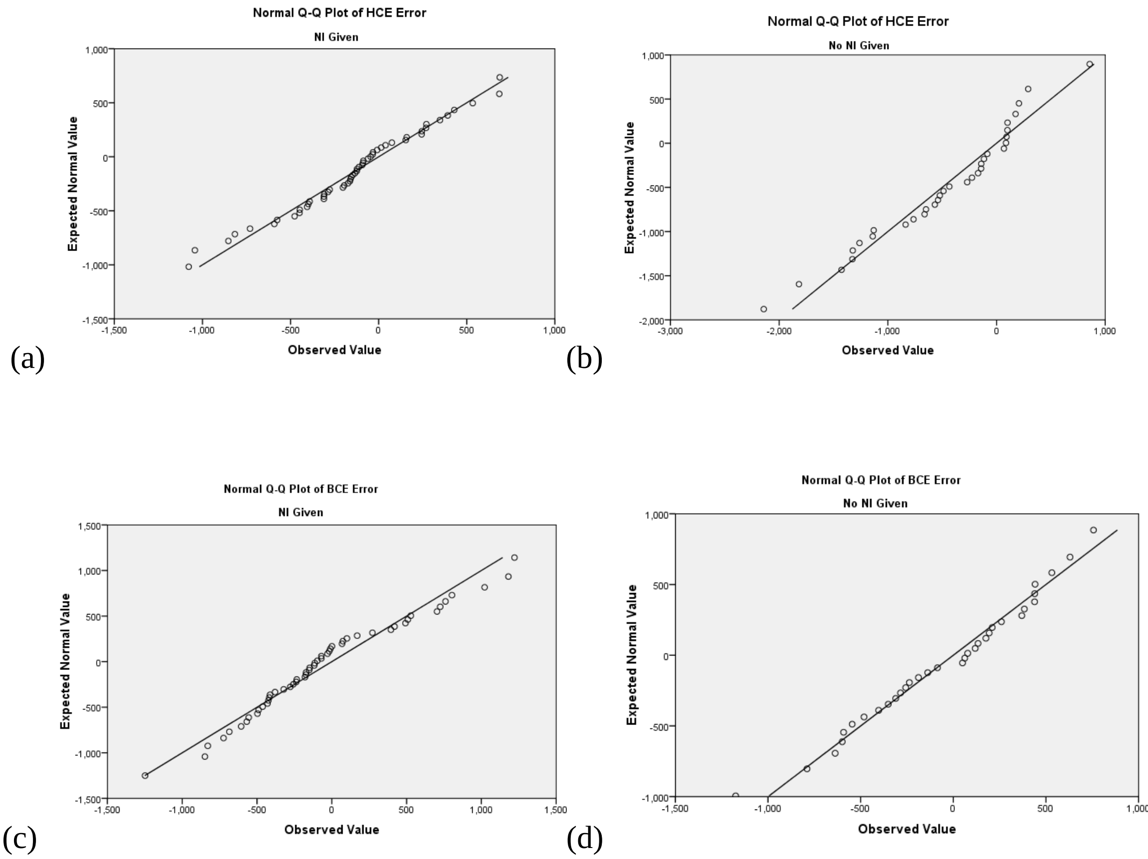


Figure 3.2. Q-Q plots showing normal distributions of CI given HCE error (a), CI given BCE error (b), CI not given HCE error (c), and CI not given BCE error (d). The closer observed values are to the reference line, the more similar the distribution is to a normal distribution.

Effects of Estimation Method and Calorie Information

Figure 3.3 shows mean HCE error and BCE error scores for both CI conditions, and Table 3.2 displays descriptive statistics for HCE error and BCE error in all conditions. A 2x2 mixed-design ANOVA revealed a main effect for estimation method ($F(1, 83) = 14.381$, $p < .001$) with HCE error higher than BCE error and a marginally significant main effect for CI condition ($F(1, 83) = 3.835$, $p = .054$) with mean error in the CI not given condition higher than mean error in the CI given condition. The analysis also revealed a significant interaction between estimation method and CI condition ($F(1, 83) = 6.384$, $p < .05$). As can be seen in Figures 3.1 and 3.3, all estimation methods underestimated caloric intake, with HCE appearing to dramatically underestimate calorie intake without the aid of CI.

Descriptive Statistics			
		HCE error	BCE error
CI Given	Sample Size	52	
	Mean	-141.37	-54
	SD	388.11	529.67
	Min	-1078	-1248.19
	Max	687	1221.2
CI Not Given	Sample Size	33	
	Mean	-490.94	-54.74
	SD	667.28	452.08
	Min	-2142	-1174.74
	Max	-857	756.57

Table 3.2. Descriptive statistics for HCE error and BCE error across both CI conditions

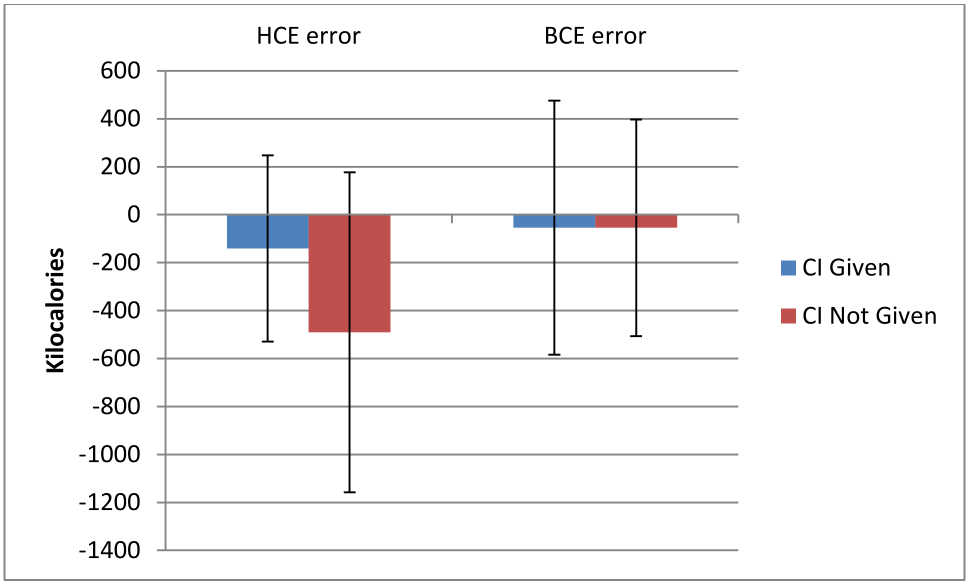


Figure 3.3. Mean BCE error and HCE error for both CI conditions. Error bars represent standard deviations.

Post-hoc Analyses. The effect of estimation method was examined for CI given and CI not given separately using paired-sample t-tests. BCE error was significantly lower than HCE error in the CI not given condition ($t(32) = -3.578$, $p < .005$), but there was no difference in the CI given condition ($t(52) = -1.116$, $p = .270$). The effect of CI information presence was examined for HCE error and BCE error separately using independent-samples t-tests. Levene's test revealed that the variance in HCE error differed significantly between the CI given and the CI not given conditions ($F(1, 83) = 11.876$, $p < .005$). Since variance was not equal between conditions, an independent samples t-test with equal variances not assumed was used to compare means. The t-test showed that HCE error was significantly higher in the no CI condition than in the CI condition ($t(45.89) = -2.731$ $p < .01$). Levene's test revealed no significant difference in variance between CI info conditions for BCE error ($F(1, 83) = .182$, $p = .671$). An independent samples t-test showed that mean BCE error for the CI info condition did not differ significantly from mean BCE error in the no nutrition info condition ($t(83) = -.007$, $p = .995$).

Gender Effects and Overall Calorie Intake

Hypothesis 3 was tested using Pearson's r to examine the relationship between body fat percentage, BMI, caloric intake, HCE error, and BCE error. Correlation matrices of age, BMI, body fat percentage, calorie intake, HCE error, and BCE error are shown in Table 3.3, including separate matrices for overall scores and for scores split by CI condition. Age is also included for exploratory purposes. Of note, HCE error shared a stronger correlation with caloric intake in the CI not given than in the CI given condition, indicating that caloric intake was more closely related to human estimation errors without calorie information. A *post-hoc* two-tailed, independent samples z-test was used to examine the difference between this correlation and revealed that kcal intake shared a significantly stronger correlation with HCE error in the CI not given than in the CI given condition ($z = 3.31$, $p < .001$). BCE error shared a significant overall correlation with kilocalorie intake, but it is similar in both CI conditions and not significant in the CI not given condition. Also, body fat percentage shared a moderate correlation with HCE error, but only in the CI not given condition.

Correlation Matrices							
		Age	Body Fat %	BMI	Kcal Intake	HCE Error	BCE Error
Overall	Age	1					
	Body Fat %	.524**	1				
	BMI	.345**	.684**	1			
	Kcal Intake	-.167	-.297**	.007	1		
	HCE Error	.216*	.158	.037	-.674**	1	
	BCE Error	-.068	-.036	-.017	-.400**	.241*	1
No CI	Age	1					
	Body Fat %	.597**	1				
	BMI	.318	.530**	1			
	Kcal Intake	-.184	-.387*	.167	1		
	HCE Error	.311	.388*	.010	-.845**	1	
	BCE Error	.099	.284	.231	-.316	.264	1
CI Given	Age	1					
	Body Fat %	.497**	1				
	BMI	.366**	.755**	1			
	Kcal Intake	-.152	-.282*	-.133	1		
	HCE Error	.135	.061	.129	-.439**	1	
	BCE Error	-.159	-.180	-.139	-.479**	.274*	1

Table 3.3. Pearson's correlations for age, body fat percentage, BMI, calorie intake, HCE error, and BCE error.
**. Correlation is significant at the .05 level (2-tailed).*
***. Correlation is significant at the .01 level (2-tailed).*

Mean HCE error and BCE error are displayed for men and women in both CI given and CI not given conditions are shown in Figure 3.4, and descriptive statistics are shown for gender across all conditions in table 4. A 2x2x2 mixed-design ANOVA was used to assess the effect of gender on estimation method and the presence of CI, with estimation method as a within-subjects factor and gender and CI condition as between-subjects factors. There was no significant main effect for gender ($F(1, 81) = .820$, $p = .368$). There was, however, a significant interaction between gender and CI condition ($F(1, 81) = 5.682$, $p < .05$) and a significant interaction between gender and estimation method ($F(1, 81) = 8.608$, $p < .005$). There was also a significant three-way interaction between gender, CI condition, and estimation method ($F(1, 81) = 5.059$, $p < .05$). As can be seen in Figure 3.4, it appears that men dramatically underestimate calorie intake in the absence of CI, but women appear to not be as affected. Subsequently, all post-hoc analyses were repeated, separating conditions by gender, to examine the potential effects of gender differences on the outcomes.

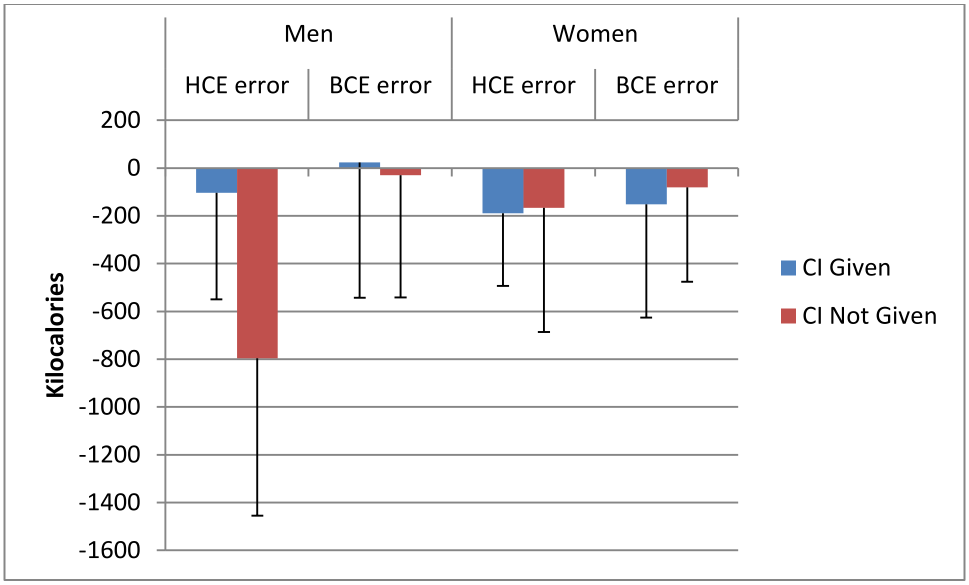


Figure 3.4. Mean scores across all conditions for men (a) and women (b). Error bars represent standard deviations.

Descriptive Statistics for Gender					
		Men		Women	
		HCE error	BCE error	HCE error	BCE error
CI Given	Sample Size	29		23	
	Minimum	-1078.00	-848.54	-1078.00	-1248.19
	Maximum	687.00	1221.20	269.00	760.04
	Mean	-103.93	23.21	-188.58	-151.36
	SD	445.45	565.72	304.1	474.63
CI Not Given	Sample Size	17		16	
	Minimum	-2142.00	-1174.74	-1426.00	-637.77
	Maximum	175.00	756.57	857.00	630.08
	Mean	-795.77	-29.65	-167.06	-81.4
	SD	659.4	511.32	518.56	394.53

Table 3.4. Descriptive statistics for gender across all conditions.

Post-hoc Analysis of Gender. Levene's test revealed a significant difference in variance between CI conditions for HCE error of men ($F(1, 43) = 4.318$, $p < .05$) but no significant effect for women ($F(1, 36) = 3.203$, $p = .082$). Further t-tests revealed a significant effect for menu condition on the HCE error of men ($t(24.70) = -3.842$, $p < .005$) but not for women ($t(37) = .163$, $p = .872$). No significant differences were found for the effect of menu condition on BCE error for either gender. Repeated-measures ANOVAs revealed a significant main effect for estimation method for men in the CI not given condition ($F(1, 16) = 20.293$, $p < .001$) but not for men in the CI given condition ($F(1, 28) = 1.062$, $p = .312$). There was no significant main effect of estimation method for women in either the CI given ($F(1, 22) = .185$, $p = .671$) or the CI not given ($F(1, 15) = .440$, $p = .517$) conditions.

Levene's test shows no significant difference between CI conditions for the variance of overall calorie intake ($F(1, 82) = 2.487$, $p = .119$) and a 2-tailed t-test shows no significant difference in calorie intake for either CI condition ($t(83) = 1.323$, $p =.189$). Levene's test also reveals no significant difference in variance of kcal intake between the two genders ($F(1, 82) = 1.408$, $p = .239$). However, males did consume significantly more kilocalories that women ($t(83)=-4.161$, $p < .001$). Furthermore, when overall calorie intake is added as a covariate into a Univariate ANCOVA, the effect of gender on HCE error disappears ($F(1, 80) = .278$, $p =.599$), but now has a significant effect on BCE error (F(1, 80 = 12.199, $p < .005$) such that kcals derived from bite count tend to overestimate slightly for men but underestimate for women.

DISCUSSION

The first hypothesis of this study was that human calorie estimates would be more accurate in the presence of calorie information than in its absence. The findings of this study support this hypothesis, showing that humans are able to estimate their caloric intake for a meal to within 13% with calorie information and within 37% without calorie information on average. This is similar to the findings of Elbel (2011), who found that the introduction of calorie information reduced errors in calorie estimates from 24% to 14%, and the findings of Roberto et al. (2010) who were able to reduce errors in estimation from an average 49% to an average of 38% after providing calorie information.

The second hypothesis was that estimations of caloric intake derived from bite count would be more accurate than human estimates without calorie information. This hypothesis was also supported, showing that estimations based on bite count were accurate on average to within 5% of actual intake compared to 37% for human estimates without calorie information and 13% for human estimates with calorie information, although this difference was only significant in the no calorie information given condition. As expected, there was no difference between CI conditions for BCE error.

The third hypothesis was that BMI, body fat percentage, total caloric intake, and gender would all be related to human calorie estimation accuracy. Previous studies have obtained mixed results regarding the relationship between BMI and calorie estimation accuracy. Some studies have found that underreporting increases with increases in BMI

(Carels et al. , 2006; Johnson et al., 1994; Kretsch et al, 1999). However, our results were more in line with previous work that has found no relationship between the two (Carels et al., 2007; Martin et al., 1996). Interestingly, percent body fat did share a significant, albeit small, negative correlation with HCE error in the CI not given condition. Previous work has favored examining BMI as a possible correlate of underreporting and calorie estimation errors (possibly because of its ease of measurement), and the relationship between percent body fat and calorie estimations has been largely unexplored. While age was positively correlated with BMI and percent body fat, it shared no relationship with either BCE error or HCE error. Of the variables examined, overall caloric intake shared the strongest relationship with both HCE error and BCE error, indicating that the accuracy of both human and bite count estimates of caloric intake decreased as actual caloric intake increased. Oddly enough, the relationship between BCE error and caloric intake was significant in the CI given condition but not in the CI not given condition.

The results showed a significant three-way interaction between gender, CI condition, and estimation method. Post-hoc analyses revealed that calorie estimates for women are not significantly affected by the presence or absence of calorie information, and men are perform worse at estimating calories than women without the presence of calorie information. This would, at first, seem to support previous research showing that women were better at calorie estimates than men (Krukowski et al., 2006). However, when controlling for the effect of overall calorie intake, the gender effect disappears, suggesting that males were worse at estimating calories only because they, in fact, ate more calories than women.

Post-hoc analyses for the effects of gender on BCE error revealed that when controlling for the effect of calorie intake, gender has an effect on the accuracy of the bite counter device, such that it overestimated slightly for men and underestimated slightly for women. This is likely a result of the equations used to determine kilocalories-per-bite for both men and women, which were derived from another study that derived KPB by comparing bite count to kilocalories as measured by a 24-hour dietary recall, which is known to underestimate calorie intake (Johansson, Wikman, Ahren, Halllmans, & Johansson, 2001). This may be especially true for meals that are higher in overall calorie content, as evidenced by the significant relationship between overall calorie intake and human estimation accuracy.

Sources of Variance for HCE and BCE

A variety of the factors discussed previously likely contributed to the large margins of error and variances found for human calorie estimates with and without calorie information. Our findings were in line with previous studies that found that humans are generally poor at estimating calories (Stanton & Tips, 1990). "Calorie" is a meaningless term to many people, with only a third aware of human daily energy requirements (Elbel, 2011). Two participants, who we excluded as outliers, estimated that they had consumed 4,500 calories in one meal. One of those was even given calorie information and still estimated consuming 4,500 calories. Perhaps calories are difficult to estimate because they aren't interpretable without a fair amount of knowledge about energy balance and energy density. However, even with training, high error is present (Visona & George, 2002). One advantage of using the bite counter device as a tool for self-monitoring as that a "bite" is a unit of measurement that people can understand and they already relate to portion consumption. A human who would not normally use calorie information may have a better intuitive understanding of bite count as a proxy for amount consumed.

Portion size perception also likely played a role in HCE errors found in this study. Previous work has found that both food and container size and shape can impact individuals' estimates of portion size (Chandon & Orbadayeva, 2009; Garber et al., 2008; Scisco et al., 2012). The food items served in Harcombe came in a variety of shapes, sizes, and containers. While not a goal of this study, the dataset could be examined for the effect of food shape and container type on HCE errors.

The results of this study indicate a gender effect similar to the findings of Krukowski et al. (2006). However, Krukowski did not examine the possibility of calorie intake mediating the effect of gender on calorie estimation errors. Unfortunately, for the present study there was an imbalance of gender between the CI conditions, and while there is some evidence that the gender effect found in this study may be accounted for by total calorie intake, a formal mediation analysis should be performed on data collected specifically to examine gender. This relationship between calorie intake and HCE error is of particular interest. Calorie intake shared a stronger relationship with HCE error than

BMI or percent body fat, and accounted for gender differences. Previous work has shown that the effect of BMI on errors in calorie estimates may be mediated by overall caloric intake, which can lead to poorer calorie estimates (Chandon & Wansink, 2006 and 2007). Furthermore, the effect of calorie intake on human calorie estimates may be, itself, caused by errors in portion size estimation.

Comparison to Other Methods

One of the primary weaknesses of traditional self-report methods is the well-documented, systematic underreporting (Lichtman et al., 1992; Livingstone & Black, 2003; Martin et al., 1996; Muhlheim et al., 1998; Rumpler et al., 2008; Subar et al., 2003; Tooze et al., 2004; Trabulsi & Schoeller, 2001). This study found a similar pattern; average human calorie estimates across all conditions were lower than actual calorie intake. While bite count estimates were significantly more accurate than human estimates, they still underestimated calorie intake. One possible cause of this is that our KPB equations were derived from a study that compared bite count to caloric intake as measured by a 24-hour dietary recall, which has been shown to underreport calorie intake (Johansson et al., 2001). Hence, the prediction equations were derived in such a way to accurately predict caloric intake as measured with a self-report device that is likely to produce underestimations. Therefore, the equations would likely produce underestimation. Future work should work on the development of equations with ground truth calorie meals that are not based on self-report.

The bite counter offers the significant advantage of removing human biases and perceptual errors from the equation in measuring EI, making it more objective than classical forms of self-report and modern forms that attempt to use technology in combination with self-report to improve estimates. The digital photography method described by Williamson et al. (2003) attempts to improve upon these measures by having a trained nutritionist examine photographs taken by participants. While training can improve calorie estimates, this method still relies on human perception, and is subsequently subjective. Other tools, like the Bite Counter, are being developed that will attempt to automatically, inexpensively, and objectively monitor EI in real-world scenarios, but these tools are still very new, meaning as of yet there is not a lot of published research on them.

The Importance of Monitoring EI

The findings of this study support previous work that has shown that the presence of calorie information can improve calorie estimates (Elbel, 2011; Roberto et al., 2010). It is important that calorie information be present so that individuals can make informed food choices. There does appear to be a growing trend among legislators of making it mandatory for restaurants to make calorie information available (Baerman & Lavizzo-Mourey, 2008; Burton et al., 2006). However, as described previously, the effectiveness of this as a method of reducing weight gain is still questionable, as many people either don't understand calorie information or simply wouldn't use calorie information even if it was present (Krukowski et al., 2006).

Bite Count as a Proxy for Calorie Intake

When examining the value of bite count as a proxy for EI, it is important first to determine the purpose of monitoring EI. Monitoring EI accurately may be more important for researchers than it is for individuals who are trying to lose weight, and the bite counter may have different values as a proxy for EI depending on what the goal of the user is. The results of this study show that while BCE may be, on average, more accurate than HCE, there is still a large amount of variance in the error, indicating that while estimates may be very accurate over time, it may not be a good proxy for energy intake at the meal level for an individual compared to DLW and pre-measured foods, but it is likely equivalent to self-report measures with the advantage of being unbiased. This error variance is likely because estimations based on bite count currently do not account for energy density in any way, indicating that meals with a lot of foods that are low in energy density will be overestimated and meals with a lot of high ED foods will be underestimated. It should be noted, however, that the variance of estimation error for BCE was still lower than that of HCE without CI given, indicating that even without taking ED into consideration, bite count is a better proxy for EI than most humans.

Beyond Counting Calories

The most important factor contributing to successful weight loss is not necessarily accurate calorie counting, but the act of consistent self-monitoring itself (Burke et al., 2009; Helsel et al., 2007). Butryn et al. (2007) found that participants in a weight loss study who simply weighed themselves regularly were more likely to lose weight and keep it off, and the more often they reported self-monitoring, the greater the success. Perhaps the greatest strength of the bite counter device is not in its ability to count calories, but in its ability to keep users cognizant of how much they are eating and to let them know when they should push the plate away. To serve this purpose, it is not necessary that bite count be an accurate proxy for energy intake, but that it may be a reasonable proxy for portion consumption.

The Bite Counter also has other self-monitoring applications. It could be used as a device to promote overall “mindful eating” by forcing users to pay attention to their overall intake, their rate of eating, their meal times, and their total number of meal sessions per day. Recently, eating rate has been investigated as a possible correlate of meal-level energy intake (Guss & Kissileff, 2000, Takayama et al. 2002). The Bite Counter has been shown to be useful as a device for slowing eating rate and reducing energy intake (Scisco et al., 2011). There is also evidence that people with higher BMIs are more prone to aberrant meal patterns and snacking sessions, and that numerous small meal sessions may reduce obesity (Drummond, Crobie, & Kirk, 1996; Ma et al., 2003; Pearcey & Castro, 2002). While it has yet to be examined for this purpose, the Bite Counter could be used as a tool to regulate eating patterns by prompting users to eat at certain times and warning users when they are snacking outside of a scheduled time period.

While an accurate measure of calorie intake can be obtained by diligently measuring portions and using what nutrition information may be available, it is a terribly tedious and time consuming process. Many individuals who are trying to monitor their intake may not have the time to measure out portions or may not have the ability, depending on the setting. Many others won't use nutrition information even if it's readily available. An individualized estimation of calorie intake derived from bite count offers an objective, convenient, and easily understandable alternative to traditional methods. A device that monitors bite count and provides feedback to users could be used as a tool for self-monitoring that may be a powerful weapon in the fight against obesity.

Limitations

The primary limitation of this study was also one of its greatest strengths. One of the main purposes of this study was to capture a large sample of meal data from a realistic cafeteria environment. While this goal was accomplished, it made it extremely difficult to confidently determine true calorie intake. A conservative approach was taken so that only those meals that kilocalorie content could be confidently determined were used in the data analysis, and subsequently 184 participants who had complete data were excluded from the final analyses. Additionally, while the Harcombe cafeteria workers are trained to serve standard portions and the foods served were usually consistent with what was on the menu, it was still not a fully controlled laboratory environment. There were many times foods were served that did not appear on the menu. Also, many items (such as drinks and desserts) were consistently absent from the menu. Participants in the CI given condition who were making their estimates often did not have full nutritional information available to them. However, the results indicate that these participants still made better estimations than participants in the CI not given condition.

Another limitation of this study is that the equations used to determine individualized kilocalories-per-bite were derived from data collected in a separate, free-living type of study. Kilocalories were determined for this other study based on 24-hour dietary recalls, which are known to underestimate total calorie intake (Johansson et al., 2001). Therefore, rather than having equations that were derived from true calorie intake, equations derived from a known underestimate were used. However, the results reveal that even with this known error, these equations were better at estimating calorie intake than humans.

Another serious limitation of this study is the lack of certain items available on the daily menus. Had each item consumed by each participant been present on the daily menus, it is possible that human calorie estimates in the CI given condition may have been improved, possibly to the point of being significantly more accurate that bite count calorie estimates. However, this would not affect the findings that BCE is more accurate than HCE in the no CI given condition.

A final limitation of this study is that while the cafeteria setting used was far more realistic than many laboratory studies, the results still cannot be fully generalized to real world environments. While there were a wide variety of foods to choose from, selection was limited to the foods that Harcombe supplied. Also, participants ate their meals often sitting with total strangers while tethered to a computer and being observed by both experimenters and cameras mounted in the ceiling above them. This artificial setup could potentially have altered a variety of things, such as how much food participants were willing to eat, how many trips they made to the buffets, and what foods they chose to consume.

Future Directions

Based on the findings of this study, overall caloric intake should be examined as a possible mediator for the effects of gender, BMI, and percent body fat on human calorie estimates and calorie estimates based on bite count. It may be that all of these factors can be explained by the general tendency of humans to underreport caloric intake by greater margins as overall caloric intake increases.

Future studies should also compare the acceptability of bite count to that of calorie information. Calorie information is an abstract measure that is often disregarded even in its presence. If bite count is a more acceptable measure, perhaps it would be used by people who wouldn't use calorie intake to try to track eating. The effects of food and container size and shape on HCE and BCE should also be further examined. It may be that bite count is a better measure for some types of food than others. For example, it may be far more accurate at examining the calorie content of 'main course' dishes than desserts or salads, indicating that perhaps users wanting an accurate measure of calorie intake should avoid foods especially high or low in energy density.

While we only used a subset of participants for whom we were most confident in our measures of their true calorie intake, because portion sizes were not controlled there is some inherent error in our measure. Future studies should examine the relationship between bite count and EI in a more controlled laboratory studied where calorie intake can be monitored accurately. To generate a realistic food selection, data collected in this study could be examined for the most common food selections, and similar items can be used with more controlled portions. Such a study could be used to further refine the equations used to calculate KPB, and subsequently get a better individualized estimate of calorie intake. Also, should future studies be conducted in a similar cafeteria-like setting, food selection should be controlled by limiting it to items for which calorie content can be confidently determined.

A source of error in converting bites to kilocalories is ED. Currently, the Bite Counter does not take ED into account when determining calorie intake. A bite of lettuce is counted as the same number of calories as a bite of cake. This is a likely cause four the large amount of variance in BCE error found in this study. While bite count may provide an consistent reading of kilocalorie intake at the day, week, or monthly level, specific meal-level and bite-level estimates could still be inaccurate, which could lead to users not trusting and subsequently, not using the device. Future studies should examine the viability of incorporating some form of ED input into the device. Perhaps participants could label meals as snacks, desserts, or appetizers, or they could rank a meal by its relative perceived overall ED. Along this line, future studies should examine human abilities to estimate the relative ED of meals and calculate how this could be used to refine the KPB equations.

Conclusions

Obesity is a major health problem in the United States, and currently no single treatment is making clear headway on a population scale. It is a multi-faceted problem, meriting investigation from multiple disciplines and treatment at both societal and individual levels. For researchers to better understand obesity there needs to be tools that can accurately monitor calorie intake in the field. However, most of the commonly used tools are either costly or prone to subjective error. At the individual level, self-monitoring is one of the most critical aspects of successful weight loss and weight loss maintenance, yet there is a dearth of tools that can do this process easily and accurately. A device that can automatically detect bites of food offers the potential to address both of these problems by measuring free living energy intake and serving as a tool to help individuals track their eating. While a significant amount of research still needs to be done, this tool could prove to be a valuable weapon in the fight against obesity.

APPENDICES

Appendix A

Sample Daily Menu

Menu for 1/26/2012; Dinner

Deli	**Serving Size**	**Calories**
• Signature Chips	1, 1 ozw	242.52
• Ham, Provolone, & Salami Wrap	1 Wrap	422.38
• Chicken Ranch Mesquite Wrap	1 Wrap	709.53
Dessert		
• Chunky Chocolate Chip Cookies	1 Cookie	125.59
Exhibition		
• Baby Bok Choy	3 pieces	12.5
• Hunter’s Chicken	8 fl oz	471.12
• Jasmine Rice	1 cup	126
Grill		
• Shoestring French Fries	3 ozw	261.82
• Hot Dog	1 dog	297.02
• Homestyle Chicken Sandwich	1 Sandwich	433.24
• Monte Cristo Sandwich	1 Sandwich	442.89
Homeline		
• BBQ Turkey London Broil	3 ozw	94.17
• Buttermilk Mashed Potatoes	1 cup	124.69
• Cauliflower	1 cup	14.76
• Broccoli	1 cup	19.05
Nature’s Marketplace		
• Garden Burger	1 burger	315.52
• Szechuan Tofu	1 cup	118.28
Pasta		

• Pasta	1 each	813.77

Pizza	**Serving Size**	**Calories**
• Breadsticks	1 stick	106.3
• Cheese Pizza	1 slice	250.12
• Pepperoni Pizza	1 slice	293.88
• Meatball Pizza	1 slice	312.63
• Sweetzza Chocolate Peanut Butter	1 piece	334.24
• Garden Salad	1 serving	47.28

Salad Bar

• Pesto, Red Pepper, and Orzo Salad	1 cup	173.35
• Waffle Bar	1 Waffle	619.05
• Salad Bar	1 serving	350.53

Appendix B

Online Pre-screening Questionnaire

What is your Participant Number?

Please list any known food allergies:

Do you normally eat breakfast?

Do you normally eat lunch?

Do you normally eat dinner?

Have you ever been diagnosed with an eating disorder?

Do you follow a special diet? If so, please describe:

Appendix C

Demographics

What is your age?

What is your gender?

Are you left or right handed? (If you are ambidextrous, please list the hand that you use more often for eating):

How much do you weigh (pounds)?

How tall are you (feet, inches)?

What is your ethnicity?

Are you a student?

Please list three times that you are available to participate in the study.

Appendix D

Post-Study Questionnaire

(1) While eating, I was aware of the device on my wrist.

1	2	3	4	5
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

(2) The device on my wrist caused me to change my arm, wrist, or hand movement while eating.

1	2	3	4	5
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

(3) While eating, I was aware of the video camera.

1	2	3	4	5
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

(4) The video camera caused me to change my arm, wrist, or hand movement while eating.

1	2	3	4	5
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

(5) I ate my meal faster than I would normally eat.

1	2	3	4	5
Strongly Disagree	Disagree	Neutral	Agree	Strongly Agree

(6) While eating I took larger bites than I normally would take when eating the same food.

1	2	3	4	5

Strongly Disagree Disagree Neutral Agree Strongly Agree

(7) I ate my meal slower than I would normally eat.

1 2 3 4 5

Strongly Disagree Disagree Neutral Agree Strongly Agree

(8) While eating I took smaller bites than I normally would take when eating the same food.

1 2 3 4 5

Strongly Disagree Disagree Neutral Agree Strongly Agree

(9) I felt comfortable eating my meal during the study.

1 2 3 4 5

Strongly Disagree Disagree Neutral Agree Strongly Agree

(10) Overall I felt I ate the same way I always eat.

1 2 3 4 5

Strongly Disagree Disagree Neutral Agree Strongly Agree

(11) Please estimate the number of calories that you just consumed: ____________

Appendix E

Experimental Protocol

Eating Session

1. 24 hours before each participant is scheduled to have their eating session, send them the following e-mail:

Dear Participants,

I am sending you this e-mail to remind you of your participation in the eating study. You are scheduled for tomorrow (date) at time. We will be meeting in Brackett Hall, Room 421 at your scheduled time.

Thank you,
(experimenter)

2. Refer to the **Undergraduate Assistant Protocol** for details on the undergrad's role in the procedure.
3. CI team members will be interacting with the participants; the Graduate Assistant's job is to monitor the equipment and oversee the session to ensure that no significant problems arise.
4. **Before leaving the lab, make sure you bring the following items:**
    a. The Experimenter Notebook (this may be kept in the cafeteria).
    b. The participant compensation ($10 per participant).
    c. The key for the equipment cabinet (hanging by the door in James's and Mike's office).
    d. Your ID tag.
    e. The External Hard drive (if you are doing a data backup).
5. Arrive at Harcombe at the scheduled start time. The undergraduates will be greeting the participants in the lab.
6. Stand in line to enter the cafeteria. Greet the cashier and let them know that you are here for the eating study, and 6 more people should be following shortly.
7. Prepare the table and boot up the equipment (refer to **Computer Boot Up**).
8. Call one of the undergrad assistants that are helping out for that day. Phone numbers will be in the experimenter notebook.

9. Once the participants arrive, monitor their activities and ensure that the CI members are adhering to the **Undergraduate Assistant Protocol**.
10. Once the participants return with their food, begin recording.
    a. Start the video recording **before** you start the scale/bite counter recording.
    b. To begin the video recording, right click on the video screen.
    c. Click "Manual record."
    d. Click the colored square in the EatStat program to begin recording bite and scale data.
11. Make a note of any problems or anomalies that arise.
12. Monitor the equipment to make sure that everything is running as it should be.
13. If the participant finishes or goes to get seconds, stop the recording.
    a. Stop the scale/bite counter data **before** stopping the video.
    b. Click the colored square in the EatStat program to pause recording.
    c. Right click the video monitors.
    d. Click "Manual Record" to end the video recording.
14. Resume the data recording when the participant returns with seconds or thirds.
15. At some point in the session, make sure to give the CI assistants the compensation and the compensation forms.
16. Once the session is finished, shut down the equipment (unless you are doing a backup) and help the CI assistants bus the tables.
17. Wipe all of the trays down with the Clorox Wipes.
18. Put the trays, the experimenter notebook, and the Clorox wipes in the equipment cabinet and lock it up.
19. Cover up the table, and reposition the "Reserved" sign.

Computer Boot-up

1. Remember to bring the key that is hanging on the black karabiner by the door in room 421.
2. Arrive in Harcombe at the participant's scheduled arrival time.
3. Unlock the cabinet and boot up both laptops.
4. The password for each laptop is "tiger5".
5. Click "EatStat.exe". This is the program that monitors the bite count and the scale data.
6. Click "Start" then "Record." This will not actually begin recording data; it will just begin monitoring the devices. (Do this on each laptop)
7. Clicking "Record" will open a new window showing the video from two of the four cameras. The top laptop will show stations 1 and 2, and the bottom laptop will show stations 3 and 4:

Station 1	Station 2
(Blank)	(Blank)

(Blank)	(Blank)
Station 3	Station 4

   a. Make sure that each camera is focused on the correct station.

8. Verify that the Gyroscope readout on the EatStat window is reading roughly 1.2.
9. If there are any errors, close all windows and restart them. If this does not fix the problem, contact the graduate assistant.
10. Once the equipment is ready, call the assistant in Brackett and tell them that you're good to go.

Data Recording

1. Once all of the participants have been allowed to go get food, begin the recording.
2. Always start the video first and end the video last.
3. Right click on EACH video and choose "Manual Record."
4. Within the EatStat window, click the green square button with the station number. The button will change to red.
5. Once the participants have returned and have begun eating, check all of the data readouts and make sure they are changing as they should.
6. It is not necessary to constantly monitor the laptops. However, check them from time to time to make sure that there are no errors (e.g. frozen screens, equipment failures, etc.)
7. When the graduate assistant tells you to end the recording, click the red square buttons in both EatStat windows.
8. Right click each video and click manual record again.

Video Conversion

A: Before Video Conversion:

1: Note down the approximate time when the subject has started eating their meal.

2: Once the subject has finished his meal, note down the end time and go to the corresponding camera recording folder on the relevant laptop.

3: Every recording creates the new ".dat" file. The recorded "dat" files are stored in the specific naming convention i.e. "CameraName | S00A | Year (4) | Month (2) | Date (2) | Hrs (2) | Min (2) | Sec (2) | msec (3)" and file stores the recording lasting up to 5 minutes.

The file size should be around 30 MB for 5 minutes recording duration. There will be multiple dat files for one meal depending on the duration. Verify the dat files for start time and size.

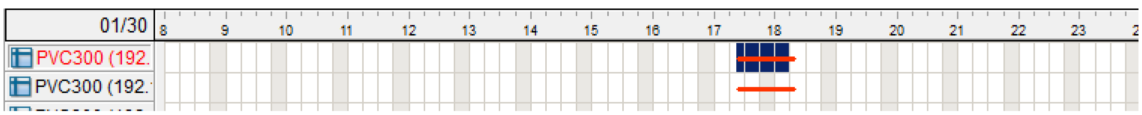
B: Video conversion:

1: Open the “Playback System” from the “Start menu”.

2: Click “Open Recording and provide username and password as “admin/admin”.

3: Check whether the same day is highlighted in the calendar in the left corner.

4: Select the recording for required camera (as shown below) depending upon the particular subject under recording and click OK. (The top row is camera 1 and the bottom row is camera 2)



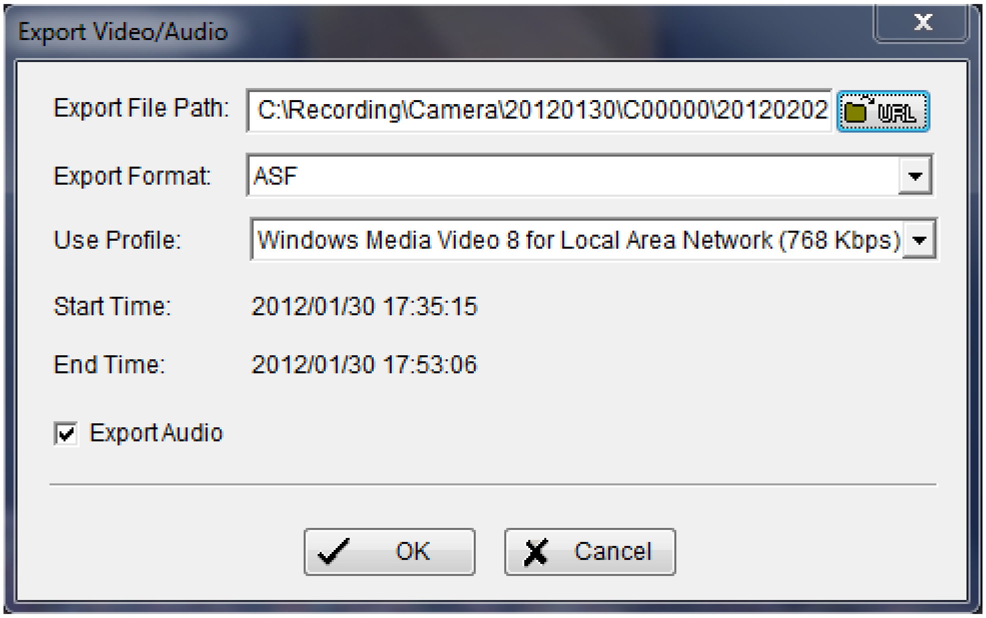
5: The video will be loaded in the playback system.

6: Scroll bar can be used to start video at required time.

7: Once the start time is set click the “Cue In” (red circled button below) this specifies the start time of video conversion. Slide the scroll to the end of the required end time and click “Cue Out” (green circled button below).

8: After this click “Save Video”. In the dialog box provide the converted file destination and name.

(The file destination should be the same recording folder for that subject i.e. C00000 or C00001 and file name should be of the format “| Year (4) | Month (2) | Date (2) | Hrs (2) | Min (2) | Sec (2) | msec (3).asf” ex: “20120202113610778.asf”. It can be taken from the recorded .dat file name in the recording folder as mentioned in step A:3).The Export Format should be set to “ASF”. Set the “Use Profile” to “Windows Media 8 for Local Area Network (768 kbps) as shown below. Also check the “Export Audio”.



9: Click OK and the process will start indicating the progress in the dialog.

Appendix F

Undergraduate Assistant Protocol

Prior to Subject Arrivals

1. Dress Professionally!
2. Arrive at least 15 minutes before the participant is scheduled to arrive.
3. All of the necessary materials will be on James's desk. A post-it note will be on top of the folders with each participant's name and participant number. Use this to match up participants with their correct folders. Once you are done, shred the post-it and throw it away.
4. Prior to the participants' arrival, make sure their subject folders are prepared with:
    a. The consent form (2; 1 for the participant to sign, 1 for them to take after completion)
    b. The Participant Note Sheet
    c. SLIM Scale (2; Labeled START and END)
    d. The post-study questionnaire
    e. The menu for that day
    f. Food Logs (3)
    g. LAM scale
5. Also ensure that the subject folders themselves are labeled with the following information:
    a. Participant Number
    b. Date and Time
    c. Station Number
    d. Menu or No-Menu (this refers to whether or not the participant is allowed to use a menu to make calorie estimations at the end of the study).
6. Two experimenters should meet the participants in the lab; the graduate assistant will go to set up the equipment.
7. **Each CI team member present is responsible for two of the four participants**. Decide beforehand who will be in charge of whom.
8. You will interact primarily with your two participants; this includes:
    a. Giving them forms
    b. Taking their measurements
    c. Attaching Bite Counters
    d. Debriefing

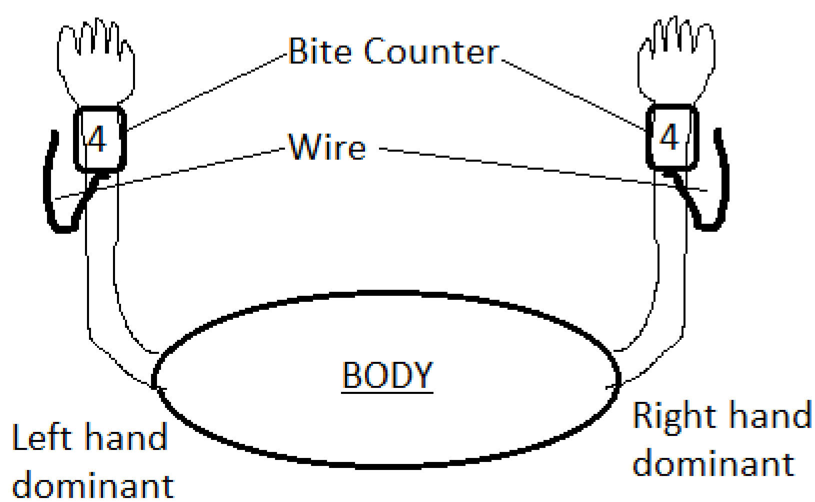
9. Have the consent form prepared on a clipboard with a pen for the participant to fill out. **Note: The Start SLIM scale will not be given in the lab, but in Harcombe.**
10. Upon the participant's arrival, introduce yourself and thank them again for their participation.
11. Give them the consent form, and instruct them to read it, initial each page and sign and date the last page of the form.
12. Once the participant has finished reading and signing the consent form, measure height (to the nearest ¼ inch) and weight (to the nearest ½ pound) using the scale. Record all measurements on the **Participant Note Sheet**.
    a. Power on the device, and wait for it to start up and zero itself.
    b. Extend the stadiometer so that it is above the participant's head.
    c. Ask the participant to step onto the scale with their back to the stadiometer.
    d. Level the stadiometer with the participant's head, and record height and weight.
    e. Measure height to the nearest quarter inch.
13. Measure the participant's body fat percentage.
    a. Turn the device on.
    b. Press set twice.
    c. Adjust each parameter to that of the participant. Press set after each one to move it to the next.
    d. Instruct the participant to hold the device out in front of them with their arms straight and with the feet shoulder width apart.
    e. Record BMI and Body fat percentage.
14. Take the participant's waist and hip measurements (to the nearest ¼ inch). Have female assistants measure female participants. If none are present, or if the participant prefers, they may measure themselves.
    a. Using the measuring tape, measure the waist at the smallest point near the navel.
    b. Measure the hips around the buttocks.
15. The graduate assistant should call you to confirm that the equipment is ready.
16. Once all of the measurements have been taken and the computer technician has called to confirm that the equipment is prepared, lead the participants to Harcombe dining hall.

.**Upon Arrival at Harcombe**

1. Do not eat any food without paying!

2. When you arrive at the station, sit the participants at a separate table (if available; if not, sit them at the station.
3. Give each participant a SLIM scale and instruct them to complete it.
4. Give the participants the following instructions:
    a. **"You are allowed to select anything you want."**
    b. **"We ask that you try to use just one plate per line. For example, if you want a burger and fries and some pizza, you can put the burger and fries on one plate, but put the pizza on a different plate."**
    c. **"You are free to make as many trips as you like before you start eating; if it's too much to carry, come and set it down, and then you can go back and get more."**
    d. **"Please try to eat as you normally would. The purpose of this study is the development of the wrist worn device; we are not interested in your specific eating behavior."**
        i. Be sure you emphasize this point. Participants tend to want to be accommodating, but it is important that they eat as though the bite counter wasn't there.
    e. **"There are scales beneath your trays that are measuring the weight change in your food. We ask that if you set your silverware down, please set it on the napkin beside your tray. Also, please try to keep your hands off of the tray."**
    f. **"Please note that there is sensitive equipment and wiring on the underside of the table. Please try to avoid jolting the table with your knees."**
    g. **"When you return, please do not set the plates on the trays just yet; set them to the side. We will give you further instructions once you've returned.**
5. Once the participants return, tell each of them their station number.
    a. Make sure that they do not place the plates on the tray, but to the side. **Note: You do not have to wait for all of the participants to return before beginning the next steps.**
6. Fill in the participant food logs, asking about portion sizes, additions and subtractions, etc. Use the menus provided to you in the subject folders to make sure that you are labeling the food items correctly (this can be done after the fact, while the participants are eating). **Note: There will <u>always</u> be a menu available for you to use to enter food, but participants will only use these <u>half</u> the time.**
    a. Ask the participants if the item was self-serve or if it was served by a cook.

b. Ask the participants if they got the normal portion, or if they requested smaller or larger portions.
c. As the participants if the made any unusual additions (such as ketchup, mayo, etc.) or if they requested any subtractions from the items (e.g., no chicken in the chicken and rice).
d. Each food item gets its own entry (even if it's on the same plate as another meal item).
e. **Note**: Drinks are considered separate food items. Ask them what drink they got, and whether or not they used ice.
f. Note on the meal sheet the time that each participant **begins eating** by asking the graduate assistant what the time is on the computer (do not use watches/cell phones).
g. Start a new data sheet for each course (that is, each time the participant gets up to get more food).
h. Each food item gets its own entry (even if it's on the same plate as another meal item).
i. **If there are any food items on the plates that are <u>not</u> on the menus, make a note of those items on the menu.**

7. Attach a bite counter to your two participants. Make sure that you are placing it on the hand that they use for eating, and that the wire is running from the wrist to the body, and is on the outside side of the arm. It should look like this:
   a. 

8. **Note: Make sure the bite counter is oriented to the position displayed in the picture! The orientation should be off by no more than 20 degrees; that is, it should be as straight on the arm as possible. If it is not, tighten the wrist band.**
9. Instruct the participants to place the food items on the tray, one at a time.

10. Make sure that the tray is balanced on the scale, and no part of the tray is touching the table itself. This makes sure that the scale is capturing the full weight of the food, and none of the weight is resting on the table.
11. Instruct the participants to begin eating:
    a. **"You may begin eating. Remember: eat as you normally would. You are allowed to go get seconds, but let one of us know if you do by raising your hand. Also, raise your hand if you are finished eating."**
    b. **IMPORTANT: "When you are finished with a course, DO NOT combine your plate waste or stack your plates; leave each item on its own plate, and we will clear them for you."**
12. If the participant goes to get seconds or completes the meal, unload their used dishes into the bus pan in the following way:
    a. Remove silverware, placing them off the tray.
    b. Remove each dish one at a time, placing it to the side of the tray.
    c. The goal is to allow the scale to get a good reading of the weight change for each dish.
    d. **Note: Participants will want to continue using the same drink. This is fine; just remove it like any other dish, but don't bus it, just set it to the side and replace it on the tray once the participant has returned.**
13. Replace the tray with a fresh one, and wipe down the used tray with a Clorox wipe.
14. Once the participant finishes the meal, unhook them from the bite counter.
15. Upon each participant's completion of the meal, give them the post-meal questionnaire, the end LAM scale, and the End SLIM scale.
    a. If the participant's folder is labeled "MENU", then give them a copy of the menu. (If it says NO-MENU, then do not give them one).
    b. If they are given a menu, say the following: **"The last question of the survey asks you to make an estimation of the number of calories that you've consumed. Please use this menu to help with your estimations."**
    c. Make sure that participants are not sharing menus; it's best to make sure they are sitting separately from each other.
16. Debrief each participant quietly:
    a. **"Thank you for agreeing to participate in this study. Our team's goal is to develop a tool called the "Bite Counter" that can help people monitor and reduce their food intake, which will help them lose weight. The purpose of this experiment is to assess the relationship between bite count and calorie intake for a wide variety of meals. The**

data collected from this experiment will help us to further develop the Bite Counter to more accurately measure a person's caloric intake. Do you have any questions? (…)

   b. **Please sign and date this form. Also, if you are a Clemson Student, please write down your CUID number. If you are not a student, please write down your address. (…)**
   c. **Would you like a copy of your consent form? (…) Once again, thank you for your participation.**

17. Have the participant sign the appropriate compensation form. Use the provided cover sheet to hide other participants' information. **Note: The subject folders are labeled "Student" or "Non-Student." If the participant is a student, have them sign the "Student" compensation form. If they are a non-student, have them sign the "non-student" compensation form.**
18. Give the participants their compensation ($10).
19. If they've requested a copy of the consent form, make sure you give them the UNSIGNED copy in the back of the folder.
20. Load the finished participant's used dishes into the bus pan.

Appendix G

Ground Truth Protocol

Protocol for Determining Ground-Truth Bite Count

1. Open the file to be ground-truthed.
    a. Open up the program "EatStatReview.exe."
    b. Click "File" in the top-left corner.
    c. Click "Load."
    d. Navigate to the appropriate participant folder, and the appropriate course subfolder where available.
    e. There should only be one visible file, named by year, month, day, hour, minute, second, millisecond. It will be in the format of **yyyymmddhhmmssmmm** (e.g. "20120419132734051.txt").
2. The program should load up with the data for the participant. The screen will be laid out in the following format (see Figure 1):
    1. System Controls: A list of all of the controls for marking weight changes, playing the video, and marking bites.
    2. Video Data
    3. Scale Data: Shows changes in the weight on the scales.
    4. Bite-Counter Data: Shows changes in the sensors within the bite counter.

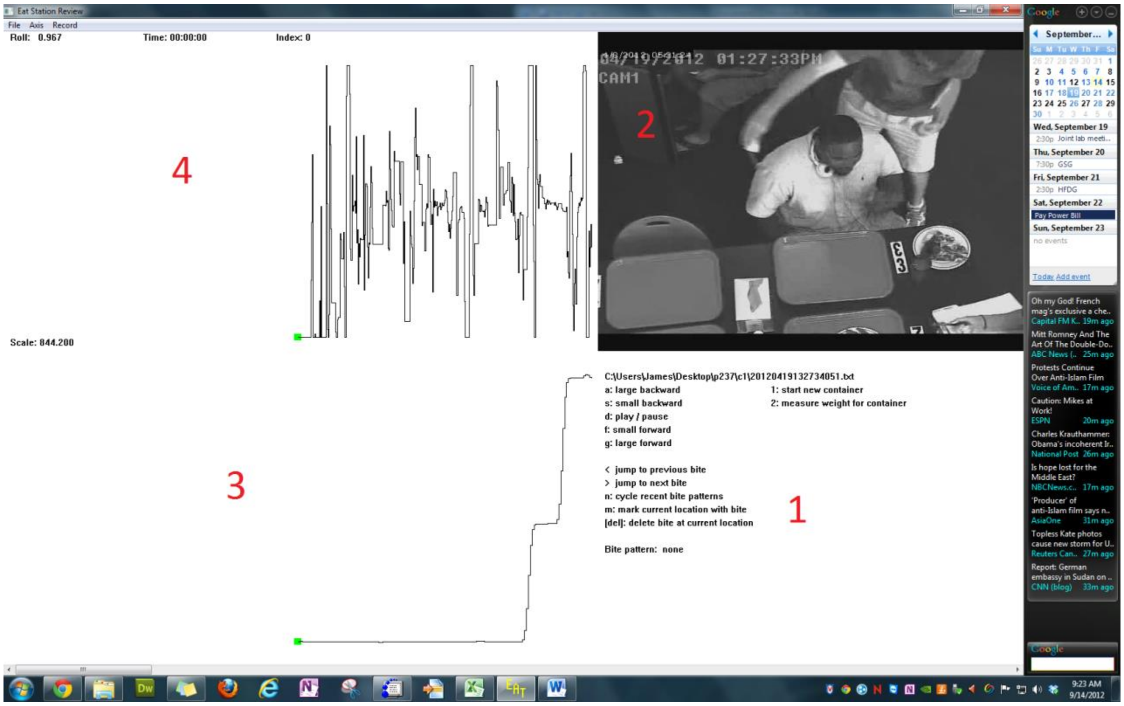


Figure 1: Initial Eatstat Screen Layout

3. Begin playing the video. Pressing “d” moves the data in the direction and rate selected by the “a, s, f, g” keys, at a constant rate. Pressing “d” again will pause the video, and you can move through the data frame-by-frame using the “a, s, f, g” keys.
4. Be on the lookout for any technical problems that may occur that will make the bite marking process impossible or inaccurate. If such a problem occurs, make a note of it and label it ‘technical,’ and move on to the next video. These problems include but not limited to:
    a. The video and the data files are out of sync. You will notice this if the scale data does not change in sync with the plates being added to the tray in the video file.
    b. Video crashes consistently in the same spot (Note that videos will crash periodically, but it will not always crash consistently. If a video crashes, your data is saved automatically and will all be loaded when you re-open the file).
    c. Video skips frames or freezes.
    d. Data is not visible.
    e. Food items are present on the plate, but not in the data file.
    f. Food items in the data file are incorrect.

5. As you do the bite marking, also be on the lookout for “non-technical” problems. These are problems with the participant’s behavior that do not prevent you from analyzing the file. If such a problem occurs, make a note of it and label it “non-technical,” but continue to analyze the file to the best of your ability. These include, but are not limited to:
    a. Participant is wearing a hat, and it is not clear when bites occur.
    b. Specific food items are not clearly visible.
    c. Different food items are indistinguishable from one another.

Marking Container Weights

1. Your first task is the mark when containers are added to or removed from the tray. Look for the tell-tale plateaus in the Scale Data section of the interface, as shown in Figure 2. Each plateau is indicative of a new container being added to the tray.

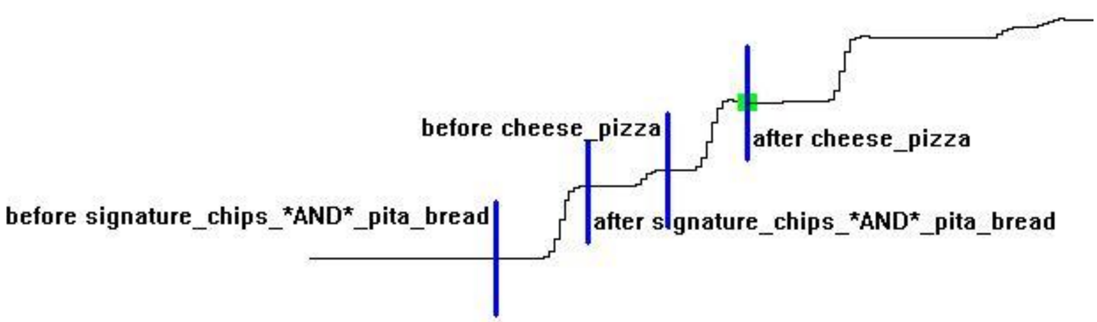


Figure 2: Scale data line with container markers.

2. These plateaus should sync up with containers being added to or removed from the tray in the video. If they do not, create an error note and move on to the next file.
3. Move the cursor to the bottom of the first plateau. Press “1” to define the contents of the first container. Note: You will only press the “1” key the first time you measure each container. For each of the 3 subsequent measurements, you will press the “2” key.
4. A dialogue box (Figure 3) will appear that lists each food item selected by the participant. Select all of the items that are visible in the container that is currently being added to the tray.

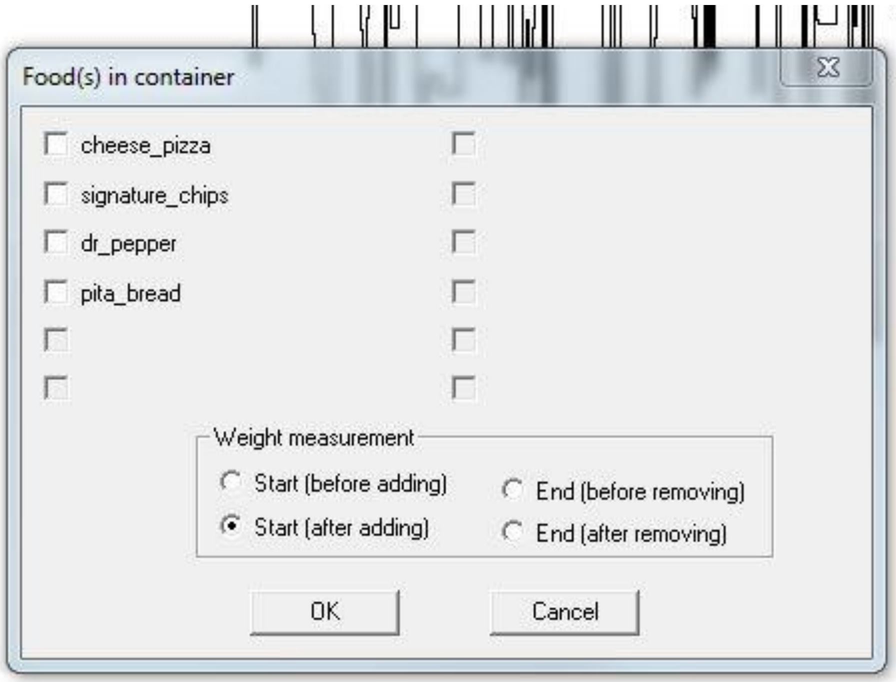


Figure 3: The container-marking dialogue box.

5. There are four options at the bottom of the dialogue box: Start (before adding), Start (after adding), End (before removing), and End (after removing).
6. Both "Start" options are used at the beginning of the meal, one to place a mark before the container is added and one to place a mark after a container is added. The "End" options are used at the end of the meal, before and after the container is removed.
7. For this first container, choose "Start (before adding)" and press ok. A blue mark will appear on the scale data line listing all of the foods for that container.
8. Move the cursor to the most stable (flattest) point at the top of the first plateau. Press the "2" key.
9. This dialogue box is very similar to the first one, except that the foods are already combined for the first container. Select "Start (after adding)" and click ok.
10. Repeat this procedure for all containers, at both the beginning and the end of the meal.

Marking Bites

1. Navigate through the file using the a, s, f, g, and h keys as described above.

2. Each time the participant takes a bite of food or a sip of drink, pause the file. A bite/sip is defined as **the point at which the pixels of the food touch the pixels of the participant's mouth**. See figure 4 for an example.

Figure 4: A bite is defined as the point where the pixels of the food touch the pixels of the participant's mouth.

3. Sometimes the participant will take bites or sips in rapid succession. Only mark them as separate bites if there is a one second gap between them (1 second is the equivalent of pressing the "g" key once).
4. Once you've identified a bite, press the "m" key to mark it.
5. A dialogue box will appear (Figure 5). Select the food item that is being eaten, what utensil is being used, what container the food item is in, and what hand is being used to take the bite.

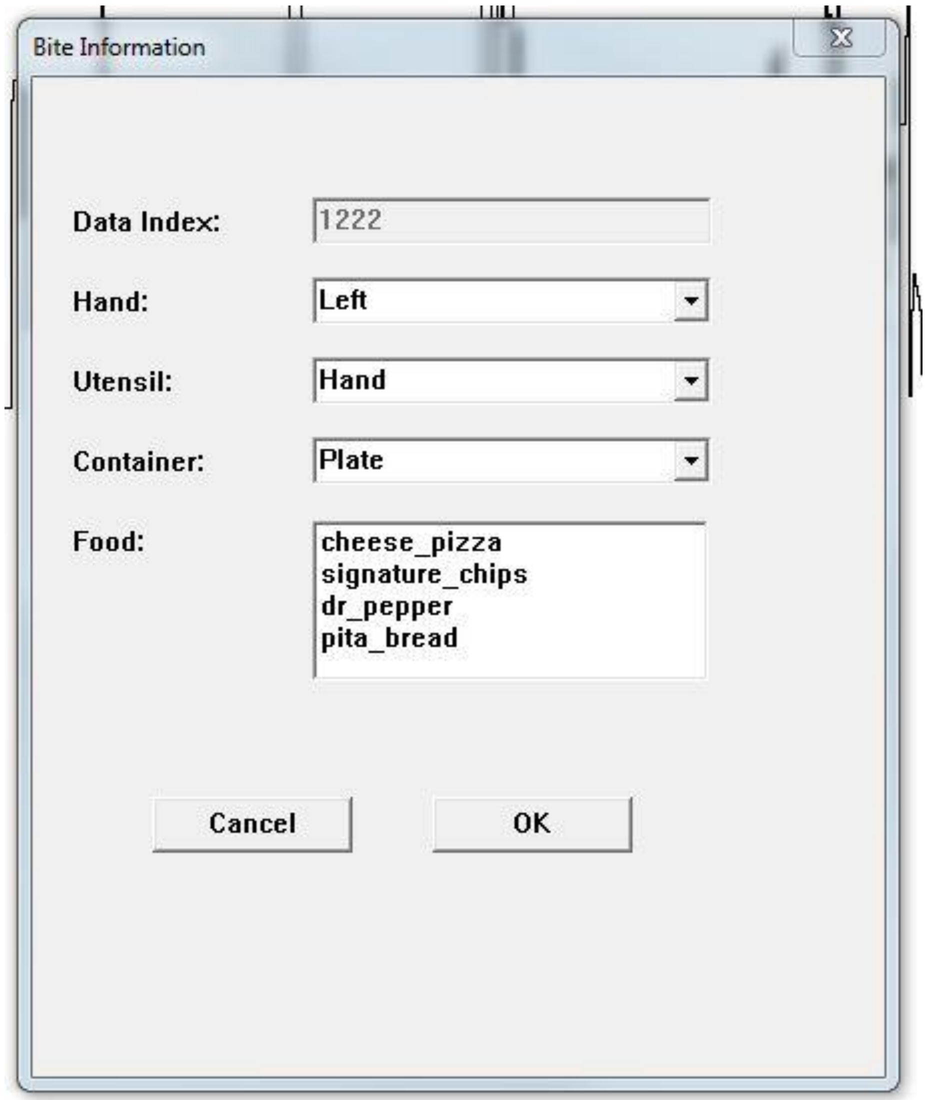


Figure 5: The bite marking dialogue box

6. You’ll notice that participants will often take bites of the same foods without changing hands, utensils, or containers. These are called “bite patterns.” Using the “n” key, you can cycle through recorded bite patterns. Bite patterns are displayed in the lower-right hand corner of the screen. When you press the “m” key, the dialogue box will open up with all of the options selected for the bite pattern that is currently displayed.
7. You can select and move between specific bites using the “<” and “>” keys.
8. You can delete as selected bite using the “Delete” key.

Appendix H

Portion Estimation Protocol

Protocol for Estimating Portion Consumption

1. Open your **Estimation Excel file**.
2. **NOTE**: DO NOT add, delete, or rearrange rows. Once you finish your estimations, your columns will be copied and pasted into a master file, so if you rearrange anything, your estimations will be out of order. If you feel a change needs to be made, add a comment to the Excel file in an appropriate place.
3. Find a food item that currently has no estimation.
4. Login to PARL and download the appropriate **before and after screenshots** if they are available (these will be available if another estimator has already completed this file).
5. If the screenshots are NOT available (or if they aren't working appropriately), perform steps 6 through 12. Otherwise, skip to step 13. (Note: some screenshots have been made, but were made in the wrong format and don't work appropriately. Delete these and perform steps 6 through 12).

Making Screenshots

6. If the screenshots are not available, download the appropriate .m1v video file to your desktop and double click it to open it up. (Note: the best media player for this task is VLC media player. If you don't have it, I suggest you Google, download, and install it; it's free and fast).
7. Maximize the video so that it takes up the full screen and skip ahead until you reach the point where **all the plates are on the tray, but the first bite has not yet been taken**. If any food item is obscured (say, a glass is blocking it), find an earlier spot where all of the food items are visible, but it must be before the first bite is take.
8. VLC Media player has a feature that allows you to create screenshots of whatever is playing in the video. Click "Video" then "Take Snapshot".
9. Rename the screenshot file using the following naming template: **pxxx_cx_screenbefore**
10. Return to the video and skip ahead to the end of the video. Find a point **after the last bite has been taken, but before the plates have been removed**.
11. Repeat steps 7 through 9, except use the following naming template: **pxxx_cx_screenafter**

12. Upload both screenshot files to the appropriate participant folder on PARL (but DON'T delete them from your desktop until after you've made your estimations).

Making Estimations

13. Open both screenshots. Look at the **before** picture and try to make an estimate of the starting portion size for that participant. You'll notice in your excel file that you have a column for "Portion" and a column for "Units." The 'portion' column should only contain numbers, and the 'units' column is where you type the units. For example:

Food Item	**Portion**	**Unit**
pepperoni pizza	2	slices
mashed potatoes	.25	plate
coca cola	.5	glass
grapefruit	.25	grapefruit

14. For all items that are in discreet units, you will label them as the number of discreet units of that item. These items include but are not limited to: cake, hot dogs, sandwiches, cheeseburgers, pizza, chicken fingers, corn dogs, etc. You should record them as "2 | cheeseburgers" or "6 | pieces". Limit units to one word, and use 'pieces' as a default if you're unsure.
15. For all non-discreet items, list them as a decimal of the container that they are in. For example: .80 large bowl, .50 large plate, .25 small plate, .8 glass etc. Use your best judgment on this. Only use a 1 if it is very close to completely full of that item. The following are the ONLY unit words we'll be using for non-discreet items:
    a. Glass
    b. Mug (coffee)
    c. Large Plate (Most plates are "Large Plates")
    d. Small Plate (Usually just for deserts)
    e. Large Bowl (Used for soups/salads)
    f. Small Bowl (Usually just for ice cream or yogurt)
16. Compare the before and after screenshots side by side. An example of this is shown in Figures 1a and 1b.

a. 

b . 

Figure 1: Before (a) and after (b) screenshots used to visually estimate starting portions and portions consumed.

17. Estimate the **percentage of the starting portion that the participant has consumed by the end of the meal.** For example, if the participant had half a glass of coke at the start, and 1/5 of a glass of coke by the end, then that participant consumed **80%** of that item.
18. As you're making your estimates, please make note of the following points:
    a. A fruit is 100% consumed if there is nothing left but rinds or peels.
    b. Do not worry too much about crumbs. For example, if there are a few bread crumbs left from a sandwich, and you're inclined to mark it as 98% consumed, go ahead and mark it as 100% consumed.
    c. Other food debris (e.g. sandwich and pizza crusts) **DO** count, as they are a source of calories. These should be included in your estimations.
19. Type your estimate into the appropriate column in the excel file.

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